# Essays on Consumption Smoothing

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by

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*to my parents and wife for their unconditional love and support throughout the years, and my daughter Cheuk Ning for helping me to dream about our future.*

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## Abstract

This dissertation investigates the consumption smoothing ability of households when they are hit by uninsurable income shocks.

The first chapter investigates what is the true extent of income shocks to individuals, particularly for the female. Previous literature has focused exclusively on the residual uncertainty on male earnings, neglecting the female counterpart. One reason is because the majority of female do not participate in the labor market and focus on home production. Contrary to what is usually assumed in the literature, we model female endogenous participation choice and uncover their residual wage shock using an industry standard permanent and transitory wage model. We find that ignoring their participation decision would lead to a downward biased wage shock. Using our wage shocks estimate, we build a life cycle model to investigate the relationship between female labor force participation and family inequality. Through numerical simulation, we also shed lights on the insurance value provided by female labor supply in smoothing wage shocks. Our results suggest that although increase female labor force participation would lead to more inequality in a household level, female labor supply goes a long way in providing insurance value for smoothing wage shock.

The second chapter contains a succinct literature review of what we know and what do not know for the consumption smoothing and income shocks. In particular, we will review what theory, in particular, the life cycle permanent income hypothesis, has to say about the consumption response to different degree of income shocks. We will then discuss what will happen when we depart from the assumptions in the permanent income hypothesis. The degree of the consumption response to income shocks can help us to understand the interplay between consumption inequality and income inequality. In particular, it can provide us an identification strategy to figure out why and when does consumption inequality has to follow income inequality. Finally, we will discuss some open questions remained in the literature. We will see why income shocks may not be that permanent after all. More importantly, we will see why there is a great

need for the research frontier to look for a parsimonious income process that can on one hand explains the empirical facts and on the other hand robust to alternative identification strategies.

# Contents

# List of Figures

# List of Tables

# Chapter 1

# Female Labor Participation and Family Earnings Inequality

## 1.1 Introduction

Family earnings inequality has increased in the past three decades in the US. Meanwhile, female labor participation has also increased dramatically with male participation staying almost the same. The disproportionate growth in wives' labor participation with high earnings husbands has led to the question:[1] Does female labor participation increase family earnings inequality? And, if so, by how much?

Researchers provide mixed answers to this question. On the one hand, Shorrocks (1983), Lerman and Yitzhaki (1985) and Karoly and Burtless (1995) argue that wives' earnings contribute to family income inequality. On the other hand, Cancian and Reed (1998) and Daly and Valletta (2004) argue the opposite is true. Most of the

[1]See Ryscavage (1979) for an early discussion of the disproportionate increase in the female labor participation with high-earnings husbands.

above studies above use accounting exercises to decompose changes in overall inequality into a set of component parts. The main drawback of this approach is that the component parts may reflect exogenous as well as endogenous changes, but the approach does not make a distinction between them.[2] In this paper, we build a structural model to solve this problem. By doing this, we are able to know how much of the change in inequality of total family earnings is caused by exogenous changes in each source of income.

Our approach to quantify the impact of female labor participation on family earnings inequality involves the following steps. First, following Attanasio, Low, and Sanchez-Marcos (2008), we build a standard life cycle income fluctuation problem in which: (i) there is a household with two potential earners which we call husband and wife; (ii) the couple receives separate wage shocks that are potentially correlated; (iii) the husband always works while the wife can choose whether to work or not; and (iv) there is age-specific fixed costs that influence the labor supply choice by the wife.

Second, solving such a model requires simulation of wages throughout the life-cycle. To do that, we assume a joint wage process for both genders. The only paper that we are aware of that explicitly estimates a joint wage process is Hyslop (2001), and there has not been other studies which challenge or support his result. It is not surprising to see why it is the case. In a recent survey by Heathcote, Storesletten, and Violante (2009), the authors argue,

"*More work is required to uncover the joint process for husband and wife labor market risk, a task complicated by the fact that market wages are not observed for spouses who specialize in home production...*"

The approach used in Hyslop (2001) only focuses on women that participate in the labor force. However, as argued by Krueger, Perri, Pistaferri, and Violante (2010)

[2]For example, to say that changes in mean wives' earnings account for X percent of the change in mean family earnings does not imply that family earnings would have dropped by that percentage if wives' earnings had not changed. Other sources could have responded to the decline in wives' earnings

and shown in our empirical analysis, such an approach can yield biased estimates of the wage process due to selection issue. One of the main contributions of this paper is to explicitly control for this potential bias in our estimation. The estimation procedure goes as follows: we first regress wages of both the husband and wife on a set of observables like education levels, then use the residuals and the methods of moments to obtain estimates of wage shocks variances. Due to the selection issue mentioned above, there can potentially be selection bias in the female wage regression, which leads to biased estimates of the wage shocks' variances and correlations. We follow Meghir, Low, and Pistaferri (2010) to use the two-step approach proposed by Heckman (1979) to correct for the selection bias. Controlling for the selection bias leads to substantial changes in the various estimates: (i) the variance of the female permanent shock increases from 0.017 to 0.031; and (ii) the variance of the female transitory shock increases from 0.033 to 0.058.[3]

Third, we calibrate the age-specific fixed costs using the female labor participation rate over the life-cycle. Using the calibrated fixed costs of participation and the estimated variances of wage shocks, we simulate the model and conduct counterfactual experiments. The main finding is that female labor participation increases inequality, both in terms of family earnings and consumption. In particular, if all wives do not participate in the labor market, the variance of log family earnings growth and the variance of log consumption growth drop by 30% and 60%.

This paper focuses on quantifying the impact of female labor participation on family earnings inequality. By doing so, we abstract away from other possible explanations for the rise in earnings inequality in the literature.[4] Moreover, we abstract from other possible factors that could have affected the participation decision of fe-

[3]Although we do not find selection effect will significantly bias the estimates for the correlation of male and female shocks, we do find the correlations for both permanent and transitory shocks are time-varying. This is in contrast to Hyslop (2001), who estimates the correlation of permanent shocks to be 0.15 between 1979 and 1985.

[4]We refer the reader to Gottschalk and Smeeding (1997) for an excellent survey of the literature.

male such as marriage and divorce, or decision to have a kid.

This paper is related to several others. Attanasio, Low, and Sanchez-Marcos (2008) uses a similar model to explain the increase in labor participation of mothers between 1940s and 1950s cohorts. Our work also shares some similarities with the literature that highlights the self-insurance role provided by the labor supply (Low (2005), Floden (2006), Pijoan-Mas (2006) and Heathcote, Storesletten, and Violante (2010)). However, we focus primarily on the labor supply decision on the extensive margin (whether to participate in the market), rather than on the intensive margin (how many hours to work) as in the aforementioned papers. This choice is primarily driven by the fact that most of the heterogeneity in hours worked is accounted for by movement in and out of employment by workers, which is especially true for female workers. (Chang and Kim (2006), Attanasio, Low, and Sanchez-Marcos (2008)) The closest paper that is related to our work is Attanasio, Low, and Sanchez-Marcos (2005). They discuss the role that female participation can play as an insurance mechanism against shocks to future earnings. The most important difference between our paper with theirs is we also focus on the consumption insurance and smoothing implication from the female labor force participation channel.

The rest of the paper is organized as follows. Section 1.2 provides stylized facts on the increasing family earnings inequality and labor participation rates of both genders to justify our choice to only model female the working decision. Section 1.3 presents the life-cycle income fluctuation model. Section 1.4 discusses the wage process, identification strategy and the estimates of the wage process parameters. Section 1.5 presents the estimates of the calibrated parameters. Section 1.6 quantifies the impact of female labor participation on family income inequality and consumption inequality in various counterfactual experiments. Section 1.7 concludes.

## 1.2 Stylized Facts

In this section, we provide stylized facts to motivate our question by illustrating the potential differences in earnings growth and consumption growth between two groups of household: one with a working wife (dual earner) and another one without (single earner). To justify our choice to only model female labor participation, we provide evidence of participation of both genders, over time and over life cycle.

We borrow the data set from Blundell, Pistaferri, and Preston (2008) for illustrating some stylized facts. The panel data on which Blundell, Pistaferri, and Preston (2008) constructed are in turn based on Panel Survey of Income Dynamics (PSID) and Consumer Expenditure Survey (CEX) between 1978-1992.

### 1.2.1 Inequality: Single vs Dual Earners

Here we define single earners as households in which wives participate less than 10% of the time in the data. And dual earners are households in which wives participate more than 90% of the time in the data. We use the variance of family earnings growth and consumption growth as a measure of inequality.

We calculate the family earnings growth after controlling for some observables like the education levels of both husbands and wives, then compare the variances of these growth between the two groups. The family earnings growth of single earners is more volatile than those of dual earners. As Figure 1.1 shows, the earnings' growth variances of single earners are significantly higher than those of dual earners. On average they are three times higher than the variances of dual earners. The difference of variances is robust under different measures of single and dual earners.

Similarly, we calculate the family consumption growth after controlling for observables, then compare the variances of consumption growth between the two groups. The consumption growth of single earners is also more volatile. Figure 1.2 shows that the consumption growth variances of single earners are higher. The difference is

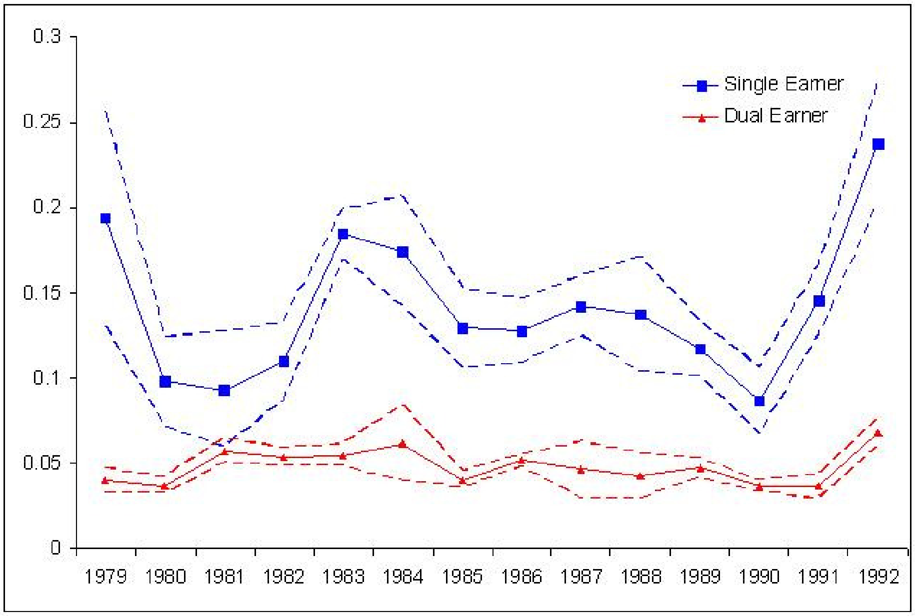


Figure 1.1: Variance of family earnings growth

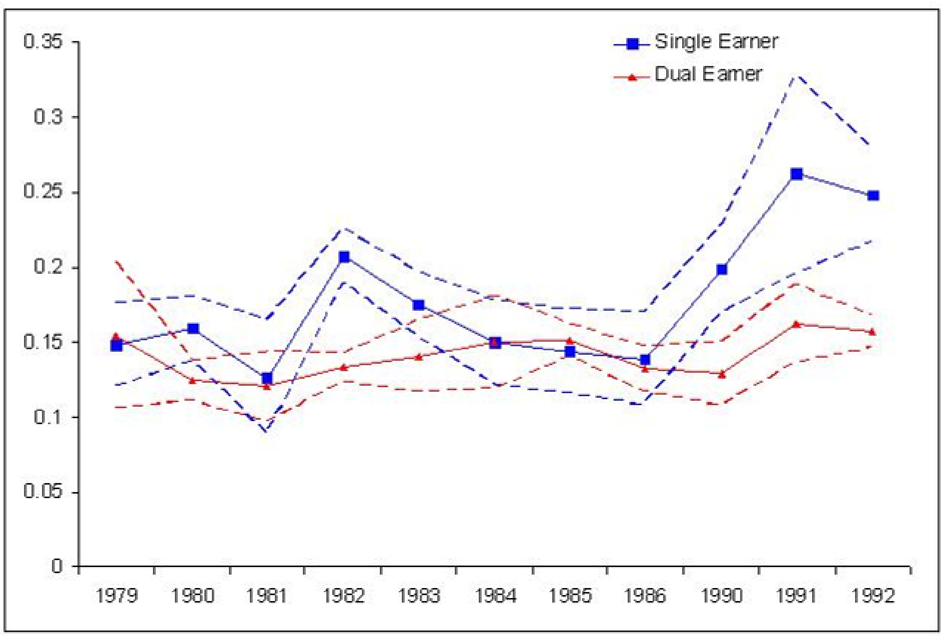


Figure 1.2: Variance of family consumption growth

significant about half of the time over the sample period.

### 1.2.2 Labor Participation Rate: Wife vs Husband

In this paper, we only model wives' participation choice, abstracting away from husbands' participation decision. Other than the computation constraint, it is also because the female participation rate is significantly lower than the male's counterpart in the data.

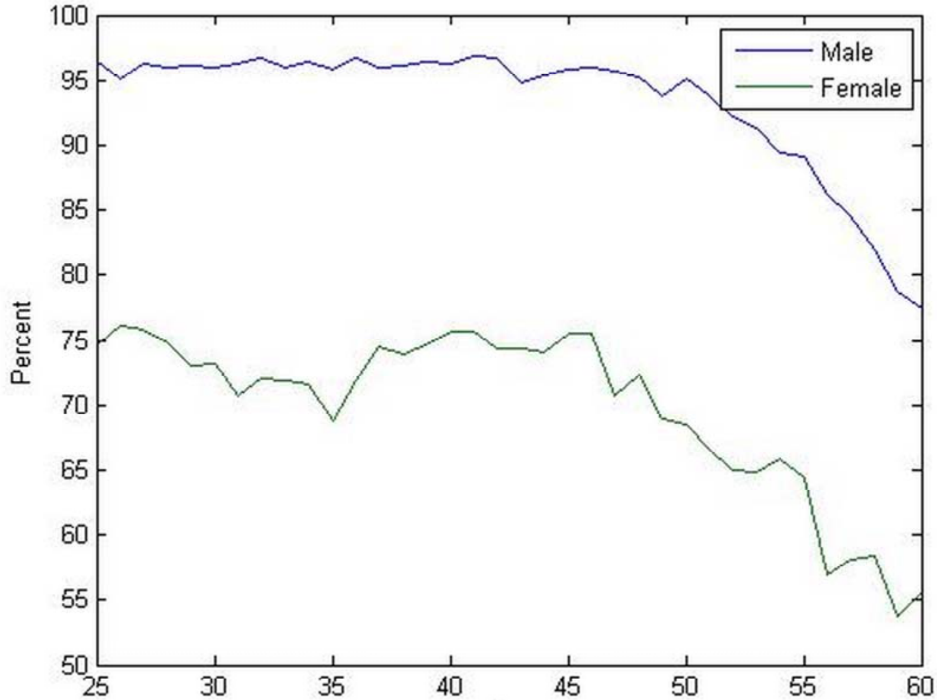


Figure 1.3: Labor participate for male and female over life cycle

We provide evidence on this on both life cycle and time dimension. From a life cycle perspective, figure 1.3 plots the participation rates for both male and female against their life cycle. It shows that the participation rates of female are 20% lower than the male's counterpart throughout the life cycle. While less than 75% of wives participate in the labor market throughout their life, more than 80% (90% if we consider husbands aged below 50) of husbands do.

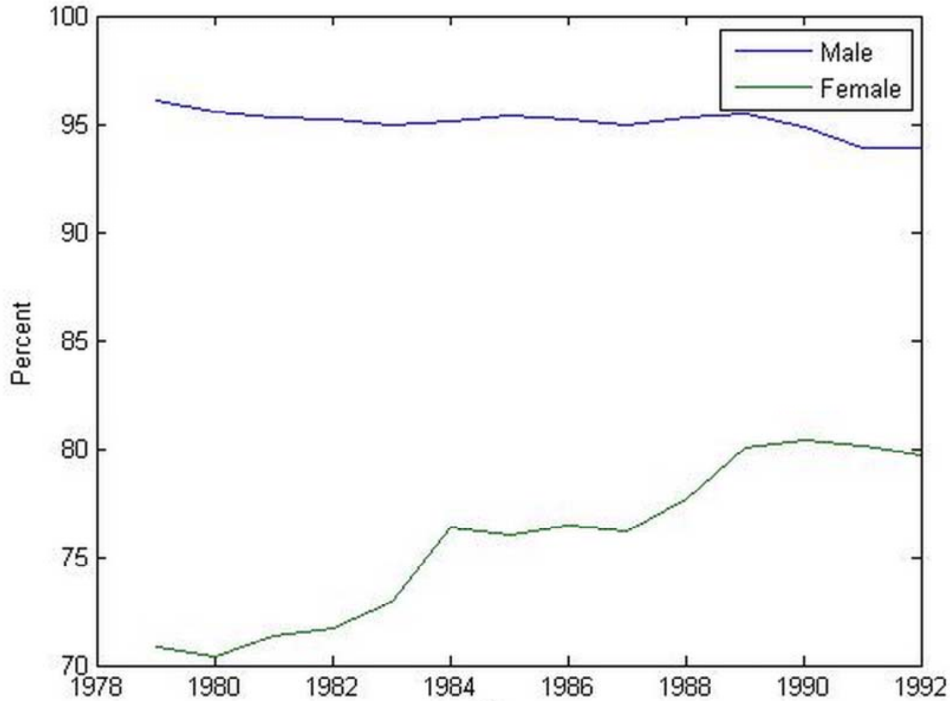


Figure 1.4: Labor participate for male and female over life cycle

Similarly, figure 1.4 compares the participation of the two genders over the years. Even though female participation has increased to about 80% in 1992, it is still significantly lower than the male participation (about 95%).[5] Key takeaways from figures 1.1 to 1.4 are 1) The impact from the increase in income inequality and consumption inequality in the eighties has affected single earner more than dual earner; and 2) Labor participation of female has increased substantially in the same period. In linking up observations 1) and 2) through a structural model with statistical measure of income shocks, it is possible for us to quantify the insurance value provided by the added worker effect.

[5]Figures 1.3 and 1.4 are generated by regressing the gender specific participation rates on a full set of age and time dummies. The estimated coefficients of the dummies are then used to generate the two figures.

## 1.3 Model

The model that we use is a standard life cycle income fluctuation problem with three extra features. First, each household in the model has two potential earners which we called male and female. Second, only female chooses whether to work or not, while male always does. Finally, there is fixed cost of working that would influence the labor supply choice by female. We assume a unitary view of household in which consumption is viewed as a public good. On the other hand, each member within the household may receive different realization from a stochastic wage process introduced later. We assume male and female are of the same age and they maximize expected lifetime utility by choosing consumption, saving and the female labor supply. For simplicity, we assume the they remain married throughout the rest of the lifetime. We also abstract from human capital formulation, fertility and home production for the household. We use fixed cost as a reduced-form approach to capture all of these potential important channel for explaining the labor supply choice for female. Our defense for this choice is our model is not about a theory of labor supply of female, but rather a theory of family earning and hence ultimately, on household consumption. Market is incomplete because of the absence of private insurance market against the wage risk.

