

THE LABOR SUPPLY RESPONSE TO (MISMEASURED BUT) PREDICTABLE WAGE CHANGES

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Abstract

Most panel data studies of intertemporal labor supply assume classical measurement error. Recent validation studies refute this assumption. In this study I address non-classical measurement error explicitly. I use data on males from the Panel Study of Income Dynamics Validation Study to purge measurement error from the Panel Study of Income Dynamics. I find a large amount of predictable wage variation in the data, even after accounting for measurement error. However, there is almost no labor supply response to these predictable wage changes. Therefore, failure to control for non-classical measurement error cannot explain the low estimated labor supply elasticities in other papers.

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1 Introduction

This paper estimates the intertemporal elasticity of substitution, accounting explicitly for measurement error. Several influential studies, using person-specific year-to-year variation in hours and wages estimate a small (usually between 0 and .5)¹ intertemporal elasticity of substitution (MaCurdy (1981), Altonji (1986), Abowd and Card (1989), Holtz-Eakin et al. (1988), Ziliak and Kniesner (1999)). All of the studies use data from the Panel Study of Income Dynamics (PSID). However, Heckman (1993) argues that “the low estimated value of the intertemporal-substitution elasticity found in panel data studies appears to be a consequence of non-standard measurement-error problems”.²

Previous PSID studies assume the measurement error structure their estimation strategy can accommodate, without asking what error structure they should want to accommodate. They assume either that measurement error in hours and wages is white noise (Holtz-Eakin et al. (1988), Ziliak and Kniesner (1999)) or white noise with a fixed effect (Altonji (1986), Abowd and Card (1987,1989)). These assumptions imply that wages or wage changes two years in the past are valid instruments for current wage changes. However, the literature on measurement error indicates that measurement error in hours and wages is not white noise (see the references in Bound et al. (2001)). Instead, measurement error in wages is autocorrelated and is correlated with true hours and wages. This means that using twice lagged wages and wage changes will not overcome the “division bias” problem which biases labor supply elasticities downwards.³

In this study I develop a modified instrumental variables estimator to estimate the intertemporal elasticity of substitution. The estimator accounts for the measurement error problems described above. The analysis proceeds as follows.

¹These estimates are significantly below the assumed elasticities in most Real Business Cycle models. Therefore, the PSID studies cast doubt on the microfoundations of the Real Business Cycle literature.

²Another potential statistical problem with the PSID studies is small sample bias. Lee (2001) finds that the estimated intertemporal elasticity of substitution is .5 when using standard instruments in the PSID and accounting for small sample bias.

³These problems in the PSID studies motivate several new labor supply studies using natural experiments (Oettinger (1999), Mulligan (1995, 1999), Camerer et al. (1997), Carrington (1996)). While these new studies raise important criticisms, they produce no new consensus. For example, Camerer et al. (1997) estimate the intertemporal elasticity of substitution to be -.7, whereas Mulligan’s estimate is 2. One problem with these studies is that they focus on small groups (Camerer et. al. on taxi cab drivers, Oettinger (1999) on stadium vendors) or isolated instances (Carrington (1996) measures the intertemporal elasticity of substitution using evidence from the Alaska oil pipeline boom). These specific cases may not generalize to the population as a whole.

First, I set up the standard intertemporal labor supply model. The object of interest in this model is the labor supply response to anticipated wage changes. I use last year's wage change to predict this year's wage change. Last year's wage change should have good predictive power if there is a transitory component to wages. A transitory wage change represents an event such as high wages being paid for a short period of time, as in the Alaskan Oil Pipeline boom of the 1970s (Carrington, 1996). If workers anticipate that transitory wage changes disappear, then transitory wage changes can identify the labor supply response to anticipated wage changes.

While using last year's wage change has great power in predicting the current wage change, it introduces potential measurement error biases. The estimator developed in this paper accounts for the covariance of measurement error with true variables and the autocovariances of measurement error.

Finally, I estimate the labor supply response to predictable wage changes, controlling explicitly for measurement error in hours and wages. I estimate the properties of measurement error using the Panel Study of Income Dynamics Validation Study (PSIDVS). I then use this information about measurement error to purge measurement error from the PSID. I find a large transitory component of wages, even after controlling for measurement error.

I find that failure to properly control for measurement error when estimating the intertemporal elasticity of substitution can lead to misleading inferences about the intertemporal elasticity of substitution. However, I also find that controlling explicitly for measurement error does not overturn the conclusions of previous PSID studies of the intertemporal elasticity of substitution. The estimated intertemporal elasticity of substitution is close to zero with a standard error of .25.

The paper proceeds as follows. Section 2 describes the labor supply model and how I control for measurement error when estimating the intertemporal elasticity of substitution. Section 3 describes the PSID data. It also describes the PSIDVS data that I use to estimate the properties of measurement error. Section 4 presents estimates of the model of wage dynamics and estimates of the intertemporal elasticity of substitution. Section 5 concludes.

2 Estimating the Intertemporal Elasticity of Substitution

In this section I present a standard life-cycle labor supply model. I also present a wage prediction equation. The central implication of the life-cycle labor supply model is that hours changes are positively correlated with predictable wage changes. Lastly, I consider how to address issues of measurement error in estimating the labor supply response to predictable wage changes.

2.1 The Intertemporal Labor Supply Model

I begin with the standard intertemporal labor supply model. The specification is similar to MaCurdy (1985). Preferences take the form:

$$U = E_0 \sum_{t=1}^T \beta^t \left(v(c_{it}) - \exp(-\alpha_{it}/\sigma) \times \frac{h_{it}^{1+\frac{1}{\sigma}}}{1+\frac{1}{\sigma}} \right) \quad (1)$$

where U is the expected discounted present value of lifetime utility, c_{it} is consumption, $v(\cdot)$ is some increasing concave function, and h_{it} is hours worked. The parameter σ is the intertemporal elasticity of substitution, which is the object of interest in this study. Lastly, α_{it} is the preference for work. Define A_{it} as assets, r_t the interest rate, and W_{it} the true wage. Individuals choose labor supply⁴ and consumption paths to maximize equation (1) subject to the dynamic budget constraint

$$A_{it+1} = (1 + r_t)(A_{it} + W_{it}h_{it} - c_{it}) \quad (2)$$

which results in the labor supply function:

$$\log h_{it} = \sigma \log W_{it} + \sigma \log \lambda_{it} + \alpha_{it} \quad (3)$$

which in first differences is

$$\Delta \log h_{it} = \sigma \Delta \log W_{it} + \sigma \Delta \log \lambda_{it} + \Delta \alpha_{it}, \quad (4)$$

⁴Most labor supply models assume that individuals choose their work hours given the wage. This rules out the complications created by contracting models (see Rosen (1985) and Abowd and Card (1987), for example).

where Δ is the first difference operator (e.g., $\Delta \log h_{it} = \log h_{it} - \log h_{it-1}$) and λ_{it} is the marginal utility of wealth.

The Euler equation implies that individuals equate expected marginal utility across time according to

$$\lambda_{it-1} = \beta(1 + r_{t-1})E_{t-1}\lambda_{it} \quad (5)$$

where rational expectations⁵ implies that innovations to the marginal utility of wealth, denoted ε_{it} , should be uncorrelated with lagged values of the marginal utility of wealth:

$$\lambda_{it} = E_{t-1}\lambda_{it} + \varepsilon_{it} \quad (6)$$

Equations (5) and (6) can be rewritten as

$$\frac{\beta(1 + r_{t-1})\lambda_{it}}{\lambda_{it-1}} = \left(1 + \frac{\beta(1 + r_{t-1})\varepsilon_{it}}{\lambda_{it-1}}\right) \quad (7)$$

Taking logarithms of both sides of (7) and approximating $\log(1 + \frac{\beta(1+r_{t-1})\varepsilon_{it}}{\lambda_{it-1}})$ yields

$$\log \lambda_{it} - \log \lambda_{it-1} + \log \beta(1 + r_{t-1}) = \log \left(1 + \frac{\beta(1 + r_{t-1})\varepsilon_{it}}{\lambda_{it-1}}\right) \approx \frac{\beta(1 + r_{t-1})\varepsilon_{it}}{\lambda_{it-1}} \quad (8)$$

Throughout I will assume that the approximation in (8) holds with equality. As innovations in the marginal utility of wealth become arbitrarily small, equation (8) becomes an arbitrarily close approximation.

