Abstract

Using data from the Medical Expenditure Panel Survey from 1996 to 2010, this study extends the work of Storesletten et al. (2004) to estimate how cross-sectional household earnings risk profiles vary over household composition. I model the household variability as a class of ARMA(1,1) processes, allowing for covariation in the transitory and permanent component between spouses. I use information from the sample of singles to restrict moment conditions in the general method of moments (GMM) estimation for couples. The purpose of this research is threefold: Is there any evidence of risk-sharing among married couples? What are the relative contributions of the income variance of the man and of the woman of the household to the family earnings variability? Is the increase in the covariance of the man’s and woman’s earnings mostly due to the increase in the covariance of their permanent or transitory component? I find that the cross-sectional earnings variation of the male spouse is the main driving force behind household earnings instability, accounting for approximately 60 percent of the total variation. Moreover, I find significant evidence of risk-sharing in the case of transitory shocks for couples, suggesting that spouses can insure his or her partner against unexpected labour market instability. Lastly, I find no evidence of risk-sharing among couples in response to a permanent labour market shocks.

Keywords: Idiosyncratic earnings risk, risk-sharing
1 Introduction

Households consisting of multiple individuals do not make decisions in the same manner as those of single individuals. The unitary model of the household, where the household is treated as a single decision making agent, has consistently failed to find support in the consumption data.\(^1\) McElroy and Horney (1981), Apps and Rees (1988), Chiappori (1988, 1992), and Browning and Chiappori (1998) propose a model of collective household, which allows for individual preferences and bargaining between household members. Storesletten et al. (2004a,b) present a model to decompose the labour income process of a household into permanent or transitory components in the unitary model framework. To the extent that labour market choices reflect joint decision making in a household (Blundell et al., 2005), the approach of Storesletten et al. (2004a,b) may be misleading since the model failed to take into account the differences in the risk profiles between single and non-single households. This study extends Storesletten et al. (2004b) to understand how cross-sectional household earnings risk profiles vary over household composition.

Permanet and transitory income dispersions of the singles are likely different than those of married couples. Pooling resources may reduce income risk if the spousal shocks are imperfectly (or negatively) correlated. For instance, spouses who work in different industry may not be impacted by labour market shocks at the same time or with the same magnitude. Gottschalk et al. (1994) suggest that the dispersion in transitory income is primarily related to labour market instability. Among married couples, this may reflect more complicated joint decisions, for example, married couples adjust their relative labour supply in managing labour income risk (Blundell et al., 2008, 2014). Many studies, such as that of Lundberg (1985) and Stephens (2002), find that married women increase their work hours in respond to her spouse’s loss of employment.\(^2\) Rising cross-sectional inequality in permanent income among individuals is generally a result of a skill-biased technological change, changes in the ratio of human capital to physical capital, or an increase in international trade (Katz and Autor, 1999; Beaudry and Green, 2005). Permanent income inequality among households with multiple individuals could be attributable to assortative mating–men and women of similar characteristics such as education, geographical location, and income are more likely to marry one another.\(^3\) I find evidence of insurance against transitory income shock among

\(^1\)See e.g. Blundell et al. (2007); Lundberg et al. (1997); Orazio and Lechene (2002); Chiappori et al. (2002)

\(^2\)Lundberg (1985) assumes that unemployment is a transitory reduction in earnings while Stephens (2002) present his study in terms of “displaced workers” who faced permanent earnings loss.

\(^3\)Many recent research confirm the presence of assortative mating. For example, Shore (2010, 2013) find that individuals with volatile incomes tend to marry each other, and Greenwood et al. (2014) concludes that assortative mating partially explain income inequality.
married couples, suggesting spouses can promptly respond to an unexpected labour market instability experience by his or her partner. Nonetheless, I do not find such confirmation in regard to the permanent shock–couples are not able to insure against permanent income inequality.