We discuss the maximization problem of the household in detail. Household in each period derive utility from household consumption and potential disutility from female labor supply. The instantaneous utility in period $t$ takes the following form

$$u\left(c_t, L_t\right) = \frac{c_t^{1-\gamma}}{1-\gamma} \exp\left(\theta L_t\right)$$

where $c_t$ is the consumption and $L_t$ is a indicator function for the female labor supply. The component for consumption follows a standard constant relative risk aversion utility with risk aversion parameter $\gamma$. The exponential function for $L$ measure the disutility from working with parameter $\theta$. Notice that if $\gamma > 1$ (which is the empirically relevant case), we need $\theta > 0$ so that working reduces the utility. The household lives up period $T$, and dies afterwards leaving no bequest. Let $V_t$ denotes the lifetime utility of the household, we can write down the maximization problem as

$$\max_{c,L} V_t = E_t \sum_{s=t}^{T} \beta^{s-t} u\left(c_s, L_s\right) \tag{1.3.1}$$

subject to

$$A_{t+1} = R\left(A_t + W_t^m + \left(W_t^f - F_t\right) L_t - c_t\right) \tag{1.3.2}$$

and

$$A_{t+1} \geq 0 \tag{1.3.3}$$

where in (1.3.1), $\beta$ is the discount factor and $E_t$ is the expectation operator. (1.3.2) is the intertemporal budget constraint, where $A_t$ are the assets that brought into the beginning of the period, $R$ is the interest rate and $W_t^m$ and $W_t^f$ are the wage income received by husband and wife respectively. Finally, $F_t$ represent the fixed cost of work and it's assumed to be age-dependent. $F$ will capture any important factors for affecting the labor supply decision for the wife other than the wage and asset income. In any given period, households cannot borrow as they face a tight borrowing constraint (1.3.3).

Let $w_t^g = \log(W_t^g)$ denotes the log of wage for gender $g =$\{male,female\}.We assume $w_t^g$ follow a simple permanent-transitory component process and is comprised of three components in logs

$$w_t^g = X_{it}^g \varphi^g + p_t^g + \varepsilon_t^g \tag{1.3.4}$$

where $X_{it}^g$ is a vector of regressors including age, $p_t^g$ and $\varepsilon_t^g$ are the stochastic portions of wage income. $p_t^g$ is a permanent component and $\varepsilon_t^g$ is a transitory component. The permanent component $p_t^g$ in turn follows a random work process[6]

$$p_t^g = p_{t-1}^g + \eta_t^g$$

Each of the shocks $\varepsilon_t^g$ and $\eta_t^g$ follows a joint normal distribution with mean 0 and corresponding variance-covariance matrix $\Sigma_\varepsilon$ and $\Sigma_\eta$ given by

$$\Sigma_\varepsilon = \begin{bmatrix} \sigma^2_{\varepsilon^m} & \rho_\varepsilon \sigma_{\varepsilon^m} \sigma_{\varepsilon^f} \\ \rho_\varepsilon \sigma_{\varepsilon^m} \sigma_{\varepsilon^f} & \sigma^2_{\varepsilon^f} \end{bmatrix} \text{ and } \Sigma_\eta = \begin{bmatrix} \sigma^2_{\eta^m} & \rho_\eta \sigma_{\eta^m} \sigma_{\eta^f} \\ \rho_\eta \sigma_{\eta^m} \sigma_{\eta^f} & \sigma^2_{\eta^f} \end{bmatrix}$$

where $\sigma^2$ denotes the variance of the shock and $\rho$ denotes the correlation coefficient between male and female shock. Other than the potential correlation between male and female, the shocks $\varepsilon_t^g$ and $\eta_t^g$ are orthogonal to each other, and independent over time and across households in the economy.

The state for the household problem consists of asset at the beginning of the period $(A_t)$ and the current wage income by the male and the female $\left(W_t^m, W_t^f\right)$. We can write the dynamic programming problem for the household as

$$V_t\left(A_t, W_t^m, W_t^f\right) = \max_{c_t, A_{t+1}, L_t} u\left(c_t, L_t\right) + \beta E_t\left[V_{t+1}\left(A_{t+1}, W_{t+1}^m, W_{t+1}^f\right)\right]$$

subject to

$$A_{t+1} = R\left(A_t + W_t^m + \left(W_t^f - F_t\right) L_t - c_t\right)$$

with

$$A_{t+1} \geq 0 \text{ and } L_t \in \{0, 1\}$$

The presence of the discrete choice $L_t$ introduces non-convexity to the value function

[6]We make a strong assumption on the persistence of the permanent shocks. In the empirical literature, prominent studies such as Guvenen (2009) offer an alternative approach which emphasis the role of the heterogenous income profile in shaping the persistence of the permanent shocks. However, these studies only focus on a single process of male earning, which is different from the joint process considered in this paper.

which make this problem much more difficult to solve than standard income fluctuation problem. In particular, Euler equation is not enough to characterize the optimal choice as first order condition is not sufficient to the solution of the problem. (See Rios-Rull (1995) for a detailed explanation)

There is no analytical solution to our model. Thanks to the finite nature of our problem, we can start with a terminal condition $V_{T+1} = 0$ and solve the dynamic programming problem recursively through a backward iteration. We tackle the problem of the non-convexity by discretizing our state space and restrict the optimal choice for saving to lie on our assumed grid. Optimal consumption is then backed out from the budget constraint, conditional on the female participation decision. [7]

Despite the lack of analytical solution, we can still look at the intuitions for affecting the female labor participation in this model. Firstly, female that has a lower realization of the female wage will less likely to participate as she cannot cover the fixed cost of participation. Secondly, if the wage between the male and the female are significantly different, then the lower wage female may choose to not to participate and rely on the wage income from the male. Finally, the wealth effect from the accumulation of saving may deter the participation decision as household will rely more on interest income that labor income.

## 1.4 Estimating the Wage Process

### 1.4.1 Data

The PSID data for estimating the wage process are drawn from the 1968-2006 family and individual-merged files. The PSID started in 1968 with an initial sample

[7]The obvious disadvantage of discretization is the curse of dimensionality. In our model, the dimensionality problem is amplified by the assumed permanent-transitory income process. As the income process contains a random walk component, this necessities a lot of grid point for a reasonable discrete approximation of the continuous random walk process.

of approximately 5,000 households. Of these, roughly 3,000 households were representative of the US population (the SRC sample), and about 2,000 were low-income families (the SEO sample). Thereafter, both the original families and their split-offs (children of the original family who form their own families) have been followed. The survey was annually administered between 1968 to 1996, and after that, it had been switched to an biennual basis. In the PSID all the survey answers are retrospective. In our sample, we focus on families with a male head and discard those experience changes in membership of the head or the wife. We also exclude the SEO sample to make our result comparable to the existing studies. Our primary income measure is hourly wage, constructed by dividing the reported labor income by the annual hours of work. [8] We keep couples with age between 25 and 60 to avoid issues related to retirement. Households with the male hourly wage below half of the minimum wage, and working hour below 260 per year are also discarded in order to reduce implausible outliers at the bottom of the wage distribution. It is important to note that the hourly wage and working hours restriction are only applicable to male only, and we do not impose any restriction to the female other than the age restriction. The final sample used in our estimation is composed of 2,927 families with 25,332 family-year observations.

In the permanent transitory wage process (1.3.4), we need to identify gender specific permanent and transitory shocks ($\sigma_\eta^g$, $\sigma_\varepsilon^g, g = \{m, f\}$), and the correlation of the permanent shocks ($\rho_\eta$) and transitory shocks($\rho_\varepsilon$) between the husband and wife. Typically, the econometrician will regress log wage on observable captured by the term $X_{it}^g$ in (1.3.4) and construct sample moments from the residuals of that regression for inferring the shocks. As a result, any bias or misspecification incurred in the first stage regression will pass to residuals and affect the subsequent inference. In the context of modeling the wage risks faced by the female, a first complication is selection

[8]Labor income in the PSID includes all income from wages, salaries, commissions, bonuses, overtime and the labor part of self-employment income. Annual hours of work includes working hours for main job, plus other extra jobs and the overtime.

effects due to non-participation. Wages are not observed for non-participants, and non-participation depends on wages. Krueger, Perri, Pistaferri, and Violante (2010) argue such selection effect would bias the estimate of the variances of offered wages when participation decision is endogenous. As for those female who are not working do not have a wage, estimating the variance using only those who work will bias the true variance downward. The reason is simple, since around 20-30% of female do not participate, not including them in the sample is like cutting left tail of the offered wage distribution. The consequence of that would give us an impression that female wage are not that different. One possible approach to control for the potential bias is to write a reduced form model of participation. (Heckman (1979)) Since male participation has been above 95%, we only model the participation of female:

$$M_{it}^* = X_{it}^f \varphi^f + B_{it}\vartheta + \pi_{it} \tag{1.4.1}$$

where $M_{it}^*$ is the utility from participation, and we observe the indicator $M_{it} = \mathbf{1}\{M_{it}^* > 0\}$. Here $B_{it}$ is a vector of exclusion restrictions, which is also referred as selection variables in the literature. We pick unearned income (proxy by transfers from others) and house value as the exclusion restrictions in our model. They serves as an proxy for the wealth effect that would affect the female to work, but it would not affect the female wage, conditional on $X_{it}^f$. Let us denote $s_{it} = X_{it}^f \varphi^f + B_{it}\vartheta$. The unobserved "taste for work" $\pi_{it}$ is correlated with the permanent component $p_{it}$:[9]

$$\begin{bmatrix} \pi \\ p^f \end{bmatrix} \sim N \left[ \mathbf{0}, \begin{bmatrix} 1 & \rho_{\pi p^f} \\ \rho_{\pi p^f} & \sigma_{p^f} \end{bmatrix} \right] \tag{1.4.2}$$

Making use of (1.3.4), (1.4.1) and (1.4.2), we can compute the wage for female labor

[9] We assume there is no correlation between participation shock and transitory shock. Our stance is that transitory shock may not have much to do with participation decision. As shown in Meghir and Pistaferri (2004), it is impossible to identify measurement error and transitory shock separately, it's not clear whether the decision to participate is due to genuine measurement error of wage or a transitory wage shock.

participants as:

$$E[w^f_{it}|M^*_{it} > 0, X^f_{it}, B_{it}] = X^f_{it}\varphi^f + E[p_{it}|M^*_{it} > 0, X_{it}, B_{it}] \quad (1.4.3)$$
$$= X^f_{it}\varphi^f + \rho_{\pi p^f}\lambda(s_{it})$$

The term is $\lambda(s_{it})$ is the Mill's ratio, which is defined as $\lambda(s_{it}) = \frac{\phi(s_{it})}{\Phi(s_{it})}$ with $\phi(\cdot)$ and $\Phi(\cdot)$ denoting the p.d.f. and c.d.f. of the standard normal distribution respectively. In general ,when there's no selection issue, $E[p_{it}|M^*_{it} > 0, X_{it}, B_{it}]$ would be zero. However, when there is selection, the expectation would be non-zero and if we ignore this fact, the estimate of $\varphi^f$ would not be consistent and so does the residual wage. The idea in Heckman (1979) is to use the participation equation (1.4.1) to control for any factors other than $X^f$ in the first step and break down the term $E[p_{it}|M^*_{it} > 0, X_{it}, B_{it}]$ into a piece called selection term ($\rho_{\pi p^f}\lambda(s_{it})$) and another piece which purely represent random shock with mean zero. [10]

In the second step, we can then estimate

$$w^f_{it} = X^f_{it}\varphi^f + \rho_{\pi p^f}\lambda(s_{it}) + v_{it}$$

only on those female who work, with $E[v_{it}|M^*_{it} > 0, X^f_{it}, B_{it}] = 0$.

### 1.4.2 Identification

In this section, we explain the identification of the wage process described above. As mentioned earlier, after 1996 (survey year 1997), the data frequency of PSID goes from annual to biennual and it becomes challenging to estimate the model using the entire data series. In the rest of this section, we will follow Heathcote, Perri, and Violante (2010) to compute moments using a two year lag. In doing so, this would ensure consistency between the first part of the sample (i.e.,from 1968 to 1996) with

[10] That's the reason why in (1.4.3), the shock would disappear after taking expectation.

the second part of the sample (i.e. from 1998 onwards). In the appendix, we will trim the data sample by only focusing the first part of the sample to discuss the identification strategies and estimation in the annual case.

To identify the variance of the wage shocks, we can define the adjusted residuals as $\Delta^2 w_{it}^g = w_{it}^g - w_{it-2}^g$. For illustration purpose, it is instructive to discuss the identification for the case when there is no selection bias. Consider the following moment conditions

$$E(\Delta^2 w_{it}^g) = E\left(\eta_t^g + \eta_{t-1}^g + \varepsilon_t^g - \varepsilon_{t-2}^g\right) = 0 \tag{1.4.4}$$

$$\begin{aligned} E[\Delta^2 w_{it+2}^g \Delta^2 w_{it}^g] &= E\left[\left(\eta_{t+2}^g + \eta_{t+1}^g + \varepsilon_{t+2}^g - \varepsilon_t^g\right)\left(\eta_t^g + \eta_{t-1}^g + \varepsilon_t^g - \varepsilon_{t-2}^g\right)\right] \\ &= -\sigma_{\varepsilon_t^g} \end{aligned} \tag{1.4.5}$$

$$\begin{aligned} E(\Delta^2 w_{it}^g \Delta^2 w_{it}^g) &= E\left[\left(\eta_t^g + \eta_{t-1}^g + \varepsilon_t^g - \varepsilon_{t-2}^g\right)\left(\eta_t^g + \eta_{t-1}^g + \varepsilon_t^g - \varepsilon_{t-2}^g\right)\right] \\ &= \sigma_{\eta_t^g} + \sigma_{\eta_{t-1}^g} + \sigma_{\varepsilon_t^g} + \sigma_{\varepsilon_{t-2}^g} \end{aligned} \tag{1.4.6}$$

Equation (1.4.4) states that the mean of the residuals is zero, due to the mean zero assumption of the shocks. This condition is only true where is no selection bias. Due to the assumption of the the orthogonality of the shocks and the serial independence of the shocks, equations (1.4.5) and (1.4.6) will identify the variance of transitory and permanent shocks respectively. The first set of moments (1.4.5) identifies $\sigma_{\varepsilon_t^g}$ for $t = 1969, ...., 1994, 1996, 1998, 2000, 2002, 2004$.Then, given estimates for $\sigma_{\varepsilon_t^g}$, the second set of moments (1.4.6) identifies $\sigma_{\eta_t^g} + \sigma_{\eta_{t-1}^g}$ for $t = 1971, ..., 1994, 1996, 1998, 2000, 2002, 2004$.[11]

Equations (1.4.4) to (1.4.6) are gender specific. That means the knowledge of the

[11] As suggested by Heathcote, Perri, and Violante (2010), one can use more moments to identify more parameters in the early part of the sample where PSID was administered annually. In the appendix, we illustrate such approach and show that it has no apparent difference in the estimated trend for permanent and transitory shocks.

variance and covariance structure of residual wages for each gender is sufficient to obtain estimates for the variances of permanent and transitory shocks for that particular gender. On the contrary, the covariance structure between male and female is required for the identification of the correlation coefficients between variances of permanent and transitory shocks. To see this, consider the following moment conditions

$$\begin{aligned} E[\Delta^2 w^m_{it+2}\Delta^2 w^f_{it}] &= E\left[\left(\eta^m_{t+2}+\eta^m_{t+1}+\varepsilon^m_{t+2}-\varepsilon^m_t\right)\left(\eta^f_t+\eta^f_{t-1}+\varepsilon^f_t-\varepsilon^f_{t-2}\right)\right] \\ &= -\rho_{\varepsilon_t}\sqrt{\sigma_{\varepsilon^m_t}\sigma_{\varepsilon^f_t}} \end{aligned} \tag{1.4.7}$$

$$\begin{aligned} E(\Delta^2 w^m_{it}\Delta^2 w^f_{it}) &= E\left[\left(\eta^m_t+\eta^m_{t-1}+\varepsilon^m_t-\varepsilon^m_{t-2}\right)\left(\eta^f_t+\eta^f_{t-1}+\varepsilon^f_t-\varepsilon^f_{t-2}\right)\right] \\ &= \rho_{\eta_t}\sqrt{\sigma_{\eta^m_t}\sigma_{\eta^f_t}}+\rho_{\eta_{t-1}}\sqrt{\sigma_{\eta^m_{t-1}}\sigma_{\eta^f_{t-1}}}+\rho_{\varepsilon_t}\sqrt{\sigma_{\varepsilon^m_t}\sigma_{\varepsilon^f_t}}+\rho_{\varepsilon_{t-2}}\sqrt{\sigma_{\varepsilon^m_{t-2}}\sigma_{\varepsilon^f_{t-2}}} \end{aligned} \tag{1.4.8}$$

Given estimates for $\sigma_{\varepsilon^m_t}$ and $\sigma_{\varepsilon^f_t}$, the first set of moments (1.4.7) identifies the correlation coefficient for transitory shocks $\rho_{\varepsilon_t}$ for $t = 1969, ...., 1994, 1996, 1998, 2000, 2002, 2004$.[12] Similarly, the second set of moments (1.4.8) identifies the correlation coefficients $\rho_{\eta_t}+\rho_{\eta_{t-1}}$ for $t = 1971, ..., 1994, 1996, 1998, 2000, 2002, 2004$.