Combining (8) and (4) results in

$$\Delta \log h_{it} = \sigma \Delta \log W_{it} - \sigma \log \beta(1 + r_{t-1}) + \sigma \frac{\beta(1 + r_{t-1})\varepsilon_{it}}{\lambda_{it-1}} + \Delta \alpha_{it}. \quad (9)$$

The object of interest in this study is σ , which is a measure of the substitution effect associated with a wage change.

⁵If workers have rational expectations then at time t they know their state variables $\Delta \log W_{it}$, r_t , α_{it} , the Markov process that determines the evolution of the state variables, and optimize accordingly.

2.2 Using Lagged Wage Changes to Predict Current Wage Changes

Equation (9) shows that there are three determinants of hours changes that are potentially correlated with wage changes: the interest rate, preference changes, and expectation errors. I must control for all three objects in order to obtain a consistent estimate of σ . I remove the correlation between wage changes and both the interest rate and preference changes by using residuals from regressions of wage and hours changes on a full set of year dummy variables, health status, age and education in the analysis.⁶ Throughout the rest of the paper, $\log W_{it}$ is redefined as the true wage residual and $\log h_{it}$ is redefined as the true hours residual.⁷

Time t wage changes $\Delta \log W_{it}$ are correlated with the time t expectation errors ε_{it} if wage changes are unanticipated. However, if individuals have rational expectations then expectation errors are uncorrelated with information known to the individual at time $t - 1$. Therefore, the wage can be instrumented using time $t - 1$ information. A natural instrument is last year's wage change, $\Delta \log W_{it-1}$. Consider the following model of wage growth:

$$\Delta \log W_{it} = \delta + \gamma \Delta \log W_{it-1} + \eta_{it}. \quad (10)$$

Predicted wage growth, $\widehat{\Delta \log W_{it}}$ is then

$$\widehat{\Delta \log W_{it}} = \delta + \gamma \Delta \log W_{it-1}. \quad (11)$$

Individuals may use more information than what is used in equation (11), but must use at least the information used in equation (11) when forecasting wage changes.

Inserting equation (11) into equation (9) (and netting out year effects and preference shifters) shows that the instrumental variables estimate of σ is

$$\sigma = \frac{Cov(\Delta \log h_{it}, \widehat{\Delta \log W_{it}})}{Cov(\Delta \log W_{it}, \widehat{\Delta \log W_{it}})} = \frac{Cov(\Delta \log h_{it}, \Delta \log W_{it-1})}{Cov(\Delta \log W_{it}, \Delta \log W_{it-1})} \quad (12)$$

where the above objects are population moments. The labor supply response to these pre-

⁶Section 3 describes the procedure more fully. By construction, the hours residuals are uncorrelated with the year effects (and thus the interest rate) and with observable preference shifters such as health. Using these hours residuals, the only determinants of hours changes will be wage changes and unobserved preference changes.

⁷The relationship between measured hours, the measured hours residual, and the true hours residual is described in equations (14) and (25).

dictable wage changes identifies the intertemporal elasticity of substitution. For example, if wages have a transitory component, wage changes will be negatively correlated across time, i.e. $Cov(\Delta \log W_{it}, \Delta \log W_{it-1}) < 0$. Testing whether σ is positive will then be equivalent to testing whether $Cov(\Delta \log h_{it}, \Delta \log W_{it-1})$ is negative.

2.3 The Problem of Measurement Error

Given that measurement error is pervasive in wage and hours data, measurement error must be purged from equation (12). In most studies, measurement error is assumed to be white noise (Altonji (1986), Holtz-Eakin et al. (1988), Ziliak and Kniesner (1999)) or white noise with a fixed effect (Abowd and Card (1987, 1989)). However, validation studies (Bound et al. (2000)) have refuted these assumptions. The validation studies have shown that measurement error in wages and hours is negatively correlated with true wages and hours. Bound et al. (1994) refer to this as “mean reverting measurement error”. One potential explanation for mean reverting measurement error is that workers underreport transitory changes in wages and hours.⁸

The validation studies also suggest that the serial correlation properties of measurement error may be more complicated than a simple fixed effect. While Bound et al. (1994) find only a .09 correlation in measurement error in earnings four years apart in the Panel Study of Income Dynamics Validation Study, Bound and Krueger (1991) find a .38 correlation in measurement error in earnings two years apart when comparing matched CPS data to Social Security Earnings Records. Note that if measurement error in earnings were white noise with a fixed effect, the correlation of measurement error two years apart should be the same as the correlation of measurement error four years apart.⁹

Although many models of measurement error are consistent with the evidence, a MA(1) process with a fixed effect is a parsimonious model that is consistent with the evidence.

⁸This is potential evidence that workers tend to forget short-term changes in hours and wages. If so, it seems unlikely that workers think seriously about adjusting their work hours to transitory wage fluctuations.

⁹The Bound et al. (1994) study and the Bound and Krueger (1991) study each use different datasets and each has its own idiosyncratic problems. For example, one problem with the CPS study is that some people interviewed during this time period potentially had more than one Social Security number. Therefore, the validation procedure is flawed when using Social Security records as a validation source. The correlation of measurement error could be the result of two successive mismatches between the CPS and the Social Security records. Moreover, the PSID is a higher quality dataset. Problems of autocorrelation of measurement error that exist in the CPS may not exist in the PSID. The data section describes some of the problems with the PSIDVS. Nevertheless, the two studies give evidence that measurement error may be more complicated than white noise with a fixed effect.

Therefore, consider the following model of measured hours and wages:¹⁰

$$\log \tilde{W}_{it} = \log W_{it} + u_{wit}, \quad (13)$$

$$\log \tilde{h}_{it} = \log h_{it} + u_{hit}. \quad (14)$$

Measurement error in wages and hours follows:

$$u_{wit} = u_{wi} + v_{wit} + \theta_w v_{wit-1}, \quad (15)$$

$$u_{hit} = u_{hi} + v_{hit} + \theta_h v_{hit-1}, \quad (16)$$

where innovations to the transitory component of measurement error are correlated with the transitory component of wages but not with any autocorrelated component of wages, i.e. $Cov(v_{wit}, \log W_{it}) \neq 0$, $Cov(v_{wit}, v_{hit}) \neq 0$, but $Cov(v_{wit}, \log W_{it-k}) = 0$, $Cov(v_{wit}, v_{wit-k}) = 0$ for all $k \neq 0$. Moreover, assume that all the covariances of measurement error are stationary, i.e. $Cov(\log W_{it-1}, v_{wit-1}) = Cov(\log W_{it}, v_{wit})$ and $Cov(v_{wit-1}, v_{hit-1}) = Cov(v_{wit}, v_{hit})$. In Appendix B I show that first-differencing equations (13)-(16) then inserting these equations into equation (12) results in a specification for $\sigma = \frac{Cov(\Delta \log h_{it}, \Delta \log W_{it-1})}{Cov(\Delta \log W_{it}, \Delta \log W_{it-1})}$, where

$$\begin{aligned} Cov(\Delta \log h_{it}, \Delta \log W_{it-1}) &= Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1}) + (1 - 2\theta_h + \theta_h \theta_w) Cov(v_{hit}, v_{wit}) \\ &\quad + Cov(v_{wit}, \log h_{it}) + (1 - 2\theta_h) Cov(v_{hit}, \log W_{it}) \end{aligned} \quad (17)$$

and

$$\begin{aligned} Cov(\Delta \log W_{it}, \Delta \log W_{it-1}) &= Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1}) + (2 - 2\theta_w) Cov(\log W_{it}, v_{wit}) + \\ &\quad + (1 - 2\theta_w + \theta_w^2) Var(v_{wit}). \end{aligned} \quad (18)$$

Wages are usually imputed using earnings divided by hours.¹¹ Therefore, an overreport

¹⁰Recall these are measured hours and wage residuals.

