

Labor Supply Elasticities: Can Micro Be Misleading for Macro?

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Abstract

In this paper we compare in a consistent way micro and macro labor supply elasticities. The individual elasticity is obtained from the Panel Study of Income Dynamics (PSID). The aggregate, time-series, elasticity is estimated from the exact aggregation of the individual units in the PSID, each year. Our aggregation procedure is legitimate since it relies on exact aggregation of first-order conditions in a simple life-cycle labor supply model with home production. We find an individual elasticity of about 0.1, a low value that agrees with standard micro estimates. However, we find an aggregate elasticity that is much larger, i.e. about 0.9. This result derives from a pure aggregation effect: not surprisingly, most of the difference is due to the extensive margin, i.e. participation/employment decisions. An implication of our result is that micro evidence is not always a reliable guidance for calibrating aggregate macroeconomic parameters.

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1 Introduction

The intertemporal substitution between work and leisure is crucial for the explanation of aggregate fluctuations in modern macroeconomics. When stating how the benchmark RBC model should be calibrated, Prescott (1986) suggested to restrict the stochastic growth model on the basis of the available micro-econometric evidence:

“A fundamental thesis of this line of inquiry is that the measures obtained from aggregate series and those from individual panel data must be consistent. After all, the former are just the aggregates of the latter.” (op. cit., p. 22).

When labor supply is involved things are more complicated. This is pointed out by several authors (Heckman, 1993; Browning, Hansen and Heckman, 1999), and by Prescott (2006) himself. Microeconomic studies based on cross-sectional data generally report a small real-wage elasticity (e.g. Pencavel, 1986, and Killingsworth and Heckman, 1986). This is not surprising since in a static, long-run, setting the income effect is likely to prevail. What is more surprising is that the elasticity is still low in studies based on panel data (e.g. MaCurdy, 1981 and Altonji, 1986).¹

On the other hand, the macroeconomic evidence is far less numerous and is generally mixed. In their seminal paper, Lucas and Rapping (1969) find that, for the US economy (1930-1965), total hours are strongly real-wage elastic in the short-run (1.4). Among the others, Hall (1980) finds an intertemporal elasticity of substitution which is about 0.5, while Mankiw, Rothemberg and Summers (1985) reject the intertemporal substitution hypothesis by estimating the intensive margin only, i.e. hours per worker, rather than the most appropriate aggregate hours changes (Heckman, 1993).

It is well known that the RBC model requires a much larger elasticity than those estimated in micro studies in order to reproduce observed aggregate fluctuations. This is why Prescott (2006) strongly advocates that the

¹All of these are reviewed by Blundell and MaCurdy (1999).

aggregate labor supply elasticity is about 3, in spite of panel micro-estimates ranging from about 0 to about 0.2 for men and from about 0 to about 1 for married women (see Blundell and MaCurdy, 1999, for a review). Furthermore, most of the changes in aggregate hours stem from the extensive – i.e. employment/participation – rather than from the intensive margin – intertemporal adjustment of hours (Kydland, 1995). Probably this explains why the intertemporal substitution hypothesis is not rejected when applied to aggregate employment, as the work of Alogoskoufis (1987) shows for the US.

The necessity of reconciling the relatively high aggregate elasticity used in calibration studies with the low elasticity estimated in microeconomic studies brought about a number of different orientations. In some cases (e.g. Summers, 1986, and Mankiw, 1989) the whole relevance of the RBC model was denied. A more constructive orientation explored several variants of the benchmark RBC model (Prescott, 1986) in order to better accommodate the data. A precursor is the seminal work of Kydland and Prescott (1982) based on non-separability of leisure at different points in time. This was followed by the lottery (Rogerson, 1988) and the indivisible labor model (Hansen, 1985) where people either work a fixed or a zero amount of hours. Among the other relevant extensions, the introduction of government consumption (Christiano and Eichenbaum 1992), the home production model (Benhabib, Rogerson and Wright, 1991) and the introduction of taxation in general equilibrium models (Baxter and King, 1993, and McGrattan, 1994) are all noteworthy extensions of the benchmark RBC model (i.e. Prescott, 1986.) More recent studies that generate a wedge between individual and aggregate labor elasticities range from heterogeneous reservation wages (Chang and Kim, 2005, 2006) to the omission of such different variables as wealth (Ziliak and Kniesner, 1999), liquidity constraints (Domeji and Floden, 2006) and human capital accumulation (Imai and Keane, 2004), to nonlinearities in the relation between labor services and hours of work (Rogerson and Wallenius, 2007). A large aggregate elasticity is also required to explain the difference in patterns of work in Europe and the US on the basis of different tax rates (Prescott, 2004). Needless to say, this list is incomplete.

In this paper we take a different, empirical, route based on a sound and testable aggregation principle. We use all of the annual waves (1968-1997) of the Panel Study of Income Dynamics (PSID)² to estimate the Frisch labor supply elasticity via a long-enough panel to be compared with the corresponding time series estimate resulting from the exact aggregation of individual units each year.³ Thanks to this procedure, the elasticities obtained from the aggregate series and the individual panel data are fully consistent in the sense advocated by Prescott (1986). In fact we believe this is the best way they can be consistently estimated. To our knowledge, what we do is something new despite its conceptual simplicity.

We show that microeconomic estimates are not a good source for calibrating total worked hours: our panel results deliver a Frisch elasticity of 0.11, while the aggregate time-series results deliver a Frisch elasticity of 0.86, a value that is almost eight times the individual one. Moreover, we decompose the aggregate elasticity into the contribution of adjustment of hours (intensive margin) and of employment (extensive margin), finding that the latter accounts for 3/4 of the difference between the two elasticities. This means that the latter is mainly due to the positive covariance between number of workers and the wage rate. These results, which are based on observational data, complement the findings of Rogerson and Wallenius (2007) as well as Chang and Kim (2005, 2006), which are based instead on calibrating the aggregate economy.⁴

Our estimates should be interpreted with care. Partially because of data limitations, our goal is mainly methodological, in the sense that we do not aim at providing reliable estimates of labor supply elasticities, though the

²PSID data was collected every year from 1968 to 1997 and every two years from 1997 onward. As we explain below, this poses problems which we prefer to avoid by truncating the series in 1997.

³As in Macurdy (1981), the workers in our sample exclude permanently disabled or retired people and include only those units displaying nonzero wage and labor supply data for all years in the sample. The importance of this point for obtaining a reliable aggregation was independently stressed in private conversations by Edward Prescott and Richard Rogerson.