With the selection effect, the identification scheme become more involved. Consider the same set of moments that we used to identify the variance of the shocks, but only on those female who works in period $t$ and $t-2$ :

$$E(\Delta^2 w^g_{it}|M_t = M_{t-2} = 1) = \rho_{\pi\eta^g}\lambda(s_{it}) + \rho_{\pi\eta^g}\lambda(s_{it-1}) \tag{1.4.9}$$

$$E[\Delta^2 w^g_{it+2}\Delta^2 w^g_{it}|M_t = M_{t-2} = 1] = -\sigma_{\varepsilon^g_t} \tag{1.4.10}$$

[12] In general, the correlation coefficients are overly identified. Switching the gender in the moment conditions would lead to the same estimates. For example, one can show that $E[\Delta^2 w^f_{it+2}\Delta^2 w^m_{it}] = E\left[\left(\eta^f_{t+2}+\eta^f_{t+1}+\varepsilon^f_{t+2}-\varepsilon^f_t\right)\left(\eta^m_t+\eta^m_{t-1}+\varepsilon^m_t-\varepsilon^m_{t-2}\right)\right] = -\rho_{\varepsilon_t}\sqrt{\sigma_{\varepsilon^m_t}\sigma_{\varepsilon^f_t}}$ can also identify $\rho_{\varepsilon_t}$, given the knowledge of $\sigma_{\varepsilon^m_t}$ and $\sigma_{\varepsilon^f_t}$.

$$E(\Delta^2 w_{it}^g \Delta^2 w_{it}^g | M_t = M_{t-2} = 1) = \sigma_{\eta_t^g} + \sigma_{\eta_{t-1}^g} + \sigma_{\varepsilon_t^g} + \sigma_{\varepsilon_{t-2}^g} - \rho^2_{\pi\eta^g}\lambda(s_{it})[s_{it} + \lambda(s_{it})] - \rho^2_{\pi\eta^g}\lambda(s_{it-1})[s_{it-1} + \lambda(s_{it-1})] \quad (1.4.11)$$

These expectations are conditional because we only observe wage growth for those female who work in both period. Compared to the no-selection case, equation (1.4.9), which concerns with the mean of the residuals, is no longer equal to zero. It has to include any potential bias that come with selection. These biases, in turn, are captured by the correlation coefficient between the permanent shock and the unobserved taste for work ($\rho_{\pi\eta^f}$) and the mills ratio term induced by the selection term $\lambda(s_{it})$.[13] As we only model selection effect for permanent shocks, equation (1.4.10), which is used for identifying the variance of transitory shocks, is the same as equation (1.4.5) in the no selection case. As a result, this moment condition identifies $\sigma_{\varepsilon_t^g}$ for $t = 1969, ...., 1994, 1996, 1998, 2000, 2002, 2004$.Finally, equation (1.4.11) is the variance of the residuals. It states that once we have controlled for the biases induced by the selection problem, given the knowledge of $\sigma_{\varepsilon_t^g}$, it identifies $\sigma_{\eta_t^g} + \sigma_{\eta_{t-1}^g}$ for $t = 1971, ..., 1994, 1996, 1998, 2000, 2002, 2004$.

Due to the change in the data frequency after 1996, we need to make one extra assumption for identification as we don't know the average participation decision of the female in the missing year. In other worlds, $s_{it-1}$ and $\lambda(s_{it-1})$ are missing for the years after 1996. To circumvent this problem, we assume that such information can be interpolated by its preceding and following participation variables, i.e.

[13] $\rho_{\pi\eta^f}$ is of no direct interest in the estimation of wage shocks.

$$
\begin{aligned}
s_{it-1} &= \hat{s_{it-1}} \\
&= (s_{it} + s_{it-2})/2 \\
\lambda(s_{it-1}) &= \lambda(\hat{s_{it-1}}) \\
&= (\lambda(s_{it}) + \lambda(s_{it-2}))/2
\end{aligned}
$$

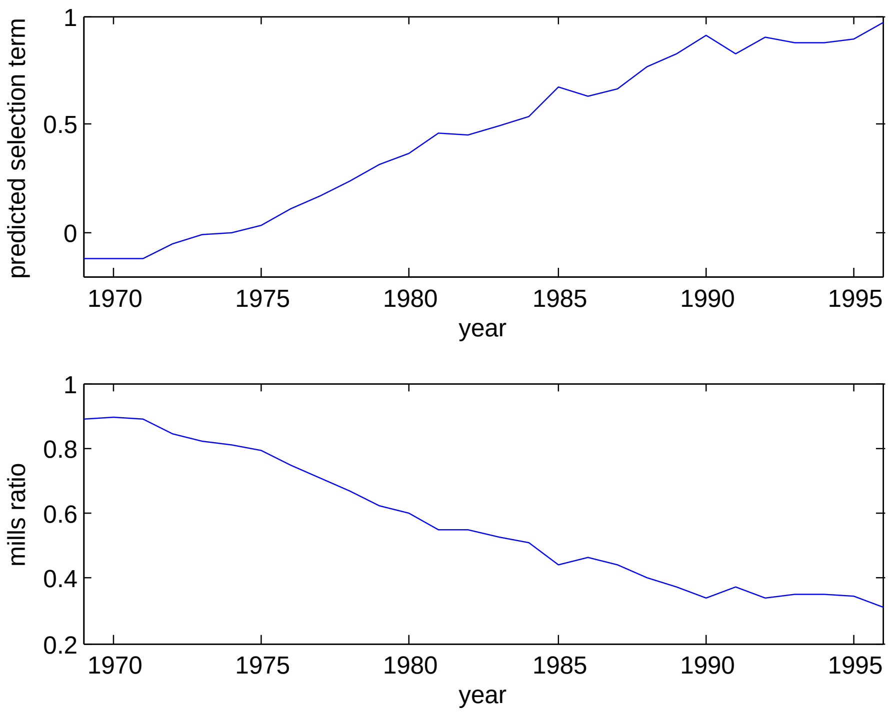


Figure 1.5: Predicted participation controls and mills ratio between 1969 to 1996

The validity of the assumption depends on whether the time series of the Mill's ratio $\lambda(s_{it})$ and the participation controls $s_{it}$ is smooth enough. We check this by plotting the mean values of both variables for the years 1969-1996 in which annual data is observed. As figure 1.5 show, the trend for both variables are reasonably smooth over the years.

In a similar fashion, we can use covariance of male and female residuals to identify the correlation coefficient between the shocks. For example, the correlation coefficients for transitory shocks are identified for $t = 1969, ...., 1994, 1996, 1998, 2000, 2002, 2004$ by

$$E[\Delta^2 w^m_{it+2} \Delta^2 w^f_{it} | M_{it} = M_{it-2} = 1] = -\rho_{\varepsilon_t} \sqrt{\sigma_{\varepsilon^m_t} \sigma_{\varepsilon^f_t}} \tag{1.4.12}$$

which is the same as in the case without selection. Once we get the correlation coefficients for transitory shocks, the correlation coefficients for permanent shocks can be identified by

$$E[\Delta^2 w^m_{it} \Delta^2 w^f_{it} | M_{it} = M_{it-2} = 1] = \begin{array}{c} \rho_{\eta_t} \sqrt{\sigma_{\eta^m_t} \sigma_{\eta^f_t}} + \rho_{\eta_{t-1}} \sqrt{\sigma_{\eta^m_{t-1}} \sigma_{\eta^f_{t-1}}} \\ +\rho_{\varepsilon_t} \sqrt{\sigma_{\varepsilon^m_t} \sigma_{\varepsilon^f_t}} + \rho_{\varepsilon_{t-2}} \sqrt{\sigma_{\varepsilon^m_{t-2}} \sigma_{\varepsilon^f_{t-2}}} \\ -\rho_{\pi\eta^f} \rho_{\pi\eta^m} [\lambda(s_{it})(s_{it} + \lambda(s_{it}))] \\ -\rho_{\pi\eta^f} \rho_{\pi\eta^m} [\lambda(s_{it-1})(s_{it-1} + \lambda(s_{it-1}))] \end{array} \tag{1.4.13}$$

which we need to control for the potential effect from the selection.

Moment conditions (1.4.4)-(1.4.8) and (1.4.9)-(1.4.13) are the basis for the estimation for the no selection case and selection case respectively. The estimator we use is a minimum distance estimator that solves the following minimization problem:

$$\min_{\theta} \left[\hat{m} - m(\theta)\right]' W \left[\hat{m} - m(\theta)\right]$$

where $\hat{m}$ and $m(\theta)$ are the vectors of the empirical and theoretical covariances with $\theta$ denoting the vector of parameters, and $W$ is a weighting matrix. Following **?**, it has become a common practice to use the identify matrix, as opposed to the optimal weighting matrix, as the weighting matrix to avoid small sample biases. Standard errors are computed by block bootstrap procedure suggested by **?**, using 500 replications. Bootstrap samples are drawn at the household level with each sample containing the same number of households as the original sample. The standard

Table 1.1: Summary Statistics, PSID 2006 panel

| Variable | Mean | Standard deviation |
|---|---|---|
| Male age | 41.07 | 9.49 |
| Female age | 38.88 | 9.08 |
| Male hourly wage | 14.83 | 18.24 |
| Female hourly wage | 10.55 | 9.73 |
| White male | 0.92 | 0.26 |
| White female | 0.94 | 0.24 |
| % of high education for male | 0.51 | 0.50 |
| % of high education for female | 0.45 | 0.50 |
| No of kids | 1.37 | 1.27 |
| Family size | 3.62 | 1.32 |
| Unearned income | 1031.25 | 3928.01 |
| House value | 85054.61 | 161094.90 |
| Northeast | 0.21 | 0.41 |
| North Central | 0.29 | 0.45 |
| South | 0.32 | 0.47 |

Note: All nominal variables are converted in real terms

errors thus account for serial correlation of arbitrary form, heteroscedasticity, as well as for the fact we use a multistep estimation procedure, preestimated residuals, and selection terms.

### 1.4.3 Estimation Results

We start by estimating the probit for female participation using the PSID data. Table 1.1 lists the summary statistics of the variables that we used in our estimation. Our regressors include a quadratic in age, race dummies, region dummies, year dummies, education dummies, as well as unearned household income and house value, which are used here as the selection variables for participation.

In Table 1.2 we report the results of a simple probit regression for female participation. All exclusion restrictions have correct sign: higher unearned income or house value increases the opportunity cost of work for female, and thus reduce the likelihood for female participation. The effects are statistically significant.

In Table 1.3 we report the estimates of the log wage for both genders. The second and the third columns compare the estimates of female wage process with and without

Table 1.2: Female Participation Probit (std. err.)

| Variable | Coefficient |
|---|---|
| Age | 0.158 (0.009) |
| $\frac{\text{Age}^2}{100}$ | -0.213 (0.011) |
| White | -0.149 (0.059) |
| Black | -0.193 (0.071) |
| Kids | -0.256 (0.018) |
| $\frac{\text{Unearned Income}}{1000}$ | -0.008 (0.002) |
| $\frac{\text{House value}}{100000}$ | -0.030 (0.007) |
| Year dummies | 1058.23(34,0%) |
| Family size dummies | 154.46 (9,0%) |
| Education dummies | 201.80 (2, 0%) |
| Region dummies | 14.16(3,0%) |
| N | 25223 |

Note: For dummies, we report their joint significance, d.f. and p-value

correcting for endogenous selection into work. To illustrate the possibility of potential bias if selection is not controlled for, we focus on the coefficient for the number of kids. Intuitively, having more kids in a family will likely reduce the offered wage rate to the female from a opportunity cost to work argument. In the no selection case, an additional kid reduces the offered wage by only two percentage points whereas the reduction in the offered wage in the selection case is 16 percentage points. The sign of the Mill's ratio suggests positive selection on unobservables, which means people who are out of work tend to be those with bad realization of their permanent component. Since, without selection, the wage loss associated with more kids is attenuated by the fact that those remain at work are higher-than-average permanent income people. The full loss of kids is revealed only after selection is taken into account.

Armed with these results, we use the residuals to the wage equations to estimate the variances and the correlation coefficients of both permanent and transitory components. As illustrated in Section 1.4.2, we take endogenous selection into account.

We first focus on the variances.[14] Figure 1.6 graphs the trend of the variances for permanent and transitory shocks for male. Similar to existing results in the literature,

[14] We only illustrate the trend of the variances of wage shocks in the main text. All our estimates with standard errors are provided in table 1.7 to 1.11 in the appendix.

Table 1.3: The Log Wage Equation (std. err.)

| Variable | Male wage | Female wage w/out selection | Female wage with selection |
|---|---|---|---|
| Age | 0.069 (0.003) | 0.055 (0.004) | 0.139 (0.008) |
| $\frac{\text{Age}^2}{100}$ | -0.065 (0.003) | -0.063 (0.005) | -0.175(0.011) |
| White | 0.053 (0.022) | -0.044 (0.027) | -0.126 (0.028) |
| Black | -0.156 (0.026) | -0.112 (0.031) | -0.013 (0.032) |
| Kids | 0.021 (0.007) | -0.023 (0.008) | -0.161 (0.015) |
| Mills ratio | | | 1.131 (0.099) |
| Year dummies | Yes | Yes | Yes |
| Family size dummies | Yes | Yes | Yes |
| Education dummies | Yes | Yes | Yes |
| Region dummies | Yes | Yes | Yes |
| N | 25262 | 17190 | 17190 |

there is a sharp increase for the estimated variance for permanent shocks in the early 1980s, and then gradually trend down in the later part of the sample.[15] For transitory shocks, similar to the findings by Heathcote, Perri, and Violante (2010), the estimated variance for transitory shocks shows a steady increasing trend throughout the sample period. In survey year 1993, the PSID has changed its interview method from manual to automated telephone interviewing and typically it would add to the presence of measurement errors. As argued elsewhere (Meghir and Pistaferri (2004)), wage data alone is insufficient to distinguish between the variance of a genuine transitory shock from that of a pure measurement error. However, the continued increase in the estimated variance of transitory shocks suggested the impact of measurement errors may not be substantial, suggesting the increasing trend reflects genuine increase in transitory variance. The key takeaways from the trend of permanent and transitory variances for male wage suggest that the majority of the increase in residual wage inequality between 1967 and 2004 was transitory nature.

Turning our focus to the female case, figure 1.7 shows the trend of permanent and transitory variances for female, with and without control for the selection effects. The overall time trends in the permanent and transitory variances are somewhat similar

[15] At each date $t$, the plotted variance of the permanent shocks is $(\sigma_{\eta_t^g} + \sigma_{\eta_{t-1}^g})/2$

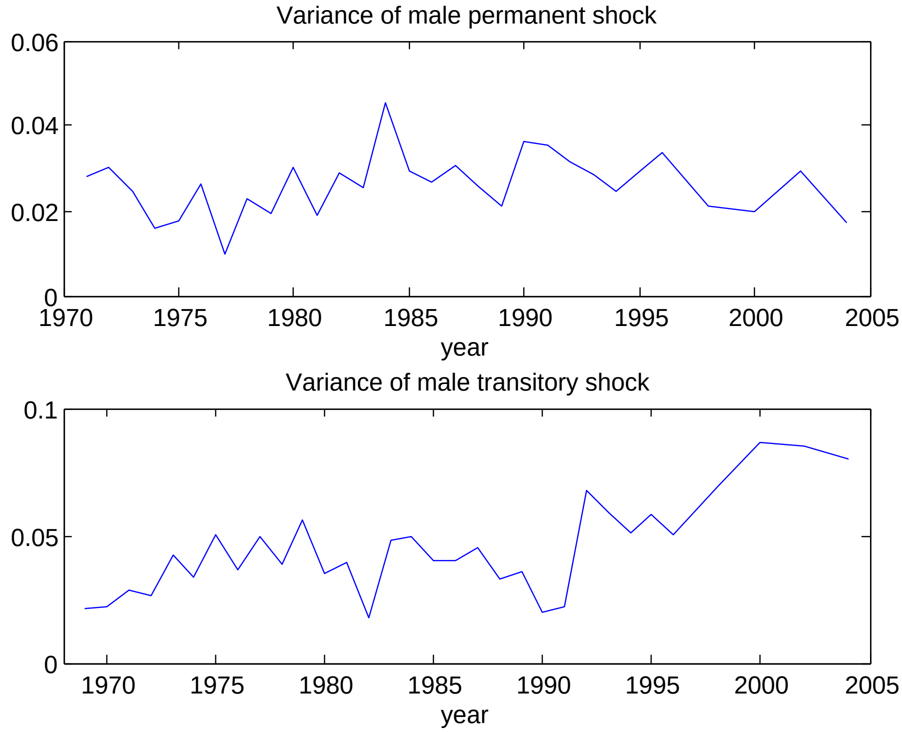


Figure 1.6: Variance of male wage shock

regardless of whether selection is controlled. For example, we can see the variance for permanent shocks for female increases steadily throughout the sample period, contrary to a more stable trend of permanent variances for the male counterpart. This may be due to the fact that the traditional division of labor in the family disadvantages women in the labor market as women devote substantially more time and effort to housework and have less time and effort available for performing market work. Although we have controlled for endogenous selection into work, we make no distinction whether the female is working full time and part time. [16] Furthermore, the endogenous selection of having a kid (i.e. having maternity leave) is not controlled in our wage estimation. As a result, those female who are pregnant to drop the labor force and re-enter labor after several years may be count as having substantial wage

[16]In our sample selection, we do not impose hours work restrictions for female.

shocks in our permanent-transitory wage model. However, this reasoning may suggest we may risk at biased the level of the variances upward, but not in its trend. Taking at face values, our estimation suggests the impact of permanent variances has played an increasing role for understanding the wage dynamics for female.

Shifting our focus on the transitory variances for female, we see that the increasing trend is less obvious when compared to the male case, suggesting again the primary cause of the increase in female wage inequality is due to high permanent uncertainty. Regarding the possibility of measurement errors when the PSID changed the interviewing procedure, we notice there is a sharp increase in the estimated transitory variances around 1992-1993, but then edged down quickly afterwards, suggesting we should be cautious in interpreting the transitory variances of wage estimates in 1992-1993 due to the impossibility in separating out true transitory shocks from measurement errors when one only look at wage data.

For both permanent and transitory variances, there is a huge drop in the level of variance estimates when selection is not taken into account, since the wage data of almost 40% of female with bad realization of permanent component are censored. This suggests controlling for selection is necessary for modeling the wage dynamics for female.

Finally, figure 1.8 graphs the correlation coefficients for permanent and transitory variances for our sample. The effect of selection seems to be less important in the covariances between male and female wages as the line for selection estimates parallel to that of no selection estimates. The time series average of the correlation coefficients for permanent and transitory variances are 0.06 and 0.07 respectively,[17] which narrowly supports assortive mating within a household. Hyslop (2001) estimates a similar bivariate process for earnings between 1979 and 1985 using the PSID. His process contains a fixed effect and a persistent component of wages which can be

[17]These are the averages for estimated variances under the selection case. The corresponding figures under the no selection case are 0.04 and 0.06 respectively.