¹¹Some authors use alternative wage measures (Altonji (1986), Ziliak and Kniesner (1999)) which potentially overcome the problems mentioned herein. However, Altonji (1986) measures the intertemporal elasticity for

of hours leads to an underreport of wages, making measurement error in hours negatively correlated with measurement error in wages, i.e. $Cov(v_{hit}, v_{wit}) < 0$. Failure to include this term will bias the estimate of $Cov(\Delta \log h_{it}, \Delta \log W_{it-1})$ upwards.¹²

Note that $Var(v_{wit})$ is positive. Thus, failure to control for this term will bias the estimate of $Cov(\Delta \log W_{it}, \Delta \log W_{it-1})$ downwards. Given that failure to control for measurement error biases $Cov(\Delta \log h_{it}, \Delta \log W_{it-1})$ upwards and $Cov(\Delta \log W_{it}, \Delta \log W_{it-1})$ downwards, the intertemporal elasticity of substitution will most likely be biased downwards. This problem, known as “division bias”, is well recognized in the labor supply literature.

What is less well recognized, however, is how “mean reverting measurement” error should affect the estimate of the intertemporal elasticity of substitution. Equations (17) and (18) show that the covariance between measurement error and true hours and wages can also create bias.

2.4 Sources of Bias when Twice Lagged Wage Changes Instrument for Current Wage Changes

As stated previously, many researchers use twice lagged wages or twice lagged wage changes to instrument for current wage changes. After controlling for preference shifters and the interest rate, the intertemporal elasticity of substitution when using twice lagged wage changes (used by Abowd and Card (1987, 1989), for example) as an instrument is

$$\begin{aligned} \sigma &= \frac{Cov(\Delta \log h_{it}, \Delta \log W_{it-2})}{Cov(\Delta \log W_{it}, \Delta \log W_{it-2})} \\ &= \frac{Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-2}) + \theta_h [Cov(v_{hit}, \log W_{it}) + Cov(v_{hit}, v_{wit})]}{Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-2}) + \theta_w [Cov(v_{wit}, \log W_{it}) + Var(v_{wit})]}. \end{aligned} \quad (19)$$

When using twice lagged wage levels as an instrument for the wage change (used by Holtz-Eakin et al. (1989), Ziliak and Kniesner (1999)), the intertemporal elasticity of substitution

a subset of the population. Moreover, his measure of the wage does not include bonuses and overtime, a potentially important source of variability in wages. Ziliak and Kniesner (1999) use earnings divided by a constant. If hours are autocorrelated but have a correlation coefficient of less than one, their procedure will produce upward biased estimates of the intertemporal elasticity of substitution.

¹²This is true only when $(1 - 2\theta_h + \theta_h\theta_w) > 0$, or when θ_h and θ_w are not “too big”. Unfortunately, we have little evidence on these two parameters. Assuming that the measurement error properties of earnings in the CPS are the same as those for hours and wages in the PSID, results from Bound and Krueger (1991) indicate that this inequality holds.

is

$$\begin{aligned}
\sigma &= \frac{Cov(\Delta \log h_{it}, \log W_{it-2})}{Cov(\Delta \log W_{it}, \log W_{it-2})} \\
&= \frac{Cov(\Delta \log \tilde{h}_{it}, \log \tilde{W}_{it-2}) - Cov(\Delta \log h_{it}, u_{wi}) + \theta_h [Cov(v_{hit}, \log W_{it}) + Cov(v_{hit}, v_{wit})]}{Cov(\Delta \log \tilde{W}_{it}, \log \tilde{W}_{it-2}) - Cov(\Delta \log W_{it}, u_{wi}) + \theta_w [Cov(v_{wit}, \log W_{it}) + Var(v_{wit})]}.
\end{aligned} \tag{20}$$

Equations (19) and (20) show that using twice lagged wage levels and changes are only valid instruments if measurement error has no MA(1) component, i.e. $\theta_h = \theta_w = 0$. If $\theta_h > 0$ and $Cov(v_{hit}, v_{wit}) < 0$, the numerator in equations (19) and (20) is biased upwards. Likewise, the denominator in equations (19) and (20) are biased downwards. This likely leads to a downward biased estimate of σ . In other words, using twice lagged wage changes only overcomes the division bias problem when there is no MA(1) measurement error component.

2.5 Estimating Equations

The restrictions necessary to identify the intertemporal elasticity of substitution (the ratio of equations (17) to (18)) are described in Table 1. The first five restrictions in Table 1 follow from equations (15) and (16) and the orthogonality and stationarity assumptions described immediately below equation (16). However, given the data in the next section, both θ_w and θ_h are still unknown without making further assumptions. In order to identify the MA(1) measurement error coefficients θ_h and θ_w using data, we need information on the correlation of measurement error across two adjacent years. Unfortunately, this does not exist in the available data. Therefore, I consider two alternative sets of assumptions about the values of θ_w and θ_h . Each set of assumptions enables me to identify the intertemporal elasticity of substitution.

Under assumption (A1) I assume $\theta_w = 0$ and $\theta_h = 0$. Assumption (A1) and the assumptions in Section 2.3 result in the final two identifying restrictions listed in Table 1. Using these identifying assumptions, equations (17) and (18) can be rewritten as

$$\begin{aligned}
Cov(\Delta \log h_{it}, \Delta \log W_{it-1}) &= Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1}) + [Cov(\log h_{it}, u_{wit}) - Cov(\log h_{it}, u_{wit-k})] \\
&+ [Cov(u_{hit}, \log W_{it}) - Cov(u_{hit-k}, \log W_{it})] + [Cov(u_{hit}, u_{wit}) - Cov(u_{hit}, u_{wit-k})], \tag{21}
\end{aligned}$$

$$\begin{aligned}
Cov(\Delta \log W_{it}, \Delta \log W_{it-1}) &= Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1}) \\
&+ 2[Cov(\log W_{it}, u_{wit}) - Cov(\log W_{it}, u_{wit-k})] + [Var(u_{wit}) - Cov(u_{wit}, u_{wit-k})] \quad (22)
\end{aligned}$$

for $|k| > 1$.

In assumption (A2) I assume that $\theta_w = -\frac{Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-2})}{(Cov(\log W_{it}, v_{wit}) + Var(v_{wit}))}$ and $\theta_h = -\frac{Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-2})}{(Cov(\log W_{it}, v_{hit}) + Cov(v_{wit}, v_{hit}))}$. Assumption (A2) is equivalent to assuming $Cov(\Delta \log W_{it}, \Delta \log W_{it-2}) = 0$ and $Cov(\Delta \log h_{it}, \Delta \log W_{it-2}) = 0$, i.e., all autocorrelation between measured wage changes and their second lag arises from the autocorrelation of measurement error. Assumption (A2) is satisfied if log wages are a random walk with white noise superimposed. Given these assumptions, equations (17) and (18) can be rewritten as:

$$\begin{aligned}
Cov(\Delta \log h_{it}, \Delta \log W_{it-1}) &= Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1}) + [Cov(\log h_{it}, u_{wit}) - Cov(\log h_{it}, u_{wit-k})] \\
&+ [Cov(u_{hit}, \log W_{it}) - Cov(u_{hit-k}, \log W_{it})] + [Cov(u_{hit}, u_{wit}) - Cov(u_{hit}, u_{wit-k})] \\
&+ 2Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-2}), \quad (23)
\end{aligned}$$

$$\begin{aligned}
Cov(\Delta \log W_{it}, \Delta \log W_{it-1}) &= Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1}) \\
&+ 2[(Cov(\log W_{it}, u_{wit}) - Cov(\log W_{it}, u_{wit-k})) + [Var(u_{wit}) - Cov(u_{wit}, u_{wit-k})]] \\
&+ 2Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-2}) \quad (24)
\end{aligned}$$

for $|k| > 1$. The two estimates of the intertemporal elasticity of substitution that I present in this paper are the ratio of (21) to (22) and the ratio of (23) to (24).

3 Data

Given the scheme for estimating the intertemporal elasticity of substitution presented above, I need information on the properties of measured wages and hours (namely the variances and covariances of wage and hours residuals) as well as the properties of measurement error (namely the variances and covariances of measurement error). I use the PSID for measuring the properties of measured wages and hours and the PSIDVS for measuring the properties of measurement error.

