# Reconciling Micro and Macro Estimates of the Frisch Labor Supply Elasticity: A Sensitivity Analysis

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**Abstract**

Microeconometric estimates of the Frisch labor supply (0 to 0.5) tend to be much lower than the values used by macroeconomists to calibrate general equilibrium models (2-4). This paper explores whether the gap in these ranges can be explained by two restrictions present in the micro Frisch elasticity that are implicitly relaxed in these values of the macro Frisch elasticity. First, the micro estimates focuses only on prime-aged married males who are the head of their household, while the macro values incorporates the whole population. Second, the micro estimates only include fluctuations in hours on the intensive margin, while the macro values also incorporate fluctuations on the extensive margin. Within a consistent microeconometric estimation strategy, this paper estimates a micro Frisch elasticity of 0.2, and, upon relaxing the two restrictions, a macro Frisch elasticity of about 3. The increase in the estimates suggests that these two restrictions can explain the gap. However, given that this paper demonstrates that the estimates of the macro Frisch elasticity are fairly sensitive to the estimation procedure, the sample of agents, and also the margins of fluctuations that are used for estimation one must careful choose the appropriate value for calibration purposes.

JEL: E24, and J22.
Key Words: Frisch labor supply elasticity; intensive margin; extensive margin; calibration.

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# 1 Introduction

A key parameter in the design and assessment of government policies for macroeconomists is the Frisch labor supply elasticity; the elasticity of hours worked with respect to wages, holding marginal utility constant. In order for macroeconomic models to match the observed amount of volatility in aggregate hours worked over the business cycle, the Frisch elasticity typically needs to be set somewhere in the range of 2 to 4.[1] In contrast, the seminal microeconometric estimates of the Frisch elasticity which are determined from hours and wage fluctuations on an individual basis are in the range of 0 to 0.54 (see MaCurdy (1981) and Altonji (1986)).

One plausible explanation for this gap is that the two values are capturing fundamentally different notions of the Frisch labor supply elasticity.[2] The microeconometric estimates tend to focus on determining a fixed parameter value that describes the responsiveness of a set of individuals' hours to changes in wages leading the estimates to incorporate two restrictions. First, the microeconometric estimates restrict the sample to only include a homogenous subset of the population, typically focusing on individuals who are male, employed, married, prime-aged, and heads of households. Second, the microeconometric estimates only incorporate fluctuations on the intensive margin. In contrast, macroeconomic calibration values are determined to align the aggregate volatility in hours over the business cycle implying that these two restrictions are relaxed. In particular, these values incorporate fluctuation in hours from the whole population, as opposed to a subset. Moreover, instead of just focusing on fluctuations on the intensive margin they incorporate fluctuations on both the intensive and extensive margin.

However, previous works tend to find that when both restrictions are relaxed

[1]See Chetty et al. (2011) for a discussion of the values used to calibrate models.

[2]An alternative approach to reconciling these values is to explore whether biases in the microeconometric estimates of the Frisch elasticity could account for the gap. Examples of these studies include: Rogerson and Wallenius (Forthcoming), Chang et al. (2011), Imai and Keane (2004), Pistaferri (2003), Chetty (2009), Domeij and Floden (2006), and Contreras and Sinclair (2008). See Keane and Rogerson (2011) for a review of this strand of the literature.

econometric estimates of the Frisch elasticity still tend to be lower than the calibration values. For example, using an estimation approach that identifies the Frisch elasticity from persistent changes in wages, Fiorito and Zanella (2012) estimate a Frisch elasticity of 0.68 when they relax both restrictions. This paper revisits the question and determines whether relaxing these restrictions can cause a large enough increase in the estimates of the Frisch elasticity to explain the gap when using an estimation approach that, consistent with Altonji (1986), identifies the Frisch elasticity from the expected variation in wages over the life cycle. In contrast to these previous studies, this paper finds that when these two restrictions are relaxed the estimates of the Frisch elasticity increase enough that they can explain the gap between the microeconometric estimates and the macroeconomic calibration values. Given the apparent sensitivity of the effect of relaxing these restrictions to the empirical specification, this paper further explores the sensitivity of estimates of the Frisch elasticity consistent with the macroeconomic calibration values.

First, as a benchmark, I estimate the Frisch elasticity consistent with the microeconometric estimates (micro Frisch elasticity) to be approximately 0.2. Next, I relax both of the restrictions and estimate the Frisch elasticity consistent with the calibration values (macro Frisch elasticity) is between 2.9 and 3.1. In particular, these restrictions are relaxed by incorporating fluctuations on the extensive margin using a pseudo panel and broadening the scope of the sample to include non-married individuals, females, secondary earners, younger individuals, and older individuals.[3] The much larger estimates of the macro Frisch elasticity indicate that under this specification the total effect of relaxing these two restrictions is consistent with the gap between the calibration values used in macroeconomic models and the original microeconometric estimates of the Frisch elasticity. Moreover, I find that the sum of the changes from independently relaxing these restrictions is much smaller than the total

[3]When estimating the macro Frisch elasticity I focus on individuals between the ages of twenty and sixty-five. Ideally, I would include all individuals who are of working age, however because of data constraints I am forced to limit the sample.

change in the estimates when both restrictions are simultaneously relaxed. Therefore, the interaction of these two restrictions (fluctuations on the extensive margin of females, secondary earnings, older, and younger individuals) is a key driver in the much larger estimates of the macro Frisch elasticity than the micro Frisch elasticity.

After demonstrating that relaxing these two restrictions can produce estimates of the macro Frisch elasticity that are consistent with the values used to calibrate macroeconomic models, I explore why my estimation strategy produces larger estimates of the macro Frisch elasticity than the previous studies. In contrast to this paper, which estimates that the macro Frisch elasticity is in the range of typical calibration values, Mulligan (1999), Faberman (2010), and Fiorito and Zanella (2012) estimate that the macro Frisch elasticity is between 0.6 and 1.6. Although these other papers estimate the macro Frisch by comparing fluctuations in hours and wages, there are differences in the specific estimation strategies. Mulligan (1999) and Faberman (2010) assume that all of the observed variation in wages is exogenous and regress changes in hours on changes in wages. In contrast, this paper, as well as Fiorito and Zanella (2012), attempt to control for likely endogeneity in observed wages.[4] However, Fiorito and Zanella (2012) use lagged wages as an instrument and estimate a much lower macro Frisch (0.68).[5] This approach implies that the macro Frisch elasticity estimates are identified from persistent changes in aggregate wages. Instead, consistent with Altonji (1986), I use age and education as instruments, which implies that I identify the Frisch elasticity from the expected variation in wages over the life cycle. I find that identifying the Frisch elasticity from these different types of variations in wages can explain why Fiorito and Zanella (2012) estimates a lower macro Frisch elasticity compared to this study.

Given that the estimates of the macro Frisch elasticity are so sensitive to the estimation strategy, I explore the overall sensitivity of these estimates. I find that

[4]The concern is that unexpected shocks to marginal utility are unobserved and correlated with both wages and hours.

[5]The estimate that is consistent with the definition of the macro Frisch elasticity uses PSID weights and calculates the cohort's average wages as the average across all wage observations.

estimates of the macro Frisch elasticity are also sensitive to the age range of individuals included in the sample. In particular, I find that if I exclude individuals from ages 55 to 65, that my estimates of the macro Frisch elasticity fall to 1.5. Interestingly, Gomme et al. (2005) demonstrate that the volatility of hours with respect to the business cycle for these older individuals is not large enough compared to prime-aged individuals to justify the large decrease when they are excluded. Moreover, Casanova (2012) demonstrates that wage changes for older individuals may not be exogenous but instead a result of selection into part-time work. Taken as a whole, these results highlight that estimates are fairly sensitive to the sample of agents, the margins of fluctuations, and type of fluctuations in wages used to identify the Frisch elasticity. Given the large range of estimates of the macro Frisch elasticity presented in this paper, when using an estimate of the Frisch elasticity as a calibration values in macroeconomic models it is imperative that the economist use a value that is estimated in such a way that it is consistent with both the implicit assumptions in the model and the question of interest. Moreover, the overall sensitivity of the estimates of the macro Frisch elasticity with respect to the instruments highlights the importance of demonstrating the robustness of the macroeconomic model to different calibration values of the Frisch elasticity.