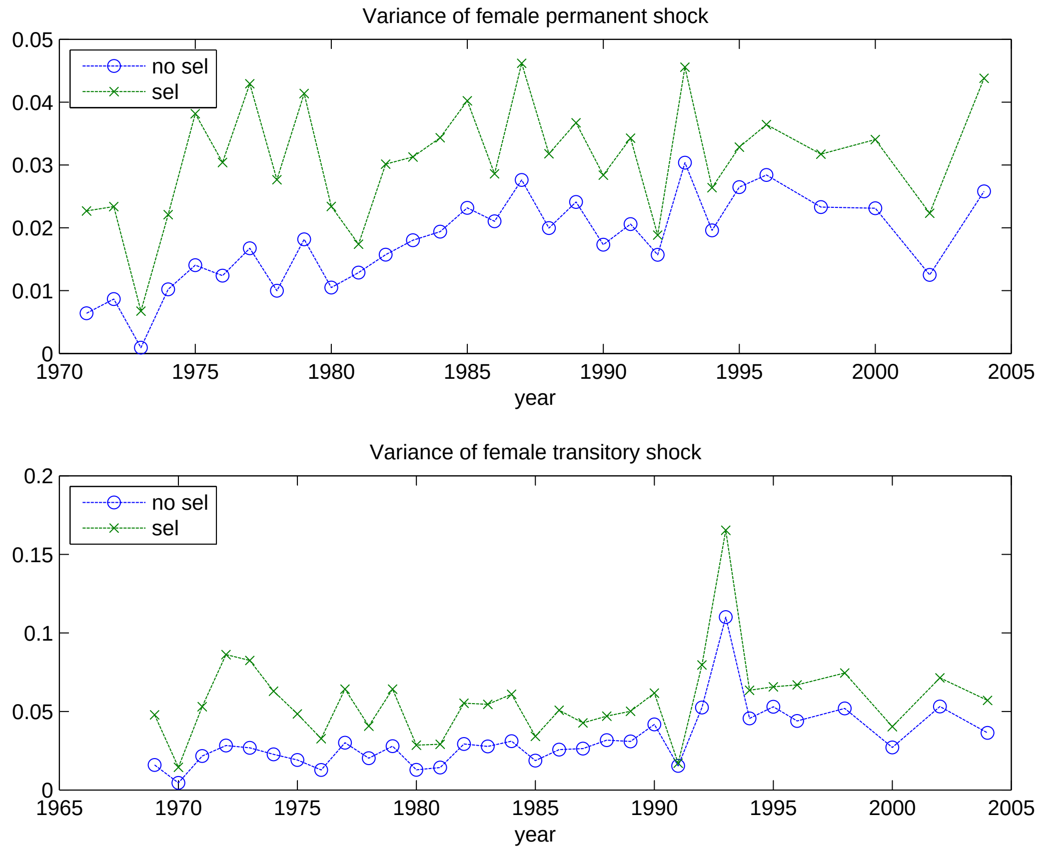


Figure 1.7: Variance of female wage shock

correlated across gender. He finds significant correlation (0.5) for the fixed effect and moderate (0.15) correlation for the persistent component. To facilitate comparison with his result, we calculate the averages of our estimated correlation coefficients for both permanent and transitory shocks for the period between 1979 and 1985 under the no selection case. The sum of the two averages can serve as a proxy for the persistent component used by Hyslop (2001).[18] This would lead to a correlation of 0.15 in our wage process which coincides with Hyslop's estimates. However, our results shown in 1.8 suggest the correlation is potentially non stationary and on a longer-horizon, the long run average may not always be 0.15. Furthermore, our estimates indicate

[18]This is because there is no transitory component in Hyslop's earning process.

the importance of modeling the endogenous selection of work by female, otherwise we may risk at under estimating the true variances for female wage. Our results thus raise concerns on recent calibrated household consumption saving models such as Attanasio, Low, and Sanchez-Marcos (2008) and Heathcote, Storesletten, and Violante (2010), which only rely on the old estimates provided by Hyslop (2001), or assuming the female receive the same level of shocks as male.

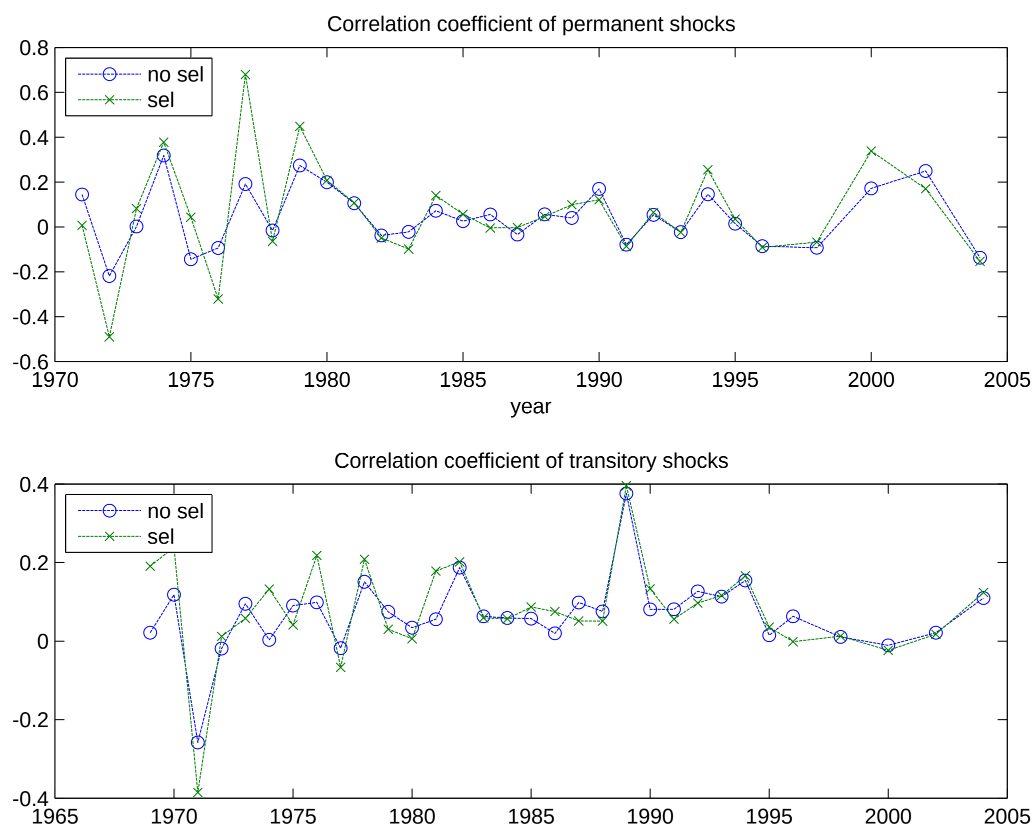


Figure 1.8: Correlation of wage shocks

## 1.5 Calibration

This section describes the parameters that we use for our life-cycle model. A model period is 6 years in real time, and household lives from ages 25 to 60. As a result, the first period in the model corresponds to ages 25-31, the second to 32-38 and so on. The partial equilibrium nature of our life-cycle model allows us to set interest rate (R) and discount factor ($\beta$) separately. Interest rate is set to 4% per year, so that the effective gross interest rate in the model is $1.04^6 \approx 1.27$. Discount factor is set at 0.99 per year, so that the effective discount factor is $0.99^6 \approx 0.94$. Coefficient of relative risk aversion ($\gamma$) is set to 1.5, which is in the reasonable range found in the empirical literature. Age dependent fixed cost ($F_t$) is chosen to match the female labor force participation over life cycle as shown in 1.3. The fit of the calibration is shown in Table 1.4. The disutiltiy for work parameter $\theta$ is set at 0.5. This parameter not only determines whether consumption and female labor supply are substitute or complement, it also affect the participation decision for female in the model. In general, there is an identification problem for $\theta$ and $F_t$ as the substitutability between consumption and labor supply may influence the participate decision for female. In future work, we plan to use both consumption and income data to pin down $\theta$ by exploring the substitutability between consumption and labor supply between single earner and dual earner.

For the variance of wage shocks and their correlation, we simply take the estimate from our wage process and multiply the corresponding estimate by six to adjust for the discrepancy between the actual time period and model period. Table 1.4 shows that the calibration does a reasonably good job in matching the calibrated moments of life-cycle female participation with the data counterpart.

Table 1.4: Calibration of life cycle participation

| Age | Model | Data |
|---|---|---|
| 27 | 0.745 | 0.758 |
| 33 | 0.709 | 0.718 |
| 39 | 0.757 | 0.747 |
| 45 | 0.739 | 0.755 |
| 51 | 0.648 | 0.666 |
| 57 | 0.561 | 0.581 |

Table 1.5: Variance of Family Earnings and Consumption Growth

| | Single Earner | Dual Earner |
|---|---|---|
| Var. of wage growth | 0.94 | 0.57 |
| Var. of consumption growth | 0.88 | 0.31 |

## 1.6 Counterfactuals

Using the estimated variances of permanent and transitory wage shocks for both genders, and the calibrated age-specific fixed costs of working, we can simulate the model and conduct various counterfactual experiments to quantity the impacts of female labor participation on family earnings and consumption inequality. In each of the following counterfactuals, we simulate 10,000 households with equally young husband and wife, and then use the simulated earnings and consumptions to compute various statistics.

### 1.6.1 Single vs Dual Earner

We first compare the variances of the growth of simulated family earnings and simulated consumption of single and dual earners in the benchmark model. We define single earner as households in which wives work less than or equal to two periods, dual earner as households in which wives work more than or equal to six periods. Table 1.5 shows that the variances of both family earnings growth and consumption are higher for single earner, consistent with the stylized facts we document in Section 1.2.

Table 1.6: Shocks Impact on Family Earnings and Consumption Growth

| | Family Earnings Growth | | Consumption Growth | |
|---|---|---|---|---|
| | Single Earner | Dual Earner | Single Earner | Dual Earner |
| $\eta_t^m$ | 0.92 | 0.77 | 0.62 | 0.61 |
| $\varepsilon_t^m$ | 0.99 | 0.74 | 0.47 | 0.34 |
| $\varepsilon_{t-1}^m$ | -1.09 | -0.82 | -0.22 | -0.17 |
| $\eta_t^f$ | 0.16 | 0.30 | 0.14 | 0.22 |
| $\varepsilon_t^f$ | 0.17 | 0.31 | 0.10 | 0.15 |
| $\varepsilon_{t-1}^f$ | -0.21 | -0.35 | 0.05 | -0.05 |
| Constant | 0.09 | 0.05 | 0.40 | 0.44 |

We then regress the family earnings growth and consumption growth on various shocks. The second and third columns of Table 1.6 reports the results of family earnings growth. The response to male's shock is smaller for dual earners, illustrating the added worker effect provided by the extra female labor participation. On the contrary, the response of female wage shocks is larger in the dual earner case because of the base effects from a stronger female wage shocks. One of the key motives for female to participate is by receiving a sufficiently high wage realization that can counter the adverse effect generated by the fixed cost of work. When faced with a larger magnitude of female shocks for the dual earner, it is no wonder why the response of family earning is larger than the single earner case in which the magnitude of female shocks experienced is smaller. For the single earner, even only the male who works inside the family, the fact that his wage realization depends on his spouse realization (because of the correlation of male and female wage shocks) explains why single earners also respond partly to female wage shocks.

The forth and fifth column of Table 1.6 report the impact on consumption growth. The impacts of wage shocks on consumption growth are smaller compared to impacts on earnings growth, due to typical consumption smoothing channel. But similar to the impacts on earnings growth, impact of husband's wage shocks decline in a dual-earner household, while those of wives' wage shocks increase.

## 1.7 Conclusion

Studies, most of them using accounting approach, provide mixed evidence on whether female labor participation increases family earnings inequality. This paper uses a structural approach to quantify the impact of female labor participation on the inequality of family earnings and of consumption.

Our structural approach involves using a standard life-cycle income fluctuation problem to model female labor participation under wage uncertainty. We use the standard permanent-transitory model to model the wage process. Since less than 70% of female in our sample participates in the labor force, there is potential selection bias in the wage process estimation. One of the main contributions of this paper is that we use the two-step approach proposed by Heckman (1979) to control for the selection bias and uncover the time series variances and correlations for male and female permanent and transitory shocks. After controlling for selection bias, we found that although the selection effect do not significantly alter the estimates for correlation, the variances for female wage shocks are severely downward biased. Without a proper account of the wage shocks, any welfare analysis would be misleading.

We calibrate the age-specific fixed costs of participation using the female participation rates over life cycle. Using the calibrated fixed costs of participation and the estimated variances of wage shocks, we simulate the model and conduct counterfactual experiments. Results suggest that although female labor participation increases inequality, there is insurance value of increased female labor force participation for smoothing against income shocks.

In future research, there are two important aspects that we plan to investigate. The first concerns with the estimation of the wage process. In our estimation, similar to the assumption made in the literature, we assume both male and female have a unit root component in their wage process. There are recent evidences, most notably by Guvenen (2009) and Guvenen and Smith (2010), that suggest the true process may not be that permanent and advocate a different process that stress on the importance of the heterogenous income slope. Extending our selection model to such framework would be interesting. Secondly, extending our partial equilibrium structural model to a general equilibrium one with careful modeling of pension and redistributive taxation can provide a framework for investigating the welfare cost of increased wage shocks. Our conjecture is that the extensive margin of labor supply would likely magnify the existing estimates in the literature.

## 1.8 Appendix

### 1.8.1 Estimates of the wage process

We provide all the variance and correlation estimates of the wage process for male and female in our PSID sample from which figures 1.6, 1.7 and 1.8 are based on. Table 1.7 reports the estimates and standard errors for the variances of permanent and transitory shocks for male. Table 1.8 reports the estimates and standard errors for the variances of permanent and transitory shocks for female, controlled for the selection bias. Table 1.9 reports the estimates as in table 1.8, but without controlling for selection. Table 1.10 reports the estimates and standard errors for the correlation coefficients between male and female permanent and transitory shocks, controlling for selection. Finally, table 1.11 reports the estimates as in table 1.10, but without controlling for selection.

Table 1.7: Parameter estimates of wage process for male

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.0210 | 0.0080 |
| 1970 | | | 0.0224 | 0.0063 |
| 1971 | 0.0281 | 0.0060 | 0.0285 | 0.0082 |
| 1972 | 0.0303 | 0.0066 | 0.0268 | 0.0058 |
| 1973 | 0.0246 | 0.0063 | 0.0425 | 0.0085 |
| 1974 | 0.0158 | 0.0046 | 0.0337 | 0.0072 |
| 1975 | 0.0176 | 0.0051 | 0.0506 | 0.0111 |
| 1976 | 0.0265 | 0.0061 | 0.0368 | 0.0073 |
| 1977 | 0.0099 | 0.0051 | 0.0495 | 0.0116 |
| 1978 | 0.0227 | 0.0052 | 0.0386 | 0.0085 |
| 1979 | 0.0194 | 0.0051 | 0.0562 | 0.0182 |
| 1980 | 0.0304 | 0.0051 | 0.0348 | 0.0074 |
| 1981 | 0.0189 | 0.0051 | 0.0394 | 0.0087 |
| 1982 | 0.0290 | 0.0059 | 0.0178 | 0.0071 |
| 1983 | 0.0255 | 0.0053 | 0.0485 | 0.0111 |
| 1984 | 0.0457 | 0.0087 | 0.0495 | 0.0105 |
| 1985 | 0.0292 | 0.0065 | 0.0403 | 0.0084 |
| 1986 | 0.0265 | 0.0047 | 0.0401 | 0.0084 |
| 1987 | 0.0307 | 0.0054 | 0.0451 | 0.0105 |
| 1988 | 0.0261 | 0.0052 | 0.0330 | 0.0060 |
| 1989 | 0.0211 | 0.0046 | 0.0359 | 0.0077 |
| 1990 | 0.0363 | 0.0059 | 0.0200 | 0.0076 |
| 1991 | 0.0354 | 0.0072 | 0.0222 | 0.0085 |
| 1992 | 0.0314 | 0.0072 | 0.0680 | 0.0132 |
| 1993 | 0.0287 | 0.0079 | 0.0589 | 0.0109 |
| 1994 | 0.0245 | 0.0054 | 0.0514 | 0.0122 |
| 1995 | 0.0292 | 0.0048 | 0.0584 | 0.0095 |
| 1996 | 0.0336 | 0.0085 | 0.0505 | 0.0087 |
| 1998 | 0.0210 | 0.0059 | 0.0693 | 0.0121 |
| 2000 | 0.0046 | 0.0055 | 0.0865 | 0.0156 |
| 2002 | 0.0293 | 0.0097 | 0.1253 | 0.0215 |
| 2004 | 0.0170 | 0.0060 | 0.0803 | 0.0120 |

Note: Minimum Distance Estimates of the parameters of the wage process for male. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications. See the main text for details.

Table 1.8: Parameter estimates of wage process for Female with selection

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.0478 | 0.0156 |
| 1970 | | | 0.0144 | 0.0125 |
| 1971 | 0.0227 | 0.013 | 0.0531 | 0.0182 |
| 1972 | 0.0234 | 0.0139 | 0.0862 | 0.0232 |
| 1973 | 0.0068 | 0.0148 | 0.0825 | 0.0375 |
| 1974 | 0.0221 | 0.0110 | 0.0629 | 0.0320 |
| 1975 | 0.0382 | 0.0144 | 0.0484 | 0.0341 |
| 1976 | 0.0304 | 0.0144 | 0.0327 | 0.0102 |
| 1977 | 0.0429 | 0.0170 | 0.0642 | 0.0213 |
| 1978 | 0.0277 | 0.0128 | 0.0407 | 0.0121 |
| 1979 | 0.0414 | 0.0174 | 0.0642 | 0.0146 |
| 1980 | 0.0234 | 0.0104 | 0.0285 | 0.0099 |
| 1981 | 0.0174 | 0.0124 | 0.0291 | 0.0109 |
| 1982 | 0.0301 | 0.0105 | 0.0552 | 0.0127 |
| 1983 | 0.0313 | 0.0102 | 0.0545 | 0.0174 |
| 1984 | 0.0343 | 0.0097 | 0.0609 | 0.0163 |
| 1985 | 0.0402 | 0.0119 | 0.0342 | 0.0108 |
| 1986 | 0.0286 | 0.0106 | 0.0508 | 0.0114 |
| 1987 | 0.0462 | 0.0090 | 0.0427 | 0.0117 |
| 1988 | 0.0318 | 0.0091 | 0.0471 | 0.0150 |
| 1989 | 0.0367 | 0.0092 | 0.0501 | 0.0112 |
| 1990 | 0.0284 | 0.0110 | 0.0617 | 0.0123 |
| 1991 | 0.0343 | 0.0092 | 0.0170 | 0.0121 |
| 1992 | 0.0188 | 0.0072 | 0.0796 | 0.0124 |
| 1993 | 0.0456 | 0.0126 | 0.1653 | 0.0249 |
| 1994 | 0.0264 | 0.0112 | 0.0634 | 0.0192 |
| 1995 | 0.0328 | 0.0056 | 0.0657 | 0.0112 |
| 1996 | 0.0364 | 0.0084 | 0.0669 | 0.0142 |
| 1998 | 0.0317 | 0.0090 | 0.0745 | 0.0179 |
| 2000 | 0.0341 | 0.0094 | 0.0403 | 0.0109 |
| 2002 | 0.0223 | 0.0097 | 0.0714 | 0.0156 |
| 2004 | 0.0438 | 0.0109 | 0.0570 | 0.0138 |

Note: Minimum Distance Estimates of the parameters of the wage process for female with selection. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications. See the main text for details.