⁴In particular, Chang and Kim assume an individual elasticity of 0.4 and find an aggregate elasticity of about 1.

individual elasticity agrees with standard estimates and the aggregate one is not far from what Lucas and Rapping (1969) found. Rather, we are interested in assessing their *relative* magnitude.

We are well aware of the fact that our procedure is not costless, for several reasons. First, the resulting aggregate time series is short, and even more so because we cannot use all of the available PSID waves (1968-2005). The reason is that after 1997 data were collected every two years. To avoid arbitrary interpolation of the microdata, we prefer using the annually released data (1968-1997) only. The obvious cost of this choice consists of a shorter time-series. This, however, strengthens our confidence in the goodness of our results as we are able to obtain a highly significant estimate even with a handful of observations. Second, PSID data do not report for all waves important variables such as wealth. Another missing variable is the real interest rate, whose nominal component might differ among individuals and groups. For the same reason, our real wage variable is before, rather than after-tax, as it should be whenever statutory or effective tax rates are not constant. Third, by defining aggregate employment as the number of individuals who work in a given wave, we are mixing variations in employment with variations in sample size. These can be substantial in the PSID, as we discuss later in the paper. We control for such variations by using dummies for the years in which the panel underwent major modifications.

On the other hand, our procedure seems to release a number of benefits. In particular, the macro dataset is based on *exactly* the same units of observation that compose the micro dataset. We are not aware of other empirical work doing this. Our aggregation is legitimate since it is derived from the aggregation of individual first order conditions under the assumption that heterogeneity takes a special form which is meaningful in macroeconomic terms. This should provide an appropriate framework for comparing aggregate and individual elasticities.

The remainder of the paper is organized as follows. In Section 2 we discuss the relevance of disentangling between the intensive and the extensive labor margin. Section 3 illustrates the theoretical model. Section 4 presents the dataset and Section 5 the results. Section 6 concludes.

2 Intensive vs. Extensive Margin

The indivisible labor case (Hansen, 1985), where individuals either work a fixed amount of hours or do not work at all, accommodates in an extreme way the well-known evidence that labor adjustment on the extensive margin dwarfs adjustment on the intensive margin. Like in Hansen (1985), if we denote by N_t employment and by $\overline{H}_t$ the average supply of hours, then aggregate labor is $H_t \equiv N_t \overline{H}_t$. By taking logs, the variance of labor input can be decomposed as follows:

$$\text{var}(\ln H_t) = \text{var}(\ln N_t) + \text{var}(\ln \overline{H}_t) + 2\text{cov}(\ln N_t, \ln \overline{H}_t).$$

The share of the total variation that is due to N_t provides a measure of the importance of the extensive margin. For quarterly US data ranging from 1955 to 1984, Hansen (1985) finds that employment changes account for 55% of the total hours deviations from the HP trend, while the hours per worker deviations account for only 20%. This pattern is observed in several countries. In HP-filtered, quarterly manufacturing data (1960-1989), for which variance is scale-free, Fiorito and Kollintzas (1994) found that the variance of employment deviations from the smooth trend always exceed the corresponding variance in the hours per worker: by a factor of about eight in the US, about four in Canada and West Germany and between two and three in the UK and in Japan, respectively.

The extensive margin is closely related to the relationship between individual and aggregate labor supply elasticities. In particular, it may explain why the latter is larger than the former. This is easy to see in a regression framework. Henceforth we use lower case for individual variables and upper case for the corresponding aggregate quantity. Denote by ε and $\mathcal{E}$ the micro and macro Frisch elasticities of labor supply, respectively, and by w_{it} and W_t the individual and mean wage rates at time t , respectively. Consider the following regression models, which we derive below in detail:

$$\text{individual} \quad : \quad \Delta \ln h_{it} = \text{const.} + \epsilon \Delta \ln w_{it} + e_{it},$$

$$\text{aggregate} \quad : \quad \Delta \ln H_t = \text{const.} + \mathcal{E} \Delta \ln W_t + E_t,$$

What is the relation between individual and aggregate elasticities? Suppose we estimate both of them using instrumental variables. Then they can be written as follows:

$$\begin{aligned} \epsilon &= \frac{\text{cov}(\Delta \ln h_{it}, \Delta \ln \widehat{w}_{it})}{\text{var}(\Delta \ln \widehat{w}_{it})}, \\ \mathcal{E} &= \frac{\text{cov}(\Delta \ln H_t, \Delta \ln \widehat{W}_t)}{\text{var}(\Delta \ln \widehat{W}_t)} \\ &= \frac{\text{cov}(\Delta \ln \overline{H}_t, \Delta \ln \widehat{W}_t)}{\text{var}(\Delta \ln \widehat{W}_t)} + \frac{\text{cov}(\Delta \ln N_t, \Delta \ln \widehat{W}_t)}{\text{var}(\Delta \ln \widehat{W}_t)}, \end{aligned} \tag{1}$$

where a hat " ^ " denotes predicted values at first-stage. That is, the micro elasticity consists of a single term, the covariance between movements of individual hours and exogenous movements of the individual wage rate, capturing adjustment on the intensive margin only. The macro elasticity is the sum of two terms, representing the intensive and the extensive margins, respectively. Notice that the second term, the covariance between variations in employment and exogenous variations in the aggregate wage rate, is positive if we move along a labor supply curve. This may be the reason why the aggregate elasticity is larger than the individual one.⁵

⁵This cannot be proved in general, since while it is true that $\text{var}(\Delta \log W_t) < \text{var}(\Delta \log w_{it})$, it is not true in general that $\text{cov}(\Delta \log (\overline{H}_t), \Delta \log W_t) > \text{cov}(\Delta \log h_{it}, \Delta \log w_{it})$. Simple numerical simulations show that the latter may be violated. However, we can take a stance about the sources of the difference based on our estimates: we report the decomposition of the aggregate elasticity later in the paper.

3 The Model

Consider an economy populated by n individuals, indexed by $i = 1, \dots, n$, and two consumption goods. The consumption good can be produced via market or home production, using a constant returns to scale technology where labor is the only input and where there are no intermediate goods. Individuals have identical preferences and the same endowment of labor services but differ in ability.

