# Reconciling Micro and Macro Estimates of the Frisch Labor Supply Elasticity

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**Abstract**

This paper explores the large gap between the microeconometric estimates of the Frisch labor supply elasticity (0-.5) and the values used by macroeconomists to calibrate general equilibrium models (2-4). These two ranges identify two fundamentally different notions, the micro and macro Frisch elasticity, respectively. Due to the different definitions, there are two restrictions in the micro Frisch elasticity that are relaxed in the macro Frisch elasticity. First, the micro Frisch elasticity focuses only on prime-aged married males who are the head of their household, while the macro Frisch elasticity represents the whole population. Second, the micro Frisch elasticity only incorporates intensive margin fluctuations in hours, while the macro Frisch elasticity includes both intensive and extensive margin fluctuations. This paper finds that relaxing these two restrictions causes estimates of the Frisch elasticity to increase from 0.2 to between 2.9 and 3.1, indicating that these two restrictions can explain the gap between the microeconometric estimates and the calibration values. However, this paper demonstrates that these estimates of the macro Frisch elasticity are sensitive to the estimation procedure and also the exclusion of older individuals, implying that calibration values used for macroeconomic models should be selected carefully.

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 macroeconomic models used to assess both government policies and the business cycle is the Frisch labor supply elasticity, the elasticity of hours worked with respect to wages, holding marginal utility constant. For example, the Frisch elasticity has large effects on the consequences of reforms to Social Security (see Imrohoroğlu and Kitao (2012)). The optimal capital and labor tax rates are also highly sensitive to the Frisch elasticity (see Peterman (2013)). Moreover, Jaimovich and Siu (2009) demonstrate that changes in demographics and how the volatility of labor supply evolves over the life cycle can account for up to one-third of the great moderation. Generally, in order for macroeconomic models to match the observed amount of total volatility in aggregate hours worked over the business cycle, the Frisch elasticity needs to be set somewhere in the range of 2 to 4.[1] In contrast to the large calibration values, the seminal microeconometric estimates of the Frisch elasticity 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. The seminal microeconometric estimates include two restrictions that are implicitly relaxed in the macroeconomic calibration values. First, the seminal microeconometric estimates restrict the sample to only include a subset of the population, typically focusing on individuals who are male, married, prime-aged, and heads of households. In contrast, macroeconomic models are calibrated to match the aggregate observed volatility in hours worked from the whole population. Second, the seminal microeconometric estimates only incorporate fluctuations on the intensive margin. Conversely, the volatility used as a target to calibrate macroeconomic models includes labor fluctuations on both the intensive and extensive margin.[2]

[1]For example, King and Rebelo (1999) and Cho and Cooley (1994) calibrate RBC models with a labor supply elasticity of 4 and 2.6, respectively. See Chetty et al. (2012) for more discussion of the typical values used to calibrate models.

[2]Incorporating fluctuations on the extensive margin seem likely to cause a large increase in the

This paper assesses whether altering the microeconometric estimation approach in order to relax these two restrictions causes a large enough increase in the estimates of the Frisch elasticity such that they fall in the range of values used in macroeconomic models. To begin, when including both restrictions, I estimate that the Frisch elasticity consistent with the microeconometric estimates (micro Frisch elasticity) is approximately 0.2.[3] Next, I estimate the macro Frisch elasticity by relaxing both of the restrictions. In particular, I include fluctuations on the extensive margin and broaden the composition to include non-married individuals, females, secondary earners, younger individuals, and older individuals.[4] By relaxing these two restrictions, I am estimating a Frisch elasticity that can be used as a parameter value in a macroeconomic model that will produce fluctuations consistent with the aggregate data.[5] I estimate that this macro Frisch elasticity is between 2.9 and 3.1. The much larger estimates of the macro Frisch elasticity indicate that the total effect of relaxing these two restrictions can explain the gap between the calibration values used in macroeconomic models and the original microeconometric estimates of the Frisch elasticity.

Interestingly, I find that accounting for each of the restrictions in isolation causes much smaller changes in the estimates of the Frisch elasticity. In particular, when I relax the composition restrictions, but only incorporate fluctuations on the intensive margin, the estimates of the Frisch elasticity increase from 0.2 to 0.9. Moreover, I find that the estimates of the Frisch elasticity are between 0.8 and 0.9 when I incorporate fluctuations on the extensive margin but restrict the composition. Since the sum of

Frisch elasticity because previous work demonstrates that in the U.S. the volatility of hours from employment is considerably more than the volatility due to fluctuations on the intensive margin (for examples see Ohanian and Raffo (2012), Hansen (1985), Kydland (1995), Cho and Cooley (1994), and Hall (2009)).

[3]The estimates are similar to the values of the estimates in the seminal studies.

[4]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.

[5]In particular this estimate of the Frisch elasticity is consistent with the notion of the parameter value for a representative agent or representative cohort in a model.

the increase in the estimates from independently relaxing these restrictions is much smaller than the total change when both restrictions are simultaneously relaxed, these results indicate that the interaction of these two restrictions plays an important role in explaining the total increase. In particular, fluctuations on the extensive margin of females, secondary earnings, and older and younger individuals play an important role in why estimates of the macro Frisch elasticity are much larger than estimates of the micro Frisch elasticity.