Table 2 describes some basic characteristics of the PSID and PSIDVS samples. Because

the PSIDVS sample only has hourly workers, I show results for both all male workers in the PSID as well as for male hourly workers in the PSID. The PSIDVS sample is older, less educated and has higher wages than both the full and hourly PSID samples. Most importantly, there is a “true” wage and hours measure which will be described below.

3.1 PSID Data

The data source used to estimate the properties of measured wages is a male subsample of the PSID for the years 1981-1987, collected by researchers at the University of Michigan. I restrict the PSID sample to the years 1981-1987 to maximize how comparable the PSID is to the PSIDVS, which has data on hours and wages and measurement error in hours and wages for 1982 and 1986. I exclude the Survey of Economic Opportunity (SEO) subsample, which oversamples the poor and minorities. Survey respondents are asked about their earnings, labor supply patterns, and other decisions during the previous calendar year. Therefore, responses are for the years 1980-1986. Wages are imputed using annual earnings divided by annual hours. Appendix A describes the sample selection criteria.

As described in section 2.2, I posit the following model of measured log hours changes, $\Delta \log h_{it}^*$, and wage changes $\Delta \log W_{it}^*$:

$$\Delta \log h_{it}^* = X_{it}G + \Delta \log \tilde{h}_{it}, \quad (25)$$

$$\Delta \log W_{it}^* = X_{it}B + \Delta \log \tilde{W}_{it}, \quad (26)$$

where X_{it} is a vector of personal characteristics and year dummy variables, and $\Delta \log \tilde{h}_{it}$ and $\Delta \log \tilde{W}_{it}$ are the hours and wage residuals. Included in X_{it} are year dummies, a third order age polynomial, education, and health. Note that $\Delta \log \tilde{W}_{it}$ is orthogonal to the interest rate by construction, as it is orthogonal to the year effects. It is also orthogonal to observable preference shifters such as health. Table 3 presents estimates for hours and wages 1980-1987. The most striking aspect of the regressions in Table 3 is how little of the variation in wages and hours these variables can explain. Note that these variables, less health, are the usual instruments for wages when estimating labor supply functions. The R^2 is .0111 for hours and .0055 for wages. In other words, variation in the business cycle, age, education and health

explains only .55% of the variation in wage movements and 1.11% of the variation in hours movements. The focus of this paper will be on the labor supply response to (the predictable component of) the remaining 99.45% of wage variation.

Table 4 reports the covariance of time t measured hours and wage changes with time $t - 1$ and $t - 2$ wage changes. There is a negative covariance between current and lagged wage changes, indicating that if wages rose last year they will fall this year. There is a positive covariance between current hours changes and lagged wage changes, indicating that if measured wages rose last year, measured hours will on average rise this year. If hours and wages were free of measurement error, Table 4 would indicate that hours rise in response to a predictable decline in the wage. This would suggest a negative intertemporal elasticity of substitution. Given the presence of measurement error, no such inference should be made. The next section describes the measurement error corrections that will be made.

3.2 Using the PSIDVS to Determine the Properties of Measurement Error in PSID Data

In order to identify the properties of measurement error, I use PSIDVS described in Bound et al. (1994). A discussion of the survey design and results follows. The PSIDVS was designed to test the properties of measurement error in the PSID. Researchers from the University of Michigan surveyed employees at a single large Detroit-area manufacturing company in both 1983 and 1987.¹³ The employees who were interviewed in 1983 and were still employed by the firm in 1987 were re-interviewed, as were an additional sample of workers who were not interviewed in 1983. This creates a small panel of workers, as well as a somewhat larger cross section of workers. The design of this survey and the questions in the survey are similar to those in the PSID, although the PSIDVS asks fewer questions than the PSID.

The company records in the PSIDVS serve as a virtually error free dataset to compare with worker reports. I will therefore regard company measures of hours and wages as true hours and wages, $\log h_{it}$ and $\log W_{it}$.¹⁴ The company has information on annual earnings

¹³Therefore, hours and earnings responses are for 1982 and 1986.

¹⁴Formally true hours are $X_{it}G + \log h_{it}$ and true wages are $X_{it}B + \log W_{it}$. So long as measurement error is uncorrelated with X_{it} it is not necessary to subtract $X_{it}G$ from hours or $X_{it}B$ from wages. There was a small negative correlation between the variance of measurement error and education. Because the PSIDVS sample has lower education than the PSID sample, this will lead to the variance of measurement error in the PSID being overestimated. However, the correlation was small and would not significantly affect the estimates.

and hours worked by all hourly employees.¹⁵ The company keeps records of earnings for tax purposes. The number of hours worked by hourly employees is measured by punch-clock. Therefore, the company has precise measures of both earnings and hours. Differences between company records and survey responses are attributed to measurement error on the part of the employee. Since the survey design of the PSIDVS is similar to the survey design of the PSID, a worker's propensity to misreport earnings and hours should be similar in the two datasets.

Table 5 presents covariances between hours, wages, and measurement error in hours and wages for male hourly workers. Three important aspects of the data are worth noting. First, there is a negative covariance between measurement error in hours and wages. This is the "division bias" problem. Second, it displays a positive covariance between wages and measurement error in hours, as well as the positive covariance between hours and measurement error in wages.¹⁶ Inspection of equations (21) and (22) shows that mean reverting measurement error tends to offset division bias. Lastly, there is evidence of serial correlation in measurement error. Failure to account for serial correlation of measurement error will lead to an overstatement of the variance of transitory measurement error. This is important because the model is identified using transitory wage variation. Therefore, if we overstate the amount of transitory wage variation attributable to measurement error, we will overstate the importance of division bias. Although the covariances between measurement error and true variables as well as the autocovariance of measurement error are statistically insignificant, they are fairly large in magnitude.

There are four major reasons why measurement error in the PSIDVS may not be comparable to measurement error in the PSID. The first reason is that I assume that the company records are perfect, and that the company records have been perfectly transcribed. Although the PSIDVS is of high quality, it is not perfect.¹⁷ This should cause the variance of mea-

¹⁵Hourly workers were paid overtime.

¹⁶These covariances are a result of mean reverting measurement error. Previous studies have found a *negative* covariance between true hours and measurement error in hours. Given that wages are imputed by dividing measured earnings by measured hours, it is unsurprising that there is a *positive* covariance between true hours and measurement error in wages and a positive covariance between true wages and measurement error in hours.

¹⁷For example, one observation in the panel was deleted because the 1987 company report of an individual's earnings in 1982 was different from its 1983 report of the same individual's earnings in 1982. Although the discrepancy was small, it is potential evidence that there were transcription errors in 1983. Although I was able to delete this observation, there are potentially other observations that are erroneous company reports or other transcription errors.

surement error to be overestimated since measurement error on the part of the firm is being attributed to measurement error on the part of the individual.

The second reason why measurement error in the PSIDVS may not be comparable to measurement error in the PSID is that the PSIDVS samples a homogenous group of workers. The PSIDVS respondents were all hourly workers¹⁸ who worked for a single firm, and most were worked full time. Table 2 shows that the standard deviation of reported wages and reported hours is much smaller in the PSIDVS sample than in the PSID sample. This may bias results for the following reason. Recall that measurement error is potentially mean reverting, i.e. $Cov(\log W_{it}, u_{wit}) < 0$. Also note that in a sample with no variability in wages it must be the case that $Cov(\log W_{it}, u_{wit}) = 0$. Therefore, since there is less variability in wages in the PSIDVS than in the PSID, the importance of mean reverting measurement error is likely smaller in the PSIDVS than in the PSID. Inspection of equations (21) and (22) shows that mean reverting measurement error tends to offset the variances and covariances of measurement error. Given that the PSIDVS likely understates the importance of mean reverting measurement error, it likely overstates the importance the division bias problem.

Third, most of the workers in the PSIDVS are older than those in the PSID and all of the workers have remained with the same employer for several years. Therefore, it may be that the workers in the PSIDVS are familiar with their earnings and hours of work and are able to report the number of hours that they work more accurately than the population surveyed by the PSID. This would tend to indicate that the variance of measurement error might be underestimated in the PSIDVS.