Table 1.9: Parameter estimates of wage process for Female without selection

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.0159 | 0.0045 |
| 1970 | | | 0.0045 | 0.0038 |
| 1971 | 0.0064 | 0.0031 | 0.0216 | 0.0062 |
| 1972 | 0.0087 | 0.0031 | 0.0283 | 0.0079 |
| 1973 | 0.0009 | 0.0037 | 0.0268 | 0.0115 |
| 1974 | 0.0102 | 0.0033 | 0.0227 | 0.0118 |
| 1975 | 0.0141 | 0.0042 | 0.0191 | 0.0121 |
| 1976 | 0.0124 | 0.0040 | 0.0127 | 0.0038 |
| 1977 | 0.0167 | 0.0051 | 0.0301 | 0.0084 |
| 1978 | 0.0100 | 0.0026 | 0.0203 | 0.0046 |
| 1979 | 0.0182 | 0.0045 | 0.0279 | 0.0060 |
| 1980 | 0.0105 | 0.0029 | 0.0128 | 0.0045 |
| 1981 | 0.0129 | 0.0055 | 0.0143 | 0.0052 |
| 1982 | 0.0157 | 0.0040 | 0.0293 | 0.0059 |
| 1983 | 0.0180 | 0.0043 | 0.0277 | 0.0092 |
| 1984 | 0.0194 | 0.0046 | 0.0311 | 0.0082 |
| 1985 | 0.0232 | 0.0054 | 0.0187 | 0.0057 |
| 1986 | 0.0210 | 0.0053 | 0.0257 | 0.0062 |
| 1987 | 0.0276 | 0.0047 | 0.0264 | 0.0068 |
| 1988 | 0.0200 | 0.0041 | 0.0317 | 0.0089 |
| 1989 | 0.0241 | 0.0048 | 0.0309 | 0.0067 |
| 1990 | 0.0173 | 0.0042 | 0.0418 | 0.0075 |
| 1991 | 0.0206 | 0.0050 | 0.0153 | 0.0071 |
| 1992 | 0.0157 | 0.0048 | 0.0525 | 0.0083 |
| 1993 | 0.0304 | 0.0073 | 0.1101 | 0.0169 |
| 1994 | 0.0196 | 0.0074 | 0.0456 | 0.0132 |
| 1995 | 0.0265 | 0.0041 | 0.0529 | 0.0081 |
| 1996 | 0.0284 | 0.0061 | 0.0439 | 0.0092 |
| 1998 | 0.0233 | 0.0055 | 0.0519 | 0.0123 |
| 2000 | 0.0231 | 0.0055 | 0.0271 | 0.0070 |
| 2002 | 0.0125 | 0.0058 | 0.0531 | 0.0110 |
| 2004 | 0.0258 | 0.0056 | 0.0363 | 0.0086 |

Note: Minimum Distance Estimates of the parameters of the wage process for female without selection. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications. See the main text for details.

Table 1.10: Correlation coefficients of wage shocks with selection

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.1907 | 0.2312 |
| 1970 | | | 0.2388 | 0.6536 |
| 1971 | 0.0075 | 0.3775 | -0.3854 | 0.3461 |
| 1972 | -0.4894 | 0.7519 | 0.0117 | 0.1758 |
| 1973 | 0.0819 | 0.7166 | 0.0577 | 0.1436 |
| 1974 | 0.3778 | 0.4071 | 0.1324 | 0.1808 |
| 1975 | 0.0436 | 0.4643 | 0.0412 | 0.3010 |
| 1976 | -0.3204 | 0.5038 | 0.2182 | 0.2122 |
| 1977 | 0.6794 | 0.8860 | -0.0668 | 0.1490 |
| 1978 | -0.064 | 0.3798 | 0.2083 | 0.1448 |
| 1979 | 0.4483 | 0.2216 | 0.0300 | 0.1421 |
| 1980 | 0.2080 | 0.1908 | 0.0061 | 0.1795 |
| 1981 | 0.1075 | 0.9471 | 0.1782 | 0.3043 |
| 1982 | -0.0489 | 0.1907 | 0.2018 | 0.4427 |
| 1983 | -0.0982 | 0.2527 | 0.0590 | 0.1474 |
| 1984 | 0.1408 | 0.1302 | 0.0566 | 0.1151 |
| 1985 | 0.0569 | 0.2460 | 0.0869 | 0.1909 |
| 1986 | -0.0039 | 0.1713 | 0.0752 | 0.1402 |
| 1987 | -0.0022 | 0.1374 | 0.0514 | 0.1647 |
| 1988 | 0.0467 | 0.1371 | 0.0510 | 0.1442 |
| 1989 | 0.0990 | 0.1826 | 0.3958 | 0.1489 |
| 1990 | 0.1213 | 0.1478 | 0.1330 | 0.2164 |
| 1991 | -0.0859 | 0.1707 | 0.0558 | 0.5567 |
| 1992 | 0.0650 | 0.2274 | 0.0970 | 0.0893 |
| 1993 | -0.0240 | 0.2033 | 0.1162 | 0.0984 |
| 1994 | 0.2551 | 0.2579 | 0.1663 | 0.1244 |
| 1995 | 0.0355 | 0.1108 | 0.0355 | 0.1108 |
| 1996 | -0.0908 | 0.1769 | -0.0015 | 0.1119 |
| 1998 | -0.0676 | 0.1934 | 0.0125 | 0.0683 |
| 2000 | 0.3383 | 0.5090 | -0.0235 | 0.0987 |
| 2002 | 0.1704 | 0.2286 | 0.0175 | 0.0723 |
| 2004 | -0.1528 | 0.1438 | 0.1235 | 0.0859 |

Note: Minimum Distance Estimates of the correlation coefficients of wage shocks with selection. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications. See the main text for details.

Table 1.11: Correlation coefficients of wage shocks without selection

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.0213 | 0.1957 |
| 1970 | | | 0.1181 | 0.5281 |
| 1971 | 0.1449 | 0.1551 | -0.258 | 0.1116 |
| 1972 | -0.2184 | 0.1638 | -0.0191 | 0.0948 |
| 1973 | 0.0022 | 0.3758 | 0.0949 | 0.1595 |
| 1974 | 0.3185 | 0.1686 | 0.003 | 0.1206 |
| 1975 | -0.1436 | 0.1325 | 0.0905 | 0.1711 |
| 1976 | -0.0937 | 0.1729 | 0.0985 | 0.1243 |
| 1977 | 0.1913 | 0.2966 | -0.0182 | 0.0747 |
| 1978 | -0.0153 | 0.1310 | 0.1509 | 0.1169 |
| 1979 | 0.2742 | 0.1227 | 0.0744 | 0.0973 |
| 1980 | 0.1992 | 0.1210 | 0.0341 | 0.1287 |
| 1981 | 0.1060 | 0.1908 | 0.0554 | 0.1665 |
| 1982 | -0.0378 | 0.1151 | 0.1872 | 0.2222 |
| 1983 | -0.0216 | 0.1155 | 0.0629 | 0.1201 |
| 1984 | 0.0723 | 0.0862 | 0.0586 | 0.0984 |
| 1985 | 0.0262 | 0.1055 | 0.0573 | 0.1465 |
| 1986 | 0.0559 | 0.0979 | 0.0197 | 0.1149 |
| 1987 | -0.0334 | 0.0951 | 0.0981 | 0.1200 |
| 1988 | 0.0565 | 0.1221 | 0.0753 | 0.1052 |
| 1989 | 0.0407 | 0.1241 | 0.3759 | 0.1190 |
| 1990 | 0.1697 | 0.1124 | 0.0807 | 0.1345 |
| 1991 | -0.0785 | 0.1350 | 0.0811 | 0.3231 |
| 1992 | 0.0539 | 0.1410 | 0.1264 | 0.0812 |
| 1993 | -0.0227 | 0.1168 | 0.1133 | 0.0773 |
| 1994 | 0.1458 | 0.1823 | 0.1541 | 0.1159 |
| 1995 | 0.0149 | 0.0852 | 0.0149 | 0.0852 |
| 1996 | -0.0856 | 0.1146 | 0.0629 | 0.1006 |
| 1998 | -0.0921 | 0.2321 | 0.0105 | 0.0651 |
| 2000 | 0.1721 | 0.4342 | -0.0108 | 0.0825 |
| 2002 | 0.2496 | 0.2581 | 0.0213 | 0.0624 |
| 2004 | -0.1371 | 0.1942 | 0.1096 | 0.0644 |

Note: Minimum Distance Estimates of the correlation coefficients of wage shocks without selection. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications. See the main text for details.

### 1.8.2 Estimation using moment conditions computed in one year lag

#### Identification

To deal with the change from annual frequency to biennial frequency after survey year 1997 in the PSID, we use moments computed using a two year lag for estimation in the main text. In this appendix, we will show that this assumption is innocuous in identifying the trend of the variances for male and female. To do so, we focus only on the period between 1968 and 1996 and re-estimate the model using moments computed using one year lag. Our main result that female variances will be biased downward if selection is not controlled for is still valid.

To start with, define the adjusted residuals as $\Delta w_{it}^{g} = w_{it}^{g} - w_{it-1}^{g}$. For illustration purpose, it is instructive to discuss the identification for the case when there is no selection bias. Consider the following moment conditions

$$E(\Delta w_{it}^{g}) = E\left(\eta_t^g + \varepsilon_t^g - \varepsilon_{t-1}^g\right) = 0$$

$$\begin{aligned} E[\Delta w_{it+1}^{g}\Delta w_{it}^{g}] &= E\left[\left(\eta_{t+1}^g + \varepsilon_{t+1}^g - \varepsilon_t^g\right)\left(\eta_t^g + \varepsilon_t^g - \varepsilon_{t-1}^g\right)\right] \\ &= -\sigma_{\varepsilon_t^g} \end{aligned} \tag{1.8.1}$$

$$\begin{aligned} E(\Delta w_{it}^{g}\Delta w_{it}^{g}) &= E\left[\left(\eta_t^g + \varepsilon_t^g - \varepsilon_{t-1}^g\right)\left(\eta_t^g + \varepsilon_t^g - \varepsilon_{t-1}^g\right)\right] \\ &= \sigma_{\eta_t^g} + \sigma_{\varepsilon_t^g} + \sigma_{\varepsilon_{t-1}^g} \end{aligned} \tag{1.8.2}$$

The first set of moments (1.8.1) identifies $\sigma_{\varepsilon_t^g}$ for $t = 1969, ...., 1996$.Then, given estimates for $\sigma_{\varepsilon_t^g}$, the second set of moments (1.8.2) identifies $\sigma_{\eta_t^g}$ for $t = 1970, ..., 1996$. Equations (1.8.1) to (1.8.2) are gender specific. That means the knowledge of the variance and covariance structure of residual wages for each gender is sufficient to obtain estimates for the variances of permanent and transitory shocks for that particular gender. On the contrary, the covariance structure between male and female is required for the identification of the correlation coefficients between variances of permanent and transitory shocks. To see this, consider the following moment conditions

$$\begin{aligned} E[\Delta w_{it+1}^m \Delta w_{it}^f] &= E\left[\left(\eta_{t+1}^m + \varepsilon_{t+1}^m - \varepsilon_{it}^m\right)\left(\eta_t^f + \varepsilon_t^f - \varepsilon_{t-1}^f\right)\right] \\ &= -\rho_{\varepsilon_t}\sqrt{\sigma_{\varepsilon_t^m}\sigma_{\varepsilon_t^f}} \end{aligned} \tag{1.8.3}$$

$$\begin{aligned} E(\Delta w_{it}^m \Delta w_{it}^f) &= E\left[\left(\eta_t^m + \varepsilon_t^m - \varepsilon_{t-1}^m\right)\left(\eta_t^f + \varepsilon_t^f - \varepsilon_{t-1}^f\right)\right] \\ &= \rho_{\eta_t}\sqrt{\sigma_{\eta_t^m}\sigma_{\eta_t^f}} + \rho_{\varepsilon_t}\sqrt{\sigma_{\varepsilon_t^m}\sigma_{\varepsilon_t^f}} + \rho_{\varepsilon_{t-1}}\sqrt{\sigma_{\varepsilon_{t-1}^m}\sigma_{\varepsilon_{t-1}^f}} \end{aligned} \tag{1.8.4}$$

Given estimates for $\sigma_{\varepsilon_t^m}$ and $\sigma_{\varepsilon_t^f}$, the first set of moments (1.8.3) identifies the correlation coefficient for transitory shocks $\rho_{\varepsilon_t}$ for $t = 1969, ...., 1996$. Similarly, the second set of moments (1.8.4) identifies the correlation coefficients $\rho_{\eta_t}$ for $t = 1970, ..., 1996$.

For the case with selection effect, we have to take into account tht potential bias from endogenous selection. Consider the same set of moments that we used to identify the variance of the shocks, but only on those female who works in period $t$ and $t-1$ :

$$E(\Delta w_{it}^g | M_t = M_{t-1} = 1) = \rho_{\pi\eta^g}\lambda(s_{it}) \tag{1.8.5}$$

$$E[\Delta w_{it+1}^g \Delta w_{it}^g | M_t = M_{t-1} = 1] = -\sigma_{\varepsilon_t^g} \tag{1.8.6}$$

$$E(\Delta w_{it}^g \Delta w_{it}^g | M_t = M_{t-1} = 1) = \sigma_{\eta_t^g} - \rho_{\pi\eta^g}^2\lambda(s_{it})[s_{it} + \lambda(s_{it})] + \sigma_{\varepsilon_t^g} + \sigma_{\varepsilon_{t-1}^g} \tag{1.8.7}$$

These expectations are conditional because we only observe wage growth for those female who work in both period. Equation (1.8.5), as in the biennial case, is non-zero in general due to the selection effect for which we have to account for. Equation (1.8.6) allows us to identify the variance of transitory shocks $\sigma_{\varepsilon_t^g}$ for $t = 1969, ...., 1996$. Finally, given the knowledge of $\sigma_{\varepsilon_t^g}$, equation (1.8.7) identifies $\sigma_{\eta_t^g}$ for $t = 1970, ..., 1996$. $\rho^2_{\pi\eta^g}$ is not of direct interest here.

For the correlation coefficients for transitory shocks with selection, the relevant moment condition is

$$E[\Delta w^m_{it+1} \Delta w^f_{it} | M_{it} = M_{it-1} = 1] = -\rho_{\varepsilon_t} \sqrt{\sigma_{\varepsilon_t^m} \sigma_{\varepsilon_t^f}} \tag{1.8.8}$$

which identifies $\rho_{\varepsilon_t}$ for $t = 1969, ...., 1996$. Once we get the correlation coefficients for transitory shocks, the correlation coefficients for permanent shocks can be identified by

$$E[\Delta w^m_{it} \Delta w^f_{it} | M_{it} = M_{it-1} = 1] = \begin{array}{c} \rho_{\eta_t} \sqrt{\sigma_{\eta_t^m} \sigma_{\eta_t^f}} \\ +\rho_{\varepsilon_t} \sqrt{\sigma_{\varepsilon_t^m} \sigma_{\varepsilon_t^f}} + \rho_{\varepsilon_{t-1}} \sqrt{\sigma_{\varepsilon_{t-1}^m} \sigma_{\varepsilon_{t-1}^f}} \\ -\rho_{\pi\eta^f} \rho_{\pi\eta^m} [\lambda(s_{it})(s_{it} + \lambda(s_{it}))] \end{array} \tag{1.8.9}$$

for $t = 1970, ..., 1996$.

### Results

We illustrate the estimation results in the following figures. Figure 1.9 and 1.10 report the trend of the estimated variance of permanent and transitory shocks for male and female. Compared to the biennial identification schemes in the main text, we note that the trend of the variances are fairly similar. For the case of female wage shocks, we notice that there is a substantial difference when selection effect is controlled for. Finally, figure 1.11 reports the correlation coefficients for permanent and transitory shocks with and without selection effect. Apparently, there is no significant difference on whether selection is taken into account.

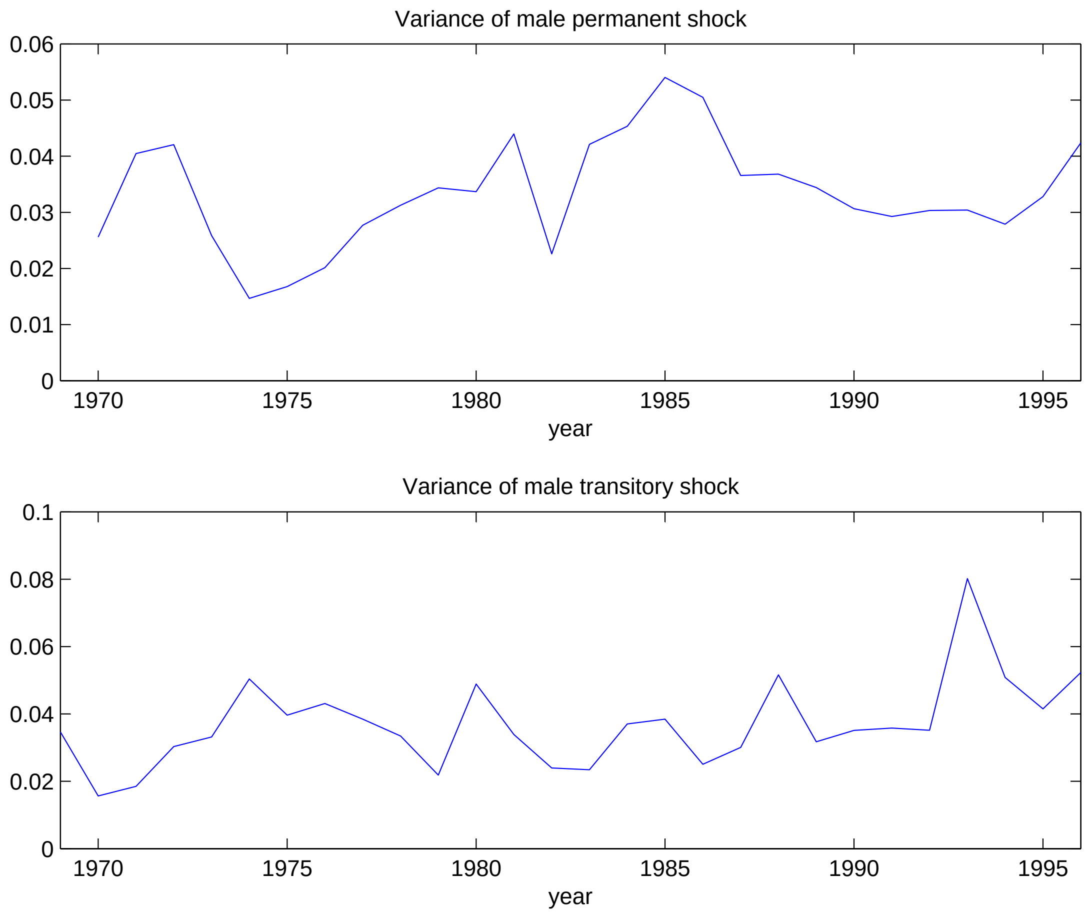


Figure 1.9: Variance of male wage shock (identification based on one year lag moment)