Denote by θ_{it} and θ_{it}^H , respectively, individual i 's ability on the market and at home at time t , and by h_{it} and h_{it}^H the fraction of hours spent producing on the market and at home. Then the total amount of the consumption good in the economy at time t is

$$c_t = c_t^M + c_t^H,$$

where

$$\begin{aligned} c_i^M &= \sum_{i=1}^n \theta_{it} h_{it}, \\ c_i^H &= \sum_{i=1}^n \theta_{it}^H h_{it}^H. \end{aligned}$$

In other words, work on the market and at home are perfect substitutes in production, and the respective outputs are perfect substitutes in consumption.⁶ Labor services can be sold on the market at an individual-specific and time-varying wage rate, w_{it} . Profit maximization in production implies that $w_{it} = \theta_{it}$ is the wage offer available to individual i at time t . Individuals are assumed to be forward-looking and markets clear. Due to data limitations, we assume that the tax rate on labor is constant, so it is immaterial whether the wage rate is pre- or after-tax. We also allow heterogeneity in the endowment of assets and other exogenous sources of income. Preferences are defined over consumption (c) and leisure (l), and are represented by the utility function $u(c_{it}, l_{it})$, a strictly increasing, twice

⁶This is a special case of the general model of Benhabib, Rogerson and Wright (1991).

differentiable, strictly quasi-concave function. The individual problem is to choose sequences of consumption, $\{c_{it}\}_{t=0}^{\infty}$, labor supply to the market, $\{h_{it}\}_{t=0}^{\infty}$, and home production, $\{h_{it}^H\}_{t=0}^{\infty}$, as well as asset holding, $\{a_{it+1}\}_{t=0}^{\infty}$ that maximize the expected discounted present value of the utility stream, given the budget and time constraints:

$$\max_{\{c_{it}, h_{it}, h_{it}^H, a_{it+1}\}} \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t u(c_{it}, l_{it}) \right]$$

subject to :

$$\begin{aligned} c_{it} + a_{it+1} &\leq w_{it} h_{it} + \theta_{it}^H h_{it}^H + (1+r) a_{it} + y_{it}, \\ h_{it} + h_{it}^H + l_{it} &= 1, \end{aligned}$$

and the no-Ponzi game condition: $\lim_{T \rightarrow \infty} \beta^T \frac{\partial u(c_{iT}, l_{iT})}{\partial c_{iT}} a_{iT+1} = 0$. In the above, β is the discount factor and r the real return on assets, both assumed to be invariant in time and across individuals, and y_{it} summarizes other (exogenous) sources of income. In order to derive a structural equation, we assume that utility is separable in both time and consumption-leisure and is of the CRRA class:

$$u(c_{it}, l_{it}) = \frac{c_{it}^{1-\gamma}}{1-\gamma} - \alpha \frac{(1-l_{it})^{1+\eta}}{1+\eta},$$

where $\alpha > 0$ determines the relative preference for leisure, γ is the coefficient of relative risk aversion (as well as the inverse of the intertemporal elasticity of substitution of consumption) and η is the inverse of the elasticity of labor supply, which in this case is the same as the intertemporal elasticity of substitution of work.

Denoting by λ_{it} the Lagrange multiplier, i.e. the marginal utility of wealth, at an interior optimum the following intratemporal and intertemporal conditions hold:

$$c_{it} : c_{it}^{-\gamma} = \lambda_{it}, \quad (2)$$

$$h_{it} : \alpha (h_{it} + h_{it}^H)^\eta = \lambda_{it} w_{it}, \quad (3)$$

$$h_{it}^M : \alpha (h_{it} + h_{it}^H)^\eta = \lambda_{it} \theta_{it}^H, \quad (4)$$

$$a_{it+1} : \lambda_{it} = \beta (1 + r) E_t [\lambda_{it+1}], \quad (5)$$

$$\lambda_{it} : c_{it} + a_{it+1} = h_{it} w_{it} + \theta_{it}^H h_{it}^H + (1 + r_t) a_{it} + y_{it}. \quad (6)$$

It is straightforward to see that individuals will either supply a positive number of hours to the market or spend a positive number of hours performing home production, but never both. In particular, in equilibrium:

$$h_{it} = \begin{cases} \alpha^{-1/\eta} (\lambda_{it} w_{it})^{1/\eta} & \text{if } w_{it} \geq \theta_{it}^H \\ 0 & \text{otherwise} \end{cases},$$

$$h_{it}^H = \begin{cases} \alpha^{-1/\eta} (\lambda_{it} \theta_{it}^H)^{1/\eta} & \text{if } w_{it} < \theta_{it}^H \\ 0 & \text{otherwise} \end{cases}.$$

It follows that θ_{it}^H is exactly individual i 's reservation wage at time t , which we denote $\tilde{w}_{it}$. Therefore, individual i at time t works on the market if his or her reservation wage, productivity at home, is below the wage offer.

The following derivation of the structural, estimable, labor supply equation is standard.⁷ We can rewrite (2), (3) and (5) in (natural) logs, provided that both consumption and labor supply are strictly positive in equilibrium, i.e. $(c_{it}, h_{it}) > (0, 0)$. In this case we have:

$$\ln c_{it} = -\frac{1}{\gamma} \ln \lambda_{it}, \quad (7)$$

$$\ln h_{it} = k + \frac{1}{\eta} \ln \lambda_{it} + \frac{1}{\eta} \ln w_{it}, \quad (8)$$

$$\ln \lambda_{it} = \ln \beta (1 + r) + \ln E_t [\lambda_{it+1}], \quad (9)$$

⁷See for instance Blundell and MaCurdy (1999).

where $k \equiv -\eta^{-1} \ln \alpha$ is a constant. Equation (8) cannot be estimated, since we do not observe λ_{it} . Notice that the conditional expectation appearing on the RHS of (9) amounts to the future realization of λ_i (i.e. of the budget constraint) plus a white noise term, ε_{it+1} . Therefore, we can write $\varepsilon_{it+1} \equiv E_t[\lambda_{it+1}] - \lambda_{it+1}$ and approximate $\ln E_t[\lambda_{it+1}]$ using a first-order Taylor expansion around the zero-error point $\varepsilon_{it+1} = 0$, or equivalently $E_t[\lambda_{it+1}] = \lambda_{it+1}$:

$$\ln E_t[\lambda_{it+1}] \simeq \ln \lambda_{it+1} + v_{it+1}, \quad (10)$$

where $e_{it+1} \equiv \varepsilon_{it+1}/\lambda_{it+1}$ is the scaled forecast error. Using this approximation and adopting the notational convention, for any variable X , $\Delta X_t \equiv X_t - X_{t-1}$, we can rewrite (8) and (9) in first differences :

$$\Delta \ln h_{it} = \frac{1}{\eta} \Delta \ln \lambda_{it} + \frac{1}{\eta} \Delta \ln w_{it},$$

which leads, after defining $e_{it} \equiv \Delta v_{it}$ to the following estimable equation:

$$\Delta \ln h_{it} = \frac{1}{\eta} \Delta \ln w_{it} + e_{it}. \quad (11)$$

Equation (11) allows us to estimate η^{-1} , the intertemporal (Frisch, or λ -constant) elasticity of labor supply as determined by first order condition (8). This is the response of labor supply to the wage changes. We label (11) the “micro regression.”