In the study most similar to this paper, Fiorito and Zanella (2012) also estimate the implications of relaxing these two restrictions on estimates of the Frisch elasticity. However, in contrast to this paper, Fiorito and Zanella (2012) find that relaxing the two restrictions only causes their estimates of the Frisch elasticity to increase to 0.68 implying that these restrictions cannot explain the whole gap.[6] This paper demonstrates that the lower estimates of the macro Frisch elasticity in Fiorito and Zanella (2012) and this paper are due to different estimation strategies which imply two main differences. First, the two papers use different instruments to isolate the exogenous variation in wages. The instruments that Fiorito and Zanella (2012) use have a very small F-statistic in the first stage regression. This relatively small F-statistic could indicate that these alternative instruments used in Fiorito and Zanella (2012) are weak, leading to a downward bias in their estimate of the Frisch elasticity. Second, the two papers are identifying the Frisch elasticity from different variation in wages which implies different underlying assumptions in order for each of these types of variation to be exogenous.

A common practice in macroeconomics is to use a calibrated parsimonious model. The results of this paper have two implications for calibration exercises. First, in addition to being sensitive to the estimation strategy, I find that the estimates of the macro Frisch are sensitive to whether older individuals are included in the data set. Given the sensitivity of the estimates, it is important to test the robustness of

[6]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.

the results from a macroeconomic model with respect to the calibration value of the Frisch elasticity.

Second, the results in this paper demonstrate that it is imperative that the estimated values used for calibration be consistent with the underlying macroeconomic model being used in the analysis. For example, if a macroeconomist is using a model that does not include retirement, and it is important that the fluctuations in hours and wages over the business cycle are consistent with the data for the specific question being examined, then the calibration value will need to be in line with the larger macro Frisch elasticity estimates in this paper. However, if an economist is asking a question that centers on changes in hours on the intensive margin and retirement decisions are not relevant, then the model should not include the larger calibration value, instead using a value in line with the estimates of the micro Frisch elasticity.

Overall, 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.[7] 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 which would not include the interaction from relaxing these two restrictions. Although Rìos-Rull et al. (2012), Mulligan (1995), Heckman and MaCurdy (1980), Blau and Kahn (2007), and Kimmel and Kniesner (1998) demonstrate that 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.[8] Similarly,

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

[8]Some of these works focus on compensated elasticities as opposed to the Frisch elasticity. For example, Kimmel and Kniesner (1998) demonstrate 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. In a related study,

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 heads of their households, the Frisch elasticity is smaller than the values used for calibration.

There are a few exceptions, other than Fiorito and Zanella (2012), that examine both restrictions in tandem. These other studies include Mulligan (1999), Faberman (2010), and Chetty et al. (2012). In contrast to this paper, which estimates that the macro Frisch elasticity is in the range of typical calibration values, these other studies estimate that the macro Frisch elasticity is lower, between 0.6 and 1.6. Although all the estimates are determined by comparing fluctuations in hours and wages, there are numerous differences in the specific estimation strategies. For example, in contrast to this paper, which uses instrumental variables to try to isolate the fluctuations in wages that are exogenous from innovations to marginal utility, Mulligan (1999) and Faberman (2010) assume that the observed variation in wages is exogenous and regress changes in hours on changes in wages.

Chetty et al. (2012) also use a different approach to estimate the macro Frisch elasticity. The authors 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. Overall, Chetty et al. (2012) estimate lower values than this study for both pieces of the macro Frisch elasticity. Since Chetty et al. (2012) use a number of studies to form their estimates, there are a number of difference between the studies used to inform their estimate and the estimation strategy in this paper (see section 5.2 for detailed discussion).

An additional strand of the literature that lends further evidence to the higher values of the macro Frisch elasticity, consistent with my estimates, are a number of studies that examine whether the microeconometric estimates of the Frisch elasticity are biased estimates of the deep parameter value. Examples of the reasons for these

Jaimovich et al. (2013) attempt to understand why labor supply elasticities may differ by age.

biases include not accounting for liquidity constraints, endogenous human capital, discrete labor choices, or uninsurable risk. These alternative studies include Rogerson and Wallenius (2013), Chang et al. (2011), Imai and Keane (2004), Pistaferri (2003), Chetty (2012), Domeij and Floden (2006), and Contreras and Sinclair (2008) (see Keane and Rogerson (2011) for a review of this strand of the literature). These studies tend to find that when they account for the potential biases the estimates of the Frisch elasticity increase, and in some cases the increase is large enough that the estimates fall in the range of values used to calibrate macroeconomic models. These higher estimates of the deep parameter value provide additional support for using larger estimates of the macro Frisch elasticity as calibration values.

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, and section 4 presents the estimates of the micro and macro Frisch elasticity. Section 5 compares these estimates to estimates from other studies, examines the robustness of the estimates, and discusses the implications of these results for calibration values. Finally 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 to estimate the Frisch elasticity in a reduced form setting (Altonji (1986) and MaCurdy (1981)).[9] Next, I describe my estimation strategy for the Frisch labor supply 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,

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

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, $\chi^c_{i,j}$ is a parameter that controls the taste for consumption, $\chi^h_{i,j}$ 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

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

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

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

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

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

[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 combining it with equation 5 results in the second specification,

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

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 change 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. In particular, the original estimates of the Frisch elasticity used the following specifications:

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

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

where TS is a vector of variables controlling for changes in tastes, and $\delta$ is a set of annual dummies.[11] 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.[12]

[11] 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.

