# The Labor Supply of Elderly Mexican Women

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Abstract

This paper estimates the labor supply response to an increase in the marginal wage rate among middle-aged to elderly Mexican women. Using data from the National Survey of Occupation and Employment, I find that an increase in the marginal wage rate is associated with an increase in worked hours. The results suggest that the marginal wage rate elasticities are greater for older women than for their younger counterparts.

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## 1 Introduction

The purpose of this study is to estimate the labor supply response among Mexican middle-aged to elderly women to changes in the marginal wage rate. This is of particular interest in the context of an ageing population, lower fertility rates, and increased life expectancy. In Mexico, the share of women aged 50–70 increased from 13% in 2010 to approximately 17% in 2018. This increasing trend is expected to continue in coming years, and the share of women in this age group is expected to be close to 24% t by 2050 (CONAPO, 2017). Furthermore, the population aged ≥65 represented 7.2% of the total population in 2018 and is predicted to increase up to 10.3% by 2030 and to 16.8% by 2050 (CONAPO, 2017).

Some stylized facts are of importance when analyzing the labor supply of Mexican women. First, like in other Latin American countries, there has been an increase in female labor force participation in Mexico since the late 1960s, where a relevant factor is a strong negative correlation between fertility rates and labor force participation (Gasparini and Marchionni 2015). The birth rate in Mexico decreased from 20.2 births per thousand people (btp) in 2010 to 17.1btp in 2017, while women's participation in the labor force increased from 55% to 61% in the same period. The decline in btp is expected to continue and to fall to 11.3btp by 2050[2]. However, despite increased labor force participation, there has been virtually no changes to weekly hours worked; Mexican women between 50 and 70 years old have worked approximately 21 hours per week on average between 2004 and 2017.[3] In 2017, female life expectancy in Mexico was 75 years and is expected to increase to 83 years by 2050 (CONAPO, 2017).

These facts are likely to restrain social security spending in the future, since a larger share of elderly persons will require increased expenditures on pension benefits or transfers from the government to those who are not eligible for a pension. For example, in 2017, pension expenditure represented 3.12% of Mexico's GDP and if the current pension system prevails, pension expenditure is expected to increase to 5.2% of the GDP by 2030 (Villareal and Macias,

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[2] https://www.macrotrends.net/countries/MEX/mexico/birth-rate

[3] This average reflects both labor force participants and non-participants. When only participants are considered, the average number of weekly hours worked is approximately 36.

2020). Vogel et al. (2017) suggest that labor market policies that focus on the extensive margin by increasing the retirement age imply strong welfare gains for all future generations.

In this paper, I analyze how middle-aged to elderly women change their participation in the workforce in response to an increase in the marginal (net-of-tax) wage rate. It is important to understand how the labor supply of women at older ages reacts to economic incentives that could eventually make them increase the time they spend in the labor market after they are eligible for retirement. If women have incentives to join or remain in the labor force, and if those who are already working would work more hours later in life, tax collection could increase and thus alleviate some of the restraints on social security. In the data used below, approximately 39% of women aged 50–70 do not participate in the labor market, suggesting a substantial labor supply reserve.

While a large number of studies have examined the labor supply behavior of males (Pencavel 2002, Devereux 2004) and women (Eissa and Hoynes 2004, Bargain 2005, Blau and Kahn 2007), these studies mostly focus on the prime-age to pre-retirement age population in the US (Blau and Kahn 2007) and in Europe (Blomquist 1996, van Soest et al. 2002).[4] Attanasio et al. (2018) studied the labor supply of women aged 25 to 60 in the US and showed that there is substantial heterogeneity in their labor supply elasticities. The study also shows that the response to wage changes declines with age, and that women with the lowest wage levels have larger wage elasticities.

To my knowledge, there are only a few studies addressing the labor supply behavior of women in Mexico. Gómez and Campos-Vázquez (2010) estimated the wage elasticity of the labor supply of married women who are between 25 and 55 years old using 1990 and 2000 census data and found that women with children <5 years of age are less attached to the labor force than the average married woman. They also found that the labor supply elasticity ranged from 1.52–3.32 in 1990 and from 0.65–1.18 in 2000. The least amount of elasticity in 1990 was reported for women in the 45–54-year-old group, while in 2000, the elasticity for this group was the greatest. These elasticities are large when compared to corresponding elasticities for women aged 20–60 in the US. For example, Kuma and Liang (2005) show that for the year 1990, the elasticity was no larger than 0.6, while in 2000 they estimated an elasticity below 0.2.

Some studies focus on the labor supply of elderly Mexicans, although they do so without reporting or addressing the relationship between labor supply and wages. Juárez (2010) focuses on a so-called 'nutrition transfer' for individuals aged ≥70 years and finds that the transfer reduces the labor force participation of single men aged ≥70 by 46%. For women, the point estimate is negative, but not statistically significant. Avila-Parra and Escamilla-Guerrero (2017) found that expanding the pension program did not reduce the labor force participation of Mexican adults between 66 and 69 years of age.