We derive the analogous “macro regression” by exact aggregation of the relevant units. Solving equation (3) for h_{it} and aggregating across all individuals that in equilibrium at time t supply a positive number of hours (these are $N_t \leq n$), yields aggregate labor supply:

$$N_t \overline{H}_t = \sum_{i=1}^{N_t} \left(\frac{\lambda_{it} w_{it}}{\alpha} \right)^{-\frac{1}{\eta}}, \quad (12)$$

where $\overline{H}_t$ represents aggregate hours per-worker at time t . The key to aggregation is the relation between the individual and the mean wage implied

by the model. To see this, denote by $\overline{W}_t \equiv n^{-1} \sum_{i=1}^n \theta_{it} = \overline{\theta}_t$ the mean productivity of individuals, regardless of whether they work on the market or not. The following relation, trivially, holds:

$$w_{it} = \frac{\theta_{it}}{\overline{\theta}_t} \overline{W}_t. \quad (13)$$

On the other hand, mean productivity of workers, i.e. those who supply a positive number of hours to the market, can be computed as follows:

$$W_t \equiv \sum_{i=1}^n \theta_{it} \mathbb{I}[\tilde{w}_{it} \leq w_{it}],$$

where $\mathbb{I}[\cdot]$ is the indicator function. In any period t there exists a real number $\xi_t \leq 1$ such that

$$\overline{W}_t = W_t^{\xi_t}.$$

Notice that $\xi_t = 1$ if and only if all individuals are employed. Therefore, when $\xi_t \neq 1$ the extensive margin comes into play, as movements in employment are possible. Replacing this equation into (13), then back into (12) and taking logs we have:

$$\ln(H_t) = K + \frac{\xi_t}{\eta} \ln W_t + \frac{1}{\eta} \ln(\sum_{i=1}^{n_t} \lambda_{it} \theta_{it}) + v_t, \quad (14)$$

where $H_t = N_t \overline{H}_t$ denotes aggregate labor supply, $K \equiv \ln \alpha$ is a constant and $v_t \equiv \Theta_t / \overline{\theta}_t$ is the ratio between workers and population average productivities. Notice that multiplying both sides of the Euler equation (5) by θ_{it} , aggregating across workers at time t and taking logs yields:

$$\ln \sum_{i=1}^{n_t} \lambda_{it} \theta_{it} = \tilde{K} + \ln \sum_{i=1}^{n_t} E_t[\lambda_{it+1} \theta_{it}], \quad (15)$$

where $\tilde{K} \equiv \ln \beta (1 + r)$ is a constant. As before, we can approximate the log of the aggregate expectation:

$$\ln \sum_{i=1}^{n_t} E_t[\lambda_{it+1} \theta_{it}] \simeq \ln \sum_{i=1}^{n_t} \lambda_{it+1} \theta_{it} - \Xi_t, \quad (16)$$

where Ξ_t is a function of the aggregate forecast error at time t . Replacing (16) into (15) we can write:

$$\ln \sum_{i=1}^{n_t} \lambda_{it+1} \theta_{it} - \ln \sum_{i=1}^{n_t} \lambda_{it} \theta_{it} = -\tilde{K} + \Xi_t.$$

Using this equation, and defining the aggregate differential error $E_t \equiv \Delta \Xi_t$, we can rewrite equation (14) in first differences:

$$\Delta \ln (H_t) = \frac{\xi_t}{\eta} \Delta \ln W_t + E_t, \quad (17)$$

which is the exact aggregate analog of (11), and which we can use to estimate $\xi_t \eta^{-1}$. This is the aggregate Frisch elasticity, or the response of aggregate labor supply to the mean wage rate, keeping constant the marginal utility of wealth of all individuals. The model implies that in each period the macro elasticity is different from the micro one if and only if $\xi_t \neq 1$, i.e. if there are some individuals who allocate zero hours to market production. On the other hand, if $\xi_t = 1$ the two elasticities coincide. This is intuitive: if $\xi_t = 1$, any adjustment of labor supply cannot take place on the extensive margin, since everybody is working. Therefore, in this simple model the two elasticities are different because, like in Chang and Kim (2005), the reservation wage distribution is nondegenerate and so there are some individuals who are adjusting on the extensive margin in response to wage shocks. For estimation purposes, we need to treat ξ_t as a constant. This assumption is not so strong if the employment rate does not vary too much over time.

To summarize, referring to the notation introduced earlier in the paper, we will estimate models (11) and (17) where a constant is added to account for a possible trend:

$$\text{individual} \quad : \quad \Delta \ln h_{it} = \text{const.} + \epsilon \Delta \ln w_{it} + e_{it}, \quad (18)$$

$$\text{aggregate} \quad : \quad \Delta \ln H_t = \text{const.} + \mathcal{E} \Delta \ln W_t + E_t, \quad (19)$$

Of course the first difference of the relevant wage rate is endogenous because it is determined in equilibrium. In a rational expectation framework, we use appropriate autoregressive terms as instruments.⁸ Furthermore, it is well known that the estimate of the individual elasticity may suffer from ignoring the zero-hours wages. In principle we do not want to perform any correction in order to make sure we are not already adjusting for the extensive margin, which is something we want the aggregate regression to take care of. In other words, we do not want to alter the full consistency and comparability between individual and aggregate elasticities. However, we show below that our results are robust to performing selection-correction using the “Heckit” estimator.