Incorporating a mechanism of intra-household dynamics in the life cycle model is not new.\textsuperscript{4} A few studies use a life cycle model that allow for correlated wage shocks between spouses in modelling the wage process. For instance, Blundell et al. (2014) examine the link between wage inequality and consumption inequality. Hyslop (2001) analyzes how one earner responds to the other earners’ wage shocks. Other studies directly seek to understand the household labour earnings risk profile while taken into account the covariation of husbands’ and wives’ earnings. For example, Shore (2010) uses Panel Study of Income Dynamics (PSID) in evaluating how the covariance of couples’ income varies over the business cycle and finds that the risk-sharing benefits of marriage are countercyclical–husbands and wives have more negatively correlated innovations to permanent income in recessions than in booms. Ostrovsky (2012) uses Canadian data to examine the impact of the changes in the correlation between spouses earnings on changes in the dispersion of family earnings. He finds a strong positive correlation between husbands’ and wives’ permanent earnings but little evidence that correlation between spouses transitory earnings determine family earnings inequality.

This study contributes to the labour income dynamics literature by decomposing the idiosyncratic income risk by singles and couples. Understanding the distinction in the income dynamics between singles and married couples is central to answering many economics questions, including household welfare (see e.g. Gottschalk and Moffitt (2009)), insurance market (see e.g. Hryshko (2012)), family labour supply (see e.g. Blundell et al. (2014); Knowles (2013)), the sources of inequality (see e.g. Huggett et al. (2011)), modelling consumption, saving, and wealth (see e.g. Ortigueira and Siassi (2013)), and the welfare costs of business cycles (see e.g. Storesletten et al. (2004b,a)). Hence, the purpose of this research is threefold: Is there any evidence of risk-sharing among married couples? What are the relative contributions of the income variance of the man and of the woman of the household to the family earnings variability? Is the increase in the covariance of men’s and women’s earnings mostly due to the increase in the covariance of their permanent or transitory component?

I perform a dummy variable regression as in Deaton and Paxson (1994) and show that the data set used in this study is comparable to PSID used in Storesletten et al. (2004b)–cross-sectional income variance increases with age and has positive relationship with the proportion

\textsuperscript{4}Much attention has been given to estimating consumption and labour supply dynamics (see for example Apps and Rees (1996, 1997); Blundell et al. (2005, 2007, 2014); Vermeulen (2002); Vermeulen et al. (2006); Browning et al. (2013); Lewbel and Pendakur (2008); Dunbar et al. (2013)), while the model generally assumes exogenous wages and take the income process of the household as given.\textsuperscript{5}
of working years that was in recession. The graphical analysis emphasizes the heterogeneity in the household earnings variation across marital status. Couples appear to have relatively flat earnings risk profile while that of singles increases with age. Earnings variability is characterized by permanent and transitory components, and among the couples, the intra-household covariances—the variability is modelled as a class of ARMA(1,1) processes. Since income variability increases with age in the U.S. (Storesletten et al., 2004a), I form age-dependent moments for the single population as well as for the couples, and estimate the model using the generalized method of moments (GMM). The identification problem in extracting parameters characterizing married couples is well-documented—researchers cannot observe how individuals in a collective setting would have acted were they not in a collective setting (Kooreman and Kapteyn, 1990). I follow identification strategy used in Browning et al. (2013); Barmby and Smith (2001); Barmby (1994) and Vermeulen et al. (2006) where the data from singles are used in identifying some parameters for couples. I assume that wages are competitive and thus the labour market does not distinguish between married and non-married individuals. This implies that singles and married individuals share some parameters that are common to both. In this fashion, I am able to extract parameters characterizing the income risk profile of married couples using observed information from individual men and women living alone.

The remainder of the paper is organized as follows. Section 2 describes the data set used in this study as well as presenting some results from simple analyses. Section 3 presents the model, and section 4 demonstrates the empirical estimation and discuss the estimates.