[12] 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.

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 changes in wages that are exogenous to unexpected changes in marginal utility.[15] This estimation strategy implies that the Frisch elasticity is estimated off of predicted changes in wages over the life cycle.[16] I determine the micro Frisch elasticity using this estimation strategy.[17]

The three previous studies that examine the effect of both restrictions in tandem use a different strategy to isolate the Frisch elasticity. 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) use 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

[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]Since age (and education) tend to evolve over the life cycle in a predictable manner, using these instruments should isolate the predictable evolution in wages over the life cycle.

[17]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.

(2012) identify the 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. This concept can be thought of as the model parameter value that governs the relationship between hours and wages for a representative agent or cohort.[18] In order to estimate the macro Frisch elasticity I alter the general estimation strategy by using a pseudo panel.[19] 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.[20] In particular, each observation 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 $t$.[21] 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

[18]The macro Frisch elasticity does not have to be equal to the average over each individual's Frisch labor supply elasticity. For example, individuals may face binding liquidity constraints, which would cause them to be less responsive to changes in wages then their deep parameter value. In this example, the responsiveness of aggregate hours would also be less responsive.

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

[20]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.

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

of aggregate hours.[22]

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 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) demonstrate 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.[23]

In order to estimate the macro Frisch elasticity, I estimate equation 9 in the psuedo panel. In contrast, there are two differences in the estimation strategy in Fiorito and Zanella (2012). First, the authors use different instruments. In addition to using different instruments, Fiorito and Zanella (2012) do not use a pseudo panel. Instead of using a pseudo panel, Fiorito and Zanella (2012) use 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,

[22]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.

[23]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) and this study 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.

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.[24]

# 3 Data

Similar to Altonji (1986), I use the Michigan Panel Study of Income Dynamics (PSID) and follow similar procedures to clean the data. I use the waves of the PSID from 1968 until 1997.[25] I calculate the real hourly wages for individuals by taking the annual labor earnings divided by the annual hours working for pay and deflate by the consumer 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.[26] 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.[27]

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[24] 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.

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

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

[27] 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.

Comparing the solid black line (macro sample) and the dashed 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.[28] Generally, the wage profiles tend 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 | 1556 |
| Family Size | 3.81 | 3.18 |
| Males | 1 | 0.48 |
| Married | 1 | 0.77 |
| Observations | 37,331 | 137,306 |

**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**

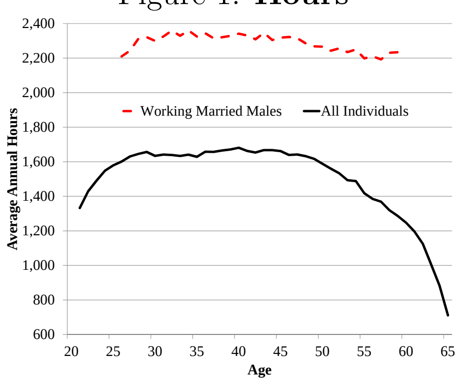
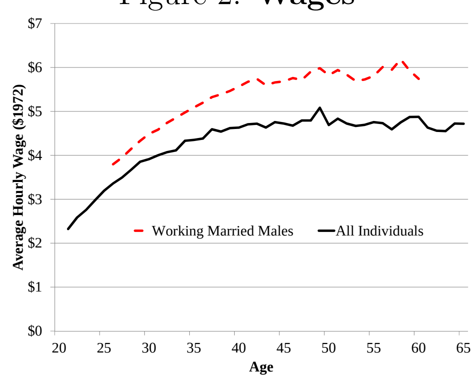



Figure 2: **Wages**




[28] 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.

# 4 Estimates of Micro and Macro Frisch Elasticity

Table 2 presents my benchmark estimates of the micro Frisch elasticity.[29] 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.[30]

Columns I and V 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.[31] The estimates (0.34 & 0.52) are close to those in Altonji (1986) (0.28 & 0.48).[32] I find that the F-statistic for the excluded instruments in the first stage is 5.3 and 13.7 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 weak enough that they may introduce some bias (see section 5.3 for a discussion of the potential bias in

[29] Consistent with previous studies, the standard errors are clustered on cohort. However, I found that there were no substantial changes to the benchmark results when the standard errors are clustered on cohort-year.

[30] 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.

[31] 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.

[32] 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.

the estimates of the macro Frisch elasticity).[33] 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 not to 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 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.[34] 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.[35] 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 all of the individual's observations are no longer excluded.[36] By allowing the panel to be unbalanced, I increase the number of observations by over ten percent; however, the

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

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

[35] In order to test whether coefficients from different regression models are statistically significant, I estimate both models in a stacked regression, clustering by cohort. I then use a standard t-test to test for equality of the coefficient of interest in each model. This test is in the spirit of a Chow test, but only examines one coefficient.

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

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.[37]

Table 2: **Micro Benchmark Results**

| **Variables Variables (s.e.)** | **Orig. I** | **Add Years II** | **Include Δ Tastes III** | **Allow Unbalanced IV** | **Orig. V** | **Add Years VI** | **Include Δ Tastes VII** | **Allow 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:** Estimates of the micro Frisch elasticity using a traditional panel. Columns I and V are estimates consistent with the estimates in Altonji (1986). The other columns sequentially change the estimation procedure to include more years (II and VI), include regressors to control for changes in tastes (III and VII), and allow for an unbalanced panel (IV and VIII). The F-stat for excluded instruments is for the 1st stage regression of changes in wages on the excluded instruments and the controls. Consistent with previous studies, the standard errors are clustered on cohort.