For the same reason, we don’t want to use many controls, although estimating a model in first differences of course reduces the need for controls. However, we check for the role of non-labor income (like income from assets, intra-family and public transfers), which are of obvious importance. Therefore we also estimate the following equations:

$$\text{individual} \quad : \quad \Delta \ln h_{it} = \text{const.} + \epsilon \Delta \ln w_{it} + \psi \Delta \ln y_{it} + e_{it}, \quad (20)$$

$$\text{aggregate} \quad : \quad \Delta \ln H_t = \text{const.} + \mathcal{E} \Delta \ln W_t + \Psi \Delta \ln Y_t + E_t, \quad (21)$$

where y and Y denote exogenous individual and mean transfers, and ψ and Ψ the associated elasticities. Notice that, in particular, equations (20) and (21) are the first-difference version of what Heckman (1993) labels the labor supply of workers and the aggregate labor supply curve, respectively. Also notice that our simple theoretical framework provides a precise link between the individual and the aggregate level, i.e. solves the aggregation problem, so that we can compare individual and aggregate elasticities in a meaningful way (see Blundell and Stoker, 2005).

⁸Levels can be preferred to changes for the efficiency reasons mentioned by Arellano (1989).

4 Data

Our data come from the Panel Study of Income Dynamics (PSID), a panel of about 8,000 households. This choice has an important disadvantage, namely missing information on assets and other relevant controls for most of the waves.⁹ However, it has an important advantage: it covers 35 years for a total of 32 waves (annually from 1968 to 1997, then biennial).

Unfortunately, for estimation purposes, our series is shorter than it might otherwise be, because in order to avoid arbitrary interpolation we only consider the annual releases. We aggregate each wave, creating an “artificial” time series. We call this artificial because the PSID is a panel of households and we use labor market data for the household head only. When the household includes a couple, the husband is conventionally defined as the head. Therefore, women are under-represented in our sample and this presumably reduces the estimated labor supply elasticity, since women’s elasticity is known to be higher (see Killingsworth and Heckman, 1986).

All nominal values are converted into real terms using the CPI deflator provided by the Bureau of Labor Statistics. An obvious problem concerns individual wages. It is well known that wage reports in the PSID are affected by measurement errors (Pischke 1995). We cannot do anything to correct this, although it is likely that measurement errors in wages are such that they only affect standard errors.

How does such artificial time series compare to real aggregate US labor data?¹⁰ In what follows we referred to historic data provided by the Bureau of Labor Statistics. Figure 1 illustrates the case for average hours worked by employed individuals. The real aggregate series is smoother, while our artificial series jumps around, although the two move together very closely, up to a difference of about 100 hours, until 1984. Even after that time, the two tend to move together. The difference in levels can be easily explained by the over-representation of men, who typically work more than women.

⁹Omitted wealth is likely to bias downward estimated elasticities, as showed by Domeij and Flodén (2006).

¹⁰We consider the year the were collected, i.e. one year before the official date of the wave.

The different volatility can be explained by the changes occurring in the panel due to attrition and—most importantly—the inclusion of new households in the survey. Part of the latter is nonrandom: the PSID automatically includes as new households children that leave a family already included in the survey. As we have already stressed above, our goal is not to provide the best possible estimate of aggregate labor supply elasticities but to look at the *relative* magnitude between individual and aggregate elasticities when both are consistently estimated. In Figure 2 we summarize the same information taking logs and using first differences. Figure 3 compares variations in the log real wage rate in the PSID and in the US. Again the two series move quite closely together, apart from a scale factor reflecting the fact that the BLS series refers to wages of production and nonsupervisory workers only, until 1989. We return on this in a moment. This graph confirms that year 1992 is anomalous in the PSID, probably because of measurement errors or other issues with the data. The best we can do is to use a dummy to control for this. Finally, Figure 4 shows together the series of the wage rate and average hours worked according to the PSID. These are consistent with NBER recessions, which are located by dashed rectangles.

The volatility of our series relative to the real ones is due to variations in the composition of the PSID relative to the US population, of course,¹¹ something we must take into account. While the modification of the composition of the panel is not a big concern when estimating of the individual elasticity, some care is needed when estimating the aggregate one. The reason is that ignoring this phenomenon we would confound variations in employment with variations in the number of workers that compose the sample. This would be very misleading. The troublesome years are those when the PSID underwent substantial modifications. Table 1 reports, for each year of annual release, the number of households present in the sample, as well as the variation of this number with respect to the previous year. After essentially physiological variations from the beginning until 1988, we notice a few major changes. First, the 1990 wave (containing data collected in 1989) was almost a third larger than the previous one: 2,200 new house-

¹¹Using PSID weights does not help, unfortunately.

holds, the so-called Latino sample, were added that year to take into account the substantial demographic changes occurred in the US since the inception of the PSID. The 1994 wave (which collected our 1993 data) also was characterized by a sizeable, although smaller, increase in sample size. Then in two successive steps (1996 and 1997 waves, i.e. our 1995 and 1996 years) sample size was drastically reduced. The effect of these changes on the comparability with real US data is clear in Figure 5, which reports the variations in the log of employment in the PSID and in the US (Source: BLS). Employment in the PSID appears to be *less* volatile than in the US. The two series move together until 1988, which makes are confident the problem of mixing variations in employment with variations in sample size has no serious consequences on our estimates. However, after this years there are clear outliers in the PSID series. We address this problem in two alternative ways. First, we construct dummy variables to control for anomalous behavior of the series in 1989, 1993, 1995 and 1996.¹² Second, we estimate the macro regression with an even shorter series, i.e. 1967-1988, showing that results do not change, and that actually using dummies in the longer series leads to more conservative estimates.

5 Results

Our main results are reported in Tables 2 and 3 below. Table 2 reports our estimates of the individual and aggregate labor supply elasticities. Columns 1 and 2 report estimates of the individual elasticity, not controlling and controlling, for non-labor income (i.e. transfers), respectively. That is, equations (18) and (20).¹³ Both models are estimated using the fixed effects estimator. The first yields a Frisch elasticity of 0.11. Controlling for non-labor income yields an insignificant estimate, but this is not a reliable

¹²The dummies are used in both the micro and the macro regressions, in order to preserve the exact correspondence between the two. However, the micro regression is also estimated without dummies, as we believe they are unnecessary here.