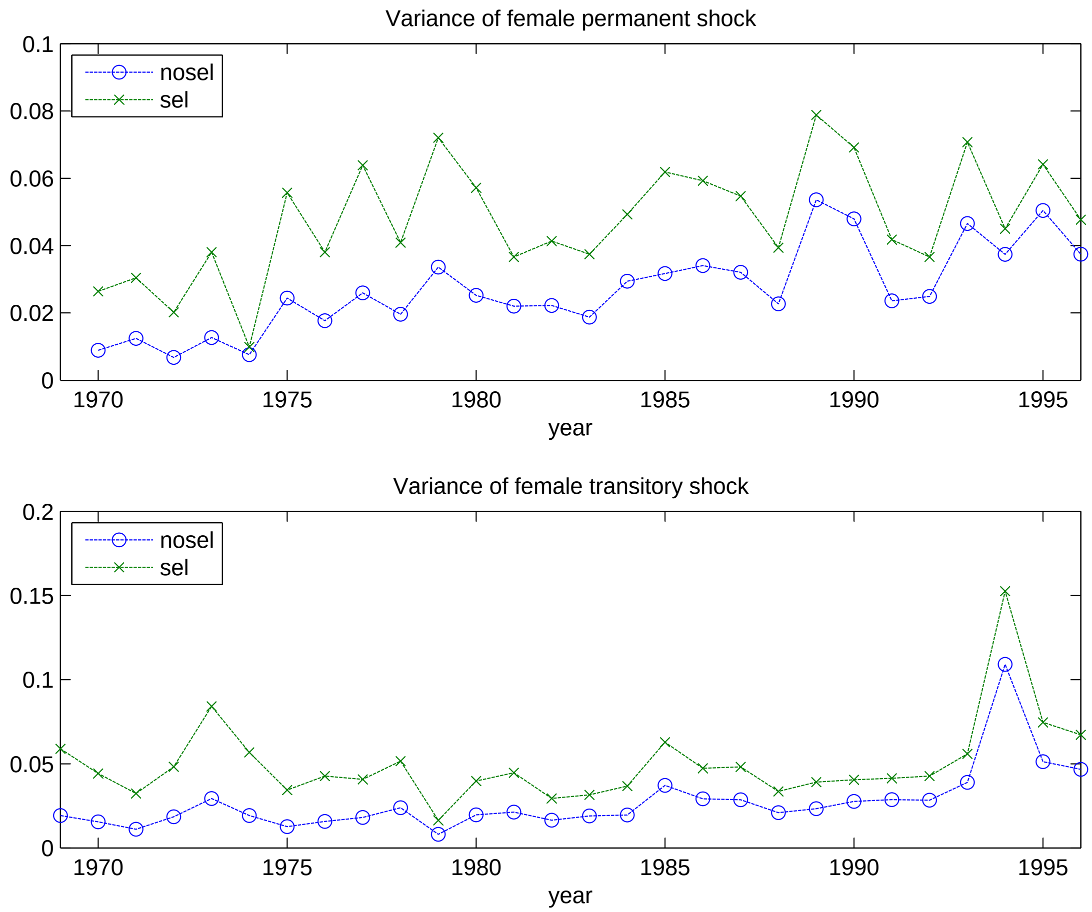


Figure 1.10: Variance of female wage shock (identification based on one year lag moment)

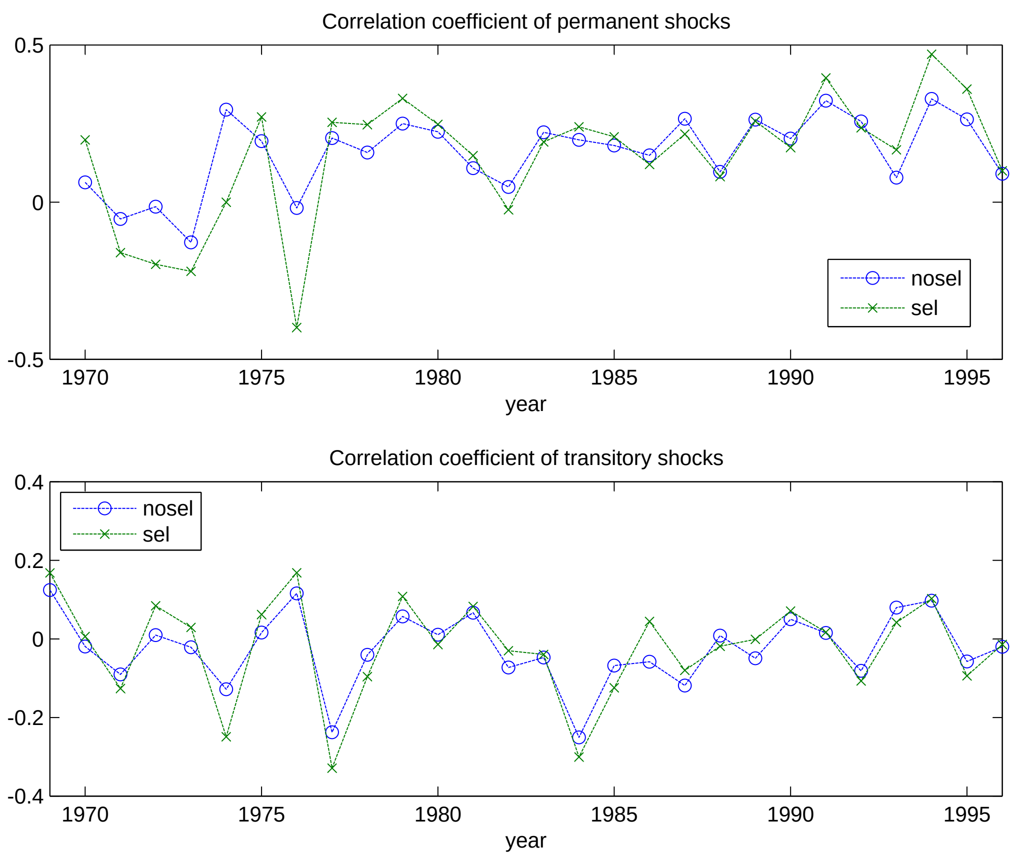


Figure 1.11: Correlation of wage shock (identification based on one year lag moment)

Table 1.12: Parameter estimates of wage process for male 1969-1996, using growth moment of one year lag

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.0346 | 0.0066 |
| 1970 | | | 0.0157 | 0.0052 |
| 1971 | 0.0256 | 0.0076 | 0.0185 | 0.0054 |
| 1972 | 0.0405 | 0.0096 | 0.0303 | 0.0074 |
| 1973 | 0.0420 | 0.0122 | 0.0332 | 0.0077 |
| 1974 | 0.0259 | 0.0085 | 0.0504 | 0.0083 |
| 1975 | 0.0147 | 0.0099 | 0.0396 | 0.0077 |
| 1976 | 0.0168 | 0.0064 | 0.0431 | 0.0093 |
| 1977 | 0.0201 | 0.0069 | 0.0384 | 0.0086 |
| 1978 | 0.0277 | 0.0122 | 0.0335 | 0.0071 |
| 1979 | 0.0312 | 0.0105 | 0.0218 | 0.0068 |
| 1980 | 0.0344 | 0.0086 | 0.0489 | 0.0129 |
| 1981 | 0.0337 | 0.0074 | 0.0339 | 0.0081 |
| 1982 | 0.0440 | 0.0084 | 0.0240 | 0.0057 |
| 1983 | 0.0226 | 0.0074 | 0.0234 | 0.0048 |
| 1984 | 0.0421 | 0.0072 | 0.0370 | 0.0102 |
| 1985 | 0.0453 | 0.0080 | 0.0384 | 0.0087 |
| 1986 | 0.0540 | 0.0118 | 0.0251 | 0.0054 |
| 1987 | 0.0505 | 0.0116 | 0.0301 | 0.0065 |
| 1988 | 0.0366 | 0.0083 | 0.0516 | 0.0140 |
| 1989 | 0.0368 | 0.0102 | 0.0317 | 0.0091 |
| 1990 | 0.0344 | 0.0114 | 0.0351 | 0.0084 |
| 1991 | 0.0307 | 0.0092 | 0.0358 | 0.0080 |
| 1992 | 0.0293 | 0.0081 | 0.0352 | 0.0062 |
| 1993 | 0.0303 | 0.0086 | 0.0802 | 0.0155 |
| 1994 | 0.0304 | 0.0125 | 0.0508 | 0.0078 |
| 1995 | 0.0279 | 0.0104 | 0.0415 | 0.0098 |
| 1996 | 0.0328 | 0.0107 | 0.0523 | 0.0129 |

Note: Minimum Distance Estimates of the parameters of the wage process for male, using growth moments of one year lag. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications.

Table 1.13: Parameter estimates of wage process for female 1969-1996, using growth moment of one year lag, with selection

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.0589 | 0.0121 |
| 1970 | | | 0.0443 | 0.0200 |
| 1971 | 0.0264 | 0.0190 | 0.0324 | 0.0139 |
| 1972 | 0.0305 | 0.0188 | 0.0483 | 0.0132 |
| 1973 | 0.0202 | 0.0165 | 0.0842 | 0.0220 |
| 1974 | 0.0381 | 0.0205 | 0.0568 | 0.0240 |
| 1975 | 0.0099 | 0.0174 | 0.0344 | 0.0118 |
| 1976 | 0.0557 | 0.0296 | 0.0427 | 0.0114 |
| 1977 | 0.0381 | 0.0147 | 0.0408 | 0.0110 |
| 1978 | 0.0639 | 0.0266 | 0.0516 | 0.0138 |
| 1979 | 0.0409 | 0.0175 | 0.0164 | 0.0077 |
| 1980 | 0.0720 | 0.0196 | 0.0398 | 0.0085 |
| 1981 | 0.0572 | 0.0210 | 0.0447 | 0.0125 |
| 1982 | 0.0366 | 0.0135 | 0.0294 | 0.0090 |
| 1983 | 0.0413 | 0.0148 | 0.0315 | 0.0074 |
| 1984 | 0.0375 | 0.0140 | 0.0368 | 0.0114 |
| 1985 | 0.0493 | 0.0160 | 0.0628 | 0.0117 |
| 1986 | 0.0619 | 0.0198 | 0.0473 | 0.0114 |
| 1987 | 0.0593 | 0.0237 | 0.0482 | 0.0102 |
| 1988 | 0.0547 | 0.0169 | 0.0336 | 0.0064 |
| 1989 | 0.0394 | 0.0123 | 0.0391 | 0.0090 |
| 1990 | 0.0788 | 0.0204 | 0.0405 | 0.0094 |
| 1991 | 0.0692 | 0.0180 | 0.0414 | 0.0079 |
| 1992 | 0.0418 | 0.0187 | 0.0427 | 0.0110 |
| 1993 | 0.0366 | 0.0154 | 0.0559 | 0.0140 |
| 1994 | 0.0707 | 0.0201 | 0.1525 | 0.0231 |
| 1995 | 0.0450 | 0.0188 | 0.0746 | 0.0148 |
| 1996 | 0.0641 | 0.0216 | 0.0672 | 0.0123 |

Note: Minimum Distance Estimates of the parameters of the wage process for female, using growth moments of one year lag and controlled for selection. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications.

Table 1.14: Parameter estimates of wage process for female 1969-1996, using growth moment of one year lag, without selection

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.0193 | 0.0035 |
| 1970 | | | 0.0155 | 0.0069 |
| 1971 | 0.0089 | 0.0039 | 0.0112 | 0.0043 |
| 1972 | 0.0124 | 0.0057 | 0.0186 | 0.0048 |
| 1973 | 0.0068 | 0.0046 | 0.0294 | 0.008 |
| 1974 | 0.0127 | 0.0056 | 0.0193 | 0.0086 |
| 1975 | 0.0076 | 0.0057 | 0.0127 | 0.0041 |
| 1976 | 0.0244 | 0.0116 | 0.0158 | 0.0043 |
| 1977 | 0.0177 | 0.0052 | 0.0181 | 0.0046 |
| 1978 | 0.0260 | 0.0093 | 0.0239 | 0.0061 |
| 1979 | 0.0196 | 0.0073 | 0.0081 | 0.0034 |
| 1980 | 0.0336 | 0.0074 | 0.0197 | 0.0041 |
| 1981 | 0.0252 | 0.0076 | 0.0213 | 0.0059 |
| 1982 | 0.0220 | 0.0061 | 0.0165 | 0.0045 |
| 1983 | 0.0222 | 0.0055 | 0.0190 | 0.0040 |
| 1984 | 0.0188 | 0.0053 | 0.0196 | 0.0061 |
| 1985 | 0.0294 | 0.0076 | 0.0372 | 0.0064 |
| 1986 | 0.0317 | 0.0098 | 0.0292 | 0.0070 |
| 1987 | 0.0341 | 0.0098 | 0.0286 | 0.0060 |
| 1988 | 0.0321 | 0.0086 | 0.0209 | 0.0039 |
| 1989 | 0.0227 | 0.0072 | 0.0234 | 0.0053 |
| 1990 | 0.0536 | 0.0124 | 0.0277 | 0.0062 |
| 1991 | 0.0479 | 0.0117 | 0.0287 | 0.0056 |
| 1992 | 0.0236 | 0.0074 | 0.0283 | 0.0071 |
| 1993 | 0.0249 | 0.0086 | 0.0390 | 0.0097 |
| 1994 | 0.0466 | 0.0115 | 0.1091 | 0.0167 |
| 1995 | 0.0374 | 0.0116 | 0.0513 | 0.0108 |
| 1996 | 0.0504 | 0.0148 | 0.0467 | 0.0088 |

Note: Minimum Distance Estimates of the parameters of the wage process for female, using growth moments of one year lag and without controlling for selection. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications.

Table 1.15: Correlation coefficients of wage shocks 1969-1996, using growth moment of one year lag, with selection

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.1679 | 0.1432 |
| 1970 | | | 0.0060 | 0.4015 |
| 1971 | 0.1981 | 0.6160 | -0.1262 | 0.3591 |
| 1972 | -0.1606 | 0.5648 | 0.0842 | 0.1383 |
| 1973 | -0.1975 | 1.1145 | 0.0290 | 0.1171 |
| 1974 | -0.2203 | 3.0836 | -0.2491 | 0.1778 |
| 1975 | 0.1132 | 3.3065 | 0.0621 | 0.1642 |
| 1976 | 0.2709 | 0.3435 | 0.1682 | 0.1432 |
| 1977 | -0.399 | 1.1297 | -0.3287 | 0.1324 |
| 1978 | 0.2537 | 0.4960 | -0.0959 | 0.1509 |
| 1979 | 0.2464 | 0.4028 | 0.1081 | 0.3372 |
| 1980 | 0.3299 | 0.1573 | -0.0143 | 0.1850 |
| 1981 | 0.2473 | 0.1589 | 0.0827 | 0.6592 |
| 1982 | 0.1482 | 0.1395 | -0.0300 | 0.2013 |
| 1983 | -0.0241 | 0.2577 | -0.0394 | 0.1379 |
| 1984 | 0.1917 | 0.1639 | -0.3006 | 0.1875 |
| 1985 | 0.2397 | 0.1402 | -0.1243 | 0.1007 |
| 1986 | 0.2079 | 0.1499 | 0.0444 | 0.1161 |
| 1987 | 0.1199 | 0.1682 | -0.0800 | 0.1364 |
| 1988 | 0.2166 | 0.1770 | -0.0189 | 0.1224 |
| 1989 | 0.0818 | 0.1855 | -0.0011 | 0.1327 |
| 1990 | 0.2574 | 0.1543 | 0.0707 | 0.1127 |
| 1991 | 0.1737 | 0.1675 | 0.0171 | 0.1143 |
| 1992 | 0.3953 | 0.5218 | -0.1072 | 0.1277 |
| 1993 | 0.2365 | 0.2578 | 0.0420 | 0.0679 |
| 1994 | 0.1665 | 0.6988 | 0.1024 | 0.104 |
| 1995 | 0.4705 | 0.5358 | -0.0939 | 0.0963 |
| 1996 | 0.3596 | 0.2595 | -0.0143 | 0.0851 |

Note: Minimum Distance Estimates of the correlation coefficients for wage shocks, using growth moments of one year lag and controlling for selection. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications.

Table 1.16: Correlation coefficients of wage shocks 1969-1996, using growth moment of one year lag, without selection

| Year | Permanent Component | | Transitory Component | |
|---|---|---|---|---|
| | Estimates | std err | Estimates | std err |
| 1969 | | | 0.1244 | 0.0841 |
| 1970 | | | -0.0195 | 0.1991 |
| 1971 | 0.0630 | 0.1889 | -0.0903 | 0.1742 |
| 1972 | -0.0535 | 0.1924 | 0.0095 | 0.0982 |
| 1973 | -0.0143 | 0.2922 | -0.0214 | 0.0679 |
| 1974 | -0.1279 | 0.4780 | -0.1283 | 0.1236 |
| 1975 | 0.2941 | 1.2301 | 0.0160 | 0.1022 |
| 1976 | 0.1939 | 0.2504 | 0.1158 | 0.0979 |
| 1977 | -0.0187 | 0.1471 | -0.2377 | 0.0950 |
| 1978 | 0.2036 | 0.2639 | -0.0407 | 0.0869 |
| 1979 | 0.1580 | 0.1509 | 0.0572 | 0.2527 |
| 1980 | 0.2500 | 0.0944 | 0.0106 | 0.1149 |
| 1981 | 0.2237 | 0.1281 | 0.0668 | 0.0860 |
| 1982 | 0.1081 | 0.0949 | -0.0728 | 0.1269 |
| 1983 | 0.0484 | 0.1485 | -0.0474 | 0.0902 |
| 1984 | 0.2221 | 0.1393 | -0.2508 | 0.1194 |
| 1985 | 0.1979 | 0.0958 | -0.0679 | 0.0795 |
| 1986 | 0.1801 | 0.1352 | -0.0582 | 0.1232 |
| 1987 | 0.1489 | 0.1243 | -0.1189 | 0.0965 |
| 1988 | 0.2653 | 0.1078 | 0.0082 | 0.0888 |
| 1989 | 0.0964 | 0.1329 | -0.0493 | 0.1192 |
| 1990 | 0.2624 | 0.1186 | 0.0501 | 0.1009 |
| 1991 | 0.2022 | 0.0921 | 0.0151 | 0.0983 |
| 1992 | 0.3226 | 0.2014 | -0.0812 | 0.1100 |
| 1993 | 0.2568 | 0.1991 | 0.0797 | 0.0626 |
| 1994 | 0.0781 | 0.1735 | 0.0971 | 0.0834 |
| 1995 | 0.3284 | 0.3204 | -0.0576 | 0.0861 |
| 1996 | 0.2632 | 0.2080 | -0.0199 | 0.0631 |

Note: Minimum Distance Estimates of the correlation coefficients for wage shocks, using growth moments of one year lag and without controlling for selection. Standard Errors (std err) are obtained by block-bootstrap based on 500 replications.

# Chapter 2

# Review of consumption response

## 2.1 Introduction

The purpose of this chapter is to review recent developments in household's consumption response to income[1] shocks.[2] One common theme in this literature is to know how households would adjust their ex-post consumption and saving choice if they are hit by different degree of income shocks. Household's consumption response can on one hand shed light on the insurability or smoothing ability of income shocks (i.e. the ability of household to withstand adverse scenario), thus providing an answer to the welfare consequence of income uncertainty. On the other hand, the reaction of household's consumption to income shocks can help us understand the underlying nature and causes of income shocks, together with their implications to the evolution of consumption inequality.

The literature for the optimal consumption choice under income uncertainty is vast. Rather than giving a comprehensive literature review on this subject[3], I will

[1]The definition of income varies across studies. Typical income measures include hourly wage, labor earnings and the sum of labor income and financial income, net of taxes and transfers within a household(family income)

[2]By income shocks, it generally refer as the residual component of the change in income, conditional on observable such as race, education, martial status and age.