The contribution of this paper is an estimation of labor supply elasticity with respect to the marginal wage rate for Mexican women aged 50–70, as well as examine how this elasticity varies between age-groups in this interval. To this end, I use the ENOE surveys from 2005 to 2017. First, I follow a two-step methodology (Blundell and MaCurdy 1999) to control for selection bias, and afterwards I use an instrumental variable tobit model to estimate the labor

[4]A common finding is that the wage elasticity of labor supply for women is larger than the corresponding elasticity for men, and that the latter is similar across countries (Evers et al. 2008). For extensive reviews of the literature, see Pencavel (1986), Blundell and MaCurdy (1999), and Evers et al. (2008).

supply of the whole sample of women and of women that participate in the labor force, respectively. The results suggest that cohorts of older women have larger marginal wage rate elasticities than cohorts of younger women. The reported marginal wage rate elasticities for women who participate in the labor force range from 0.02–0.10. The elasticities estimated for the entire sample range from 0.29–0.66. I also estimate a labor supply model that controls for random effects. The model is estimated for women participating in the labor force; the qualitative results do not differ from the results of the instrumental variable model tobit model. In this case, the elasticities are smaller and range from 0.01–0.08. The results are in line with studies for developed countries that find that older individuals have larger elasticities than their younger counterparts (Mroz 1987; French 2005; Keane and Rogerson 2015; Attanasio et al. 2018).

The rest of the paper is structured as follows. Section 2 discusses the data and section 3 outlines the empirical model. The results are presented in section 4. Finally, conclusions are drawn in section 5.

## 2 Data

The data were obtained from the National Occupation and Employment Survey (Encuesta Nacional de Ocupación y Empleo or ENOE). The ENOE has been collected quarterly since 2005 by the National Institute of Geographic Statistics and Information and is the consolidation and fusion of the National Urban Employment Survey and the National Employment Survey. As a result, the ENOE includes urban and rural observations. The ENOE sample includes 120,260 households. The survey contains demographic information for individuals aged ≥12 years, as well as detailed information on employment and unemployment status.

The design of the ENOE includes a five-quarter rotating panel of households. Each household is interviewed every 3 months for a period of 15 months, so there are 5 observations for each household (and consequently for all the individuals in said household). The design is such that in any given cross section of the ENOE, 20% of the households are in their first interview, 20% are in their second interview, etc. I use data for women aged 50–70 years old from the first quarter of 2005 to the last quarter of 2017.[5]

Although the ENOE reports variables that are relevant to the study of labor supply, it does not collect information about non-labor income. Non-labor income may affect the number of hours a person works, since increased non-labor income means that an individual can afford to work fewer hours. To control for (at least some of) the effects of non-labor income, I include women's marital status and the number of children. These variables can act as proxies of non-labor income, since Mexican women are likely to receive financial support from their children and husband in the form of money transfers (Gomes, 2007).[6]

In this paper, I study both participants and non-participants in the labor market. Furthermore, I exclude women working in the agricultural sector, women who are self-employed, women who work in the informal sector, and women who have two jobs.[7] These groups are excluded

[5]This was the last quarter available for the data at the time of completing this study.

[6] I also estimated a specification of the labor supply for those aged 65–70 that includes a dummy variable indicating whether the individual is receiving pension-based income. I chose this age group since the retirement age is 65. The wage elasticities of the labor supply derived from this estimation were similar to those shown in Table 6 in section 4.3.

[7] From the ENOE total sample, approximately 34.5% of women work in the informal sector, 6.8% are self-employed, and 2.7% work in the agriculture sector. I do not address non-participants who work in the informal sector. One way to deal with the complications of work in the informal sector would be to consider that the individual has three choices when deciding to participate in the labor market: she can decide to participate in the formal sector, the informal sector, or not to participate

to avoid difficulties relating to measuring their hours and earnings, not to mention that people working in the informal sector do not pay taxes. The final sample is an unbalanced panel with 125,985 distinct women, where each woman is observed in different quarters within a year.[8] Women are observed on average 2.7 times, which gives a total of 242,066 observations in the sample. Among these, 136,533 participated in the labor force while 105,533 did not. Only a total of 37,310 women are observed over five quarters.

Table 1 shows the mean values and standard deviations of the variables used in this study. We observe that participants on average work 37 hours per week. The wages are presented in real terms, and we observe that the hourly gross wage rate is approximately MXN48 (USD2.37), while the hourly marginal wage rate net-of-tax is approximately MXN41 (USD2.02).[9] The marginal tax rate is on average 11%, but is smaller for older women who, on average, earn less. For example, the hourly gross wage rate for women aged 50–55 years is on average MXN49 (USD2.42), while for women aged 66–70 years, hourly gross wage averages MXN39 (USD1.91). The average hourly marginal wage rate is also lower for older women; it is 34MXN (1.68USD) for the oldest cohort, while it is approximately 42MXN (2.07USD) for the youngest. The data suggests, on average, older women work fewer hours and earn less, although differences between groups are not large. For example, if the youngest group is compared to the oldest group, the difference in working hours is approximately 5 hours per week, while the difference in the hourly marginal wage rate is approximately 8MXN (0.39USD).[10]

Compared to non-participants, those who participate in the labor force average more years in education, fewer children, and a smaller percentage of them are married. For example, when looking at the 50–70 group, participants have on average 3 more years of education and 2 fewer children than non-participants. Finally, in this same age group, the share of married women is approximately 70% for participants and 86% for non-participants.

Among those who participate, the share of married women as well as the hourly wage rates are smaller for the older cohorts.

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at all (Pradhan and van Soest, 1995). I exclude women in the agricultural sector, since their incentives to work may differ from those characterizing other sectors. For example, the ENOE shows that most households that depend on the agricultural sector own the land they farm and use it to procure their own food and to sell their harvest. Furthermore, the decision to work and the hours of work are dependent on the seasons; for example, more hours of work and more participation might be needed when preparing the land and during harvest, while less work might be needed in between these periods.