2 Data, Descriptive Analysis, and Simple Decomposition

The data set used in this study is the longitudinal files of Medical Expenditure Panel Surveys (MEPS) household component from 1996 to 2010. For each cohort, MEPS collects five rounds of data from each household for the period of two years. I pool 15 longitudinal files, panel 1 to 15, to form an overlapped panel data. Each household is selected into the sample based on 2 criteria: (1) total family income is positive; and (2) age 23 to 60 years old at time of the interview.

Family income is derived by aggregating total personal income of the reference person of the family and his or her spouse/partner and total personal income is simply a sum of all sources of income except tax refunds and capital gains. In general, the reference person is

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6In Browning et al. (2013); Barmby and Smith (2001); Barmby (1994) and Vermeulen et al. (2006), they assume that one’s preference does not change as a result of marriage.
defined as the household member 16 years of age or older who owns or rents the home. If more than one person meets this description, the household respondent identifies one from among them. If the respondent is unable to identify a person fitting this definition, the questionnaire asks for the head of household and this person is then considered the reference person for that reporting unit.

A MEPS family generally consists of two or more persons living together in the same household who are related by blood, marriage, or adoption, as well as foster children. Two unmarried persons living together who consider themselves a family unit are also considered to be a family in this data set. Single people who live with neither a relative nor a person identified as a significant other have also been assigned a family ID value and a family-level weight.

Total family earnings are adjusted to common 2010 dollars using the Consumer Price Index (CPI). I ignore earnings of parents and of children of the reference person and concentrate entirely on the reference person and his or her spouse. One person in the couple household is allowed to make zero income as long as the total income of the household is positive. This is done to avoid heterogeneity from family with more than two major sources of income and from couples with one spouse in debt.

I drop 7 observations who report having same sex partner and 2 observations who report having two spouses. I also exclude 516 households whose spouse became out of scope (death or separated) during the period of the survey. The final sample size is 31,623 singles and 32,664 couples.

Table 1 provides mean and standard errors of some characteristics of the population by marital status and by gender. The average age of single women is the same as that of married women while married men are on average older than single men. Single men (women) have higher average income than married men (women), but this is mostly due to the fact that one of the spouses makes zero income. The average income of the two spouses together is relatively close to the average income of the single men, but is significantly higher than that of the single women. The proportions of educational attainment appear to be stable across gender and across marital status. Approximately 45% of the samples possess a high school degree, almost 20% has a bachelor degree, and about 7% has a graduate degree.

The objective of this study is to analyze the unexplained part of household earnings. To extract the random component, $\epsilon_{ht}$, I begin by a simple regression of $y_{ht}$, log earnings of household $i$ of age $h$ at time $t$, based on the following equation:

$$ y_{ht} = x_{ht}^\prime \beta + \sum_{t=1}^{T-1} Y_t + \epsilon_{ht} $$

(1)
Table 1: Summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Single Male</th>
<th>Female</th>
<th>Couple Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>39.36</td>
<td>40.80</td>
<td>42.62</td>
<td>40.58</td>
</tr>
<tr>
<td></td>
<td>(10.73)</td>
<td>(10.74)</td>
<td>(9.48)</td>
<td>(9.38)</td>
</tr>
<tr>
<td>Log income</td>
<td>10.24</td>
<td>9.97</td>
<td>9.90</td>
<td>6.51</td>
</tr>
<tr>
<td></td>
<td>(0.94)</td>
<td>(0.97)</td>
<td>(3.69)</td>
<td>(8.38)</td>
</tr>
<tr>
<td>Couple’s log income</td>
<td></td>
<td></td>
<td>10.99</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.79)</td>
<td></td>
</tr>
<tr>
<td>Median no. of children</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