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 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

[37] 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 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.[38]

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

| **Variables (s.e.)** | **Micro I** | **Macro II** | **Micro III** | **Macro IV** |
|---|---|---|---|---|
| ΔW | 0.23 | 2.88 | 0.22 | 3.1 |
| | (0.09) | (0.67) | (0.09) | (0.68) |
| Δkids | -0.01 | -0.28 | -0.01 | -0.28 |
| | (0.01) | (0.11) | (0.01) | (0.11) |
| Δkidsunder6 | 0.01 | -0.15 | 0.01 | -0.21 |
| | (0.01) | (0.12) | (0.01) | (0.14) |
| Δbigcity | 0 | 0.18 | 0 | 1.09 |
| | (0.01) | (0.31) | (0.01) | (0.51) |
| 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 | 16.96 | 3.6 |
| F-stat (P-value) | 0 | 0.01 | 0 | 0 |
| Hansen J-Stat | 19.39 | 10.81 | 19.5 | 6.38 |
| J-Stat (P-value) | 0 | 0.09 | 0 | 0.38 |

**Notes:** Columns I and III are the benchmark estimates of the micro Frisch elasticity. Columns II and IV are estimates of the macro Frisch elasticity using a pseudo panel. The F-stat for excluded instruments is for the 1st stage regression of changes in wages on the excluded instruments and the controls. Consistent with previous studies, the standard errors are clustered on cohort.

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

[38] 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.

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 are the heads of households.[39] 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).[40] 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 (from approximately 0.2 to 0.9).

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

[39]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 are estimates from a sample that includes both married and single prime-age males who are heads of households.

[40]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.) | Add Micro I | Add Single II | Add Females III | Add Secondary Earners IV | Add Younger & Older V | Add Micro VI | Add Single VII | Add Female VIII | Add Secondary Earners IX | Add Younger & Older 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:** Estimates of the effects of relaxing the composition restrictions for the micro Frisch elasticity using a traditional panel. Columns I and VI are the benchmark estimates of the micro Frisch elasticity. Columns II-V and VII-X report estimates of the Frisch elasticity when the restrictions on single individuals, females, secondary earners, and older and younger individuals are sequentially relaxed. The F-stat for excluded instruments is for the 1st stage regression of changes in wages on the excluded instruments and the controls. Consistent with previous studies, the standard errors are clustered on cohort.

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 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 the larger macro Frisch elasticity estimates. However, the sum of these changes is not large enough to explain the difference in my estimates of the micro and macro Frisch elasticity. Thus, 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 for estimates of the macro Frisch to be large enough 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 produce a large estimate of the macro Frisch elasticity.

Table 5: **Extensive Margin Effects**

| **Variables Variables (s.e.)** | **Micro I** | **Include Extensive Margin II** | **Micro III** | **Include Extensive Margin IV** |
|---|---|---|---|---|
| $\Delta$W | 0.23 | 0.84 | 0.22 | 0.88 |
| | (0.09) | (0.17) | (0.09) | (0.19) |
| $\Delta$kids | -0.01 | -0.04 | -0.01 | -0.03 |
| | (0.01) | (0.02) | (0.01) | (0.02) |
| $\Delta$kidsunder6 | 0.01 | 0.06 | 0.01 | 0.06 |
| | (0.01) | (0.04) | (0.01) | (0.04) |
| $\Delta$bigcity | 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:** Estimates of the effect of including the extensive margin. All estimates are for prime-age married males who are the heads of households. Column I and III are the benchmark estimates of the micro Frisch elasticity using a traditional panel and only including individuals who are working. Column II and IV are estimates in a pseudo panel that include individuals not working. The F-stat for excluded instruments is for the 1st stage regression of changes in wages on the excluded instruments and the controls. Consistent with previous studies, the standard errors are clustered on cohort.

# 5 Sensitivity of Estimates

In this section I provide some context for the results from this paper. In particular, I begin by discussing the potential reasons for the different estimates in Fiorito and Zanella (2012) and Chetty et al. (2012). Next, I test the sensitivity of the results in this paper with regard to weak instruments and also the ages of individuals included in the sample. I summarize the implications of my results for calibration and then end by presenting the estimates of the unconditional Frisch elasticity.

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

Similar to this exercise, Fiorito and Zanella (2012) also try to determine if relaxing the two restrictions explains 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 macro Frisch elasticity, 0.68.[41] There are two differences between the estimation strategy in my paper and the one in Fiorito and Zanella (2012). First, as opposed to polynomials of age and education, Fiorito and Zanella (2012) use five lags of wages as their instruments. Second, instead of using the cohort's average value for hours and wage 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.