[8] The number of women is larger than the number of households because there are households with more than one generation of women. For example, take a grandmother, daughter, and granddaughter living in the same household.

[9] In the dataset we don't see the hourly wage. Instead, we see monthly earnings (E) and monthly worked hours ($h$). Both are measured with error. Suppose the true values for a person are ($E, h$), and the observed values are:

$$E^0 = E + e_1$$

$$h^0 = h + e_2$$

The hourly wage 'wage' is constructed as $w^0 = E^0/h^0$. Note that when $e_2$ is positive, hours of work are overestimated, and the observed wage is lower. Likewise, when $e_2$ is negative, observed hours are lower than they were, and the wage is higher. This is called the problem of 'division bias': there is negative correlation between hours and the hourly wage caused by measurement error in hours (Borjas, 1980). I do not test for division bias, since I do not find a negative correlation between hours of work and the marginal wage rate, but I encourage future research to consider this issue in more detail.

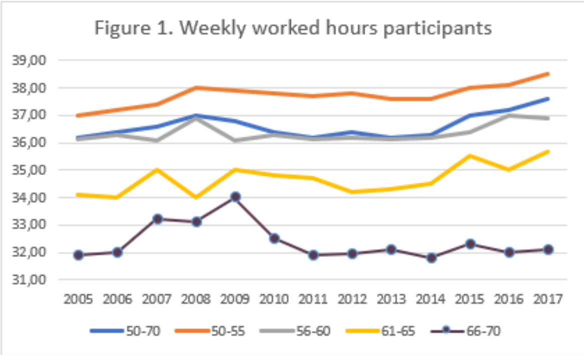
The marginal wage rate is defined as the gross wage rate times one minus the marginal tax rate. 'MXN' stands for Mexican Pesos; the average exchange rate in July 2018 was MXN20.22 per 1USD. The 2018 minimum wage in Mexico was MXN88.36 (USD4.36) per day. The wages are presented in 2018 CPI adjusted MXN (Mexican Pesos). Source: www.banxico.org.mx

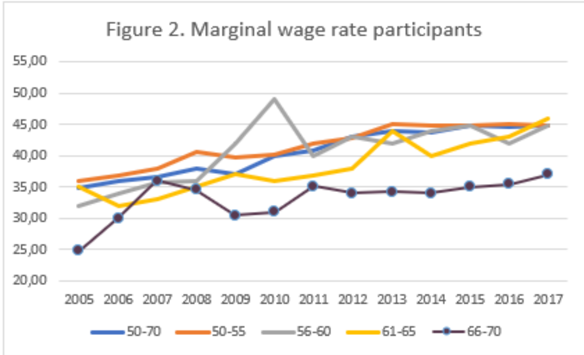
[10] The data is used later to impute wages according to the methodology section, the description of the summary statistics of the imputed hourly wages are presented in the appendix.

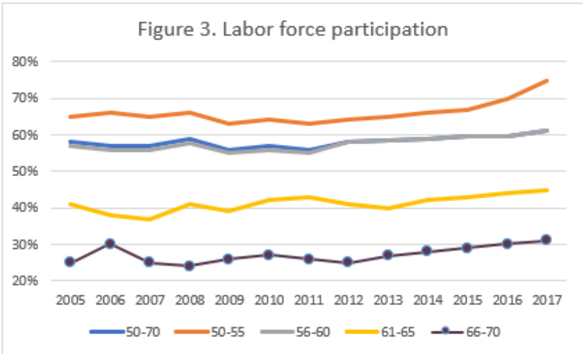
**Table 1: Summary Statistics.**

| Age Group | 50–70 | 50–55 | 56–60 | 61–65 | 66–70 |
|---|---|---|---|---|---|
| **Participants** | | | | | |
| Weekly Worked Hours | 36.82 | 37.62 | 36.62 | 34.73 | 32.47 |
| | (14.35) | (13.81) | (14.56) | (15.39) | (16.13) |
| Hourly Gross Wage Rate (w) | 48.27 | 49.73 | 47.55 | 45.97 | 38.79 |
| | (78.03) | (66.73) | (97.13) | (88.85) | (55.15) |
| Hourly Marginal Wage Rate ($w^n$) | 40.78 | 41.88 | 40.24 | 38.94 | 33.73 |
| | (54.61) | (47.45) | (66.81) | (61.98) | (40.08) |
| Marginal Tax Rate | 11.37% | 11.71% | 11.06% | 10.83% | 10.23% |
| Age | 55.56 | 52.41 | 57.68 | 62.60 | 67.56 |
| | (4.57) | (1.61) | (1.39) | (1.39) | (1.41) |
| Education years | 9.41 | 10.12 | 8.91 | 7.88 | 6.45 |
| | (5.12) | (4.91) | (5.11) | (5.29) | (5.12) |
| Number of Children | 2.88 | 2.71 | 3.01 | 3.21 | 3.50 |
| | (2.13) | (1.85) | (2.23) | (2.65) | (3.16) |
| Married | 69.81% | 71.91% | 69.04% | 64.98% | 58.01% |
| Observations | 136,533 | 79,757 | 35,485 | 15,471 | 5,820 |
| **Non-Participants** | | | | | |
| Age | 55.23 | 52.59 | 57.88 | 62.89 | 67.81 |
| | (5.66) | (1.62) | (1.42) | (1.43) | (1.42) |
| Education years | 6.05 | 7.18 | 6.12 | 5.07 | 4.21 |
| | (4.49) | (4.55) | (4.43) | (4.20) | (3.91) |
| Number of Children | 4.41 | 3.78 | 4.34 | 4.94 | 5.54 |
| | (2.99) | (2.46) | (2.86) | (3.27) | (3.64) |
| Married | 86.12% | 86.93% | 86.82% | 85.49% | 83.47% |
| Observations | **105,533** | **40,929** | **28,096** | **21,374** | **15,134** |

Standard deviations in parenthesis. The wages are presented in 2018 CPI adjusted MXN (Mexican Pesos). An observation is defined as a woman in a particular quarter at a particular year, and each woman is observed on average 2 times in the data set. There is a total of 242, 066 observations. The observations correspond to 125,985 women. Of the total number of observations, 25.22% are observed once, 23.42% twice, 19.06% three times, 17.36% four times, and 15.09% five times.