Generally, this work builds on previous research that examines the gap between the microeconometric estimates of the Frisch elasticity and the values used in macroeconomic models. Rogerson and Wallenius (2009) demonstrate in a simulated model that due to different treatment of the extensive margin the macro and micro Frisch elasticities are conceptually different and can lead to large differences in their values.[6] However, empirical studies have generally been unable to reconcile the gap by relaxing these restrictions. Most of these studies tend to examine each restriction in isolation. Although Rìos-Rull et al. (2012), Mulligan (1995), Heckman and Macurdy (1980), Blau and Kahn (2007), and Kimmel and Kniesner (1998) demonstrate that

[6]Furthermore, Chang et al. (2011) show that estimates of the micro elasticity from aggregate data that includes a decision on the extensive margin will include large biases.

relaxing the restriction on the composition causes an increase in the estimates of the Frisch elasticity, they find that this restriction alone cannot fully explain the gap.[7] Similarly, Chetty et al. (2011), Gourio and Noual (2009), and Chang and Kim (2006), estimate that when they relax the restriction on the extensive margin, but focus on just prime-aged married males who are the head of their household, the Frisch elasticity is smaller than the values used for calibration.[8] This paper, along with Mulligan (1999), Faberman (2010), and Fiorito and Zanella (2012), are different in that they try to assess the effect of both restrictions in tandem.

The rest of the paper is organized as follows: section 2 derives the estimation equations from a simple labor supply model, section 3 describes the data and discusses how I construct the pseudo panel, section 4 presents the estimates of the micro and macro Frisch elasticity, section 5 examines the robustness of the estimates, and section 6 concludes.

# 2 Labor Supply Model

In this section, I introduce the typical maximization problem for an individual and use it to derive two different specifications that have been used used to estimate the Frisch elasticity in a reduced form setting (Altonji (1986) and MaCurdy (1981)).[9] Next, I separately describe my estimation strategy for the Frisch labor supply elasticity.

[7]Some of these works focus on compensated elasticities as opposed to the Frisch elasticity. For example, Kimmel and Kniesner (1998) demonstrates that married and single individuals have different compensated elasticities. Although Frisch elasticities and compensated elasticities can be different, the variation in the compensated elasticity between the various groups indicates that there will also tend to be variation in the Frisch labor supply elasticity from the various groups.

[8]Chetty et al. (2011) use a different approach than most of the other studies and use a meta analysis of separate quasi-experimental studies to independently determine the parts of the macro Frisch elasticity that come from the intensive and extensive margins. The authors use estimates of the participation rate elasticity as a proxy for the portion of the macro Frisch elasticity that comes from fluctuations on the extensive margin. Appendix A describes the strong assumptions necessary in order for the participation rate elasticity to be an unbiased estimate of the contribution of fluctuations on the extensive margin to the macro Frisch elasticity.

[9]Since the estimation strategy in MaCurdy (1981) is replicated in Altonji (1986), the estimation strategies in Altonji (1986) serve as a complete set. Therefore, for notational convenience, I only cite Altonji (1986) when discussing the estimation strategies.

## 2.1 Derivation of estimation equations

Given a typical utility function that is homothetic and separable in consumption and labor, an individual $i$ at age $s$ solves the following problem,

$$\max E_s \sum_{j=s}^{J} \beta^{j-1} \left( \chi_{i,j}^c \frac{\mu c_{i,j}^{1+\frac{1}{\mu}}}{1+\mu} - \chi_{i,j}^h \frac{\gamma h_{i,j}^{1+\frac{1}{\gamma}}}{1+\gamma} \right) \tag{1}$$

subject to

$$c_{i,j} + a_{i,j+1} = w_{i,j} h_{i,j} + (1+r_t) a_{i,j}, \tag{2}$$

where $E_s$ represents the expectation operator at age $s$, $J$ is the age of death, $c_{i,j}$ is consumption of individual $i$ at age $j$, $h$ is hours worked, $\chi_{i,j}^c$ is a parameter that controls the taste for consumption, $\chi_{i,j}^h$ is a parameter that controls the taste for work, $\beta$ is the discount rate, $a_j$ is savings, and $r_t$ is the after-tax return to savings. The first order conditions for the individual are

$$\lambda_{i,j} = \chi_{i,j}^c c_{i,j}^{\frac{1}{\mu}} \tag{3}$$

$$\lambda_{i,j} w_{i,j} = \chi_{i,j}^h h_{i,j}^{\frac{1}{\gamma}} \tag{4}$$

$$\lambda_{i,j} = E_j \beta \Psi_{j,j+1} (1+r) \lambda_{i,j+1}{}^{10} \tag{5}$$

where $\lambda$ is the marginal utility of consumption. The parameter of interest, $\gamma$, is the Frisch labor supply elasticity.

I derive two different specifications which have been used to determine $\gamma$. I derive the first specification, which relates hours to consumption, tastes, and wages, by taking the logs and combining equations 3 and 4

$$\ln h_{i,j} = \gamma [\frac{1}{\mu} \ln c_{i,j} + \ln \chi_{i,j}^c - \ln \chi_{i,j}^h + \ln w_{i,j}]. \tag{6}$$

[10] This is the intertemporal Euler equation for an individual at the age of $j$. If the individual is solving at a different age, then the expectation operator should be adjusted accordingly.

Taking the difference between two ages of the log of equation 4 and manipulating the resulting equation leads to the second specification,

$$\Delta \ln h_{i,j+1} = \gamma[-\ln \beta - \ln(1 + r_t) + \xi_{i,j+1} + \Delta \ln w_{i,j+1} - \Delta \ln \chi^h_{i,j+1}]. \tag{7}$$

where $\Delta$ represents the change over one year, and $\xi_{i,j+1} \equiv \lambda_{i,j+1} - E\lambda_{i,j+1}$ is the unexpected changes to marginal utility. Equation 7 relates the change in hours to the change in wages and preference parameters. I refer to equation 6 as the level specification and equation 7 as the change specification.

## 2.2 Estimation strategy

The seminal estimates of the micro Frisch elasticity, such as Altonji (1986) and MaCurdy (1981), come from specifications based on equations 6 and 7. Since both the taste parameters and the unexpected changes to marginal utility are unobserved and could be correlated with wages, it is important to either use instruments to isolate the orthogonal part of wages or use controls for these unobserved variables.[11]

The original estimates of the Frisch elasticity used the following specifications:

$$\ln h_{i,j} = \gamma \ln w_{i,j} + \beta \ln c_{i,j} + \zeta \mathrm{TS}_{i,j} + e_{i,j} \tag{8}$$

$$\Delta \ln h_{i,j+1} = \gamma \Delta \ln w_{i,j+1} + \delta + \zeta \Delta \mathrm{TS}_{i,j} + \epsilon_{i,j}, \tag{9}$$

where TS is a vector of variables controlling for changes in tastes, and $\delta$ is a set of annual dummies.[12]

[11] There is an additional concern about measurement error. Most individuals are not paid hourly. Therefore, to determine an hourly wage, typically economists divide an individual's total income by the total hours he works in a given period. This procedure leads to the possibility that the hours and wage estimates contain correlated measurement error. This measurement error is an additional reason why instruments are typically used for wages.

[12] In particular, because instruments are used for wages, the controls for tastes are used to control for correlation between the instruments and hours. $\delta$ is included in the change specification to control for annual changes in the after-tax return to capital.

Altonji (1986) estimates the Frisch elasticity with three different versions of these equations. The first two estimates (tables one and two in Altonji (1986)) are based off of the change specification. His third estimate (table four in Altonji (1986)) is based off of the level specification. I focus on the specification from table 2 of Altonji (1986) because the other estimation strategies (table 1 and table 4) in Altonji (1986)) can only be estimated on a small subset of the entire population.[13] In this specification, the author uses age, education, education squared, interactions between age and the polynomials of education, the education of the parents, and the parents' economic status as instruments for wages.[14] These instruments are used to isolate the change in wages that are exogenous to unexpected changes in marginal utility.[15] Since these variables are known in advance, one would not expect them to be correlated with unexpected shocks to marginal utility. Using these instruments, the estimates are being identified from expected changes in wages over the life cycle. I determine the micro Frisch elasticity using this estimation strategy.[16]

The three previous studies that examine the effect of both restrictions in tandem use a different approach. Mulligan (1999) and Faberman (2010) do not use instruments; instead these works assume that changes in wages are exogenous and identify the Frisch elasticity from all the changes in wages. Although Fiorito and Zanella (2012) uses instruments for wages, they use lagged wages as opposed to polynomials of age and education. In contrast to identifying the Frisch elasticity from the predictable variation in wages over the life cycle, Fiorito and Zanella (2012) identify the

[13] In both alternative estimates, the author uses a second wage series in the data that exists only for hourly employees.

[14] The variable indicating economic status for the parents is not available for secondary workers. Therefore, I do not present results using this instrument. However, in the sample that contained parental economic status, I found that excluding this instrument did not impact the results.

[15] In addition, these instruments are used to account for measurement error in reported wages. I focus on the specifications in columns one and three that include age as an instrument but not as a control.

[16] I make some small adjustments to the estimation strategy. In particular, I add some additional regressors to control for possible changes in tastes which may be correlated with age. The variables I include to control for tastes are whether an individual lives in a city with a population larger than 500,000, the number of children, and the number of children under six.