Since the Frisch elasticity is the elasticity conditional on a constant marginal utility, an unbiased estimation strategy must control for any changes in marginal utility. Given that individuals are intertemporal maximizers, individuals will make decisions in order to equate current marginal utility with expected future discounted marginal utility. Hence, the Frisch elasticity can be determined by regressing changes in hours on changes in wages as long as the variation in wages is orthogonal to any unexpected innovations in marginal utility. The key difference between the strategy in this paper and Fiorito and Zanella (2012) is how the two different approaches diverge in order to isolate variation in wages that is orthogonal to unexpected changes

[41]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.

in marginal utility. In particular, Fiorito and Zanella (2012) estimate the macro Frisch elasticity in a time series data set and use lagged wages as instruments. This alternative approach implies that the estimates in Fiorito and Zanella (2012) are being determined from changes in aggregate wages that tend to persist over numerous years. This variation is most likely due to business cycle effects. In contrast, age and education as instruments in a panel data set, this paper determines the Frisch elasticity from changes in a cohort's wages over the life cycle.

Table 6 explores the quantitative effects of these differences in the estimation strategy. In particular, column I provides my benchmark estimates of the macro Frisch elasticity. Following Fiorito and Zanella (2012), column II presents the estimates the macro Frisch using five lags of wages as opposed to age and education as the instruments and ignores the panel dimension of the data and use the population's average value for hours and wage, as opposed to the cohort's average value, as an observation. Incorporating these two differences imply that the estimates are being determined from persistent variation in aggregate wages over time. These changes in the estimation strategy cause the estimates to decrease a statistically significant amount.[42] The large statistically different estimates of the macro Frisch elasticity using my methodology (column I) and using the methodology consistent with Fiorito and Zanella (2012) (column II) indicate that the differences in estimation strategies are responsible for the different findings in this paper compared to Fiorito and Zanella (2012).

There are two reasons why using these distinct types of wage variation may lead to the large differences in the estimates of the macro Frisch elasticity. First, the F-statistic on the excluded instruments in the first stage regression is much smaller when using the instruments from Fiorito and Zanella (2012) as opposed to age and education. In particular, the F-statistic in column II is small enough that one cannot

[42] 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.

reject the null hypothesis that the coefficients on the instruments in the first stage are jointly zero at the 10 percent level. In contrast, the F-statistic in my specification is large enough to reject the null hypothesis.[43] The low F-statistic could indicate that these alternative instruments are weak leading to a bias.[44] If the instruments are exogenous, then the potential bias from weak instruments will tend to bias the two stage least squares (2SLS) estimates towards the ordinary least squares (OLS) estimate. I find that for both estimation strategies, the OLS estimates are much smaller than the estimates using 2SLS. Thus, if the instruments are valid, then weak instrument bias would tend to cause smaller estimates of the Frisch elasticity. Hence, if the instruments from Fiorito and Zanella (2012) are indeed weak, then this bias could explain the lower estimates of the macro Frisch elasticity using these instruments compared to my benchmark estimates using age and education as instruments.

A second potential explanation for the smaller estimates of the macro Frisch elasticity using the alternative specification could because persistent variation in aggregate wages is not orthogonal to unexpected changes in marginal utility. In particular, after an individual's wage changes his response will incorporate his prediction of how much of this change will persist and how much will dissipate in future periods. If on average, individuals tend to under or over predict the fraction of the changes in wages that will persist, then changes in aggregate wages will be correlated with unexpected changes in marginal utility and the estimates from this alternative approach will be biased. One could imagine that these types of systematic errors could occur at the beginning of a deep recession when individuals may under predict the amount of a decrease in wages that will persist into the future, not realizing the severity of the impending recession and instead thinking that these changes will reverse themselves in the near future. Although this potential endogeneity could also help explain

[43] Although the F-statistic using my specification is large enough to reject the null hypothesis that the instruments are not correlated with the endogenous regressor, it is still small enough to elicit concern of bias due to weak instruments. Thus, section 5.3 explore the direction and size of the potential bias from weak instruments in my specification.

[44] See Chernozhukov and Hansen (2005) for a discussion.

the smaller estimates of the macro Frisch using the alternative specification, it is important to note that my specification could also be affected by endogeneity. My estimation strategy implies that the Frisch elasticity is being determined from the cohort's wage variation over the life cycle that can be predicted by changes in age and education. Thus, if the errors in predicting this wage growth are systematically biased in one direction, then my estimates of the Frisch elasticity would be affected by endogeneity bias. Taken as a whole, the results from my paper and Fiorito and Zanella (2012) demonstrate that whether estimates of the macro Frisch elasticity are as large as the calibration values is sensitive to which variation in wages is used for identification.

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

| **Variables (s.e.)** | **Benchmark I** | **No Panel & Alt. Inst. II** |
|---|---|---|
| ΔW | 3.1 | 0.42 |
| | (0.68) | (0.26) |
| Δkids | -0.28 | |
| | (0.11) | |
| Δkidsunder6 | -0.21 | |
| | (0.14) | |
| Δbigcity | 1.09 | |
| | (0.51) | |
| Observations | 1,288 | 18 |
| Yr. Dummies | Yes | No |
| Years | 68-97 | 68-91 |
| Ages | 20-65 | 20-65 |
| Instruments | Age & Educ | Lag Wage |
| Type of Data | Pseudo Panel | Time Series |
| **1st Stage** | | |
| F-stat (Excl. Inst.) | 3.6 | 1.5 |
| F-stat (P-value) | 0 | 0.15 |
| Hansen J-Stat | 6.38 | 4.5 |
| J-Stat (P-value) | 0.38 | 0.21 |

**Notes:** Column I is the benchmark estimates of the macro Frisch elasticity from this paper. Column II is an estimate of the macro Frisch elasticity consistent with the methodology in Fiorito and Zanella (2012). In particular these estimates are determined using the alternative instruments from Fiorito and Zanella (2012) and using an aggregate time series as opposed to a pseudo panel. Consistent with previous studies, the standard errors are clustered on cohort.