Figures 1 and 2 show the weekly worked hours and marginal wage rates for participants. We can see that hours worked per week were relatively steady until 2014 for the age groups 50–55 and 56–60, as well for the 50–70 cohort; after this period, they were characterized by a slightly increasing trend. This may have been a result of small increases in the real minimum wage. The peak in the weekly marginal wage rate in 2010 for women aged 56–60 is explained by women with large earnings entering the survey in that year.

Figure 3 shows the share of women participating in the labor force from 2005–2017 divided into five age groups. For the first three groups (blue, gray, and orange lines) there was an increase in participation between 2013–2017 of approximately 6%, while for the two oldest cohorts (yellow and dark blue lines) the increase was approximately 4% and 7%, respectively. The increase in participation in recent years has been larger than the increase in weekly worked hours for those who participate. For example, in the period between 2013 and 2017, weekly worked hours increased by approximately 2.4%, 2.3%, and 0.16% for women aged 50–70, 56–60 and 66–70, respectively. As in other Latin American countries, more women have joined the labor force in recent years, but at the same time, weekly worked hours have only increased modestly (Gasparini and Marchionni, 2015). The weekly worked hours have increased at most 2 hours since 2005 in most of the cohorts, even when the real minimum wage has increased and after reforms were made to the tax system.

The income tax schedule had two major reforms during this period, in 2008 and again in 2014 (see Table 2). The first reform added three new brackets at the top of the income range while simultaneously reducing the taxable income range for the remaining brackets. For example, in 2007, the tax rate for those with a monthly labor income higher than MXN8601.5 (USD425.4) was 28%, while in 2008 it changed to 17.92%. The 2014 reform increased the top tax rate by creating 3 new brackets with a tax rate of 32%, 34%, and 35% for those earning more than MXN363.38 (USD17.97), MXN484.51 (USD23.96), and MXN1453.5 (USD71.88), respectively.[11]

[11] Taxation is defined in terms of yearly income; the monthly schedules of the Mexican tax code are calculated by dividing the yearly income by 12. For example, according to the tax code, an individual with yearly earnings of 120,000 MXN has a monthly income of 10,000 MXN and is assigned a 30% income tax.

| Table 2. The Income Tax Schedule in Mexico 2005-2017*. | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Monthly Earnings MXN lower limit | upper limit | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
| 0.01 | 496,07 | 3.0% | 3.0% | 3.0% | 1.9% | 1.9% | 1.9% | 1.9% | 1.9% | 1.9% | 1.9% | 1.9% | 1.9% | 1.9% |
| 496,08 | 4,206,41 | 10.0% | 10.0% | 10.0% | 6.4% | 6.4% | 6.4% | 644% | 6.4% | 6.4% | 6.4% | 6.4% | 6.4% | 6.4% |
| 4,206,42 | 7 399,42 | 17.0% | 17.0% | 17.0% | 10.9% | 10.9% | 10.9% | 10.9% | 10.9% | 10.9% | 10.9% | 10.9% | 10.9% | 10.9% |
| 7,399,43 | 8,601,5 | 25.0% | 25.0% | 25.0% | 16.0% | 16.0% | 16.0% | 16.0% | 16.0% | 16.0% | 16.0% | 16.0% | 16.0% | 16.0% |
| 8,601,51 | 10,298,35 | 30.0% | 29.0% | 28.0% | 17.9% | 17.9% | 17.9% | 17.9% | 17.9% | 17.9% | 17.9% | 17.9% | 17.9% | 17.9% |
| 10,298,36 | 20,770,29 | 30.0% | 29.0% | 28.0% | 19.9% | 19.9% | 21.4% | 21.4% | 21.4% | 21.4% | 21.4% | 21.4% | 21.4% | 21.4% |
| 20,770,91 | 32,736,83 | 30.0% | 29.0% | 28.0% | 22.0% | 22.0% | 23.5% | 23.5% | 23.5% | 23.5% | 23.5% | 23.5% | 23.5% | 23.5% |
| 32,736,84 | 62,500 | 30.0% | 29.0% | 28.0% | 28.0% | 28.0% | 30.0% | 30.0% | 30.0% | 30.0% | 30.0% | 30.0% | 30.0% | 30.0% |
| 62,500,01 | 83,333,33 | 30.0% | 29.0% | 28.0% | 28.0% | 28.0% | 30.0% | 30.0% | 30.0% | 30.0% | 32.0% | 32.0% | 32.0% | 32.0% |
| 83,333,34 | 250,000 | 30.0% | 29.0% | 28.0% | 28.0% | 28.0% | 30.0% | 30.0% | 30.0% | 30.0% | 34.0% | 34.0% | 34.0% | 34.0% |
| 250,000,01 | ∞ | 30.0% | 29.0% | 28.0% | 28.0% | 28.0% | 30.0% | 30.0% | 30.0% | 30.0% | 35.0% | 35.0% | 35.0% | 35.0% |

*Mexican income tax code. The official gazette of the Mexican Federation: https://www.dof.gob.mx/nota_detalle.php?codigo=5640505&fecha=12/01/2022. The table shows the marginal tax per year and income bracket.