**Education:**

<table>
<thead>
<tr>
<th>Education</th>
<th>Single Male</th>
<th>Female</th>
<th>Couple Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower than high school</td>
<td>0.23</td>
<td>0.25</td>
<td>0.22</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>(0.42)</td>
<td>(0.43)</td>
<td>(0.42)</td>
<td>(0.40)</td>
</tr>
<tr>
<td>High school</td>
<td>0.46</td>
<td>0.46</td>
<td>0.43</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>(0.50)</td>
<td>(0.50)</td>
<td>(0.50)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>Bachelor degree</td>
<td>0.18</td>
<td>0.15</td>
<td>0.18</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(0.35)</td>
<td>(0.38)</td>
<td>(0.39)</td>
</tr>
<tr>
<td>Graduate degree</td>
<td>0.06</td>
<td>0.06</td>
<td>0.10</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.25)</td>
<td>(0.30)</td>
<td>(0.28)</td>
</tr>
<tr>
<td>Other degrees</td>
<td>0.07</td>
<td>0.08</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.28)</td>
<td>(0.30)</td>
<td>(0.28)</td>
</tr>
</tbody>
</table>

N 12,534 19,089 32,664 32,664

Data source: MEPS 1996 to 2010 (Panel 1 to 15)

Standard errors in parentheses

where \( x_{ht} \) is a vector of explanatory variables including age and its polynomials, highest level of education attained (less than high school, high school, undergraduate degree, graduate degree, and other degrees), number of children (1,...,4 or more), and gender. \( Y_t \) is a year dummy variable indicating the survey year, and \( \epsilon_{ht} \) is the idiosyncratic random error. Note that \( h \) runs from 23 to 60, and \( t \) runs from 1996 to 2010. It is assumed that \( E(\epsilon_{ht}^2) = 0 \) so that \( Var(\epsilon_{ht}) = E(\epsilon_{ht}^2) = \sigma_{ht}^2 \). Consequently, the estimated variance is \( \hat{\sigma}_{ht}^2 = (\hat{\epsilon}_{ht})^2 \), where \( \hat{\epsilon}_{ht} = y_{ht} - \hat{y}_{ht} \), and \( \hat{y}_{ht} \) is the linear prediction obtained from the regression in equation 1.7

The estimation of parameters of interest in this study hinges on variation in the cross-sectional variance between different cohorts of similar ages.8 Following Storesletten et al. (2004b), I demonstrate the importance of variations in the cross-sectional variance according to age by performing a dummy variable regression as in Deaton and Paxson (1994):

\[
\hat{\sigma}_{ht}^2 = a_t + b_h + e_{ht},
\] (2)

7The estimates of the \( \beta \)s obtained from regression of equation 1 are not of interest to this study.
8The parameters of interest are those characterizing the idiosyncratic earnings risk described in section 3
where \(a_c\) and \(b_c\) are sets of dummy variables indicating birth cohort and age effects and \(e_{ht}\) are residuals. Birth cohort is defined as one’s birth year, i.e. \(t - h\). In total, there are 37 age dummies and 52 birth cohort dummies. Note that there is no constant in this regression, and thus I am able to obtain all 52 coefficients of birth cohort dummies and 37 coefficients of age dummies. The omitted age is 40, and thus other age coefficients are interpreted as effects relative to age 40.

![Figure 1](image.png)

**Figure 1:** Cross-sectional variance of log income

Figure 1 plots the coefficients of each age from dummy variable regression in equation 2. The lines are plotted such that they all go through an unconditional variance of log income at age 40. Figure 1a reveals that, on average, the cross-sectional income variance increases with age. This fits the stylized fact of the U.S. data on income, which is that inequality increases with age (Storesletten et al., 2004a). This essentially motivates using age-specific moments in characterizing the idiosyncratic earnings risk profiles in this study. Two other major patterns emerge from graph 1a. First, female’s cross-sectional variance is relatively flat across age group with a jump at the end of the working life. Second, male’s cross-sectional variance is lower than that of female at an earlier age, but catches up with that of women in later years.