Fourth, transitory wage shocks could be more or less important in this firm than for other firms. Potentially, both the variance of measurement error and the covariance of measurement error with true variables may be affected by the size of the transitory wage shocks.¹⁹ The extent of possible bias created by measurement problems in the PSIDVS is unclear. The next

¹⁸Both salaried and hourly workers were interviewed, but the company has records for hours worked only for hourly workers. Although the PSIDVS has no information about measurement error in hours for salaried workers, it does have information about measurement error in earnings (which is used to impute wages) for salaried workers. The variance of measurement error in earnings for salaried workers is .0232 and the variance of measurement error in earnings for hourly workers is .0221, so the estimates for the two groups are not statistically different from each other. Likewise, the covariance of measurement error in earnings with reported hours and reported earnings are also not statistically different for the two groups.

¹⁹Bound et al. (1994) show that both earnings and hours were significantly lower in 1982 than in 1986, potentially because of the 1982 recession. Table 5 shows that many of the variances and covariances of measurement error are larger in 1982 than in 1986.

section reports results assuming that any possible bias is small.

4 Results

4.1 Estimates Using Measurement Error Corrections

Table 6 shows four estimates of the intertemporal elasticity of substitution, as well as first stage statistics. The necessary covariances for estimation are in tables 4 and 5. The sample selection criteria are described in appendix A. Appendices C and D describe computation of standard errors and the first stage F and R^2 statistics.

The estimates in column (1) make no corrections for measurement error. The estimated intertemporal elasticity of substitution is negative. When assuming measurement error is white noise, as in column (2), the intertemporal elasticity of substitution is positive.²⁰ The reason for the change in sign is that the estimates in column (2) account for the division bias problem. As mentioned previously, failure to account for measurement error results in downward biased estimates of the intertemporal elasticity of substitution. However, the estimates in column (2) do not account for the correlation between true variables and measurement error. Column (3) accounts for the correlation of measurement error with true variables. It shows that accounting for “mean reverting measurement error” reduces the estimated intertemporal elasticity of substitution. The estimates in column (3) assume that there is no MA(1) component to measurement error, however. Column (4) assumes that all covariation in hours and wage changes with twice lagged wage changes arises from measurement error. Making this assumption reduces the estimate of the intertemporal elasticity of substitution again. Although there is insufficient data to distinguish which assumption about the MA(1) component of measurement error is better, both columns (3) and (4) indicate an intertemporal elasticity of substitution that is close to zero. Moreover, they are not statistically different from each other, regardless of whether or not the PSID sample is restricted to hourly workers. However, all estimates in columns (3) and (4) are statistically different from .7 and -.5 when using all workers and are statistically different from .9 and -.7 when using hourly workers, meaning that the estimates can reject a very large estimate of the intertemporal elasticity of substitution.

²⁰Note, however, that standard errors are large. The large standard errors are the result of the small sample size of the PSIDVS. It would be useful to re-estimate the model using new validation data if it becomes available.

4.2 Estimates Using Alternative Instruments for Wage Changes

Table 7 presents estimates of the intertemporal elasticity of substitution using different instruments for the time t wage change. The hours and wage change measures are again residuals from regressions on an age cubic, education, year dummies and changes in health status.²¹ Of the seven sets of estimates, columns (1)-(3) use instrument sets similar to other authors.²² Column (1) uses an instrument set ($\Delta \log \tilde{W}_{it-2}$) similar to Abowd and Card (1987, 1989). Column (2) uses an instrument set ($\log \tilde{W}_{it-2}$) used by Holtz-Eakin et al. (1988). Column (3) uses an instrument set similar to Altonji (1986), who uses both the level and first difference of the first lag of the reported current hourly wage of hourly workers, denoted $\log \dot{W}_{it-1}$ and $\Delta \log \dot{W}_{it-1}$, to instrument for $\Delta \log \tilde{W}_{it-2}$. Because the two measures are constructed differently, measurement error in $\log \dot{W}_{it-1}$ and in $\Delta \log \dot{W}_{it-1}$ should be uncorrelated with measurement error in $\log \tilde{W}_{it}$.²³ This overcomes the division bias problem. Unfortunately, it is likely that most of the transitory wage variation comes from overtime and bonuses. Moreover, \dot{W}_{it} refers to a given point in time, whereas the relevant wage measure is the wage over the calendar year. Therefore, most of the year-to-year variation in the hourly wage is likely missing when using \dot{W}_{it} . This will reduce the predictive power of the first stage R^2 and will also make measurement error in this wage measure negatively correlated with the true wage. If measurement error in \dot{W}_{it} is negatively correlated with the true wage, the measure becomes an invalid instrument.

Columns (1)-(3) show that the estimates of the intertemporal elasticity of substitution are higher when using $\log \dot{W}_{it}$ than when using $\log \tilde{W}_{it}$ as an instrument. One possible reason for this discrepancy is that serially correlated measurement error in $\log \tilde{W}_{it}$ is biasing the estimated intertemporal elasticity of substitution downwards. In section 2.4 I showed that serially correlated measurement error most likely biases the intertemporal elasticity of substi-

²¹I also tried a more standard approach. That is, include the age cubic, education, year dummies and changes in health status as right hand side regressors in the second stage. The different approach did not lead to substantially different estimates.

²²Data from 1969 to 1996 were used in the analysis, although the same coding decisions (outlined in Appendix A) were used as in the previous subsection.

²³Altonji (1986) notes that the current hourly wage measure \dot{W}_{it} refers to the wage at the time of the interview whereas the earnings divided by hours measure \tilde{W}_{it} refers to hours and earnings over the previous calendar year. In order to make the two wage measures refer to the same time period, I use the hours and earnings measures reported at time $t + 1$ to generate \tilde{W}_{it} .

tution downwards when using either $\log \tilde{W}_{it}$ or $\Delta \log \tilde{W}_{it}$ as an instrument. In columns (4) and (5) the sample is restricted to hourly workers who have data on $\Delta \log \dot{W}_{it-2}$ and $\Delta \log \tilde{W}_{it-2}$. In columns (6) and (7) The sample is restricted to hourly workers who have data on both $\log \dot{W}_{it-2}$ and $\log \tilde{W}_{it-2}$. Since the same people are being used to estimate the intertemporal elasticity of substitution, we should think that both $\log \dot{W}_{it-2}$ and $\log \tilde{W}_{it-2}$ should yield the same results and both $\Delta \log \dot{W}_{it-2}$ and $\Delta \log \tilde{W}_{it-2}$ should yield the same results in the absence of serially correlated measurement error. If serially correlated measurement error is affecting estimates when using the $\log \tilde{W}_{it}$ measure of wages, then we should see higher estimates of $Cov(\Delta \log \tilde{h}_{it}, \text{instrument})$ and lower estimates of $Cov(\Delta \log \tilde{W}_{it}, \text{instrument})$ when using $\log \tilde{W}_{it-2}$ instead of $\log \dot{W}_{it-2}$ as the instrument. It appears that there is evidence for this claim, although differences are statistically insignificant. Therefore, there is some evidence that serially correlated measurement error leads to downward biased estimates of the intertemporal elasticity of substitution when using twice lagged wages.²⁴ However, the most important thing to note is that all estimates are close to zero. These results, combined with the results in the previous subsection, show that person-specific year to year variation in hours is uncorrelated with person-specific year to year variation in wages.

5 Conclusions

In this paper I estimate the labor supply response to predictable wage changes. Using data from the PSID and the PSIDVS, I find a large transitory component to wages, even after correcting for measurement error. Since, by definition, the transitory component of wages vanishes over time, workers should anticipate that transitory wage shocks should vanish. This means that workers can predict some wage changes, and thus the labor supply response to these predicable wage changes identifies the intertemporal elasticity of substitution.

Using data from the PSIDVS, I find that that measurement error in hours and wages is correlated with true hours and wages. I also find that measurement error is serially correlated. This violates the assumptions of many previous PSID studies of intertemporal labor supply and will most likely lead to downward biased estimates of the intertemporal elasticity of substitution.

²⁴Ziliak and Kniesner (1999) also find evidence that the \tilde{W}_{it} measure leads to downward biased estimates.

However, properly controlling for measurement error does not overturn the qualitative findings of the previous PSID studies. Depending on the assumed autocorrelation structure for measurement error, point estimates are $-.03$ to $.10$ with a standard error of $.25$. A conservative range for the intertemporal elasticity of substitution is $-.5$ to $.6$. Although the range is wide, an estimate of $.6$ is still well below the elasticities used in the Real Business Cycle literature.