## 3 Empirical Specification

Identifying the response of the labor supply to wages is not an easy task, since several issues are simultaneously at play. Selection and endogeneity issues, as well as a lack of data are among the obstacles in the empirical identification of the causal links between the female labor supply and its covariates.

The selection issue—which results from the decision of whether to work/participate in the labor market—implies that gross wage rates are unobserved for non-participants. If only the observations that report positive hours of work and positive wages were considered, the labor supply estimation would suffer from selection bias. Women with strong preferences toward work will tend to participate more in the labor market regardless of their own wage. To account for selection in the estimation, I follow a two-step methodology (Blundell and MaCurdy 1999). First, I estimate the participation equation, followed by the estimation of a gross wage equation. In these estimations I consider the panel structure of the data and use a random effects specification for the unobserved components. The labor force participation equation is estimated by a probit model. The estimates of the participation equation are then used to calculate the inverse Mills ratio (imr), which is included as an additional explanatory variable in the log wage estimation.[12]

Following Triest (1990), I exclude education from the labor supply equation, and include it in both the labor force and wage imputation estimations. I do not consider health, non-labor income, or ethnicity (Triest, 1990) in the estimations, because the ENOE does not report these variables. I also exclude higher-order terms for education or age as well as interaction terms between these, because adding them to the estimations produces multicollinearity problems. The variables used in each estimation are presented in more detail in the following paragraphs.

The participation equation includes variables describing women's preferences to participate in the labor force such as her age, education, number of children, and marital status. These variables are chosen because they are identified by economic theory as well as by earlier empirical studies as relevant determinants undergirding a woman's choice to participate in the labor force (Killingsworth and Heckman, 1986), and they are commonly included in the ENOE. The participation equation is as follows:

$$p_{it} = X_{it}\alpha_1 + Yr_t\alpha_2 + Q_t\alpha_3 + v_i + e_{it} \qquad (1)$$

where $p_{it}$ takes the value 1 if individual $i$ participates in the labor force, and takes the value 0 otherwise. The subscript $i$ refers to the individual, and $t$, for simplicity, to the survey's year and quarter. $X_{it}$ is a vector of individual characteristics such as age, education, children, and marital status. Age is defined as the year of the survey minus the year of birth, while the education variable denotes the individual's years of schooling. The variable for children indicates the

[12] The inverse Mill's ratio is obtained from the participation equation (1); it represents the marginal probability of a woman being employed at a specific wage rate, given her individual characteristics and prevailing market conditions. The ratio reflects the idea that women with large negative wage errors are not working, so the expected value of the wage error is no longer zero for some of the women who do work.

number of children that are alive at the time of the survey, and marital status indicates whether the individual is married. *Yr* is a vector of year dummies and *Q* is a vector of quarter dummies which capture time-specific effects and indicates the time when the survey took place. Finally, $v_i$ is the individual-specific random effect and is normally distributed with mean 0 and variance $\sigma^2_v$. The idiosyncratic component is denoted by $e_{it}$ and is independent and identically distributed (iid) with mean 0 and variance 1, independent of $v_i$.[13]

The second step is to estimate a log-gross wage equation for participants which corrects for the selection effect using the results from the estimation of the participation equation. The results from estimating this wage equation are useful for imputing log gross wages to all individuals in the sample, whether or not they are participating. For simplicity's sake, I assume that the log-gross wage equation takes a standard human capital form, where the log gross wage depends on the individual's age and education (Blundell et al. 2001), as well as year and quarter dummies and the inverse mills ratio to control for selection.[14] The log gross wage equation is as follows:

$$logw_{it} = S_{it}\beta_1 + imr_{it}\beta_2 + Yr_t\beta_3 + Q_t\beta_4 + z_i + u_{it} \tag{2}$$

where $w_{it}$ denotes the hourly wage rate for individual *i* in a specific year and quarter, $S_{it}$ is a vector containing the variables age and education, and $imr_{it}$ is the inverse Mills ratio. The equation is estimated as a random-effects specification, as mentioned before, where $z_i$ is the individual-specific random effect and is normally distributed with mean 0 and variance $\sigma^2_z$, $u_{it}$ is the idiosyncratic effect, and is iid with mean 0 and variance 1, independently of $z_i$. The log gross wage equation is estimated for those who work, and log-gross wages are imputed for all individuals in the dataset. The marginal tax rate is identified based on the earnings and the log-marginal wage rate is calculated as follows[15];

$$logw^n_{it} = logw_{it} + \log(1 - \tau_{it}) \tag{3}$$

where $w^n$ is the marginal net wage rate, $log\ w$ is the imputed log gross wage rate, and $\tau$ is the marginal tax rate. The imputed wages are presented and discussed in section 4.

The second issue is the endogeneity of the marginal wage rate. To address this problem and include non-participants, I estimated two regressions using an instrumental variables tobit model[16], according to equation (4) for each age group. The first model uses the log-marginal wage rate if an individual worked the mean weekly hours as the instrument for the log-marginal rate, and the second model uses the log-marginal wage rate if an individual worked 40 hours per week (which corresponds to a full-time working week) as instruments.[17] These instruments are correlated with the marginal wage rate, but are not affected by the

[13] The results for the participation equation are presented in Table A1 in the appendix.