## 5.2 Comparison with the Estimation Strategy in Chetty et al. (2012)

Chetty et al. (2012) also examine whether calibration values are consistent with micro evidence on the response of hours to changes in wages. The study uses a meta-analysis approach that relies on estimates of the macro Frisch elasticity from previous studies. In particular, they examine separate studies that estimate the elasticity on the intensive margin and other studies that determine the elasticity on the extensive margin. They determine that the macro Frisch elasticity is .54 and .32 on the intensive and extensive margins, respectively. Thus the total Frisch elasticity in their study of 0.86 is far below the estimates in this paper.

The smaller estimate of the macro Frisch elasticity in Chetty et al. (2012) is driven by smaller estimates of the elasticity on both the intensive and extensive margins. On the intensive margin, the authors estimates that the Frisch elasticity is .54 lower than the range of .91-.93 found in my study. The lower estimate of the intensive margin Frisch elasticity come from the estimates in Pistaferri (2003) and Bianchi et al. (2001) which tend to focus on different populations than my study.[45] In particular, these two studies examine Italy and Iceland, respectively. It is possible that differences in labor market structures or cultural norms could lead these foreign countries to have different labor market elasticities than the United States.

Turning to the estimates of the Frisch elasticity on the extensive margin in Chetty et al. (2012), the authors use six studies to inform their estimate. There are numerous differences between these studies and the estimates in my study that could potentially lead to different estimates. These differences can be classified into three general categories. First, all of these other studies estimate the participation rate elasticity as opposed to the Frisch elasticity. Second, many of these other studies tend to examine different populations than the whole U.S. labor force. Third, these estimates tend to

[45]The estimate from Bianchi et al. (2001) is further manipulated in Chetty (2012) in order to derive an intensive margin Frisch elasticity.

be derived from different types of wage and hours fluctuations.

Chetty et al. (2012) focus on estimates of the participation rate elasticity in order to determine the Frisch elasticity on the extensive margin, which does not need to provide the same the contribution to the aggregate Frisch elasticity as the contribution from variations on the extensive margin. For illustrative purposes, 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 $n$. For the moment assume all the individuals in the third group would not have worked if the wage did not increase in the second period. 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 can be rewritten as, $\frac{P_n' h_n'}{P_e h_e} + \frac{h_e' - h_e}{h_e}$. The first term of the expression represents the percent change in hours from the new workers (fluctuations on the extensive margin). The second term represents the percent change in hours from the increase in hours worked from individuals who work in both periods (fluctuations on the intensive margin). Since Chetty et al. (2012) use the participation rate elasticity as the contribution of new workers to the aggregate Frisch elasticity, they implicitly calculate the percent change in hours from the extensive margin 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 ($h_e = h_n'$). This estimate of the contribution from the extensive margin can be biased if these new workers tend to work a different number of hours than other workers. In particular, if new workers who enter because of an increase in wages tend to work more hours, then the estimates could be biased downwards. In contrast, if these workers tend to work less hours, then the estimate of the contribution will be biased upwards.[46]

The second main difference between the studies surveyed in Chetty et al. (2012) and my study is that the other studies tend to focus on different populations. In particular, many of the studies focus on workers in countries other than the United States. Again, it is possible that differences in cultural norms and labor market institutions could lead to different elasticities across countries. The other studies that do focus on the United States tend to focus on only a subset of population that typically have lower incomes (for example, public school teachers in California or laborers in Alaska). It is possible that these subsets of the population with lower incomes could be less responsive on the extensive margin to fluctuations in wages, as liquidity constraints could mean that these individuals have less ability to intertemporally smooth their consumption.

The third main difference between the studies that Chetty et al. (2012) rely on to determine the extensive margin Frisch elasticity and my study is that they tend to use different variation in wages. For reasons discussed in section 5.1, when estimating the macro Frisch elasticity it is important to control for changes in marginal utility. The six studies that contribute to the estimate in Chetty et al. (2012) come from estimates of the participation rate elasticity from two general sources of wage variation. First, two of the studies examine changes in aggregate hours over time after a change in taxes (Bianchi et al. (2001)) or wages (Carrington (1996)). In order for this variation to be exogenous to changes in marginal utility, the individuals need to predict how these changes will affect their net wage rate in the future. It seems plausible that individuals did not fully understand how these shocks would affect their wages immediately, implying that this variation is not exogenous.[47] The remaining four studies rely

[46]Determining the direction of the bias is not possible in the PSID because it is unclear which workers who begin working in a given period are choosing to work because of an increase in wages and which are choosing to start working for other factors.

[47]This concern seems particularly relevant for Carrington (1996) which uses changes in wages in Alaska during a boom in oil production. Although the boom may constitute an exogenous labor

on kinks or discontinuities in wages over the life cycle due to retirement or welfare programs. These changes in implicit wages may not be exogenous in the case of the studies that rely on variation in welfare programs, since these individuals may not be able to smooth their consumption due to liquidity constraints. Moreover, since some of the studies rely on kinks in retirement programs for lower earning populations, liquidity constraints could also cause this wage variation to be correlated with changes in marginal utility.