Figure 1b emphasizes the heterogeneity in the household earnings variation across marital

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9Storesletten et al. (2004b) demonstrate similar results using the PSID.
status while figure 1c and 1d emphasizes the heterogeneity in the earnings variation across gender among singles and among non-singles. The cross-sectional variance of log earnings among couples is relatively flat across age in comparison to that of singles. Moreover, figure 1c demonstrates that single men appear to have relatively lower variance than single women at early age, but the variance increases with age and exceeds that of women around age 45. Figure 1d shows further decomposition among couples into man and woman of the household. Cross-sectional variance of woman of the household is higher than that of man of the household for all ages. The gap between the two genders does not appear to vary across different age groups.

![Figure 2: Cohort effects](image)

Since this study follows quite closely the methodology outline in Storesletten et al. (2004b), and that it is also the first to use the MEPS in this type of analysis, I provide another figure to confirm that this data set does not portray any irregularities in comparison to the PSID used in Storesletten et al. (2004b). Figure 2 plots the cohort coefficients from dummy variable regression against the fraction of contractionary years each cohort experiences in their working period.\(^\text{10}\) The graph shows a clear positive relationship between cross-sectional variance and fraction of contractionary years, which is in accord with the findings in Storesletten et al. (2004b).

Lastly, I assume that household income variance of a couple of age \(h\) at time \(t\) is charac-

\(^{10}\) The aggregate Gross National Product (GNP) levels are used in defining economic contractions and expansions from 1958 to 2010. GNP data is obtained from U.S. Department of Commerce: Bureau of Economic Analysis and is converted to 2010 dollars using the CPI and to per capita terms by dividing with the total population, which is obtained from the U.S. Census Bureau: Population Division website. An expansion or contraction is classified according to whether the growth rate in U.S. GNP was above or below its sample mean.
\[
\text{Var}_t^h(aY_m + bY_w) = a^2\text{Var}_t^h(Y_m) + b^2\text{Var}_t^h(Y_w) + 2ab\text{Cov}_t^h(Y_m, Y_w) \tag{3}
\]
where \(Y_m\) is income of a man and \(Y_w\) is income of a woman. \(\text{Var}_t^h(aY_m + bY_w)\) is obtained from calculating variance of total income of the household of each age cohort of each \(t\) and stack them into a vector of 570 elements–38 age cohort and 15 cycles of survey. \(\text{Var}_t^h(Y_m), \text{Var}_t^h(Y_w),\) and \(\text{Cov}_t^h(Y_m, Y_w)\) are obtained in a similar way using income variance of a man of the household and of a woman of the household. Note that this characterization does not apply to single population. The estimation is done using unconditional and conditional cross-sectional age-specific variances. The terms \(a^2, b^2,\) and \(2ab\) can be seen as weight contribution of the cross-sectional variance from the man of the household, from the woman of the household, and from their covariance.\(^{11}\) These terms are normalized so that the sum is unity. Estimated coefficients can be found in table 2. This simple calculation reveals a relative contribution of each component of the household variance. In both conditional and unconditional cases, the cross-sectional variance of the man of the household is the main driving force behind the household earnings instability, accounting for approximately 60 percent of the total variation. The cross-sectional variance of the woman of the household on the other hand, only accounts for about 6 percent. Table 2 also illustrate that covariance between the two spouses are not negligible in terms of explaining the overall household earnings variability. The covariance between male and female of the household accounts for about 36 percent of the total earnings dispersion.