[14] The gross wage equation does not include working experience, since this variable is not reported by the ENOE.

[15] The marginal tax rate for non-participants is estimated considering the weekly ISR table published by the federation. It is assumed that if the non-participating individual were to enter the labor market, she would work 5 days per week and 8 hours per day, which corresponds to a full-time workday. This way, the weekly income is divided by 40 hours to obtain an approximation of the ISR table per hour. With this table, it is possible to assign the marginal tax rate to non-participants. Similar results were obtained when the ISR table per hour was estimated considering a 7-day week, as well as 5-hour workdays.

[16] For a description of the tobit model see Bierens (2004), and for the instrumental variables tobit model, see Newey (1987), Miranda and Rabe-Hesketh (2006), and Finlay and Magnusson (2009).

[17] The gross wage rate is calculated by dividing weekly earnings by the number of weekly worked hours; 40 hours is considered as a full-time working week according to Mexican law, or, alternatively 8 working hours per day.

individual's choice of hours of work.[18] Both models allow for intragroup correlation (Papke and Wooldrige 2008) to account for the panel structure of the data. A semi-log specification that allows for zero hours of work is adopted to estimate the labor supply defined as weekly hours worked $h_i^*$ (Blundell et al. 2001),[19]

$$h_i^* = \begin{cases} h_i \ if h_i \ > 0 \\ 0 \ otherwise \end{cases}, \tag{4}$$

where

$$h_i = C_i\gamma_1 + logw_i^n\gamma_2 + Yr_i\gamma_3 + Q_i\gamma_4 + b_i \tag{5}$$

Here $C_i$ is a vector containing the variables age, children, and marital status and $b_i$ is assumed to be normally distributed with mean 0 and variance.

Even if equation (5) considers the panel structure of the data, it does not estimate a random effects model. Due to the difficulty of estimating a censored model with panel data and endogeneity (Honoré et al., 2004) an alternative is to estimate the parameters of a random effects model using the sub-sample of individuals who report positive hours. In this case, the labor supply equation has the following form,

$$h_{it} = C_{it}\eta + logw_{it}^o\gamma + Yr_i\psi + Q_i\varsigma + imr_{it}\lambda + f_i + g_{it}, \tag{6}$$

The logarithm of the observed marginal wage rate is denoted by $logw_{it}^o$ and is instrumented via the log-marginal wage rate if an individual worked the mean weekly hours, while the components $f_i$ and $g_{it}$ capture random specific and idiosyncratic effects.

[18] To test the exclusion restriction (which states that the instrument should not directly affect the dependent variable) I include one of the two instruments in the main regression (the log-marginal wage rate if an individual worked the mean weekly hours) while using the remaining regression as the instrument (the log-marginal wage rate if an individual worked 40 hours) and vice versa. If the "instrument" (now as a covariate in the labor supply regression) is not statistically significant in the labor supply regression, it supports to some degree the notion that it does not have a direct effect on the hours of work (Bound et al. 1995, Staiger and Stock 1997, Stock and Yogo 2005). The latter must be interpreted with caution since there could be other factors such as measurement error or sample size limitations that prevent detecting a small direct effect. The results of these regressions showed that none of the instruments were statistically significant when added as covariates in the labor supply estimation (i.e., this supports the exclusion of the instruments from the substantive equation), while the estimated effects of the marginal wage rate—the endogenous regressor—were similar to those presented below (i.e., this suggests that there is little evidence of overidentification).

[19] In this case an observation "i" is an individual in a particular year and quarter; i.e., the same individual can be present in the data more than one time. The standard errors are clustered by the individual's identification number to allow for intragroup correlation.

# 4 Results

## 4.1 Imputed wages

Table 3 shows the mean of the imputed log gross wages obtained from equation (2) as well as the log marginal wage rates calculated for participants and the whole sample, respectively. (See the Appendix for the results of the estimation of equation (2)). Table 3 shows that both log gross and log marginal wage rates are larger for younger cohorts. The imputed log gross wages for women that participate in the labor force are on average 1.9% larger than their observed log gross wages. The Table also shows that log-imputed wages for participants are approximately 6% larger than those for non-participant women.[20]

**Table 3. Summary Statistics: mean imputed gross and marginal wage rates.**

| Age Group | 50–70 | 50–55 | 56–60 | 61–65 | 66–70 |
|---|---|---|---|---|---|
| **All women** | | | | | |
| Imputed log w | 3.86 | 3.91 | 3.84 | 3.78 | 3.61 |
| | (3.25) | (3.28) | (3.27) | (3.20) | (2.97) |
| Imputed log $w^n$ | 3.49 | 3.54 | 3.47 | 3.41 | 3.23 |
| | (2.86) | (2.89) | (2.88) | (2.81) | (2.7) |
| Marginal tax rate | 27.67% | 29.85% | 28.39% | 27.57% | 28.15% |
| Observations | 242,066 | 120,686 | 63,581 | 36,845 | 20,954 |
| **Participants** | | | | | |
| Observed log w | 3.78 | 3.81 | 3.76 | 3.73 | 3.56 |
| | (4.13) | (3.97) | (4.35) | (4.26) | (3.78) |
| Observed log $w^n$ | 3.62 | 3.65 | 3.61 | 3.58 | 3.43 |
| | (3.79) | (3.65) | (4.00) | (3.92) | (3.49) |
| Imputed log w | 3.99 | 4.01 | 3.97 | 3.94 | 3.79 |
| | (3.35) | (3.35) | (3.37) | (3.34) | (3.16) |
| Imputed log $w^n$ | 3.62 | 3.65 | 3.61 | 3.58 | 3.42 |
| | (3.93) | (4.11) | (3.90) | (4.31) | (4.16) |
| Marginal tax rate (imputed) | 26.58% | 27.88% | 27.45% | 26.43% | 25.47% |
| Observations | 136,533 | 79,757 | 35,485 | 15,471 | 5,820 |
| **Non-Participants** | | | | | |
| Imputed log w | 3.74 | 3.78 | 3.74 | 3.71 | 3.59 |
| | (3.11) | (3.14) | (3.14) | (3.08) | (2.89) |
| Imputed log $w^n$ | 3.50 | 3.53 | 3.48 | 3.46 | 3.30 |
| | (2.71) | (2.74) | (2.74) | (2.68) | (2.49) |
| Marginal tax rate | 21.25% | 23.87% | 20.89% | 20.15% | 19.31% |
| Observations | 105,533 | 40,929 | 28,096 | 21,374 | 15,134 |