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Appendix A: Sample Selection Criteria Below is the sample selection criteria used for analysis. Table 8 describes the sample selection criteria that were used. The left hand side column refers to the selection criteria, the next four columns refer to observations deleted

from the PSIDVS where R refers to respondent observations and V refers to the validation (i.e. firm) observation of the individual. The right hand column refers to observations from the PSID. The initial subsample consisted of all males in the relevant years with hours greater than zero.

A “-” implies that the sample selection criteria was not used to delete observations. The only selection criteria used for the validation reports is that they are not missing and that the firm reports be internally consistent (i.e. that a firm’s 1987 report of a worker’s 1982 earnings be the same as the 1983 report of the same worker’s earnings). I use no other criteria for the validation reports in the PSIDVS since I have no information on the true measures of hours and wages in the PSID. For 1983 I delete respondent reports of multiple job holders because the hours question refers to hours on all jobs, whereas the validation report refers only to hours worked on the main job. For 1987 the hours question refers to the main job. Two respondents reported the firm was not their main job.

I also deleted observations where there were earnings and hours assignments (i.e. the reports were inaccurate). Unfortunately, earnings in 1983 were missing the assignment variable.

Appendix B: Derivation of Estimating Equations

This appendix gives the algebra behind equations (17) and (18). The numerator for the

equation for σ , equation (17), is²⁵

$$\begin{aligned}
& Cov(\Delta \log h_{it}, \Delta \log W_{it-1}) \\
= & Cov(\Delta \log \tilde{h}_{it} - \Delta u_{hit}, \Delta \log \tilde{W}_{it-1} - \Delta v_{wit-1}) \\
= & Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1}) - Cov(\Delta u_{hit}, \Delta W_{it-1} + \Delta u_{wit-1}) - \\
& Cov(\Delta \log h_{it} + \Delta u_{hit}, \Delta u_{wit-1}) + Cov(\Delta u_{hit}, \Delta u_{wit-1}) \\
= & Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1}) - Cov(\Delta u_{hit}, \Delta W_{it-1} + \Delta u_{wit-1}) - \\
& +Cov(\Delta \log h_{it} + \Delta u_{hit}, \Delta u_{wit-1}) + Cov(\Delta u_{hit}, \Delta u_{wit-1}) \\
= & Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1}) - Cov(\Delta u_{hit}, \Delta \log W_{it-1}) \\
& -Cov(\Delta \log h_{it}, \Delta u_{wit-1}) - Cov(\Delta u_{hit}, \Delta u_{wit-1}) \\
= & Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1}) \\
& -Cov(v_{hit} - (1 - \theta_h)v_{hit-1} - \theta_h v_{hit-2}, \log W_{it-1} - \log W_{it-2}) \\
& -Cov(\log h_{it} - \log h_{it-1}, v_{wit-1} - (1 - \theta_w)v_{wit-2} - \theta_w v_{wit-3}) \\
& -Cov(v_{hit} - (1 - \theta_h)v_{hit-1} - \theta_h v_{hit-2}, v_{wit-1} - (1 - \theta_w)v_{wit-2} - \theta_w v_{wit-3}) \\
= & Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1}) + (1 - 2\theta_h + \theta_h \theta_w)Cov(v_{hit}, v_{wit}) \\
& +Cov(v_{wit}, \log h_{it}) + (1 - 2\theta_h)Cov(v_{hit}, \log W_{it}) \tag{27}
\end{aligned}$$

and the denominator of σ is

²⁵Recall that since $\log h_{it}$ is a variable with zero mean and $\log W_{it-1}$ is a variable, $Cov(\log h_{it}, \log W_{it-1}) = E(\log h_{it} \log W_{it-1})$.

$$\begin{aligned}
& Cov(\Delta \log W_{it}, \Delta \log W_{it-1}) \\
= & Cov(\Delta \log \tilde{W}_{it} - \Delta u_{wit}, \Delta \log \tilde{W}_{it-1} - \Delta u_{wit-1}) \\
= & Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1}) - Cov(\Delta \log W_{it} + \Delta u_{wit}, \Delta u_{wit-1}) \\
& - Cov(\Delta u_{wit}, \Delta \log W_{it-1} + \Delta u_{wit-1}) + Cov(\Delta u_{wit}, \Delta u_{wit-1}) \\
= & Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1}) - Cov(\Delta \log W_{it}, \Delta u_{wit-1}) \\
& - Cov(\Delta u_{wit}, \Delta \log W_{it-1}) - Cov(\Delta u_{wit}, \Delta u_{wit-1}) \\
= & Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1}) - Cov(\Delta \log W_{it}, \Delta u_{wit-1}) \\
& - Cov(\Delta u_{wit}, \Delta \log W_{it-1}) - Cov(\Delta u_{wit}, \Delta u_{wit-1}) \\
= & Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1}) \\
& - Cov(\log W_{it} - \log W_{it-1}, v_{wit-1} - (1 - \theta_w)v_{wit-2} - \theta_w v_{wit-3}) \\
& - Cov(v_{wit} - (1 - \theta_w)v_{wit-1} - \theta_w v_{wit-2}, \log W_{it-1} - \log W_{it-2}) \\
& - Cov(v_{wit} - (1 - \theta_w)v_{wit-1} - \theta_w v_{wit-2}, v_{wit-1} - (1 - \theta_w)v_{wit-2} - \theta_w v_{wit-3}) \\
= & Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1}) + (2 - 2\theta_w)Cov(\log W_{it}, v_{wit}) + \\
& +(1 - 2\theta_w + \theta_w^2)Var(v_{wit}). \tag{28}
\end{aligned}$$

Appendix C: Obtaining Standard Errors

This appendix describes the procedure to obtain standard errors for both the first stage wage regression and the second stage estimate of the intertemporal elasticity of substitution. Estimation of both is similar so I focus on estimates of the intertemporal elasticity of substitution for concreteness.

There are several econometric problems in estimating the standard error. First, estimates of $Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1})$ and $Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1})$ come from the PSID whereas the other objects come from the PSIDVS. Second, the estimate of $Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1})$, for example, uses several years of data on the same individual, meaning that not all observations are independent of one another. Third, the same individuals are not observed in all years, making the data unbalanced. The procedure below addresses all three problems.

Consider a highly simplified version of the problem where

$$\hat{\sigma} = \frac{\frac{1}{N_A+N_B} \left(\sum_{i=1}^{N_A} A_i + \sum_{i=1}^{N_B} B_i \right)}{\frac{1}{N_U+N_V} \left(\sum_{i=1}^{N_U} U_i + \sum_{i=1}^{N_V} V_i \right)} = \frac{\bar{S}}{\bar{T}} \quad (29)$$

where A_i and B_i are individual contributions to a covariance, e.g. $A_i = \Delta \log \tilde{h}_{i85} \Delta \log \tilde{W}_{i84} - E[\Delta \log \tilde{h}_{it} \Delta \log \tilde{W}_{it}]$ and $B_i = \Delta \log \tilde{h}_{i86} \Delta \log \tilde{W}_{i85} - E[\Delta \log \tilde{h}_{it} \Delta \log \tilde{W}_{it}]$, and N_A, N_B, N_C , and N_D are the number of observations in covariance A, B, C , and D . Assuming that the wage and hours generating process is stationary,²⁶ I also enforce the restriction that $\bar{A} = \bar{B} = \frac{1}{N_A+N_B} \left(\sum^{N_A} A_i + \sum^{N_B} B_i \right)$ and $\bar{C} = \bar{D} = \frac{1}{N_C+N_D} \left(\sum^{N_C} C_i + \sum^{N_D} D_i \right)$ as they are both means of the same object. Embodied in this problem are all three previously mentioned problems.