<table>
<thead>
<tr>
<th></th>
<th>(a^2)</th>
<th>(b^2)</th>
<th>(2ab)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unconditional variance</td>
<td>0.598</td>
<td>0.051</td>
<td>0.350</td>
</tr>
<tr>
<td>Conditional variance</td>
<td>0.563</td>
<td>0.062</td>
<td>0.374</td>
</tr>
</tbody>
</table>

### 3 Model

Recall that the goal of this study is to analyze the unexplained component of the household labour earnings. The unexplained part (the residuals from the simple regression) is obtained \(^{11}\)Recall that these terms are different from the actual cross-sectional income variances of the spouses and their covariance.
from equation 1, and can be modelled for individual $i$ of age $h$ at time $t$. For single population:

$$e_{it}^h = \alpha_i + z_{it}^h + \nu_{it},$$
$$z_{it}^h = \rho z_{i,t-1}^h + \eta_{it},$$

(4)

where

$$\alpha \sim (0, \sigma_\alpha^2), \quad \nu \sim (0, \sigma_\nu^2), \quad \eta \sim (0, \sigma^2)$$
$$\alpha \perp \nu \perp \eta, \quad i.i.d.$$ 

(5)

and for couple population,

$$e_{it}^h = \alpha_i^m + \alpha_i^w + z_{it}^{hm} + z_{it}^{hw} + \nu_{it}^m + \nu_{it}^w,$$
$$z_{it}^{hm} + z_{it}^{hw} = \rho_m z_{i,t-1}^{h-1,m} + \rho_w z_{i,t-1}^{h-1,w} + \eta_{it}^m + \eta_{it}^w,$$

(6)

where

$$\alpha^m \sim (0, \sigma_{\alpha_m}^2), \quad \nu^m \sim (0, \sigma_{\nu_m}^2), \quad \eta^m \sim (0, \sigma_m^2)$$
$$\alpha^w \sim (0, \sigma_{\alpha_w}^2), \quad \nu^w \sim (0, \sigma_{\nu_w}^2), \quad \eta^w \sim (0, \sigma_w^2)$$
$$\alpha \perp \nu \perp \eta \quad \text{for both men and women, \quad i.i.d.,}$$

and \(
\text{Cov}(\eta_i^m \eta_i^w) = \sigma_{mw}^\eta \quad \text{Cov}(\nu_i^m \nu_i^w) = \sigma_{mw}^\nu
\)

(7)

The terms $\alpha_i$, $\alpha_i^m$, and $\alpha_i^w$ represent time-invariant individual specific effects for singles, the man of the household, and the woman of the household, respectively. The terms $\nu_{it}$, $\nu_{it}^m$, and $\nu_{it}^w$ capture transitory innovations to income; $z_{it}$, $z_{it}^{hm}$ and $z_{it}^{hw}$ captures permanent shock to income. Coefficient $\rho$, $\rho_m$ and $\rho_w$ determines the degree of persistence of the permanent shock. Initial condition, $z_{it}^0$, is assumed to be zero.

The cross-sectional variance of single population for each age $h$ is defined as

$$\text{Var}^{sm}(e_{it}^h) = \sigma_{\alpha_{sm}}^2 + \sigma_{\nu_{sm}}^2 + \sum_{j=0}^{h-1} \rho_{sm}^{2j} \sigma_{sm}^2$$
$$\text{Var}^{sw}(e_{it}^h) = \sigma_{\alpha_{sw}}^2 + \sigma_{\nu_{sw}}^2 + \sum_{j=0}^{h-1} \rho_{sw}^{2j} \sigma_{sw}^2$$

(8)

for single men and single women, respectively. From equations in 6 and 7, the cross-sectional
The variances of couple population, for each age $h$, is defined as

$$\text{Var}^c(\epsilon^h_{it}) = \sigma^2_{\alpha_m} + \sigma^2_{\alpha_w} + \sigma^2_{\nu_m} + \sigma^2_{\nu_w} + 2\sum_{j=0}^{h-1} \rho^2_m \sigma^2_j + \sum_{j=0}^{h-1} \rho^2_w \sigma^2_j + 2 \sum_{j=0}^{h-1} \rho_m \rho_w \sigma^2_{mw}. \quad (9)$$