Standard deviations in parenthesis. The table shows the mean of the imputed gross wage rates and marginal wage rates by age group in 2018 MXN (Mexican Pesos). The log-imputed wages are first estimated according to equation (2) and then marginal wage rates are calculated by applying the exponential to the log-imputed wages.

## 4.2 Estimates

Table 4 presents the results of the estimation of equations (4) and (5) by age group for participants and for all individuals, respectively, when the instrument is the imputed log-marginal wage rate corresponding to the mean weekly worked hours.[21] The first stage results are presented in Table A3 in the appendix and show that the instruments are significantly correlated with the log-marginal wage rate. For participants in the labor market, the estimated parameter for the logarithm of the marginal wage rate is statistically significant and positive

[20] This is the average of the differences between participants and non-participants age groups.

[21] The results for the instrument estimated at 40 hours are presented in the Appendix. I do not present these results in this section since they were similar for the two instruments. This is due to the mean hours being close to 40 hours.

for all groups, except the 50–55 group. Hence, the results suggest that an increase in the marginal wage rate increases the number of weekly worked hours. The estimates are larger for older groups. Furthermore, the estimates are positive and statistically significant for all groups when non-participants are included in the regressions. The estimates are larger for older cohorts, which suggests that the labor supply response to the marginal wage rate is larger for older cohorts, even when non-participants are included. In addition, the estimates are much larger compared to those for working women.

The rest of Table 4 shows that the estimated effects of age are statistically significant and negative for all age groups in both subsamples. The latter suggests that women spend less time in the labor market as they get older, even within small age intervals. The estimated effects of the number of children suggest that women work fewer hours per week the more children they have. The estimated effects of children are also larger when all individuals are considered in the estimations when compared to the results of participants. We can also see a negative correlation between being married and weekly worked hours. The correlation suggests that participants that are married work less than their single counterparts. For example, a married woman in the 56–60 group works approximately 2.6 hours less per week than their unmarried counterparts. This difference becomes even larger when all women are included in the estimation, as a married female in the 56–60 group works approximately 10 hours less per week than a single female.

Mexican families, especially families with members in these age intervals, often have a traditional structure, where gender roles are well-defined and adult children support their parents (Gomes, 2007). Women spend more time in household production activities and may receive non-labor income from their husband and adult children. The larger the number of children, the larger economic and social support she may receive from them at older ages, thus preferring to spend less time in the labor market. It is also expected that married women spend less time at the labor market than their single counterparts (Schmitz and Diefenthaler 1998).

**Table 4: Estimated Parameters of the Labor Supply model (equation 4).**

| Age Group | 50–70 | 50–55 | 56–60 | 61–65 | 66–70 |
|---|---|---|---|---|---|
| **Participants** | | | | | |
| $logw_i^n$ | 0.791*** | −0.099 | 1.178*** | 1.919*** | 3.254*** |
| | (0.058) | (0.081) | (0.116) | (0.179) | (0.384) |
| Age | −0.269*** | −0.116*** | −0.232*** | −0.467*** | −0.353** |
| | (0.008) | (0.031) | (0.054) | (0.087) | (0.148) |
| Children | −0.409*** | −0.432*** | −0.405*** | −0.391*** | −0.331*** |
| | (0.021) | (0.029) | (0.039) | (0.053) | (0.079) |
| Married | −2.431*** | −2.586*** | −2.418*** | −2.188*** | −1.791*** |
| | (0.094) | (0.121) | (0.187) | (0.296) | (0.499) |
| Constant | 51.746*** | 46.701*** | 49.076*** | 60.096*** | 48.451*** |
| | (0.543) | (1.618) | (3.193) | (5.568) | (10.216) |
| Prob > Chi2 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Observations | 136,533 | 79,757 | 35,485 | 15,471 | 5,820 |
| **All women** | | | | | |
| $logw_i^n$ | 8.067*** | 7.907*** | 8.741*** | 10.374*** | 13.779*** |
| | (0.103) | (0.142) | (0.215) | (0.343) | (0.731) |
| Age | −1.559*** | −0.752*** | −1.578*** | −2.753*** | −2.639** |
| | (0.014) | (0.053) | (0.098) | (0.158) | (0.264) |
| Children | −2.455*** | −2.508*** | −2.402*** | −2.472*** | −2.099*** |
| | (0.032) | (0.047) | (0.064) | (0.089) | (0.133) |
| Married | −12.501*** | −10.377*** | −13.896*** | −18.243*** | −22.476*** |
| | (0.177) | (0.225) | (0.361) | (0.579) | (0.959) |
| Constant | 93.011*** | 48.981*** | 95.418*** | 161.741*** | 142.584*** |
| | (0.911) | (2.871) | (5.775) | (10.014) | (18.156) |
| **Observations** | **242,066** | **120,686** | **63,581** | **36,845** | **20,954** |