Frisch elasticity from the persistent variation in wages. I examine the effect of these differences on the estimates of the Frisch elasticity in section 5.1.

## 2.3 Macro estimation strategy

The macro Frisch elasticity represents the percent change in aggregate hours that occur due to a one percent change in aggregate wages holding aggregate marginal utility constant. In order to estimate the macro Frisch elasticity I alter the general estimation strategy by using a pseudo panel.[17] A pseudo panel is created by taking the average values within a cohort for each age and, instead of treating each individual's value as an observation, the cohort's average at each age is treated as an observation.[18] In particular, each observations for a variable $X$ follows,

$$X_{j,t} = \frac{1}{N}\sum_{i=1}^{N} x_{i,j,t} \tag{10}$$

where $X_{j,t}$ is the pseudo panel observation for a cohort's average at age $j$, and time $t$ and $x_{i,j,t}$ is the value for individual $i$, at age $j$, and time $t$.[19] Since this approach focuses on the movements in the cohort's average, a pseudo panel offers a natural framework to identify the macro Frisch elasticity, which represents the responsiveness of aggregate hours.[20]

However, using a pseudo panel does not come without disadvantages. Ideally, each observation in the pseudo panel would be the average of the whole cohort. However, I am limited to forming the cohort's averages from the sample that is

[17]This approach was originally proposed by Deaton (1985) to transform cross-sectional data into panel data.

[18]In order to estimate equation 7, I use the natural log of the cohort's average as opposed to using the average of the natural log. Using the natural log of the average corresponds to determining the parameter value that governs the representative cohort.

[19]When constructing the cohort's average, individuals are weighted according to the weights in the PSID.

[20]An additional advantage of a pseudo panel is that non-working individuals can be included in the average. In contrast, in a traditional panel, including non-working individuals is difficult since the log of zero is undefined.

observed in the data set. Therefore, when using a pseudo panel, the economist is implicitly treating the averages from the synthetic cohort as an approximation of the true cohort's average. Results from a pseudo panel may be biased since the approximation of the cohort's average contains measurement error. However, Verbeek et al. (1992) demonstrates that with a sufficient number of individuals a pseudo panel can be treated as a genuine panel without introducing an economically significant amount of bias.[21]

In order to estimate the macro Frisch elasticity, I estimate equation 9. In addition to using different instruments, using a pseudo panel is a second divergence from Fiorito and Zanella (2012). Instead of using a pseudo panel, Fiorito and Zanella (2012) an aggregate time series where each observation is the annual averages across cohorts instead of the averages within a cohort. In particular, each observation for a variable $Z$ in Fiorito and Zanella (2012) follows,

$$Z_t = \frac{1}{N \times J} \sum_{j=1}^{J} \sum_{i=1}^{N} z_{i,j,t}. \tag{11}$$

This alternative approach implies that the authors will have far fewer data points, which could lead to less efficient estimates. Moreover, their approach is susceptible to composition bias if there are demographic changes in the population over time.[22]

[21]The size of the data set employed in this study is on the lower end of the requirements discussed in Verbeek et al. (1992), so the estimates of the coefficients might be attenuated. However, one difference from Verbeek et al. (1992) is that as opposed to creating a pseudo panel from a repeated cross-section, I use a traditional micro panel. Therefore, the cohort generally contains the same individuals over time. As a consequence, there should be less change in which individuals are observed between years in my data. You would expect that a pseudo panel built from a traditional panel, with a more consistent set of individuals, to be less susceptible to this bias.

[22]My estimation strategy will also be susceptible to composition bias; however in order for my estimates to be biased, the composition within the cohorts must change. In contrast, the estimates in Fiorito and Zanella (2012) will be susceptible to composition bias if the relative size of the cohorts changes.

# 3 Data

Similar to Altonji (1986), I use the Michigan Panel Study of Income Dynamics (PSID) and follow a similar procedures to clean the data. I use the waves of the PSID from 1968 until 1997.[23] I calculate the real hourly wages for individuals by taking the annual labor earnings divided by the product of annual hours working for pay and consumption price index for urban individuals. Observations which exhibited a 250 percent increase or 60 percent decrease in wages or consumption were treated as missing. Furthermore, observations with swings of more than \$13 or wages less than \$0.40 in 1972 dollars were treated as missing.[24] Additionally, I adjusted the age variable when an individual reported no change in their age between the annual surveys or reported a change of larger than one year.

Table 1 provides a summary of the data used to estimate the micro and macro Frisch elasticity. The micro data set includes married working males who are the heads of households and between the ages of 26 and 60. In contrast, the macro sample includes all individuals between the ages of 20 and 65. On average, individuals in the micro sample tend to be older, have higher wages, and work more hours. These differences are due to the restrictions in the micro sample. Moreover, since the micro sample is limited to heads of households, individuals tend to be part of larger families.

Figure 1 plots the average annual hours by age in the micro and macro samples.[25] Comparing the black line (macro sample) and the red line (micro sample), the profile for all individuals decreases much more rapidly towards the end of the working life. This rapid descent indicates that many older individuals stopped working. Figure 2 plots the average wage profiles for the two groups.[26] Generally, the wage profiles tend

[23] After 1997 the PSID became bi-annual and therefore, I do not include these surveys.

[24] Observations from non-working individuals are not subjected to this requirement.

[25] The plot of the macro data is not the pseudo panel, but instead, it is the averages between the different cohorts of the pseudo panel. This representation of the data was a more condensed way to provide a sense of how hours and wages vary over the life cycle.

[26] One difference between figure 1 and figure 2 is that if individuals do not work, then a zero is included in the cohort's average hours but not included in the cohort's average wage.

to be upward sloping in the beginning of the lifetime, leveling off around the age 50. The wages for the macro sample (black line) tend to be lower than the wages for the micro sample (red line).

Table 1: **Summary Statistics**

| Variables | Micro | Macro |
|---|---|---|
| Age | 41.6 | 40.8 |
| Wage | 5.4 | 4.45 |
| Hours | 2288 | 1921 |
| Family Size | 3.81 | 3.14 |
| Males | 1 | 0.56 |
| Married | 1 | 0.77 |
| Observations | 37,331 | 143,293 |

**Notes:** The averages for the micro data set include only males who are married, heads of households, working, and between the ages of 26 to 60. The averages for the macro data set include all individuals between the ages of 20 and 65.

Figure 1: **Hours**

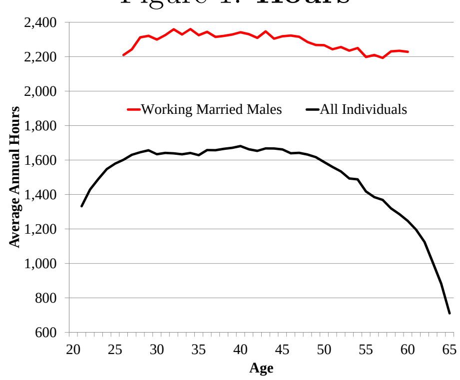
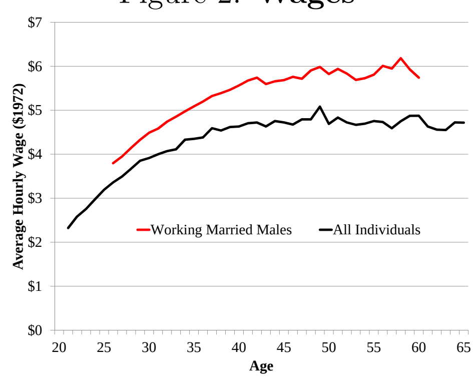



Figure 2: **Wages**




# 4 Estimates of Micro and Macro Frisch Elasticity

Table 2 presents my benchmark estimates of the micro Frisch elasticity. Columns I-IV present the results when I do not include annual dummy variables, and columns V-VIII present the results when I include annual dummies. Similar to Altonji (1986), I estimate the Frisch elasticity by regressing the change in the natural log of hours on the change in wages using age, education, education squared, interactions between education and age, mother's education, and father's education as instruments for wages in a traditional panel. Consistent with the definition of the micro Frisch elasticity, these estimates are from a sample which only includes males who are the heads of households, married, working, and between the ages of 26 and 60.[27]

Columns I and IV present the estimates when I replicate Altonji (1986) by restricting the sample to 1968-1981 and require individuals to be both married and working throughout the whole sample.[28] The estimates (0.34 & 0.52) are close to those in Altonji (1986) (0.28 & 0.48).[29] I find that the F-statistic for the excluded instruments in the first stage is 5.4 and 13.6 when I include and do not include annual dummies, respectively. The F-statistic in the specification with annual dummies is low enough that there is some concern that the instruments are not relevant.[30] The P-value on the Hansen J-statistic for overidentification of the instruments is larger when I include annual dummies, which indicates that including annual dummies leaves less unexplained variation in the second stage. The P-values are large enough for both estimates so as to not raise concerns that the instruments are invalid.