¹³The log variation in the wage rate and non-labor income are instrumented using, respectively, 3 lags (the 2nd to the 4th) of the log wage rate and log non-labor income in levels. Levels turn out to be a better instrument than differences (see footnote 8).

model, as the results of the J test indicates. Because of the presumption that the year dummies are not important in the micro regression, where we only look at the intensive margin, we re-estimated the two models without them. Columns 3 and 4 show that in fact the results are very similar. Additional results reported in Table 4 shows that our estimate of the individual elasticity is about the same when the “Heckit” estimator is used to control for self-selection into the pool of workers.¹⁴

Columns 5 and 6 report estimates of equations (19) and (21). Not controlling for mean non-labor income yields an aggregate Frisch elasticity of 0.86, which increases to about 1 but becomes insignificant when controlling for mean non-labor income.¹⁵ This second estimate, however, is meaningless because the rank condition is not satisfied with the instruments we use for non-labor income. Notice that the constant has a natural interpretation in terms of a time trend in hours worked. The difference in sign between the individual and the aggregate trend may be explained in terms of a slightly shorter workweek but higher employment. Table 5 shows that discarding the part of the series that behaves anomalously (i.e. starting in 1989) instead of using dummies does not change much, and actually increases, the estimated aggregate elasticity.

In the light of these results we focus on columns 1, 3 and 5. These show that aggregation *alone* magnifies the aggregate elasticity by 7 to 8 times. This is due to variation along the extensive margin, as illustrated in Table 3. This table evaluates empirically the two terms at the end of equation (1), i.e. it splits the aggregate elasticities sub model 3 in Table 1 into the contribution due to the intensive and extensive margins, respectively. Specifically, the dependent variable in column 7 is the first difference of log mean hours worked in the economy (intensive margin), while in column 8 is the first difference of log employment (extensive margin). The estimate

¹⁴Specifically, we estimated a random effects Probit model where the dummy variable for worker status (i.e. an individual with positive hours and wage) is regressed on age, family size, number of children, total family income, sex and self-employment status. The predicted probabilities are then used to construct the inverse Mill ratio, whose first differences is used as an additional regressor.

¹⁵Instruments are exactly like in the micro regression, see previous footnote.

forcefully shows that the extensive margin explains 3/4 of the difference between micro and macro elasticities. This result shows also an elasticity of the labor stock which is positive as required by moving along a labor supply curve and confirming the variance decomposition result that real wages affect much more employment/participation decisions than hours adjustment for a given job.¹⁶

6 Conclusions

In this paper we have estimated the individual and aggregate Frisch elasticities of labor supply, using exact aggregation of the microeconomic units on which the individual estimate is based. We found that the micro elasticity is about 0.1 and the macro elasticity is much larger, i.e. about 0.9. As expected, the difference is explained by adjustments at the extensive margin.

We do not claim that our estimates are the right ones, although our elasticities are close to what one finds in well-established literature. Given our aggregation procedure and the limitations of PSID data, we are aware of the fact that our specification does not account for such important variables as marginal tax rates, individual wealth, and after-tax return on assets though these limitations equally apply to the individual and the aggregate estimates that we compare. Moreover, what we estimate is a short-run elasticity only, because the scarcity of data points (in the aggregate dataset) prevent from exploiting a richer dynamics helping to disentangle between the short and the long-run response.

We are aware of the fact that our results apply to the PSID data only and do not necessarily hold for the US. Indeed, this limitation could provide another reason for comparing similar surveys from other countries though the same *non sequitur* applies when transferring any survey-based result to the NIPA. As far as we know, however, these comparisons that seem useful in principle cannot be currently pursued since the available international surveys (e.g. the British Panel Household Survey) are temporally shorter

¹⁶An interesting implication could also be that aggregation should not be so relevant when comparing individual and aggregate labor demand (establishment) data.

than PSID and given our preference for avoiding arbitrary interpolations of the missing data.

Another possible extension could be estimating micro and macro elasticities for separate male and female components in the light of the widely accepted evidence that women elasticity is bigger, probably because the importance of the extensive margin widens when the participation decision of a former housewife could imply that another housewife will be hired to replace her, at least partially, at home.

Despite all these limitations, the main achievement of the present paper is in showing through a very clear empirical exercise that aggregation *alone* leads to a much larger elasticity because of the implied inclusion of the extensive margin. In our model this is captured by allocation of work between market and home production. Despite being a simple empirical result, we are not aware of other econometric studies indicating the relevance of adjustments on the extensive margin based on exact aggregation of the individual units. Finally, our results show that parameter estimates from micro data are not always appropriate for calibrating the national economy. This does not imply resurrecting an old style macroeconomics paying no attention to the individual choices: on the contrary, it implies that aggregation must include the choices made on the extensive margin too.

Figure 1. Average hours worked.