## 5.3 The Effect of Weak Instruments

In this section I explore the potential bias in the estimates of the macro Frisch elasticity from weak instruments. In particular, generally the F-statistics for the excluded instruments in the macro Frisch estimates are smaller than the rule of thumb minimum value of 10 (see Table 3). Thus, I begin by examining whether the low F-statistic is because all of the instruments are weak or due to a subset of the instruments being weak. In particular, I re-estimate the macro Frisch elasticity with each of the instruments individually and find that approximately half the instruments produce F-statistics that are close to or above the rule of thumb minimum when considered on their own.[48] I find that the interaction of age and education squared is the strongest instrument on its own. The first column of Table 7 presents my benchmark estimate of the macro Frisch elasticity and the second column presents the estimate when the only instrument used is this strongest instrument, the interaction of age and education squared. I find that using just the strongest instrument causes the F-statistic for the excluded instrument to increase to approximately 13. Moreover, I find that the point estimate of the macro Frisch elasticity increases a bit. Thus this estimate continues to support the conclusion that relaxing the two restrictions can cause a large enough increase in the estimates of the Frisch elasticity to explain the gap.

demand shock, it seems plausible that individuals did not fully understand the size of the demand shock implying that there were unexpected changes to marginal utility over time.

[48]These estimates are not reported in the paper but are available upon request.

Table 7: **Macro Estimate With Selected Instrument**

| **Variables (s.e.)** | **Benchmark I** | **One Instrument II** |
|---|---|---|
| ΔW | 3.10 | 3.66 |
| | (1.02) | (1.50) |
| Δkids | -0.28 | -0.34 |
| | (0.15) | (0.20) |
| Δkidsunder6 | -0.21 | -0.27 |
| | (0.18) | (0.24) |
| Δbigcity | 1.09 | 1.26 |
| | (0.72) | (0.88) |
| Observations | 1,288 | 1,288 |
| Annual Dummies | Yes | Yes |
| Years | 68-97 | 68-97 |
| **1st Stage** | | |
| F-stat (Excl. Inst.) | 3.60 | 12.98 |
| F-stat (P-value) | 0.0 | 0.0 |

**Notes:** The estimates of the macro Frisch elasticity are from a pseudo panel which includes all individuals. Column I is the benchmark estimate of the macro Frisch elasticity and uses all of the potential instruments. Column II only uses the strongest instrument. The F-stat for excluded instruments is for the 1st stage regression of changes in wages on the excluded instruments and the controls. Consistent with previous studies, the standard errors are clustered on cohort.

To further examine the possible bias from weak instruments, I construct a confidence interval that is robust to weak instruments, heteroskedasticity, and autocorrelation using the procedure in Chernozhukov and Hansen (2008). In particular, the procedure transforms the data in order to utilize OLS so that the estimates are no longer subject to weak instrument bias. I find that this robust confidence interval spans 2.32 to 7.89. Even the lower bound of this interval is still large enough to be in the range of values used calibration macroeconomic models.[49]

## 5.4 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 8 and table 9 provide the estimates of the macro and micro Frisch elasticity for different age ranges, respectively.[50]

Focusing on table 8, 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.[51] 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 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 sizes of the changes in the hours and wage profiles are much

[49] Doing a similar exercise using the specification from Fiorito and Zanella (2012) (lagged wages in a time series) was not feasible since no single instrument was strong enough to estimate meaningful confidence intervals.

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

[51] I choose to re-estimate both the first and second stage of the regressions with the smaller sample. I limit the sample for both stages in order to determine whether an estimate of the Frisch elasticity for a representative agent or cohort from these age ranges is consistent with the macroeconomic calibration values.

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.

Table 8: **Macro Estimate by Age**

| **Variables** | **Age Range** | | | | |
|---|---|---|---|---|---|
| | **20-65** | **20-60** | **20-55** | **20-50** | **20-45** |
| **(s.e.)** | **I** | **II** | **III** | **IV** | **V** |
| ΔW | 2.88 | 1.75 | 1.5 | 0.81 | 0.51 |
| | (0.67) | (0.35) | (0.360) | (0.25) | (0.17) |
| Δkids | -0.28 | -0.11 | -0.1 | -0.03 | -0.04 |
| | (0.11) | (0.05) | (0.05) | (0.03) | (0.03) |
| Δkidsunder6 | -0.15 | -0.04 | -0.01 | 0.09 | 0.16 |
| | (0.12) | (0.08) | (0.07) | (0.05) | (0.05) |
| Δbigcity | 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 of the macro Frisch elasticity are from a pseudo panel which includes all individuals. The F-stat for excluded instruments is for the 1st stage regression of changes in wages on the excluded instruments and the controls. Consistent with previous studies, the standard errors are clustered on cohort.

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.[52] 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.[53] Further supporting this alternative interpretation, Gomme et al. (2005) find that the relative magnitude of hours fluctuations over the business cycle for older individuals compared to prime-age individuals is not large enough to support this much variation in the Frisch elasticity over the lifetime.

Table 9 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.[54]

## 5.5 Implications for Calibration

Taken as a whole, these results have two implications for calibration exercises. First, given the sensitivity of the results to the specification and ages included, there is notable uncertainty with regard to the value of the macro Frisch elasticity. Therefore, it is important for macroeconomists to check the sensitivity of their results with

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

[53] 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.