Next, I make three changes to Altonji (1986) in order to construct my benchmark estimates of the micro Frisch elasticity: (i) I extend the sample to include more waves

[27]Individuals who are students, retired, or working less than 250 hours a year are considered to not be working and excluded from this data set. As opposed to considering any individual who works less than 250 hours non-working, Altonji (1986) uses a cutoff of zero hours. I choose to use a higher threshold because I am not able to utilize all of the variables that contain reported information about retirement since the variables do not exist for secondary earners.

[28]I do not observe the wealth of the parents for secondary earners, which Altonji (1986) uses as an instrument. This lack of coverage is not a problem for Altonji (1986) because he only focuses on estimating the Frisch elasticity for the heads of households. Since I find that excluding this variable as an instrument when estimating the Frisch elasticity of the heads of households does not affect the estimates, I exclude it in all the results reported in this paper.

[29]There are a few reasons for slight differences in the estimates. First, I use the weights in the PSID. Second, following the restrictions in Altonji (1986) did not yield the same size data set as reported in the paper. Third, I use the Consumer Price Index to deflate wages as opposed to the GDP deflator.

[30]The F-statistic is lower when annual dummies are included because there are fewer degrees of freedom.

of the data, (ii) I include controls for possible changes in tastes, and (iii) I loosen the restriction that individuals must be married throughout the whole sample.[31] Columns II and VI of table 2 present estimates of the micro Frisch elasticity when I extend the sample to include the years through 1997. Including more recent data causes the estimates of the Frisch elasticity to converge to approximately 0.20. In order to control for the potential correlation between changes in tastes and the instruments, I include indicator variables for whether the individual lives in a big city, the number of children in the household, and the number of kids under the age of six in the household (columns III and VII). I find that controlling for changes in tastes causes the point estimates of the Frisch elasticity to increase a statistically insignificant amount. Although the changes are not statistically significant, the increase indicates that excluding these changes in tastes might cause a downward bias. Columns IV and VIII are estimates when I no longer require the panel to be balanced. In particular, if an individual becomes unmarried or stops working prior to age 60, then the all of the individual's observations are no longer excluded.[32] By allowing the panel to be unbalanced, I increase the number of observations by over ten percent; however, the estimates are nearly identical. I treat columns IV and VIII as my benchmark results for the micro Frisch elasticity, which I use for comparison in order to determine the effect relaxing the composition restriction and including fluctuations on the extensive margin.[33]

Next, I estimate the macro Frisch elasticity in a pseudo panel which includes hours fluctuations on both the intensive and extensive margins and broadens the scope of the sample to include all individuals between the ages of twenty and sixty-five (the

[31] Loosening this restriction is essentially allowing for an unbalanced panel.

[32] Only the observations when the individual is working and under 61 are included.

[33] One concern about these estimates is that the Hansen J-stat for overidentification of the instruments is low for all of the specifications that use the larger time period. The low J-stat is a persistent problem throughout this paper. Despite concerns about validity, I continue because the goal of this paper is to determine whether estimates of the macro Frisch using the microeconometric techniques are consistent with the values used to calibrate macroeconomic models. However, because of this concern about validity, the point estimates should be interpreted with caution.

Table 2: **Micro Benchmark Results**

| Variables (s.e.) | Orig. I | + Yrs. II | Δ Tastes III | Unbalanced IV | Orig. V | + Yrs. VI | Δ Tastes VII | Unbalanced VIII |
|---|---|---|---|---|---|---|---|---|
| ΔW | 0.34 | 0.2 | 0.23 | 0.23 | 0.53 | 0.2 | 0.23 | 0.22 |
| | (0.11) | (0.09) | (0.1) | (0.09) | (0.17) | (0.09) | (0.1) | (0.09) |
| Δkids | | | -0.01 | -0.01 | | | -0.01 | -0.01 |
| | | | (0.01) | (0.01) | | | (0.01) | (0.01) |
| Δkidsunder6 | | | 0.01 | 0.01 | | | 0.01 | 0.01 |
| | | | (0.01) | (0.01) | | | (0.01) | (0.01) |
| Δbigcity | | | 0 | 0 | | | 0 | 0 |
| | | | (0.02) | (0.01) | | | (0.02) | (0.01) |
| Observations | 9,985 | 24,380 | 24,380 | 27,88 | 9,985 | 24,380 | 24,380 | 27,880 |
| Annual Dummies | No | No | No | No | Yes | Yes | Yes | Yes |
| Years | 68-81 | 68-97 | 68-97 | 68-97 | 68-81 | 68-97 | 68-97 | 68-97 |
| **1st Stage** | | | | | | | | |
| F-stat (Excl. Inst.) | 13.7 | 21.34 | 18.83 | 23.18 | 5.32 | 17.34 | 14.59 | 16.96 |
| F-stat (P-value) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Hansen J-Stat | 6.48 | 17.9 | 19.1 | 19.39 | 4.93 | 17.98 | 19.15 | 19.5 |
| J-Stat (P-value) | 0.37 | 0.01 | 0 | 0 | 0.55 | 0.01 | 0 | 0 |

**Notes:** The F-stat for excluded instruments is for the wage regressions. Consistent with previous studies, the standard errors are clustered on cohort.

additional groups included are females, secondary earners, younger individuals, older individuals, and single individuals). The estimates of the macro Frisch elasticity range from 2.88 to 3.10 depending on whether annual dummies are included (see table 3). These estimates of the macro Frisch elasticity are statistically different from the benchmark estimates of the micro Frisch elasticity and in the middle of the range of the values used to calibrate macroeconomic models. Thus, these results indicate that relaxing these two restrictions can explain the gap between the macro-calibration values and the microeconometric estimates of the Frisch elasticity.[34]

In order to decompose the importance of each of the composition restrictions, I sequentially add each demographic group to the sample and estimate the Frisch elasticity in the traditional panel. Table 4 presents these results. Columns I-V are the results when I do not include annual dummies, and columns VI-X are the results when I include annual dummies. Columns II and VII indicate the effect of relaxing the restriction that individuals are married by including prime-age single males who

[34]Additionally, when estimating the macro Frisch elasticity, the estimates pass the Hansen J-test at the 5 percent level, which indicates that there is less concern with the instruments being endogenous.

Table 3: **Aggregate "Macro" Estimates**

| **Variables (s.e.)** | **Micro I** | **Macro II** | **Micro III** | **Macro IV** |
|---|---|---|---|---|
| ΔW | 0.23 | 3.1 | 0.22 | 2.88 |
| | (0.09) | (0.68) | (0.09) | (0.67) |
| Δkids | -0.01 | -0.28 | -0.01 | -0.28 |
| | (0.01) | (0.11) | (0.01) | (0.11) |
| Δkidsunder6 | 0.01 | -0.21 | 0.01 | -0.15 |
| | (0.01) | (0.14) | (0.01) | (0.12) |
| Δbigcity | 0 | 1.09 | 0 | 0.18 |
| | (0.01) | (0.51) | (0.01) | (0.31) |
| Observations | 27,880 | 1,288 | 27,880 | 1,288 |
| Yr. Dummies | No | No | Yes | Yes |
| Years | 68-97 | 68-97 | 68-97 | 68-97 |
| Ages | 26-60 | 20-65 | 26-60 | 20-65 |
| **1st Stage** | | | | |
| F-stat (Excl. Inst.) | 23.18 | 3.6 | 16.96 | 3 |
| F-stat (P-value) | 0 | 0 | 0 | 0.01 |
| Hansen J-Stat | 19.39 | 6.38 | 19.5 | 10.81 |
| J-Stat (P-value) | 0 | 0.38 | 0 | 0.09 |

**Notes:** The F-stat for excluded instruments is for the wage regressions. Consistent with previous studies, the standard errors are clustered on cohort.

are the heads of households.[35] Columns III and VIII indicate the effect of also incorporating females. Columns IV and IX relax the heads of households restriction and include secondary earners. Finally, columns V and X are the estimates when the age range is extended so that all working individuals between 20 and 65 are included.

I find that relaxing the marriage restriction causes an increase in the Frisch elasticity; however, since the increase is not statistically significant, it is only suggestive that single males have a higher Frisch elasticity. Next, incorporating females causes a statistically insignificant decrease (columns III and VIII).[36] In contrast, when secondary earners are included, the estimates of the Frisch elasticity approximately double (columns IV and IX). These increases are statistically significant compared to both the benchmark estimates (columns I and VI) and the prior estimates which exclude secondary earners (columns III and VIII). Similarly, incorporating younger and older individuals causes the estimates of the Frisch elasticity to once again double (a statistically significant change). Overall, comparing columns V and X to the respective benchmarks (columns I and VI), indicates that relaxing all of these composition restrictions causes a statistically significant increase in the Frisch elasticity of approximately 0.7.