[3]See Meghir and Pistaferri (2011) for a extensive survey.

focus on papers that have the following three common features: 1) the use of a structural model as opposed to reduced-form regression analysis, with clear specification of households' preference and the economic environment[4] 2) Utilizing survey-based data on consumption and income for the calibration or estimation of their model; and 3) Modeling income shocks by means of a parametric permanent and transitory process. Of course, such sampling criteria are by no means exhaustive, my preferences would be given to papers that are of relevance to my work in previous chapter, or may provide important insights for future research.

The rest of this chapter is organized as follows. Section 2.2 discusses papers that are pertinent to the optimal consumption responses to ex-post, realized income shocks. Section 2.3 reviews papers that focus on the interplay between income equality and consumption inequality. Finally, the chapter concludes with open questions and suggestions for future works.

## 2.2 Consumption responses to income shocks

This subsection starts with the basic framework for analyzing household's consumption response to income shocks. The model has its theoretical underpinning on the life cycle permanent income hypothesis (PIH) pioneered by Friedman and Modiglioni. This basic framework can serve as a reference point for more complicated model introduced later. In the model, households have a finite time horizon in which they will die for sure after a certain period, and for simplicity, they will leave no bequests. In each period, they receive a stochastic income as endowment. In a parsimonious setting, the randomness of income is modeled by the sum of two components: a permanent component and a transitory component. Mathematically,

[4]See Keane (2010) for a discussion for comparing structural models and reduced-form regressions.

if we denote $y_t$ as the logarithm of income at time t, $y_t$ is assumed to follow

$$\begin{aligned} y_t &= z_t + \varepsilon_t \\ z_t &= z_{t-1} + \eta_t \end{aligned}$$

where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ and $\eta \sim N\left(0, \sigma_\eta^2\right)$ are i.i.d. normal. In the above income process, $z_t$ is the permanent component and $\varepsilon_t$ is the transitory component. While there is no dynamics for the transitory component[5], the permanent component follows a random walk process with a error term $\eta$. In the literature, $\varepsilon$ and $\eta$ are also sometimes referred as transitory shocks and permanent shocks respectively.

Households are assumed to have a quadratic preference towards consumption ($c$), and discount the future with a discount factor $\beta$. There is a state non-contingent risk-free bond ($a$) with interest rate ($r$) available for saving purpose and for simplicity, we let $\beta(1+r) = 1$. Borrowing is not allowed. In other words, there is a non-negativity constraint imposed on $a$.[6] In each period, once households receive their endowment (i.e. uncertainty is realized), they have to decide how much to consume and save. Denote $T$ as the terminal age for the household (i.e. the household will die for sure at time $T+1$), the household problem is to choose a sequence of consumption $\{c_t\}_{t=1}^T$ and saving $\{a_t\}_{t=1}^T$, taking the stochastic income stream $\{y_t\}_{t=1}^T$ as given. The optimization problem for the household can be expressed as

$$\max_{\{c_t, a_t\}_{t=1}^T} E_t \sum_{t=0}^{T-t} \beta^t \left(b_1 c_t - \frac{1}{2} b_2 c_t^2\right)$$

subject to the periodic budget constraint[7]: $c_t + a_{t+1} = y_t + (1+r)\, a_t$ for $t = 1, ...T$

[5] In the literature, besides the i.i.d. modeling in the transitory component, it is also common to model it as a moving average process, see Abowd and Card (1989) and Meghir and Pistaferri (2004). Also, measurement error of the data can also be added. However, as Meghir and Pistaferri (2004) have shown, it is impossible to separately identify genuine transitory component from the measurement errors by only looking at income data.

[6] Of course, non-negativity constraint also applies to consumption as well.

[7] Notice that we implicitly assume it is the log of the income (instead of its level) that enters

and the non-negativity constraint for consumption and saving. The expression in parenthesis is the periodic utility function and $b_1$ and $b_2$ are constants. Hall and Mishkin (1982) show that the optimal consumption follows a random walk process

$$E_t c_{t+1} = c_t \tag{2.2.1}$$

Equation (2.2.1) is called the Euler equation, and the equality holds if and only if the constraint on $a$ is non-binding. Combing the Euler equation with the periodic budget constraint, after some tedious algebra, we can derive the following equation which relates the change in consumption to model's parameter and income shocks.

$$c_{t+1} - c_t = \frac{r\theta_t}{1+r}\varepsilon_t + \eta_t \tag{2.2.2}$$

$\theta_t \equiv \left[1 - \frac{1}{(1+r)^{T-t+1}}\right]^{-1}$ is an annuity parameter that is increasing in $t$.[8] Equation (2.2.2) states that the change in consumption will react one-to-one to permanent shocks, while its response to transitory shocks will depend on the age of the household. To see the effect of age on the consumption response to transitory shocks, let's consider a numerical example by assuming $T = 40$ and $r = 0.03$.

Figure 2.1 graphs $\frac{r\theta_t}{1+r}$ against age ($t$), it is evident that that the consumption response to transitory shocks increase with age and approach 1 when the household is near the end of his lifetime. The intuition is simple: when the household is approaching the end of his life, from his perspective, the distinction between permanent shocks and transitory shocks is becoming less and less important.

The analytical beauty of the quadratic preference gives a nice decomposition of the optimal consumption responses to permanent and transitory shocks. Despite its analytical convenience, it's well known that there is no precautionary saving motive

in the right hand side of the budget constraint. This assumption allows us to simplify the algebra substantially.

[8]In infinite horizon economies, i.e. $T \to \infty, \theta = 1$

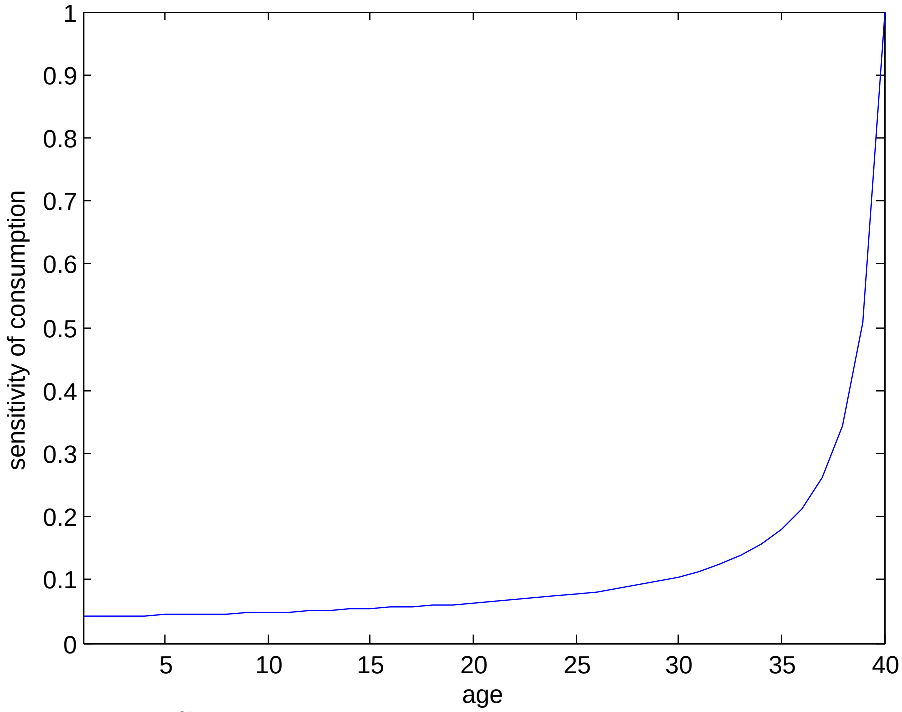


Figure 2.1: Consumption response to transitory shocks against age

under quadratic preferences[9], which is inconsistent with the empirical evidence documented by Carroll and Samwick (1997) that the precautionary component of wealth for typical U.S. households is between 20-50 percent. Although it is not difficult to extend the life cycle consumption model to more general preferences such as the commonly used constant relative risk aversion (CRRA) preferences, the lack of closed form solution for consumption usually preclude any transparent analysis on consumption responses to different income shocks under those preferences. To circumvent the lack of analytical solution under more general preferences, the recent literature has taken two different approaches: 1) to approximate the consumption function by linearizing the Euler equation and the budget constraint as in Blundell, Pistaferri, and Preston (2008) ; 2) numerically compute the consumption function by solving the life cycle

[9]In a two period partial equilibrium framework with uncertainty, Leland (1968) and Sandmo (1970) show that a risk-averse individual (i.e. second derivative of the utility function is negative) will feature precautionary saving motive as long as the third derivative of the utility function is positive. In our quadratic preference example, it can be shown that although second derivative is negative, the third derivative is actually zero.

consumption model as in Kaplan and Violante (2010).

In a simple version of the consumption model poised by Blundell, Pistaferri, and Preston (2008), the household optimization problem is the same as before except the the periodic utility function is CRRA, $\frac{c_t^{1-\gamma}}{1-\gamma}$ with $\gamma$ denotes the coefficient of relative risk aversion. The assumption $\beta\left(1+r\right)=1$ is also relaxed here. The Euler equation associated with this preference is

$$c_t^{-\gamma}=\beta\left(1+r\right)E_t c_{t+1}^{-\gamma}$$

Similar to the case under quadratic preferences, the Euler equation holds in equality if and only if the non-negativity constraint on saving is not binding. Under the assumption that the solution is interior, Blundell, Pistaferri, and Preston (2008) show that the optimal consumption rule satisfies

$$\Delta c_t \equiv \log c_{t+1}-\log c_t=\Xi_t\eta_t+\Xi_t\frac{r\theta_t}{1+r}\varepsilon_t \tag{2.2.3}$$

where $\Delta$ is the growth rate operator, $\theta_t$ is the annuity parameter defined as before and $\Xi_t \equiv \frac{\sum_{t=0}^{T-t}\frac{y_t}{(1+t)^j}}{\sum_{t=0}^{T-t}\frac{y_t}{(1+t)^j}+a_t}$ is the share of human wealth (discounted expected future labor income) over total wealth (human and financial wealth) for the household at time $t$. Comparing (2.2.2) and (2.2.3), consumption response to transitory shocks is fairly similar across the two models, but permanent shocks do not pass through one-to-one to the change in consumption under the CRRA preference.[10] The reason for this divergence lies on the household's precautionary saving motive. The relationship between household's smoothing ability of permanent shocks and the level of saving can be examined through $\Xi_t$. Notice that if the amount of saving is high, other things being equal, $\Xi_t$ will be smaller than 1, which implies there is some consumption smoothing over permanent shocks through self insurance. However, such

[10]Of course, in the case of quadratic preferences, the change in consumption is in level, while the change is in log (i.e., growth rate of consumption) in the case of CRRA preferences.

self-insurance motive will also depend on the lifespan of the household. In both data and implied from the life cycle model, the relationship between financial wealth and age for an average household is in inverted U-shaped. It implies households typically would have very few financial wealth towards the end of their life and $\Xi_t$ would be close to 1 in such scenario. That said, we would expect older households will react more to permanent shocks than younger households. With age being held at constant, a corollary of the relationship between $\Xi_t$ and $a$ would tell us a household with a lower level of wealth will also react more to permanent shocks than a wealthier household.

Armed with the approximated consumption function, Blundell, Pistaferri, and Preston (2008) estimate their model based on a panel data set of consumption and income for the U.S. from 1980-1992. Based on Equation (2.2.3), they postulate the data generating process for consumption is

$$\Delta c_t = \phi \eta_t + \varphi \varepsilon_t \tag{2.2.4}$$

where $\phi$ and $\varphi$ are the insurance (pass-through) coefficients respectively. The insurance coefficients $\phi$ and $\varphi$ measure the sensitivity of consumption growth to permanent and transitory shocks respectively. The coefficients to be estimated are $\phi, \varphi, \sigma_\eta^2$ and $\sigma_\varepsilon^2$. To illustrate the identification strategies, first note that the permanent-transitory income process can be expressed in growth rate as

$$\Delta y_t = \eta_t + \Delta \varepsilon_t \tag{2.2.5}$$

Manipulating with equation (2.2.5), it is not difficult to derive the following moment conditions for identifying the variance of permanent and transitory shocks.

$$E\left(\Delta y_t \Delta y_{t+1}\right) = -\sigma_\varepsilon^2 \tag{2.2.6}$$

$$E\left(\Delta y_t\left(\Delta y_{t-1}+\Delta y_t+\Delta y_{t+1}\right)\right)=\sigma_\eta^2 \tag{2.2.7}$$

Equations (2.2.6) and (2.2.7)show that income data alone is sufficient to identify the variance of income shocks. [11] In contrast, consumption data is needed to identify the insurance coefficients. This can be seen by looking at the following moment conditions:

$$\begin{aligned}
\frac{E\left(\Delta c_t\left(\Delta y_{t-1}+\Delta y_t+\Delta y_{t+1}\right)\right)}{E\left(\Delta y_t\left(\Delta y_{t-1}+\Delta y_t+\Delta y_{t+1}\right)\right)} &= \phi \\
\frac{E\left(\Delta c_t \Delta y_{t+1}\right)}{E\left(\Delta y_t \Delta y_{t+1}\right)} &= \varphi
\end{aligned}$$

As explained by Blundell, Pistaferri, and Preston (2008), these moment conditions provide an instrumental variable (IV) interpretation for the identification of insurance coefficients. The identification of $\varphi$ can be thought of running a regression of $\Delta c_t$ on $\Delta y_t$, using $\Delta y_{t+1}$ as an instrument. Similarly, $\phi$ is identified by the regression of $\Delta c_t$ on $\Delta y_t$, using $(\Delta y_{t-1}+\Delta y_t+\Delta y_{t+1})$ as an instrument. The GMM estimates obtained by Blundell, Pistaferri, and Preston (2008) are $\phi=0.64$ and $\varphi=0.05$. These numbers imply out of each unit increase in permanent shocks, around two-third would be transmitted to consumption growth, suggesting the existence of partial insurance. Meanwhile, the pass-through of transitory shock is small, suggesting households generally are able to smooth out transitory income fluctuation.

The linearized model under the CRRA preference may not be accurate if the non-negativity constraint on the saving $a$ is binding. Intuitively, when the household is borrowing constrained and has very little saving as buffers, he may need to adjust his consumption one-to-one to realized income shocks, regardless of whether it is permanent or transitory. Kaplan and Violante (2010) set up a realistic life cycle

[11] Note that the left hand side of (2.2.6) and (2.2.7 can be expressed as $Cov(\Delta y_t, \Delta y_{t+1})$ and $Cov(\Delta y_t, \Delta y_{t-1}) + Var(\Delta y_t) + Cov(\Delta y_t, y_{t+1})$ respectively.

consumption model which includes redistributive taxation, retirement and social security policies to investigate how the effect of the borrowing constraint may affect the estimates of insurance coefficients. They take the estimates of the variance of income shocks from Blundell, Pistaferri, and Preston (2008) for simulations. They also consider two polar extreme for the modeling of the borrowing constraints. In one extreme no borrowing is allowed. In another extreme, the household is able to borrow against the discounted value of the best realization in future income, which is referred as the natural borrowing limit. Kaplan and Violante (2010) pays special attention to the numerical errors that may be generated from the possibility of binding borrowing constraint.[12] In doing so, it is possible to check the accuracy of the identification strategies proposed by Blundell, Pistaferri, and Preston (2008), as the household's entire histories of income shocks and their optimal policy functions are available from the simulation.

Figure 2.2 graphs the age profile of insurance coefficients for both income shocks for the no borrowing case (Zero BC) and the case of natural borrowing constraint (Natural BC). The line true represent insurance coefficients obtained from the regression between simulated consumption growth and actual realization of income shocks. The line BPP corresponds to insurance coefficients generated by the IV regression of consumption growth to income growth, with the income growth instrumented by the method suggested by Blundell, Pistaferri, and Preston (2008). Salient features are follows. For the case of transitory shocks, it can be seen that insurance coefficients for transitory shocks coincide for both approaches, which support the insurance coefficient for transitory shocks is correctly identified and accurately estimated by Blundell, Pistaferri, and Preston (2008). The problem of inability to borrow affects younger households in the zero BC case. When households get older, the wealth accumulated in earlier periods can be used as a buffer for smoothing transitory shocks. In con-

[12] They solve the model numerically using the endogenous grid-point method, which is well suited to handle the binding constraint.

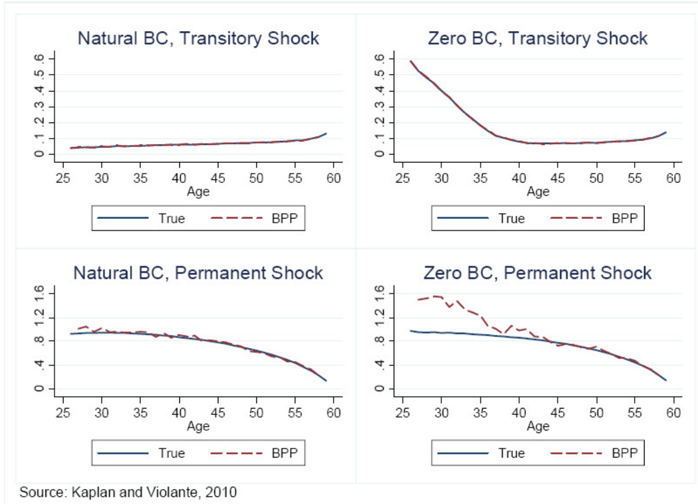


Figure 2.2: Insurance coefficients for income shocks under the two borrowing constraints

trast, once borrowing is allowed, the inability to smooth out transitory shocks is not a problem at all for the natural BC case. Shifting our focus to permanent shocks, we can see the approximation errors of the consumption function in Blundell, Pistaferri, and Preston (2008) is a greater concern now. This is especially true for younger households when they are not allowed to borrow. The insurance coefficient estimated under the IV approach is biased downwards, when compared to the theoretically true value. It raises concerns on the true insurability of permanent shocks.

In additional to the issue of binding borrowing constraint, Kaplan and Violante (2010) also find that standard model fall short in explaining the amount of insurance with respect to the permanent shock unless we assume households are very risk averse.[13] In other words, unless the risk tolerant household has substantial pre-

[13]Only when the coefficient of relative risk aversion is greater than 15, the model is able to generate enough precautionary saving motive to match the insurance coefficient for permanent shock. However, this value of risk aversion parameter is way too high for conventional economic model, as

cautionary saving motive, self-insurance motive alone does not point to the correct amount of insurance that household can achieve in the data.

In summary, the literature so far has reached a conclusion that even when income shocks are permanent, consumption need not respond by one-to-one. This suggests there exist some extent of risk sharing ability of households.

## 2.3 Has consumption inequality mirrored income inequality

Since the seminal work by Cutler and Katz (1991) and Slesnick (1993), there has been a surge of interest in studying the evolution of inequality by looking at both consumption and income. To reason is simple, as it is consumption, rather than income that enters the household preference and necessities the evaluation of any welfare consequences associated with the change in inequality.[14] Furthermore, consumption may provide valuable information in understanding the nature and cause of income inequality. This subsection reviews some of the key papers that use both income and consumption data to study the interaction between the trend of income inequality to that of consumption inequality. In particular, these studies focus on both the cause and its implications to households of why consumption inequality need not necessarily follow income inequality.