[54] 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 9: **Micro Estimate by Age**

| | **Age Range** | | | |
|---|---|---|---|---|
| **Variables** | **26-60** | **26-55** | **26-50** | **26-45** |
| **(s.e.)** | **I** | **II** | **III** | **IV** |
| ΔW | 0.22 | 0.17 | 0.07 | 0.05 |
| | (0.09) | (0.11) | (0.12) | (0.12) |
| Δkids | -0.01 | 0 | 0 | 0 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Δkidsunder6 | 0.01 | 0.01 | 0 | 0 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Δbigcity | 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 of the micro Frisch elasticity 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 1st stage regression of changes in wages on the excluded instruments and the controls. Consistent with previous studies, the standard errors are clustered on cohort.

respect to the calibration value used for the Frisch elasticity.

The second implication of the results in this paper is that it is imperative that the estimated values used for calibration be consistent with the underlying macroeconomic model being used in the analysis. In other words, the results from this paper should not be taken as support to use the larger calibration values irrespective of the question being asked and the model used to answer the question.

In particular, macroeconomic models can be grouped into three different general classes which could have potentially different calibration values based on the results in this study. First is the set of models that explicitly include decisions on the intensive and extensive margin. This type of model may be ideal if an economist was determining the effects of unemployment insurance during a recession. In this class of models there tends to be a parameter value that directly controls the Frisch elasticity on the intensive margin. This value should be calibrated roughly in the range of .2 to .9. The value should tend to be on the lower end of the range if the model is focused on matching fluctuations of individuals who are the heads of the household, while it should be on the upper end of the range if the model is focused on the whole population. Moreover, in this type of model, it is important to confirm that the variation in hours from fluctuations on the extensive margin match the variation in the data.[55]

The second class of models does not include an explicit decision on the extensive margin and fluctuations on this margin are not of interest for the question being examined. For example, if an economist is evaluating a government program that only applies to working individuals and does not affect marginal workers, it may not be of interest to include these fluctuations on the extensive margin. This type of model may be ideal to examine the implications of changes in the progressivity of the labor tax schedule over certain parts of the income distribution. Once again,

[55]These fluctuations on the extensive margin are usually not highly sensitive to the parameter that controls the Frisch elasticity on the intensive margin. See Keane and Rogerson (2011) for a discussion of the various modelling techniques.

calibration values for this type of model should be set in the range of 0.2 to 0.9 depending on what is the population of interest. However, it is important to note that by excluding fluctuations on the extensive margin, this type of model will under predict the aggregate fluctuations in hours over the business cycle.

The third type of model does not include an explicit decision on the extensive margin but those fluctuations are important for the question being examined. Most often this type of parsimonious model is being used for tractability purposes. The calibration value for this type of model should be set between 1.8 and 3.0. If the model is only focused on agents who are not close to retirement age, then a value on the lower end of the range should be used. In contrast, if retirement fluctuations on the extensive margin are of importance, then a value on the upper end of the range is more suitable.

## 5.6 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.[56] 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.[57] Selected results from these regressions

[56] 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.

[57] See section 3 of Fiorito and Zanella (2012) and Wooldridge (1995) for more details on the

are in table 10. Fiorito and Zanella (2012) note that Blundell et al. (2003) show 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 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

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.

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 Elasticity**

| **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 1st stage regression of changes in wages on the excluded instruments and the controls. Consistent with previous studies, the standard errors are clustered on cohort.

# 6 Conclusion

This paper evaluates whether relaxing two restrictions causes an increase in the estimates of the Frisch elasticity large enough to be consistent with 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-age, 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 does not cause a large enough increase in the estimates to 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.

These results are in contrast to Fiorito and Zanella (2012), which account for both differences but estimate a much lower macro Frisch elasticity of 0.68. 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 in a time-series data set. 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 in a panel data set, which implies that I identify the Frisch elasticity from predicted variation in wages over the life cycle. I find that the F-statistic for the instruments in the first stage of the regression is very smaller when I use the instruments from Fiorito and Zanella (2012). The low F-statistic using these alternative instruments could indicate that the instruments from Fiorito and Zanella (2012) are weak. Since weak instrument bias would tend to cause a smaller estimate of the Frisch elasticity, this potential bias could explain why the estimates of the macro Frisch elasticity in Fiorito and Zanella (2012) are smaller than my benchmark estimates. Overall, these results indicate that estimates of the macro Frisch elasticity are sensitive to the variation in wages used to identify the Frisch elasticity.

In addition to being sensitive to the estimation strategy, I also find that the estimates of the macro Frisch are 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. Given the general sensitivity of the estimates of the macro Frisch elasticity to the specification, it is important to test the robustness of the results from a macroeconomic model with respect to the calibration value of the Frisch elasticity.

A common practice in macroeconomics is to use a calibrated parsimonious model. Despite the large estimates of the macro Frisch elasticity in this paper, a large parameter value should not be used in all models. In particular, 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 the economist includes in the model. For example, if a macroeconomist is using a model that does not include retirement, and it is important that the fluctuations in hours and wages over the business cycle are consistent with the data for the specific question being examined, then the calibration value will need to be in line with the large macro Frisch elasticity estimates in this paper. However, if an economist is asking a question that centers on changes in hours on the intensive margin and retirement decisions are not relevant, then it may be optimal to use a lower calibration value for the Frisch elasticity in line with the estimates of the micro Frisch elasticity. Overall, the large range of estimates of the 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.

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