Table 5 tests the effect of relaxing the second restriction by incorporating fluctuations on the extensive margin. In order to estimate the Frisch elasticity, which includes fluctuation on the extensive margin, I use a pseudo panel as opposed to a traditional panel. However, since I am focusing only on the effect of the restriction on fluctuations on the extensive margin, I limit my sample to married males who are the heads of households. I find that the estimates of the Frisch elasticity increase by a statistically significant amount of between .61 and .66 when I incorporate fluctuations

[35] The estimates in columns II and VII are not an estimate of the Frisch elasticity of the single, prime-age males who are the heads of households but instead a weighted average of the married and single prime-age males who are heads of households.

[36] Note, these estimates are only incorporating heads of households that are females and not all females. Therefore, these results are not inconsistent with previous studies that generally find females supply labor more elastically.

Table 4: **Composition Effects**

| Variables (s.e.) | Micro I | +Sing. II | +Fem. III | +Sec. Earn. IV | +Age V | Micro VI | +Sing. VII | +Fem. VIII | +Sec. Earn. IX | +Age X |
|---|---|---|---|---|---|---|---|---|---|---|
| ΔW | 0.23 | 0.35 | 0.29 | 0.55 | 0.93 | 0.22 | 0.32 | 0.26 | 0.55 | 0.91 |
| | (0.09) | (0.08) | (0.08) | (0.15) | (0.11) | (0.09) | (0.08) | (0.09) | (0.14) | (0.1) |
| Δkids | -0.01 | 0 | -0.01 | -0.02 | -0.02 | -0.01 | 0 | -0.01 | -0.01 | -0.02 |
| | (0.01) | (0) | (0) | (0) | (0) | (0.01) | (0) | (0) | (0) | (0) |
| Δkidsunder6 | 0.01 | 0.01 | 0.01 | -0.03 | -0.03 | 0.01 | 0.01 | 0 | -0.03 | -0.04 |
| | (0.01) | (0) | (0.01) | (0.01) | (0.01) | (0.01) | (0) | (0.01) | (0.01) | (0.01) |
| Δbigcity | 0 | 0.02 | 0.02 | 0.02 | 0.02 | 0 | 0.02 | 0.01 | 0.02 | 0.02 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Observations | 27,880 | 49,178 | 64,259 | 87,910 | 104,348 | 27,880 | 49,178 | 64,259 | 87,910 | 104,348 |
| Annual Dummies | No | No | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Years | 68-97 | 68-97 | 68-97 | 68-97 | 68-97 | 68-97 | 68-97 | 68-97 | 68-97 | 68-97 |
| **Restrictions** | | | | | | | | | | |
| Married | Yes | | | | | Yes | | | | |
| Male | Yes | Yes | | | | Yes | Yes | | | |
| Prime Earner | Yes | Yes | Yes | | | Yes | Yes | Yes | | |
| Age 25 - 60 | Yes | Yes | Yes | Yes | | Yes | Yes | Yes | Yes | |
| Age 20 - 65 | | | | | Yes | | | | | Yes |
| **1st Stage** | | | | | | | | | | |
| F-stat (Excl. Inst.) | 23.18 | 23.86 | 23.11 | 21.22 | 34.07 | 16.96 | 23.92 | 27.89 | 25.11 | 36.41 |
| F-stat (P-value) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Hansen J-Stat | 19.39 | 16.36 | 23.73 | 30.57 | 23.87 | 19.5 | 18.55 | 25.79 | 30.34 | 23.53 |
| J-Stat (P-value) | 0 | 0.01 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Notes:** The F-stat for excluded instruments is for the wage regressions. Consistent with previous studies, the standard errors are clustered on cohort.

on the extensive margin but restrict the composition.

Individually estimating the impact of relaxing each of the restrictions, I find that broadening the scope of the sample increases the estimates of the Frisch elasticity by approximately 0.7. Similarly, I find that including fluctuations on the extensive margin increases the Frisch elasticity by between 0.61 and 0.66. The increase from individually relaxing each of the two restrictions indicates that both play an important role in reconciling the gap between the microeconometric estimates and macro-calibration values. However, the sum of these changes is not large enough to explain the whole gap. These results indicate that the interaction between broadening the scope of the sample and incorporating fluctuations on the extensive margin needs to be considered in order to explain the gap. Specifically, the fluctuations on the extensive margin of single males, females, secondary earners, young individuals, and old individuals are necessary to reconcile the whole gap.

Table 5: **Extensive Margin Effects**

| **Variables (s.e.)** | **Micro I** | **+ Extensive II** | **Micro III** | **+ Extensive IV** |
|---|---|---|---|---|
| ΔW | 0.23 | 0.84 | 0.22 | 0.88 |
| | (0.09) | (0.17) | (0.09) | (0.19) |
| Δkids | -0.01 | -0.04 | -0.01 | -0.03 |
| | (0.01) | (0.02) | (0.01) | (0.02) |
| Δkidsunder6 | 0.01 | 0.06 | 0.01 | 0.06 |
| | (0.01) | (0.04) | (0.01) | (0.04) |
| Δbigcity | 0 | -0.08 | 0 | -0.12 |
| | (0.01) | (0.11) | (0.01) | (0.14) |
| Observations | 27,880 | 980 | 27,880 | 980 |
| Yr. Dummies | No | No | Yes | Yes |
| Years | 68-97 | 68-97 | 68-97 | 68-97 |
| Ages | 26-60 | 26-60 | 26-60 | 26-60 |
| **1st Stage** | | | | |
| F-stat (Excl. Inst.) | 23.18 | 6.7 | 16.96 | 6.49 |
| F-stat (P-value) | 0.2 | 0 | 0 | 0 |
| Hansen J-Stat | 19.39 | 10.45 | 19.5 | 10.4 |
| J-Stat (P-value) | 0 | 0.11 | 0 | 0.11 |

**Notes:** The estimates are for prime-age married males who are the heads of households. The F-stat for excluded instruments is for the wage regressions. Consistent with previous studies, the standard errors are clustered on cohort.

# 5 Sensitivity of Estimates

In this section, I test the sensitivity of the results. First, I examine the effect of the alternative estimation strategy in Fiorito and Zanella (2012). Next, I determine the sensitivity of the results with regard to age. Finally, I determine whether the parametric form used in the first stage to predict wage changes affects the estimates.

## 5.1 Comparison with Fiorito and Zanella (2012) Estimation Strategy

Similar to this exercise, Fiorito and Zanella (2012) also try to determine if the conceptual differences can explain the large gap between microeconometric estimates of the Frisch elasticity and calibration values used in macroeconomic models. Despite finding similar estimates of the micro Frisch elasticity, the authors estimate a much smaller aggregate Frisch elasticity, 0.68.[37] There are two differences in the estimation strategy in this paper and Fiorito and Zanella (2012). First, as opposed to polynomials of age and education, Fiorito and Zanella (2012) use five lags of wages as their instrument. Second, instead of using the cohort's average in each year as an observation, Fiorito and Zanella (2012) do not incorporate the panel dimension of the data and treat the whole population's average in each year as an observation.

Table 6 explores the effect of these two differences in the estimation strategy. Column II estimates the macro Frisch incorporating one of these differences: using five lags of wages as opposed to age and education as the instruments.[38] I find that the estimates drop significantly when I use these alternative instruments. Column III presents the estimates when I incorporate the second difference by ignoring the panel dimension of the data and use the population's average, as opposed to the

[37]The estimate consistent with this study uses the weighted PSID sample and only incorporates observed wages. The alternative estimates are unweighted or estimates of the unconditional Frisch elasticity.

[38]Similar to my benchmark macro estimates, the first stage regression is run on the cohort level as opposed to the individual level.

cohort's average, as an observation. Incorporating this second difference causes the estimates to decrease even more, however a statistically insignificant amount.[39] The large differences between the benchmark estimates and the estimates in column III indicate that the variation in estimation strategy are responsible for the different findings in this paper and in Fiorito and Zanella (2012).