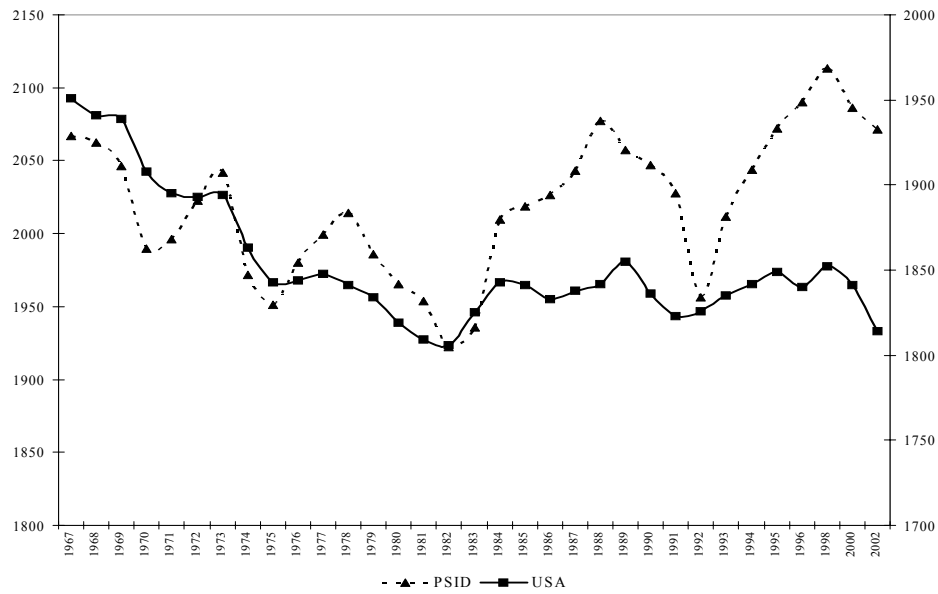


Figure 2. Variation of log mean hours worked

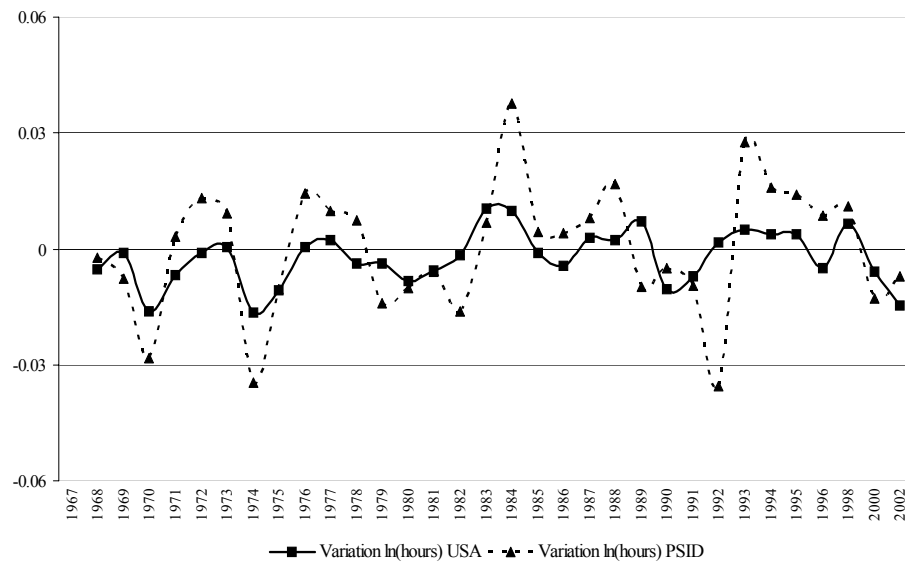


Figure 3. Variation of log real wage.

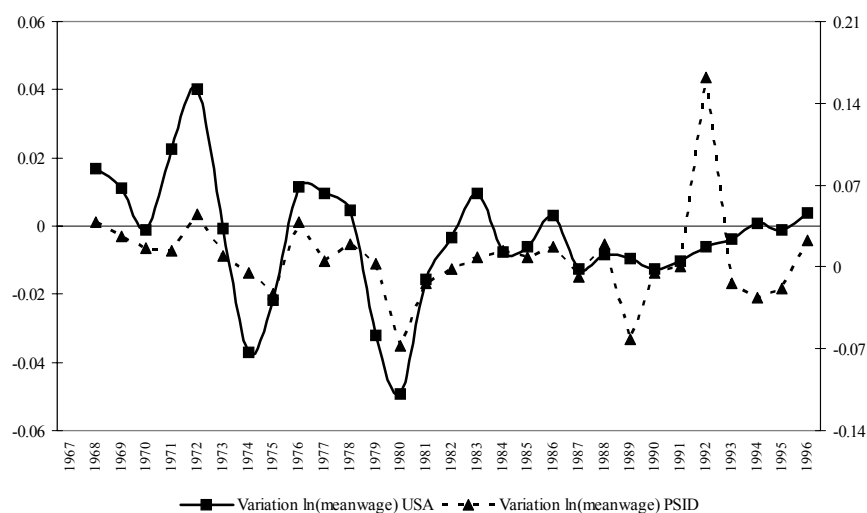


Figure 4. Average wage (right scale) and average hours (left scale) worked, PSID

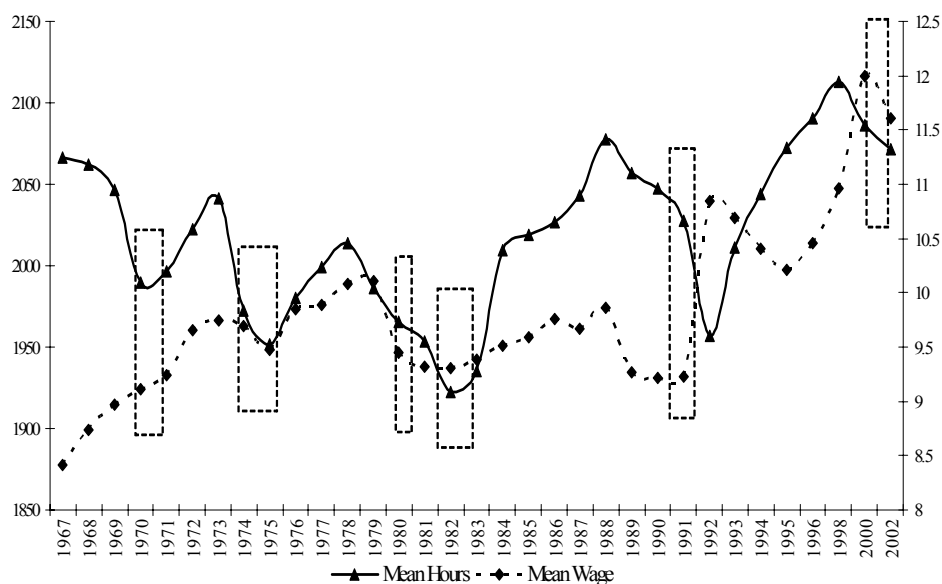


Table 1. Variation in the composition of the PSID (annual waves)

Wave	Year Collected	Sample Size	Variation on previous wave
1968	1967	4802	
1969	1968	4460	-7.12%
1970	1969	4654	4.35%
1971	1970	4840	4.00%
1972	1971	5060	4.55%
1973	1972	5285	4.45%
1974	1973	5517	4.39%
1975	1974	5725	3.77%
1976	1975	5862	2.39%
1977	1976	6007	2.47%
1978	1977	6154	2.45%
1979	1978	6373	3.56%
1980	1979	6533	2.51%
1981	1980	6620	1.33%
1982	1981	6742	1.84%
1983	1982	6852	1.63%
1984	1983	6918	0.96%
1985	1984	7032	1.65%
1986	1985	7018	-0.20%
1987	1986	7061	0.61%
1988	1987	7114	0.75%
1989	1988	7114	0.00%
1990	1989	9371	31.73%
1991	1990	9363	-0.09%
1992	1991	9829	4.98%
1993	1992	9977	1.51%
1994	1993	10764	7.89%
1995	1994	10401	-3.37%
1996	1995	8511	-18.17%
1997	1996	6747	-20.73%