The autocovariance is defined for single population as

$$E^{sm}(\epsilon^{h}_{it}\epsilon^{h-1}_{i,t-1}) = \sigma^2_{\alpha_{sm}} + \rho_{sm} \sum_{j=1}^{h-1} \rho^2_{sm} \sigma^2_{sm} \quad (10)$$

and for couple population as

$$E^c(\epsilon^{h}_{it}\epsilon^{h-1}_{i,t-1}) = \sigma^2_{\alpha_m} + \sigma^2_{\alpha_w} + \rho_m \sum_{j=1}^{h-1} \rho^2_m \sigma^2_j + \rho_w \sum_{j=1}^{h-1} \rho^2_w \sigma^2_j + (\rho_m + \rho_w) \sum_{j=1}^{h-1} \rho^2_m \rho^2_w \sigma^2_{mw} \quad (11)$$

for all $h$ and $t$.

These cross-sectional variances and autocovariances for each age $h$, as seen in equation 8 to 11, underly the GMM estimator. Note that it is straightforward how each single individual is assigned to the age cohort $h$, however, there are two people in a couple, and whose age should be used in representing the age of the couple is not clear. I choose to use the age of the reference person as defined by the MEPS as the age representing the couple.

### 4 Estimation

It is widely known in the collective household literature that this type of estimation poses some identification problems in terms of estimating parameters characterizing married couples. Specifically, the issue comes from asking the data to establish how individuals in a collective setting would have act were they not in a collective setting (Kooreman and Kapteyn, 1990). Many studies, such as that of Browning et al. (2013); Barmby and Smith (2001); Barmby (1994) and Vermeulen et al. (2006), attempt to tackle this identification issue by using data from singles to identify some parameters of couples. I keep in line with these studies, assuming that wages are competitive and the labour market does not distinguish individuals based on their marital status. Hence, singles and married people share some parameters characterizing their cross-sectional labour income risk profiles. The identification
strategy here relies on two main points; first, obtaining estimates using information from single individuals, and second, using these estimates to restrict the moment conditions used in estimating parameters for the couples.

Recall that \( \epsilon_{ht} \) captures idiosyncratic cross-sectional variation which follow the process described in 4 to 7. The parameters are estimated using GMM. The cross-sectional variances (equation 8 and 9) represent one variance for each age/time pair, \((h,t)\). For example, the moments associating with variances for single males:

\[
E_{t}^{sm} \left[ (\epsilon_{ht}^2 - \sigma_{\alpha sm}^2 - \sigma_{\nu sm}^2 - \sum_{j=0}^{2h-1} \rho_{sm}^j \sigma_{sm}^2) \right] = 0 \tag{12}
\]

where \( h \) runs from 23 to 60 and \( t \) runs from 1996 to 2010. The cross-sectional autocovariances are used in identifying \( \sigma_{\alpha} \) from \( \sigma_{\nu} \). The moments associated with autocovariances is, for single male population,

\[
E_{t}^{sm} \left[ \epsilon_{ht} \epsilon_{h-1,t} - \sigma_{\alpha sm}^2 - \rho_{sm} \sum_{j=1}^{h-1} \rho_{sm}^j \sigma_{sm}^2 \right] = 0 \tag{13}
\]

for all \( h \) and \( t \). Similarly, the moments representing variances and autocovariances for single women are

\[
E_{t}^{sw} \left[ (\epsilon_{ht}^2 - \sigma_{\alpha sw}^2 - \sigma_{\nu sw}^2 - \sum_{j=0}^{2h-1} \rho_{sw}^j \sigma_{sw}^2) \right] = 0 \tag{14}
\]

and

\[
E_{t}^{sw} \left[ \epsilon_{ht} \epsilon_{h-1,t} - \sigma_{\alpha sw}^2 - \rho_{sw} \sum_{j=1}^{h-1} \rho_{sw}^j \sigma_{sw}^2 \right] = 0. \tag{15}
\]

The parameters of interest are \( \theta_{sm} = (\sigma_{\alpha sm}, \sigma_{\nu sm}, \rho_{sm}, \sigma_{sm}) \), \( \theta_{sw} = (\sigma_{\alpha sw}, \sigma_{\nu sw}, \rho_{sw}, \sigma_{sw}) \), and \( \theta_c = (\sigma_{\alpha c}, \sigma_{\nu mw}, \sigma_{\eta mw}) \) for single men, single women, and for couples.