Table 6: **Effect of Specification in Fiorito and Zanella (2012)**

| **Variables (s.e.)** | **Benchmark I** | **Alt. Inst. II** | **No Panel & Alt. Inst. III** |
|---|---|---|---|
| $\Delta$W | 2.88 | 0.64 | 0.42 |
| | (0.67) | (0.23) | (0.26) |
| $\Delta$kids | -0.28 | | |
| | (0.11) | | |
| $\Delta$kidsunder6 | -0.15 | | |
| | (0.12) | | |
| $\Delta$bigcity | 0.18 | | |
| | (0.31) | | |
| Observations | 1,288 | 1,008 | 18 |
| Yr. Dummies | Yes | Yes | No |
| Years | 68-97 | 68-97 | 68-91 |
| Ages | 20-65 | 20-65 | 20-65 |
| Instruments | Age & Educ | Lag Wage | Lag Wage |
| Type of Data | Pseudo Panel | Pseudo Panel | Time Series |
| **1st Stage** | | | |
| F-stat (Excl. Inst.) | 3 | 23.31 | 1.5 |
| F-stat (P-value) | 0 | 0 | 0.15 |
| Hansen J-Stat | 10.81 | 6.38 | 4.5 |
| J-Stat (P-value) | 0.09 | 0.09 | 0.21 |

**Notes:** The F-stat for excluded instruments is for the wage regressions. Consistent with previous studies, the standard errors are clustered on cohort.

Making these two changes in the estimation strategy implies that the Frisch elasticity is being determined from different variation in wages. This study is identifying the Frisch elasticity from the life cycle changes in wages that can be predicted by age and education. The implicit assumption in this study is that these predicted changes

[39] I choose not to use annual dummies due to a lack of degrees of freedom. Furthermore, I limit the sample period when running the time series regression because Fiorito and Zanella (2012) point out that the wage variable they use may have fundamentally changed after 1992.

in wages are orthogonal to unexpected changes in marginal utility. In contrast, Fiorito and Zanella (2012) identify the Frisch elasticity from aggregate wages over the business cycle that can be predicted by lagged aggregate wages. This approach implicitly assumes that these lagged wages are not correlated with future marginal utility. In order for these estimates to be unbiased, on average individuals must have unbiased predictions of the persistence of aggregate wage shocks. Instead, if individuals collectively under or over assign how much of changes in aggregate wages are persistent, then the estimates from this alternative approach will be biased. One could imagine that systematic errors could occur at the beginning of a deep recession when individuals may over predict how much of shocks to wages are idiosyncratic, not realizing the severity of the impending recession. Furthermore, because the authors do not take advantage of the panel aspect of the data, if the relative importance of each cohort in the composition of the population changes over time, then the results could be biased. Overall, these results demonstrate that estimates of the macro Frisch elasticity are sensitive to which variation in wages are used for identification.

## 5.2 Estimates by age

In this section I explore whether the estimates of the Frisch elasticity are sensitive to which ages are included in the sample. Table 7 and table 8 provide the estimates of the macro and micro Frisch elasticity for different age ranges, respectively.[40]

Focusing on table 7, when I exclude individuals that are between sixty-one and sixty-five, the estimate of the macro Frisch drops from 2.88 to 1.75. The estimate drops further to 0.81 when I exclude individuals between fifty-one and sixty-five. These significant drops indicate that the estimates of the macro Frisch elasticities are not consistent over all ages and that the large estimates are primarily driven by older individuals. The reason for the larger estimates when including older individuals

[40] I do not display the estimates when the annual dummies are not included; however, the results are similar.

becomes clear after examining figures 1 and 2. The figures depict that the cohort's average hours start dropping rapidly at the age of fifty. However, the cohort's average wages drop only a small amount over the same age range. In contrast, under the age of fifty five the relative size of the changes in the hours and wage profiles are much more proportional. The disproportionate size of these movements during older ages explains why the estimates of the Frisch are so much smaller when one excludes individuals over fifty.

One interpretation of this sensitivity is that the macro Frisch elasticity changes over the life cycle. This interpretation is consistent with the econometric estimation strategy in this paper that assumes the instrumental approach isolates the exogenous changes in the wages. In particular, this interpretation implies that these changes in wages are exogenous. However, it is possible that the changes in wages may not be exogenous to the decision with regard to how many hours to work. In particular, Casanova (2012) documents that these changes in wages seem to be endogenous with the hours decisions later in life, which would imply that the variation in the estimates over age are due to a bias as opposed to fluctuations in the deep parameter value.

Casanova (2012) examines the roll of partial retirement in explaining hours and wage dynamics for older people. The author demonstrates that when one controls for partial retirement, the wage profile is upward sloping or flat throughout the whole working lifetime. In contrast the unconditional wage profile falls for older individuals.[41] She argues that the transition out of full time work to either partial or full retirement is a choice for most workers and the subsequent drop in the wage is endogenously determined in conjunction with these hours changes. If endogenous transitions to partial retirement are responsible for the shape of the lifetime wage profile for older individuals then the large estimates of the macro Frisch from the full sample are likely to be biased.[42] Further supporting this alternative interpretation, Gomme

[41]Rupert and Zanella (2012) also shows that the wage profile is flat if one focuses on a continuous cohort.

[42]Under this scenario, it seems likely that the estimates of the Frisch elasticity, when excluding individuals over the age of 55, would be far less susceptible to this type of bias.

et al. (2005) finds that the relative magnitude of hours fluctuations over the business cycle for older individuals compared to prime-aged individuals is not large enough to support this much variation in the Frisch elasticity over the lifetime.

Table 7: **Macro Estimate by Age**

| | Age Rage | | | | |
|---|---|---|---|---|---|
| **Variables (s.e.)** | **20-65 I** | **20-60 II** | **20-55 III** | **20-50 IV** | **20-45 V** |
| $\Delta$W | 2.88 | 1.75 | 1.5 | 0.81 | 0.51 |
| | (0.67) | (0.35) | (0.360) | (0.25) | (0.17) |
| $\Delta$kids | -0.28 | -0.11 | -0.1 | -0.03 | -0.04 |
| | (0.11) | (0.05) | (0.05) | (0.03) | (0.03) |
| $\Delta$kidsunder6 | -0.15 | -0.04 | -0.01 | 0.09 | 0.16 |
| | (0.12) | (0.08) | (0.07) | (0.05) | (0.05) |
| $\Delta$bigcity | 0.18 | 0.15 | 0.17 | 0.17 | 0.08 |
| | (0.31) | (0.27) | (0.25) | (0.2) | (0.19) |
| Observations | 1,288 | 1,148 | 1,008 | 868 | 728 |
| Yr. Dummies | Yes | Yes | Yes | Yes | Yes |
| Years | 68-97 | 68-97 | 68-97 | 68-97 | 68-97 |
| **1st Stage** | | | | | |
| F-stat (Excl. Inst.) | 3 | 7.19 | 3.2 | 3.31 | 4.57 |
| F-stat (P-value) | 0.01 | 0 | 0.01 | 0.01 | 0 |
| Hansen J-Stat | 10.81 | 9.48 | 11.64 | 18.39 | 17.8 |
| J-Stat (P-value) | 0.09 | 0.15 | 0.07 | 0.01 | 0.01 |

**Notes:** The estimates are from a pseudo panel which includes all individuals. The F-stat for excluded instruments is for the wage regressions. Consistent with previous studies, the standard errors are clustered on cohort.

Table 8 presents the results when I estimate the micro Frisch for different ages. Unlike the estimates of the macro Frisch, the decrease in the estimates are small when I exclude older individuals. The smaller changes in the micro Frisch elasticity could be because the micro Frisch excludes non-working individuals and focuses on younger individuals who are less likely to partially retire.[43]

These results indicate that determining which value to use in a calibrated macroeconomic model depends crucially on which question the economist is examining and

[43] Since individuals are required to work a minimum number of hours in order to be included in the sample used to estimate the micro Frisch, many individuals who are partially retired may be excluded.