Denote $N_B = N_B(N_A), N_C = N_C(N_A), N_D = N_D(N_A)$ to indicate that N_B, N_C, N_D are to be viewed as functions of N_A . Assume $\lim_{N_A \rightarrow \infty} N_B(N_A) = k_B, \lim_{N_A \rightarrow \infty} N_C(N_A) = k_C, \lim_{N_A \rightarrow \infty} N_D(N_A) = k_D$, where k_B, k_C, k_D are constants. In other words, the number of observations in each moment condition (A, B, C, D) are all converging to infinity at the same rate. Moreover, assume that $\text{plim}_{N_A \rightarrow \infty} \frac{1}{N_A+N_B} \left(\sum_{i=1}^{N_A} A_i + \sum_{i=1}^{N_B} B_i \right) = E(A)$ and $\text{plim}_{N_A \rightarrow \infty} \frac{1}{N_U+N_V} \left(\sum_{i=1}^{N_U} U_i + \sum_{i=1}^{N_V} V_i \right) = E(U)$.

Performing a Taylor's series expansion of $\hat{\sigma}$ in equation (29) around σ and squaring results in the delta method. Written in matrix format, the delta method is:

$$(\sigma - \hat{\sigma}) \sim_a N \left(0, \left(\frac{\partial \sigma}{\partial m} \right)' W \left(\frac{\partial \sigma}{\partial m} \right) \right) \quad (30)$$

where m is a covariance, e.g. $E(A)$, and W is the fourth moment matrix of the covariances needed to estimate equation (29). In practice, $\frac{\partial \sigma}{\partial m}$ and W are replaced by their sample

²⁶The stationarity assumption is not necessary for estimation of σ , but it simplifies the computation of the standard errors.

analogous:

$$\frac{\partial \hat{\sigma}}{\partial \bar{m}} = \begin{pmatrix} \frac{1}{\bar{T}} \\ \frac{1}{\bar{T}} \\ -\frac{\bar{S}}{\bar{T}^2} \\ -\frac{\bar{S}}{\bar{T}^2} \end{pmatrix}, \quad (31)$$

$$\hat{W} = \begin{pmatrix} \left(\frac{1}{N_A+N_B}\right)^2 \sum_{i=1}^{N_A} (A_i - \bar{A})^2 & \left(\frac{1}{N_A+N_B}\right)^2 \sum_{i=1}^{N_A \cap N_B} (A_i - \bar{A})(B_i - \bar{B}) & \dots & \dots \\ \left(\frac{1}{N_A+N_B}\right)^2 \sum_{i=1}^{N_A \cap N_B} (A_i - \bar{A})(B_i - \bar{B}) & \left(\frac{1}{N_A+N_B}\right)^2 \sum_{i=1}^{N_B} (B_i - \bar{B})^2 & \dots & \dots \\ \left(\frac{1}{N_A+N_B}\right) \left(\frac{1}{N_U+N_V}\right) \sum_{i=1}^{N_A \cap N_U} (A_i - \bar{A})(U_i - \bar{U}) & \left(\frac{1}{N_A+N_B}\right) \left(\frac{1}{N_U+N_V}\right) \sum_{i=1}^{N_B \cap N_U} (B_i - \bar{B})(U_i - \bar{U}) & \dots & \dots \\ \left(\frac{1}{N_A+N_B}\right) \left(\frac{1}{N_U+N_V}\right) \sum_{i=1}^{N_A \cap N_V} (A_i - \bar{A})(V_i - \bar{V}) & \left(\frac{1}{N_A+N_B}\right) \left(\frac{1}{N_U+N_V}\right) \sum_{i=1}^{N_B \cap N_V} (B_i - \bar{B})(V_i - \bar{V}) & \dots & \dots \end{pmatrix}. \quad (32)$$

\hat{W} is a symmetric matrix. $N_A \cap N_B$ refers to the number of persons that contributed to both the A_i covariance and the B_i covariance. Note that if A_i and U_i are from different datasets, $N_A \cap N_V = 0$. Therefore, if A and B were from one dataset and C and D were from another dataset, \hat{W} would be a block diagonal matrix. In practice, estimation of $\hat{\sigma}$ and its distribution is more tedious but no more complicated than what is described in this section. For example, in the absence of measurement error, equation $\hat{\sigma}$ will have five objects in the numerator and five in the denominator (one for each year of PSID data), meaning that $\frac{\partial \hat{\sigma}}{\partial \bar{m}}$ is a 10×1 vector and \hat{W} is a 10×10 matrix.

Appendix D: Derivation of the First Stage Regression

This appendix shows the procedure to control for measurement error in the first stage regression (10) as well as the procedure to obtain the relevant first stage F – *statistic* and R^2 statistic. The procedure to control for measurement error is fundamentally similar to the procedure used to control for measurement error when estimating σ directly. Consider the case where $\theta_h = \theta_w = 0$, but measurement error is correlated with true variables, as in column

3 of Table 6. The regression coefficient in the first stage is

$$\begin{aligned}
\gamma &= \frac{Cov(\Delta \log W_{it}, \Delta \log W_{it-1})}{Var(\Delta \log W_{it-1})} = \frac{Cov(\Delta \log \tilde{W}_{it} - v_{wit}, \Delta \tilde{W}_{it-1} - v_{wit-1})}{Var(\Delta \log \tilde{W}_{it-1} - v_{wit-1})} \\
&= \frac{Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1}) + 2Cov(\log W_{it}, v_{wit}) + Var(v_{wit})}{Var(\Delta \log \tilde{W}_{it-1}) - 4Cov(\log W_{it}, v_{wit}) - 2Var(v_{wit})}. \tag{33}
\end{aligned}$$

Standard errors for γ are computed using the method described in Appendix C. The t -*statistic* is γ divided by its standard error. The F -*statistic* is the square of the t -*statistic*. The R^2 is the explained sum of squares divided by the total sum of squares. An appendix available from the author describes the potential small sample bias in this problem. If the series $\Delta \log W_{it}$ is stationary, then the R^2 is

$$R^2 = \frac{\sum_{i=1}^N (\hat{\gamma} \Delta \log W_{it})^2}{\sum_{i=1}^N (\Delta \log W_{it+1})^2} \approx \hat{\gamma}^2. \tag{34}$$

Object of Interest	Data Used to Estimate Object of Interest
$Cov(\log h_{it}, v_{wit})$	$Cov(\log h_{it}, u_{wit}) - Cov(\log h_{it}, u_{wit+k}), k > 1$
$(1 + \theta_h \theta_w) Cov(v_{hit}, v_{wit})$	$Cov(u_{hit}, u_{wit}) - Cov(u_{hit}, u_{wit+k}), k > 1$
$Cov(\log W_{it}, v_{hit})$	$Cov(\log W_{it}, u_{hit}) - Cov(\log W_{it}, u_{hit+k}), k > 1$
$Cov(\log W_{it}, v_{wit})$	$Cov(\log W_{it}, u_{wit}) - Cov(\log W_{it}, u_{wit+k}), k > 1$
$(1 + \theta_w^2) Var(v_{wit})$	$Var(u_{wit}) - Cov(u_{wit}, u_{wit+k}), k > 1$
$-\theta_w (Cov(\log W_{it}, v_{wit}) + Var(v_{wit}))$	(A1) 0
	(A2) $Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-2})$
$-\theta_h (Cov(\log W_{it}, v_{hit}) + Cov(v_{wit}, v_{hit}))$	(A1) 0
	(A2) $Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-2})$
The first five identification restrictions are derived using the assumptions in Section 2.3	
(A1) and (A2) are only necessary for identifying the last two objects of interest	
(A1) is the set of assumptions that lead to estimating equations (21) and (22)	
(A2) is the set of assumptions that lead to estimating equations (23) and (24)	

Table 1: Properties of Transitory Measurement Error

Means and Standard Deviations of Variables, PSID and PSIDVS			
Variable	PSID, all	PSID, hourly	PSIDVS
Age	38.9 (10.6)	37.9 (10.9)	45.9 (16.0)
At Least High School Grad?	.84 (.37)	.73 (.44)	.65 (.35)
College Grad?	.30 (.44)	.07 (.26)	.12 (.33)
Tenure	9.5 (8.9)	8.9 (8.7)	15.1 (11.8)
log Reported Wage	2.50 (.55)	2.40 (.46)	2.90 (.19)
log Reported Hours	7.66 (.29)	7.60 (.27)	7.59 (.19)
log True Wage			2.92 (.11)
log True Hours			7.57 (.21)
	$N = 14,920$	$N = 5,521$	$N = 544$

Table 2: Descriptive Statistics, PSID (1980-1986) and PSIDVS (1982, 1986)