Figure 2.3 is taken from Heathcote, Perri, and Violante (2010), which graphs the evolution of income inequality and consumption inequality for the U.S. between 1980 to 2006, using "variance of log" as an inequality measure. The income and consumption measure is the equivalized household disposable income and non-durable consumption expenditures. It is evident that consumption inequality is substantially lower than income inequality not only in level, but also in growth rate. For example,

suggested by the literature of equity premium puzzle.

[14] It rests on the assumption that household's utility function depends on consumption only.

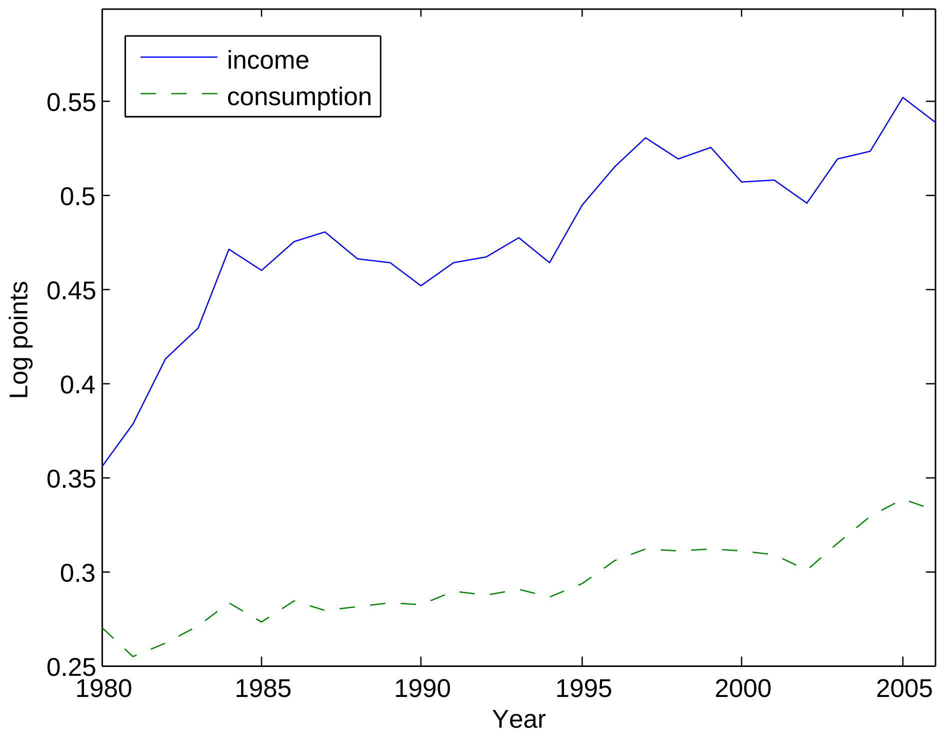


Figure 2.3: Evolution of Income Inequality and Consumption Inequality for the US: Evidence from the Consumer Expenditure Survey

over the 18 years, the increase in the variance of income is 18 log points compared to 6 log points only for consumption. The disparity of their level and trend between income and consumption inequalities also exist in other countries which include Canada, Germany, Mexico, Russia, Spain, Sweden and the U.K., as evidenced by a cross country comparison in Krueger, Perri, Pistaferri, and Violante (2010).

Blundell and Preston (1998) is the first paper that makes use of the standard PIH model reviewed earlier to understand the structural relationship between consumption and income inequalities for the U.K. between 1968-1992. As we see earlier in equation (2.2.2), the change in consumption is almost immune to any innovations in transitory shocks, while for any changes in permanent shocks, it would transmit one-to-one on consumption change. Because of the response of consumption is different for transitory and permanent income shocks, it is possible to structurally identify whether the increase in the variance of the change in consumption (a measure of consumption inequality) is due to permanent or transitory shocks. The period at which the trend of consumption and income inequalities does not coincide should also be the period where most of the change in income inequality is caused by an increase in transitory shocks. Similarly, if consumption inequality mirrors income inequality, then it must also be the period at which most of the growth in the variance of income shocks is permanent in nature. Blundell, Pistaferri, and Preston (2008) conducts similar

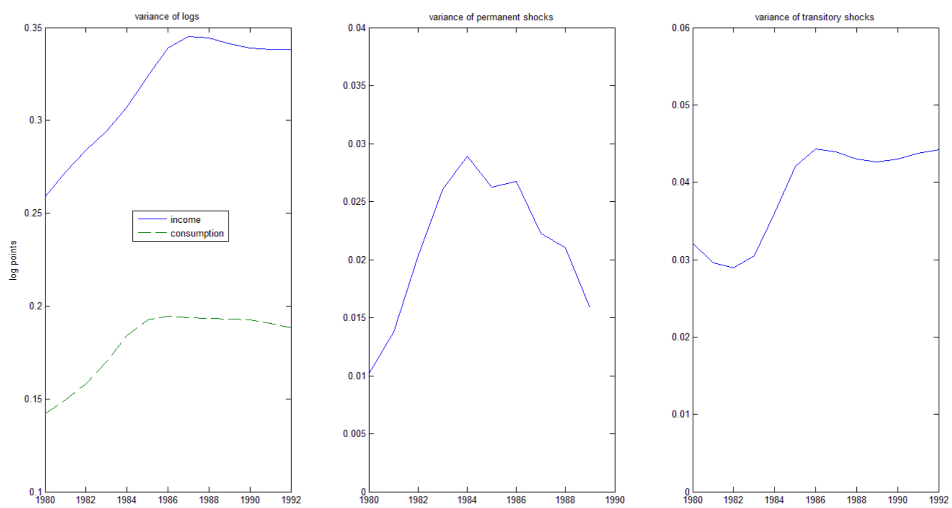


Figure 2.4: Trends of income and consumption inequalities in the U.S. and their relationship with income shocks

exercise for the U.S. over 1978-1992. Figure 2.4 illustrates the main finding. The left panel shows the well documented fact that the trend of consumption inequality moves in tandem with income inequality in the first part of the sample period.[15] From

[15] Careful readers will notice that although the same measure of inequality (the standard deviation of logs) is used, both consumption and income inequalities estimates in figure 2.4 is lower than that in figure 2.3. There are two reasons for the discrepancy. First, consumption data in Blundell, Pistaferri,

the decomposition of the income shocks (the middle and the right panel), we can see that the increase in income inequality from 1980 to 1984 paralleled with the sharp increase in the variance of permanent shocks over the same period. In their partial insurance model, such increase in the variance of permanent shocks would inevitably pass-through to the variance of consumption. To see this point, we first take variance on both sides of (2.2.4) and apply their benchmark insurance coefficient estimates to derive the following equation

$$Var(\Delta c_t) = (0.36)^2 Var(\eta_t) + (0.05)^2 Var(\varepsilon_t) \tag{2.3.1}$$

Equation (2.3.1) thus identifies that the majority of the increase in consumption inequality is due to an increase in the variance of permanent shocks[16], given that the contribution of transitory shocks to the variance of consumption growth is so small (i.e., $0.05^2 = 0.0025$). As a result, when the variance of permanent shocks started to decline after 1985, the mirroring of consumption inequality to income inequality ceased to exist.

Krueger and Perri (2005) shows that rising income inequality does not necessarily lead to an increase in consumption inequality through a risk-sharing argument, using the idea of limited commitment of contracts developed by Kehoe and Levine (1993) and Kehoe and Levine (2001). The intuition can be illustrated using the following story. Imagine there are only two agents in this world and each of them will receive a stochastic endowment in every period, and time runs forever. There is no aggregate uncertainty in the sense that the sum of their endowment is constant in every period. Two person can write a contract with each other to share the income risk. However, the contract is not enforceable (i.e., there is limited commitment of contracts), as

and Preston (2008) is imputed from the PSID. Secondly, sample selection criteria between the two studies are different.

[16] A unit increase in the variance of permanent (transitory) shock will translate to a $0.36^2 \approx 13\% (0.05^2 \approx 0.003\%)$ increase in the variance of consumption growth

agent can runaway and live in autarky forever. Agents prefer a smooth consumption profile over time and because of that, they would stay in contractual agreement to avoid volatile fluctuation in their consumption. Typically, if the dispersion between their endowment is high, agents would have incentive to honor a perfect risk-sharing contract (i.e. equal consumption for both persons in each time) as it would be really bad to live in autarky. In a model with continuum of agents which calibrated to the observed U.S. data, Krueger and Perri (2005) show that a model with limited commitment can successfully replicate the trend of consumption inequality, but a standard incomplete market model with precautionary saving motive only as in Huggett (1993) and Aiyagari (1994) cannot replicate such trend. However, Heathcote, Storesletten, and Violante (2010) show that when extra insurance channels such as intra-household risk-sharing, labor supply and redistributive government policies are introduced, a (not so) standard incomplete market is also able to replicate the trend of consumption inequality in the data.

It is well known that survey-based data is subject to measurement errors and top-coding problem. A well established evidence for household level consumption data in the U.S. is that the cross-sectional average consumption in household survey does not match with the one in the national account. Heathcote, Perri, and Violante (2010) highlight two reasons for the discrepancy. The first one is due to the conceptual difference between the survey-based consumption and consumption in the national account.[17] The second reason is the top-coding problem: consumption pattern for the very rich may be very different from the rest of the distribution, especially in luxury goods. In the context of measuring consumption inequality, it is the presence of measurement errors, rather than the top-coding problem, that may exaggerate the extent of consumption inequality. The reason for this is the problem of top-coding should in principle also affect income, but the cross-sectional average of survey-based

[17]Heathcote, Perri, and Violante (2010) give the example of medical expenditure in the U.S. The national account includes expenditure by Medicare, Medicaid and private insurers as consumption, while survey-based consumption only includes out-of-pocket medical expenses.

income matches the one in national account fairly well, suggesting top-coding problem is less of a concern for the measurement of consumption inequality.

Aguiar and Bills (2011) is a recent attempt to correct for the problem of measurement errors in survey-based consumption data. Their idea is to use data on saving and after-tax income to back out the theoretical implied consumption based on the budget constraint of the household. They show that the rise in consumption inequality after the adjustment is significantly greater than measuring the survey-based data directly. Their finding open up new challenges for understanding what is the true level and trend of consumption inequality and their implication for the household.

## 2.4 Open questions

Within the class of consumption models that features permanent-transitory income process, there is now a consensus that unless households are liquidity constrained, they are well insulated from the adverse impact of transitory shocks. Households can also partially insured themselves from permanent shocks. Despite this consensus, two unresolved questions remained: 1) Is permanent shock really permanent? and 2) What is the source of insurance for permanent shocks? The answers to these questions are important not only for academics, but also to policymakers for deciding the appropriate redistributive policies.

In the context of how permanent is permanent shock, the reason of adopting a random walk process for the permanent component of income is motivated by the fact that it is parsimonious enough to fit the data well. Furthermore, the relative short time dimension in survey-based data sets makes it impossible to distinguish a truly random walk process from a highly persistent autoregressive process (e.g. a persistence parameter of 0.95), as the short sample will bias the persistence parameter downward. The vast majority of the studies usually just assume the true persistence parameter to be unity. Because of this assumption, the random walk process is also refereed as restricted income process (RIP). On the contrary, there is an alternative view, pioneered by Lillard and Weiss (1979) that stress the importance of heterogenous income profile (HIP) for households.[18] Under HIP, income differences are partially attributed to household's individual-specific differences and partially to shocks. As a result of this, income shocks need not be so permanent to capture the individual uncertainty. In fact, the estimated coefficient for the persistence parameter under the HIP process is usually significantly less than unity. MaCurdy (1982) is the first study to test whether RIP or HIP is more appropriated for modeling income dynamics. He finds that RIP explains the data better than HIP. Inspired by his result, the majority of subsequent studies have all preferred RIP over HIP. Guvenen (2009) and Guvenen and Smith (2010) renew the debate between RIP and HIP by looking at the autocovariance structure of income and the covariance structure of income and consumption respectively. In particular, Guvenen (2009) shows that if the true data generating process is HIP, but when the econometricians estimates a mis-specified RIP process, the persistence parameter would be biased upward, thus favoring RIP over HIP even when the true process is HIP. Guvenen and Smith (2010) obtains a similar conclusion is also reached when both data for income and consumption are used. In contrast, Hryshko (2010) carries out a careful Monte Carlo study to show that if the true data generating process is RIP but the econometrician estimates it by a HIP model, then the estimated persistence parameter would be biased downward and favored the presence of heterogenous income profiles, a result that exactly reversed from that obtained by Guvenen (2009) and Guvenen and Smith (2010). That said, the assumption of whether HIP and RIP is indeed the true data generating process is crucial.

Krueger, Perri, Pistaferri, and Violante (2010) concludes from the cross country evidences that the basic permanent and transitory income process is misspecified.

[18]Well known studies for RIP include Abowd and Card (1989), Meghir and Pistaferri (2004) and Heathcote, Perri, and Violante (2010). For HIP, studies include **?**,Haider (2001) and Guvenen (2009).

They reach this conclusion by observing that different identification strategies would lead to drastically different estimates for the variance of income shocks. In the literature, the identification of the variance of shocks is either achieved by either moments conditions of income in levels or that in first differences. Equations (2.2.6) and (2.2.7) provide the moment conditions for the growth rate identification. For level-based identification, one can show that the following moment conditions can also identify the variance of permanent and transitory shocks.

$$
\begin{aligned}
E\left((y_{t+1} - y_t)y_t\right) &= -\sigma_\varepsilon^2 \\
E\left((y_{t+1} - y_{t-1})y_t\right) &= \sigma_\eta^2
\end{aligned}
$$

Theoretically speaking, if the econometric model (i.e., the income process) is correctly specified, estimates should be of expected sign and consistent across different identification schemes. In the present context, it means that the estimated variance of income shocks should be meaningful, regardless of whether the identification is achieved through first differences or levels. Based on hourly wage data for the U.S. between 1967-1996, figure 2.5 reports estimates of the variance of transitory and permanent shocks for both identification strategies. [19] [20]

Although the trend of the variances estimated under levels and first differences are fairly similar, the magnitude of the variances are drastically different. The level-based estimates of the variance in permanent shocks are substantially lower than the difference-based estimates, while the reverse is true for the variance in transitory shocks. As a non-trivial portion of permanent shocks would transmit to household's

[19] Similar result is also obtained by Heathcote, Perri, and Violante (2010) although their identification strategies are based on biannual moments (i.e. $t$ and $t-2$).

[20] In both levels and first-differences, variance of both transitory and permanent shocks in 1996 cannot be identified as its identification rests on information in 1997, which is not available. Meanwhile, there is more variances estimated under levels identification due to the fact that a whole year data is lost when computing first differences.

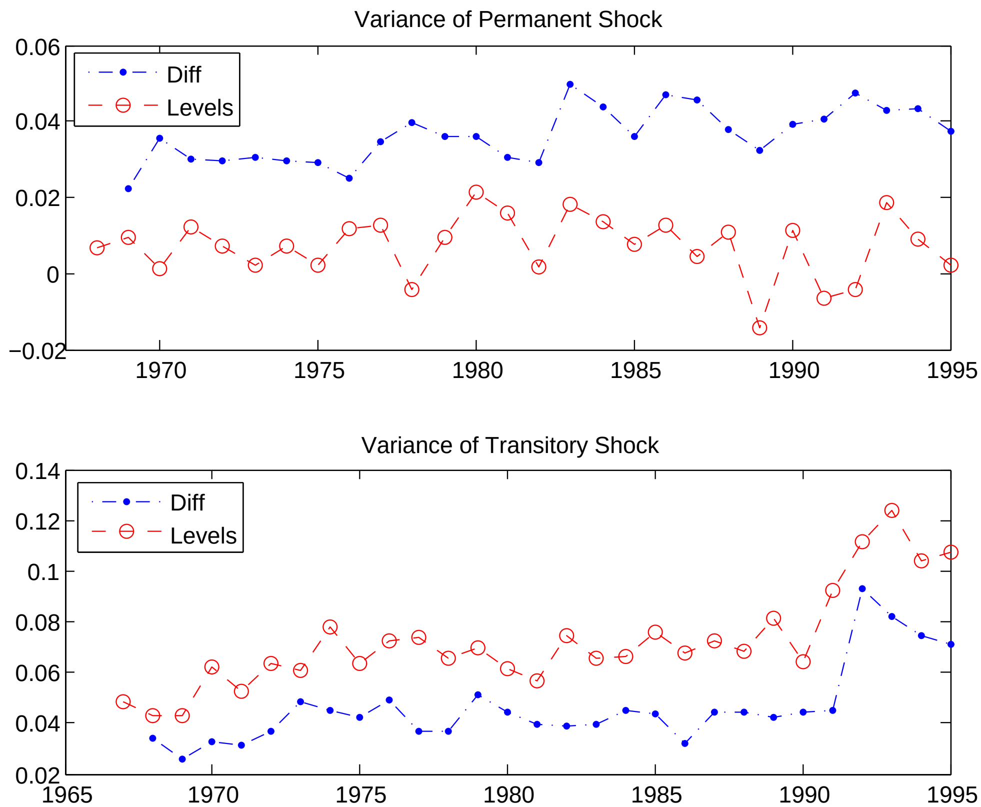


Figure 2.5: Estimates from the permanent-transitory income process in first differences and levels

consumption growth, when an overstated estimates of permanent shocks are used as an input in standard consumption and saving model, it is very likely that the model would understate the consumption smoothing ability of the household. This would also exaggerate the welfare cost of the income shocks based on the false impression that households cannot smooth their consumption effectively. Figure 2.5 also illustrates some of the level-based estimated variances for permanent shocks are negative, suggesting that mis-specification of the simple permanent transitory income process may be a serious concern. Since the source of mis-specification remains unknown, there is need to develop a new income process that is parsimonious and yet rich enough to reconcile moments of income in both level and first difference.

In Blundell, Pistaferri, and Preston (2008) and Kaplan and Violante (2010), the authors show that there is insurance available to the household over and above the self-insurance achieved through precautionary saving. Meanwhile, Krueger and Perri (2005) argues in the face of increasing income uncertainty, households commitment to share the risk has increased, coincide with easier access to financial markets in terms of both secured and unsecured borrowing. Still, the exact mechanism of how and why household can achieve insurance over and above self-insurance is not well understood. One particular issue is insurability of income shocks for younger household. In a famous study, Keane and Wolpin (1997) finds that in the U.S., prior to their entrance to labor market, most of the inequality in younger household can be attributed to their "initial conditions". In this regards, this unexplained portion of inequality must be related to their educational attainment and their interactions with teachers and parents. In a promising study, Kaplan (2010) analyzes that living with parents may be a mean for insuring the labor income risk. He confirms co-residence is a effective insurance mechanism for younger households.

Finally, it will be useful to use data for wealth and labor supply to augment our understanding of household behavior under uncertainty. Prominent example include **?** who study how to account for the life cycle variances and covariances of consumption, income and labor supply. **?** is another recent example who investigate the role of housing and durable consumption in understanding the response of consumption and wealth to unpredictable income shocks. We expect more works along this line to come in the future.

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