Table 8: **Micro Estimate by Age**

| **Variables** (s.e.) | **26-60** I | **26-55** II | **26-50** III | **26-45** IV |
|---|---|---|---|---|
| | **Age Rage** | | | |
| $\Delta$W | 0.22 | 0.17 | 0.07 | 0.05 |
| | (0.09) | (0.11) | (0.12) | (0.12) |
| $\Delta$kids | -0.01 | 0 | 0 | 0 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| $\Delta$kidsunder6 | 0.01 | 0.01 | 0 | 0 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| $\Delta$bigcity | 0 | -0.01 | -0.01 | -0.01 |
| | (0.01) | (0.01) | (0.01) | (0.02) |
| Observations | 27,880 | 25,459 | 21,939 | 17,774 |
| Yr. Dummies | Yes | Yes | Yes | Yes |
| Years | 68-97 | 68-97 | 68-97 | 68-97 |
| **1st Stage** | | | | |
| F-stat (Excl. Inst.) | 16.96 | 16.96 | 10.65 | 9.07 |
| F-stat (P-value) | 0 | 0 | 0 | 0 |
| Hansen J-Stat | 19.5 | 19.5 | 18.48 | 12.45 |
| J-Stat (P-value) | 0 | 0 | 0.01 | 0.05 |

**Notes:** The estimates are from a traditional panel which includes only prime-age married males who are the heads of households. The F-stat for excluded instruments is for the wage regressions. Consistent with previous studies, the standard errors are clustered on cohort.

how the model is specified. For example, if the model being calibrated includes both a partial retirement decision and assumes the preferences for leisure increase with age, then the parameter value should be consistent with the lower value estimated when only younger individuals are included. Alternatively, if the model being calibrated is more parsimonious and does not include either partial retirement or changes in preferences for leisure over the life cycle, then in order for the model to replicate the observed wage and hours profiles, it will need to include a larger macro Frisch value in line with the estimates which incorporate older individuals. However, if the source of variation in hours and wages is important for the question of interest this type of parsimonious model would not be appropriate even though the model matches the relative volatility of hours and wages over the business cycle. Furthermore, if the decision of when to retire and the consequences on aggregate labor are not relevant to the question being examined then the relevant value for calibration is the lower estimate of the macro Frisch elasticity obtained when examining younger individuals. Conversely, if the total aggregate fluctuations in labor including retirement are relevant to the question being examined, then the larger Frisch elasticity estimated for the bigger age range is the more relevant estimate. Overall, the large variation in the estimates of the macro Frisch elasticity indicate that it is not only important to use a calibration value that is consistent with both the model and question being examined, but also that it is important to check the sensitivity of the results with respect to the calibration value.

## 5.3 Alternative Parametric Assumptions

Section 5.2 demonstrates that the large estimates of the macro Frisch elasticity are primarily due to older individuals. In particular, the estimates are large because the relative changes in hours are much bigger than the change in wages for older individuals. Given that the Frisch elasticity is primarily identified from the predicted change in wages over the life cycle, it is of interest whether the estimates are sensitive to the parametric form used to predict these wage changes. Therefore, in this section I explore the sensitivity of the results when I use a more flexible set of polynomials of age and education as instruments.

Table 9: **Effect of Alternative Parametric Form**

| **Variables (s.e.)** | **Micro Bench. I** | **Micro Alt. II** | **Macro Bench. III** | **Macro Alt. IV** |
|---|---|---|---|---|
| ΔW | 0.22 | 0.2 | 2.88 | 2.28 |
| | (0.09) | (0.1) | (0.67) | (0.48) |
| Δkids | -0.01 | -0.01 | -0.28 | -0.19 |
| | (0.01) | (0.01) | (0.11) | (0.09) |
| Δkidsunder6 | 0.01 | 0 | -0.15 | -0.12 |
| | (0.01) | (0.01) | (0.12) | (0.11) |
| Δbigcity | 0 | 0 | 0.18 | 0.83 |
| | (0.01) | (0.01) | (0.31) | (0.38) |
| Observations | 27,880 | 27,880 | 1,288 | 1,288 |
| Yr. Dummies | Yes | Yes | Yes | Yes |
| Years | 68-97 | 68-97 | 68-97 | 68-97 |
| Ages | 26-60 | 26-60 | 20-65 | 20-65 |
| Instruments | Quadratics | Chebyshev | Quadratics | Chebyshev |
| **1st Stage** | | | | |
| F-stat (Excl. Inst.) | 16.96 | 11.83 | 16.96 | 5.2 |
| F-stat (P-value) | 0 | 0 | 0 | 0 |
| Hansen J-Stat | 19.5 | 21.5 | 19.5 | 17.17 |
| J-Stat (P-value) | 0 | 0.04 | 0 | 0.1 |

**Notes:** The F-stat for excluded instruments is for the wage regressions. Consistent with previous studies, the standard errors are clustered on cohort.

In order to test the sensitivity, instead of using quadratics, I use third order Chebyshev polynomials of age, second order Chebyshev polynomials of education, and the interaction of all the polynomials as the instruments for wages. Chebyshev polynomials are a sequence of orthogonal recursive polynomials. Using these orthogonal polynomials as instruments, as opposed to using the quadratic polynomials, allows for more flexibility in the relationship between wages and the instruments. Columns I and III of table 9 are the benchmark estimates of the micro and macro Frisch elasticity (using the quadratic polynomials of the instruments), respectively. Columns II and IV are the estimates of the micro and macro Frisch elasticity using the Chebyshev polynomials of the instruments, respectively. Focusing on the estimates of the micro Frisch elasticity, utilizing the more flexible instruments does not alter the estimates. Furthermore, comparing columns III and IV, the estimate of the macro Frisch elasticity are somewhat smaller when using the more flexible polynomials, compared to the benchmark estimates. However, the decrease is not statistically significant and the alternative estimate of the macro Frisch elasticity is still in the range of the values used to calibrate macroeconomic models. The overall finding that both of the restrictions can explain the gap between the microeconometric estimates of the Frisch elasticity and the calibration values used in macroeconomic models is robust to using these more flexible polynomials. Taken as a whole, these results indicate that the estimates of the Frisch elasticity are much less sensitive to the parametric form of this first stage than they are to the specific instruments used in the first stage.

# 6 Conclusion

This paper evaluates whether relaxing two restrictions causes an increase in the estimates of the Frisch elasticity large enough to explain the gap between the original microeconometric estimates of the Frisch elasticity and the calibration values used in macroeconomic models. The first restriction is that the micro Frisch elasticity focuses on prime-aged, married, working males who are heads of households. In contrast, the macro Frisch elasticity incorporates fluctuations in hours from the whole population. Second, the micro Frisch elasticity only includes fluctuations on the intensive margin, while the macro Frisch elasticity incorporates fluctuations in hours on both the intensive and extensive margins. Similar to previous studies, I find that relaxing either of these restrictions in isolation cannot explain the whole gap. However, when I simultaneously account for both restrictions, I estimate the macro Frisch elasticity is between 2.9 - 3.1. Since this estimate of the Frisch elasticity is in the range of typical macroeconomic calibration values, I conclude that the impact of accounting for both restrictions in tandem can be large enough to explain the gap.

However, these results are in contrast to Fiorito and Zanella (2012), who account for both differences but estimate a much lower macro Frisch elasticity of 0.68.[44] I show that the main reason for these divergent findings is due to differences in the empirical approach. Fiorito and Zanella (2012) use lagged wages as an instrument for current wages to account for endogeneity. This approach implies that they identify the Frisch elasticity from persistent changes in aggregate wages. In contrast, I use age and education as instruments for wages, which implies that I identify the Frisch elasticity from predicted variation in wages over the life cycle. These results indicate that estimates of the macro Frisch elasticity are sensitive to the variation in wages used to identify the Frisch elasticity. Moreover, I find that the estimates of the macro Frisch are also fairly sensitive to whether older individuals are included in the data set. These results, combined with other research such as Casanova (2012) and Gomme et al. (2005), suggest that the large macro Frisch elasticity estimates may overstate the deep parameter value since the variation in wages at the end of the working life may not be exogenous.

A common practice in macroeconomics is to use a calibrated parsimonious model. These results demonstrate that the value used to calibrate the Frisch elasticity in a macroeconomic model depends crucially on both the question the economist is asking and the specific features of the model he is including. For example, if a macroeconomist is using a model that does not include retirement and it is important for answering his question that the fluctuations in hours and wages over the business cycle are consistent with the data then he will need to use a value consistent in line with the large macro Frisch elasticity estimates in this paper. In contrast, if an economist is asking a question that centers on changes in hours on the intensive margin of working individuals then he may want to use a lower calibration value for the Frisch

[44]Mulligan (1999) and Faberman (2010) also find lower estimates of the elasticity. As opposed to this paper, Mulligan (1999) and Faberman (2010) do not account for the potential endogeneity of wages.

elasticity in line with the estimates of the micro Frisch elasticity. Moreover, the large range of estimates of the macro Frisch elasticity in this paper demonstrates that it is important for economists to be cognizant of the implicit assumptions associated with the estimation procedure used to determine their calibration parameter.

# A Implications of using participation rate elasticity

In order to calculate the macro elasticity, Chetty et al. (2011) adds the micro (intensive margin elasticity) and the extensive margin elasticity. The authors' value for the extensive margin comes from a meta analysis that focuses on studies that primarily estimate the labor force participation elasticity. The sum of the intensive margin elasticity and the labor force participation elasticity need not be the same as calculating the aggregate Frisch elasticity from variations on both the intensive and extensive margin. Let us consider an economy over two periods that experiences a temporary change in the after-tax wage. Let there be three populations. The first group is individuals who work in both periods which I denote with $e$. The second group is made up of individuals who do not work in either period, which I denote with $u$. The third group contains individuals who only work in the second period, who I denote as $n$. In the first period, let $h_i$ denote the hours worked on average by group $i$ and $P_i$ be the size of group $i$. Let $h'_i$ and $P'_i$ represent the hours worked by group $i$ and the size of group $i$ in the second period, respectively.