Dependent Variable:	$\Delta \log h_{it}$	$\Delta \log W_{it}$
	Estimate (S.E.)	Estimate (S.E.)
Intercept	.064 (.18)	.018 (.22)
Age	-.050 (.013)	.0028 (.0165)
Age Squared	.0013 (.0003)	-.00014 (.00039)
Age Cubed	-.000011(.000002)	.0000014(.0000030)
College Grad	.045 (.006)	.025 (.0007)
High School	.040 (.007)	-.0005 (.0087)
Health Change	-.017 (.009)	-.052 (.012)
Year Dummies also included		
R^2	.0111	.0055
$F - Statistic$	11.1	5.31
N	11,869	11,539

Table 3: OLS regressions for wage and hours changes, PSID, 1980-1987

ALL WORKERS			
$Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1})$.0090 (.0015)	$Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1})$	-.0366 (.0028)
$Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-2})$.0013 (.0014)	$Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-2})$	-.0009 (.0014)
HOURLY WORKERS			
$Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-1})$.0082 (.0026)	$Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-1})$	-.0324 (.0043)
$Cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{W}_{it-2})$.0021 (.0026)	$Cov(\Delta \log \tilde{W}_{it}, \Delta \log \tilde{W}_{it-2})$	-.0005 (.0024)

Table 4: Covariance of Hours and Wage Changes with Lagged Wage Changes, PSID, 1980-1986

Covariances of Measurement Error		
	Estimate (S.E.)	<i>N</i>
$Cov(\log W_{i82}, u_{hi82})$.0049 (.0016)	128
$Cov(\log W_{i86}, u_{hi86})$	-.0009 (.0006)	292
$Cov(\log W_{i82}, u_{hi86})$	-.0044 (.0014)	118
$Cov(\log W_{i86}, u_{hi82})$.0018 (.0013)	89
$Cov(\log h_{i82}, u_{wi82})$.0022 (.0051)	121
$Cov(\log h_{i86}, u_{wi86})$.0003 (.0021)	277
$Cov(\log h_{i82}, u_{wi86})$.0027 (.0027)	112
$Cov(\log h_{i86}, u_{wi82})$.0018 (.0021)	85
$Cov(u_{hi82}, u_{wi82})$	-.0202 (.0059)	121
$Cov(u_{hi86}, u_{wi86})$	-.0097 (.0025)	277
$Cov(u_{hi82}, u_{wi86})$	-.0018 (.0016)	81
$Cov(u_{hi86}, u_{wi82})$.0001 (.0018)	83
$Cov(\log W_{i82}, u_{wi82})$	-.0051 (.0021)	121
$Cov(\log W_{i86}, u_{wi86})$.0005 (.0007)	277
$Cov(\log W_{i82}, u_{wi86})$.0028 (.0013)	112
$Cov(\log W_{i86}, u_{wi82})$	-.0032 (.0020)	85
$Var(u_{wi82})$.0323 (.0075)	121
$Var(u_{wi86})$.0172 (.0026)	277
$Cov(u_{wi82}, u_{wi86})$.0023 (.0022)	79

Table 5: Covariances, PSIDVS

MEASUREMENT ERROR SPECIFICATION	(1)	(2)	(3)	(4)
Any measurement error?	no	yes	yes	yes
Correlated with true variables?	no	no	yes	yes
Includes MA(1) component?	no	no	no	yes
ALL WORKERS				
FIRST STAGE ESTIMATES				
γ	-.36 (.02)	-.26 (.06)	-.29 (.05)	-.31 (.05)
$F - stat$	522	18.6	39.1	47.9
R^2	.128	.067	.085	.096
SECOND STAGE ESTIMATES				
$Cov(\Delta \log h_{it}, \Delta \log W_{it-1})$.0090	-.0025	-.0021	.0005
$Cov(\Delta \log W_{it}, \Delta \log W_{it-1})$	-.0366	-.0156	-.0203	-.0221
σ intertemporal elasticity of substitution	-.25 (.04)	.16 (.27)	.10 (.26)	-.02 (.23)
HOURLY WORKERS				
FIRST STAGE ESTIMATES				
γ	-.38 (.03)	-.26 (.08)	-.30 (.07)	-.32 (.07)
$F - stat$	152	9.8	21.9	22.1
R^2	.144	.069	.093	.101
SECOND STAGE ESTIMATES				
$Cov(\Delta \log h_{it}, \Delta \log W_{it-1})$.0082	-.0033	-.0029	.0013
$Cov(\Delta \log W_{it}, \Delta \log W_{it-1})$	-.0324	-.0114	-.0162	-.0172
σ intertemporal elasticity of substitution	-.25 (.08)	.29 (.40)	.18 (.33)	-.08 (.32)
Standard errors in parentheses				
Column (1): $\sigma = \frac{Cov(\Delta \log h_{it}, \Delta \log W_{it-1})}{Cov(\Delta \log W_{it}, \Delta \log W_{it-1})}$				
Column (2): $\sigma = \frac{Cov(\Delta \log h_{it}, \Delta \log W_{it-1}) + Cov(u_{hit}, u_{wit})}{Cov(\Delta \log W_{it}, \Delta \log W_{it-1}) + Var(u_{wit})}$				
Column (3): ratio of equation (21) to equation (22)				
Column (4): ratio of equation (23) to equation (24)				

Table 6: Estimates of the Intertemporal Elasticity of Substitution Under Different Measurement Error Assumptions, 1981-1987 PSID, 1982, 1986 PSIDVS

Group	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instrument	All	All	Hourly	Hourly	Hourly	Hourly	Hourly
	$\Delta \log \tilde{W}_{it-2}$	$\log \tilde{W}_{it-2}$	$\Delta \log \tilde{W}_{it-1}$, $\log \tilde{W}_{it-1}$	$\Delta \log \tilde{W}_{it-1}$, \tilde{W}_{it-2}	$\Delta \log \tilde{W}_{it-2}$	$\log \tilde{W}_{it-2}$	$\log \tilde{W}_{it-2}$
FIRST STAGE ESTIMATES, DEPENDENT VARIABLE IS $\Delta \log \tilde{W}_{it}$							
γ	-.023 (.006)	-.037 (.003)	.014(.017), -.036 (.007)	-.20 (.011)	.010 (.019)	-.033 (.005)	-.023 (.006)
$F - stat$	15.4	127.7	12.8	3.2	.25	34.16	13.2
R^2	.0005	.0035	.0022	.0009	.0000	.0026	.0010
N	31620	36331	11706	9874	9874	13193	13193
SECOND STAGE ESTIMATES, DEPENDENT VARIABLE IS $\Delta \log \tilde{h}_{it}$							
$Cov(\Delta \log \tilde{h}_{it}, instrument)$.00019	.0010		.0003	-.0004	.0002	-.0002
$Cov(\Delta \log \tilde{W}_{it}, instrument)$	-.00222	-.0104		-.0013	.0002	-.0064	-.0035
intertemporal elasticity of substitution							
σ	-.18(.18)	-.10(.06)	.18(.19)	-.23 (.48)	-2.0 (3.9)	-.03 (.15)	.06 (.25)
First stage regression: $\Delta \tilde{W}_{it} = \delta + \gamma instrument + \eta_{it}$ Standard errors in parentheses							

Table 7: Estimates of the Intertemporal Elasticity of Substitution Under Different Instrument Sets, PSID 1969-1996

Criterion for Deletion	1983 (R)	1983 (V)	1987 (R)	1987 (V)	PSID
HOURS					
Initial observations	339	173	449	296	19160
Hours < 500 or Hours > 4500	3	-	1	-	793
Age < 25 or age > 65	4	0	10	3	2130
Hours were assigned	50	-	9	-	476
Multiple job holders	23	-	-	-	-
Firm is not main job	-	-	2	-	-
Remaining observations	259	173	427	293	15761
WAGES					
Earnings missing	7	0	0	0	0
Wages < \$3 or > \$100 (1987 dollars)	0	-	0	-	569
Earnings accuracy	-	-	28	-	258
1987 Validation data different from 1983 Validation data	-	1	-	-	-
Missing education or health	-	-	-	-	14
Remaining observations	245	172	399	293	14920

Table 8: Sample Selection