In estimating parameters for couples, I obtain estimates for singles (\( \hat{\theta}_{sm} \) and \( \hat{\theta}_{sw} \)) using moments conditions suggested by equations in 12 and 15 in the first stage. I then use these estimates as proxies for the parameters of the man and of the woman of the household accordingly by plugging the estimates directly into moment conditions for couples in the second stage. I allow for these married couple moments to include a “marriage effect”, \( \sigma_{\alpha c}^2 \), which capture any time-invariant couple specific effects for the non-single population. The parameters identified in the second stage are \( \sigma_{\alpha c}, \sigma_{\nu mw}^\nu \) and \( \sigma_{\eta mw}^\eta \). The moments associated
with couples are:

\[
E_t^c \left[ (\epsilon_{it}^h)^2 - \dot{\sigma}_{\alpha_m}^2 - \dot{\sigma}_{\alpha_w}^2 - \dot{\sigma}_{\alpha_c}^2 - \dot{\sigma}_{\nu_m}^2 - \dot{\sigma}_{\nu_w}^2 - 2\sigma_{mw}^\nu - \sum_{j=0}^{h-1} \rho_m^2 \dot{\sigma}_m^2 \\
- \sum_{j=0}^{h-1} \rho_w^2 \dot{\sigma}_w^2 - 2 \sum_{j=0}^{h-1} \rho_m^j \dot{\rho}_w^j \sigma_{mw}^\eta \right] = 0 \tag{16}
\]

and

\[
E_t^c \left[ (\epsilon_{it}^h \epsilon_{i,t-1}^h)^2 - \dot{\sigma}_{\alpha_m}^2 - \dot{\sigma}_{\alpha_w}^2 - \dot{\sigma}_{\alpha_c}^2 - \dot{\sigma}_{\nu_m}^2 - \dot{\sigma}_{\nu_w}^2 - \rho \sum_{j=1}^{h-1} \rho_m^{2(j-1)} \sigma_m^2 + \dot{\rho}_w \sum_{j=1}^{h-1} \rho_w^{2(j-1)} \sigma_w^2 \\
- (\dot{\rho}_m + \dot{\rho}_w) \sum_{j=1}^{h-1} \rho_m^{j-1} \dot{\rho}_w^{j-1} \sigma_{mw}^\eta \right] = 0 \tag{17}
\]

The estimated parameters can be found in table 3. I find large individual effects for singles, \(\sigma_\alpha = 0.747\) for single men and \(\sigma_\alpha = 0.881\) for women. For the persistent shock, the autocorrelation is higher for single women than for single men, \(\rho = 1.069\) for females, and \(\rho = 0.996\) for males. Transitory shocks are zero for the single population. I do not find couple’s marriage effect, \(\sigma_\alpha = 0.\). I find some evidence of risk-sharing in the case of transitory shocks for couples, \(\sigma_{mw}^\nu = -0.294\). This suggest that spouses can insure his or her partner against unexpected labour market instability. In terms of permanent shocks, I do not find such risk-sharing evidence. [TO BE COMPLETED]

<table>
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<th>(\sigma_\alpha)</th>
<th>(\sigma_\nu)</th>
<th>(\rho)</th>
<th>(\sigma)</th>
<th>(\sigma_{mw}^\nu)</th>
<th>(\sigma_{mw}^\eta)</th>
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<td>0.996</td>
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<td>–</td>
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<tr>
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<td>–</td>
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<td>-0.294</td>
<td>-0.007</td>
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References