The aggregate Frisch elasticity is the percent change in hours divided by the percent change in wages. The percent change in hours can be written as $\frac{P_e h'_e + P'_n h'_n - P_e h_e}{P_e h_e}$, which simplifies to, $\frac{P'_n h'_n}{P_e h_e} + \frac{h'_e - h_e}{h_e}$. The first part of the expression represents the percent change in hours from the new workers (fluctuations on the extensive margin). The second part of the expression represents the percent change in hours from the increase in hours worked from individuals who work in both periods (fluctuations on the intensive margin). Chetty et al. (2011) uses the change in the participation rate elasticity as the contribution of new workers to the aggregate Frisch elasticity and therefore calculates the percentage change in hours as $\frac{P'_n}{P_e} + \frac{h'_e - h_e}{h_e}$. These two expressions are only equivalent if new workers work on average the same number of hours as existing workers did in the first period ($h_e = h'_n$). If these new workers who enter after the wage increase tend to work more hours than the old workers worked prior to the wage increase, then the estimates in Chetty et al. (2011) will be biased downward.

# B Unconditional Frisch Elasticity

This paper focuses on estimates of the macro Frisch elasticity consistent with the macro definition. Specifically, the macro Frisch elasticity is estimated from a pseudo panel that includes unconditional changes in hours and the observed changes in wage which exclude the potential wages for non-working (no-work) individuals.[45] Since the calibration values for macroeconomic models are determined from these series, these are the relevant data for the question in this paper. However, for other questions, the aggregate unconditional Frisch elasticity may be of interest. The key difference is that the unconditional Frisch elasticity accounts for possible selection bias from non-working individuals. This section provides estimates of this alternative concept.

In order to account for selection bias, I follow the procedure in Fiorito and Zanella (2012) in which the authors predict the wages for non-working individuals using a Heckman-type correction for selection bias.[46] Selected results from these regressions are in table 10. Fiorito and Zanella (2012) note that Blundell et al. (2003) shows empirically that when they create an aggregate wage which includes a similar selection corrected predicted wage for non-workers, most of the aggregation bias is removed from their aggregate wage series. One complication in this specification is that some individuals who indicate they retired or work less than 250 hours still report labor income. Therefore, I estimate the Frisch elasticity with two different wage series for

[45] In this estimate of aggregate wage, if an individual reports not working but still reports a wage that information is included in the pseudo panel.

[46] See section 3 of Fiorito and Zanella (2012) and Wooldridge (1995) for more details on the correction procedure. The variables used to predict employment at the first stage are gender, race, marital status, number of kids and a set of polynomials and interactions between age and education. One difference between Fiorito and Zanella (2012) and this study is that the level, as opposed to the natural log, of wages is predicted.

each cohort. First, I incorporate predicted wages for individuals who do not report any income and observed wages for all others in the cohort's average (predict missing). Second, I incorporate predicted wages for individuals who report that they are retired or work less than 250 hours and use the observed wages for all others in the cohort's average (predict non-working).

Table 10: **Significance Tests for Selection Correction Regressions**

| | **Participation Equation** | | | | | | | | **Wage Eq.** |
|---|---|---|---|---|---|---|---|---|---|
| **Var.** | **1968** | **1970** | **1975** | **1980** | **1985** | **1990** | **1995** | **1997** | **All Yrs.** |
| Married | 0.216 | 0.00749 | 0.822 | 0.430 | 9.120 | 15.80 | 10.79 | 24.88 | 1.910 |
| | (0.642) | (0.931) | (0.365) | (0.512) | (0.00253) | (7.04e-05) | (0.00102) | (6.11e-07) | (0.167) |
| Kids | 18.35 | 20.92 | 27.44 | 42.88 | 34.44 | 18.11 | 17.72 | 43.10 | 21.04 |
| | (1.84e-05) | (4.78e-06) | (1.62e-07) | (5.82e-11) | (4.38e-09) | (2.09e-05) | (2.56e-05) | (5.21e-11) | (4.50e-06) |
| Sex | 1484 | 1180 | 1143 | 925.5 | 514.8 | 751.4 | 355.8 | 459.8 | 450.1 |
| | (0) | (0) | (0) | (0) | (0) | (0) | (0) | (0) | (0) |
| Age polys | 0.0227 | 3.010 | 3.636 | 1.785 | 8.009 | 2.871 | 4.234 | 6.194 | 0.777 |
| | (0.989) | (0.390) | (0.162) | (0.618) | (0.0458) | (0.0468) | (0.0358) | (0.0414) | (0) |
| Educ. Polys | 12.72 | 4.034 | 1.792 | 0.557 | 5.562 | 7.962 | 6.662 | 6.371 | 19.38 |
| | (0.00528) | (0.133) | (0.617) | (0.757) | (0.0620) | (0.238) | (0.237) | (0.103) | (0.460) |
| Age x Educ. | 13.40 | 8.377 | 4.364 | 3.679 | 12.35 | 11.29 | 14.34 | 26.37 | 14.34 |
| | (0.0199) | (0.137) | (0.498) | (0.596) | (0.0303) | (0.0459) | (0.0136) | (7.58e-05) | (0) |
| Inverse Mills | | | | | | | | | 9.454 |
| | | | | | | | | | (0) |
| All Variables | 2949 | 2905 | 3808 | 4647 | 4890 | 6928 | 6379 | 4360 | 304.9 |
| | (0) | (0) | (0) | (0) | (0) | (0) | (0) | (0) | (0) |
| Obs | 7,806 | 7,430 | 9,172 | 10,336 | 10,987 | 14,436 | 15,146 | 9,978 | 226,822 |

**Notes:** The participation regression is done on an annual basis. Only selected years of the participation regression are included. The test statistic for the participation equation is a $\chi^2$. The test statistic for the wage equation is an F-test. P-values for each test are included in the parenthesis. The age polys. included are age, age$^2$, and age$^3$. The education polys. included are education, education$^2$, and education$^3$. The test statistics for age, education, and interactions are joint tests of significance. Both the wage and participation regressions are done with mean values included for all variables. The significance of the mean values is not included in the table.

Table 11 presents the estimates of the unconditional aggregate Frisch elasticity using both definitions of not working. The estimates of the unconditional aggregate Frisch elasticity range from 1.68 to 2.64. I find that when I control for selection bias by predicting wages for those who do not report wage information, the estimates of the Frisch elasticity are significantly lower compared to the estimates of the macro Frisch elasticity. However, when I only control for selection by predicting wages for all of those who report not working. the change in the estimates is smaller.

Table 11: **Aggregate Unconditional Frisch**

| **Variables (s.e.)** | **Macro I** | **Uncond. II** | **Uncond. III** | **Macro IV** | **Uncond. V** | **Uncond. VI** |
|---|---|---|---|---|---|---|
| Δ W(observed) | 3.1 | | | 2.88 | | |
| | (0.68) | | | (0.67) | | |
| Δ W (predict missing) | | 1.68 | | | 1.78 | |
| | | (0.45) | | | (0.43) | |
| Δ W (predict no-work) | | | 2.41 | | | 2.64 |
| | | | (0.36) | | | (0.44) |
| Δkids | -0.28 | -0.16 | -0.23 | -0.28 | -0.16 | -0.21 |
| | (0.11) | (0.07) | (0.06) | (0.11) | (0.06) | (0.07) |
| Δkidsunder6 | -0.21 | -0.02 | -0.15 | -0.15 | -0.06 | -0.23 |
| | (0.14) | (0.08) | (0.07) | (0.12) | (0.08) | (0.08) |
| Δbigcity | 1.09 | 0.18 | 0.12 | 0.18 | 0.63 | 0.41 |
| | (0.51) | (0.17) | (0.18) | (0.31) | (0.27) | (0.29) |
| Observations | 1,288 | 1,288 | 1,288 | 1,288 | 1,288 | 1,288 |
| Yr. Dummies | No | No | No | Yes | Yes | Yes |
| Years | 68-97 | 68-97 | 68-97 | 68-97 | 68-97 | 68-97 |
| Ages | 20-65 | 20-65 | 20-65 | 20-65 | 20-65 | 20-65 |
| **1st Stage** | | | | | | |
| F-stat (Excl. Inst.) | 3.6 | 4.85 | 8.39 | 3 | 6.17 | 8.22 |
| F-stat (P-value) | 0.01 | 0 | 0 | 0 | 0 | 0 |
| Hansen J-Stat | 6.38 | 20.21 | 9.09 | 10.81 | 18.73 | 7.73 |
| J-Stat (P-value) | 0.38 | 0 | 0.17 | 0.09 | 0 | 0.26 |

**Notes:** The F-stat for excluded instruments is for the wage regressions. Consistent with previous studies, the standard errors are clustered on cohort.

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