Figure 5. Variation of log employment
Top: 1969-1996. Bottom: 1969-1988

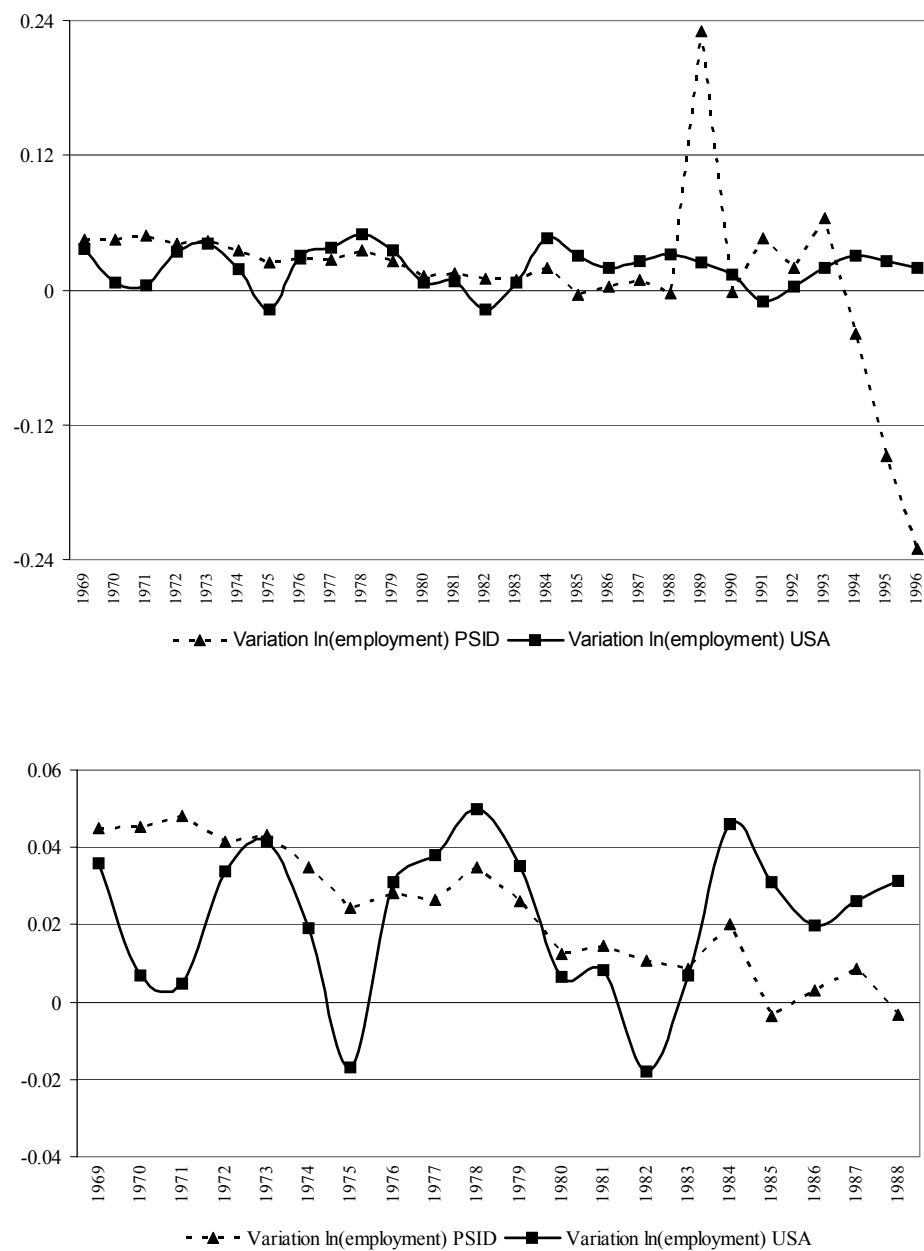


Table 2. Individual and aggregate Frisch elasticities.

	Individual				Aggregate	
	$\Delta \ln(h_{it})$				$\Delta \ln(H_t)$	
	1	2	3	4	5	6
$\Delta \ln(\text{wage})$	0.11** (0.04)	0.07 (0.05)	0.13** (0.04)	0.09* (0.05)	0.86** (0.33)	1.10 (0.90)
$\Delta \ln(\text{transfers})$	- (0.01)	-0.01 (0.01)		-0.01 (0.01)	- (0.39)	-0.16 (0.39)
Constant	-0.005** (0.00)	-0.00 (0.00)	-0.01** (0.00)	-0.006* (0.00)	0.02** (0.00)	0.02* (0.01)
Year dummies	yes	yes	no	no	yes	yes
First-stage F -stat	73.0	-	171.9	-	10.3	
Rank condition	yes	yes	yes	yes	yes	no
J -stat	1.93	9.86	1.85	10.03	1.67	5.79
p-value	0.38	0.04	0.40	0.04	0.43	0.22
Observations	72,121	57,810	72,121	57,810	26	26
Individuals	7,763	7,180	7,763	7,180	-	-

* Significant at 10%; ** Significant at 5% or better

Table 3. Sources of the aggregate elasticity

	$\Delta \ln(\overline{H}_t)$	$\Delta \ln(N_t)$
	5	6
$\Delta \ln(\text{wage})$	0.29 (0.23)	0.57 (0.27)
Constant	0.00 (0.00)	0.02 (0.00)
Observations	26	26

Table 4. Individual Frisch elasticity.

	$\Delta \ln(h_{it})$			
	1	2	3	4
$\Delta \ln(\text{wage})$	0.11** (0.04)	0.13** (0.04)	0.08* (0.04)	0.09** (0.04)
Constant	-0.005** (0.00)	-0.01** (0.00)	-0.00 (0.00)	-0.004** (0.00)
Year dummies	yes	no	yes	no
Heckit	no	no	yes	yes
Observations	72,121	72,121	72,121	72,121
Individuals	7,763	7,763	7,763	7,763

* Significant at 10%; ** Significant at 5% or better

Table 5. Aggregate Frisch elasticity.

	$\Delta \ln(H_t)$	
	1	2
$\Delta \ln(\text{wage})$	0.86** (0.33)	0.95** (0.39)
Constant	0.02** (0.00)	0.02** (0.00)
Years	1967-1996	1967-1988
Effective Observations	26	18

* Significant at 10%; ** Significant at 5% or better

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