*p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses. All specifications include year and quarter controls. The table shows the estimation of the iv tobit model in Stata. The Wald test was conducted in tobit and not iv tobit regressions to see whether the presence of endogeneity could be rejected. The Wald test examines whether the error terms in the structural equation and the reduced-form equation for the endogenous explanatory variable are correlated (Wooldridge, 2002). If the test is statistically significant, the null hypothesis of exogeneity is rejected. The Wald tests for most regressions were statistically significant, implying the presence of endogeneity.

Table 5 shows the results of estimating equation (6). We can see that the estimated effects of the logarithm of the observed marginal wage rate are positive and statistically significant for all age groups. As before, the estimates are smaller for the younger age groups. In contrast to the results of equation (5), the estimates are smaller, except for the 50–55 age group, and the estimate for the 50–55 age group is statistically significant in this case. The fraction of variance due to $f_i$ (rho) is different from zero and indicates that the panel-variance component is important, and that this estimator differs from the pooled estimator. Although the qualitative results of both equations for participants are similar, the magnitudes of the estimates differ depending on the choice of model.

**Table 5: Estimated Parameters of the Labor Supply model (equation 6).**

| Age Group | 50–70 | 50–55 | 56–60 | 61–65 | 66–70 |
|---|---|---|---|---|---|
| $logw_{it}^{o}$ | 0.593*** | 0.562** | 0.857*** | 1.253*** | 2.816*** |
| | (0.063) | (0.095) | (0.122) | (0.201) | (0.391) |
| Age | –0.119*** | –0.096** | –0.174*** | –0.375*** | –0.253*** |
| | (0.011) | (0.062) | (0.074) | (0.097) | (0.156) |
| Children | –0.382*** | –0.394*** | –0.377*** | –0.325*** | –0.297*** |
| | (0.032) | (0.042) | (0.067) | (0.078) | (0.082) |
| Married | –1.897*** | –1.911*** | –2.165*** | –1.754*** | –1.236*** |
| | (0.097) | (0.168) | (0.192) | (0.321) | (0.501) |
| Inverse Mills Ratio | 0.054*** | 0.125*** | 0.037*** | 0.009*** | 0.924*** |
| | (0.007) | (0.007) | (0.007) | (0.005) | (0.015) |
| Constant | 36.125*** | 26.245*** | 35.682*** | 45.342*** | 31.928*** |
| | (0.452) | (1.437) | (2.911) | (4.857) | (9.873) |
| Prob>Chi2 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| $R^2$ | 0.328 | 0.365 | 0.287 | 0.301 | 0.292 |
| Sigma_f | 0.235 | 0.168 | 0.193 | 0.211 | 0.257 |
| Sigma_g | 0.279 | 0.232 | 0.365 | 0.382 | 0.395 |
| rho | 0.415 | 0.344 | 0.219 | 0.234 | 0.297 |
| Observations | 136,533 | 79,757 | 35,485 | 15,471 | 5,820 |

*p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses. All specifications include year and quarter controls. The table shows the estimates of a random effects regression with endogenous covariates in Stata (xtivreg). Rho is the fraction of variance due to $f_i$, and is different from zero, suggesting that the panel-variance component is important and that the estimator is different from the pooled estimator.

## 4.3 Elasticities

Table 6 shows the marginal wage elasticity by age group for participants and all individuals, respectively. The elasticity derived from equation 5 for participants aged 50–70 shows that a 1% increase in the marginal wage rate is associated with a 0.021% increase in weekly hours worked. The table shows that the elasticities are smaller for younger women compared to their older counterparts.[22] Thus, the elasticity is larger for women close to retirement, but it is even larger for those in the post-retirement age group. The elasticities for all women (participants and non-participants) are larger, and suggest that the increase in working hours varies from 0.34% to 0.65% when the marginal wage rate increases by 1%.[23] The elasticities for participants derived from equation (6) show similar properties, although they are smaller than those from equation (5) (except for the 50–55 group), and the elasticity for the 50–55 group is statistically significant. These results suggest that older females react more to changes in the marginal wage rate than their younger counterparts.

A possible interpretation of the results, in line with earlier research (Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001; Blundell, 2001), is that the labor supply response at the extensive margin (labor force participation) is more sensitive than the intensive margin (hours of work.

[22] The t-test showed that these differences were statistically significant.

[23] It is possible for women to belong to two different age groups in the data—in some cases, a woman that is 55 years old at the beginning of the survey will be 56 by the end of it. A total of 5,467 women—4.3% of all women in the sample—belong to two different groups. The results presented here includes women belonging to two different age groups. I also estimated two more specifications. In the first, I placed the intersecting observations in the lower age-group while in the second specification these were placed in the upper age-group. The elasticity results of these two specifications did not differ extensively from the baseline specification.

**Table 6: Marginal Wage Elasticities.**

| Age Group | 50–70 | 50–55 | 56–60 | 61–65 | 66–70 |
|---|---|---|---|---|---|
| **Participants** (equation 5) | 0.021*** | -0.002 | 0.032*** | 0.055** | 0.101*** |
| | (0.001) | (0.002) | (0.003) | (0.005) | (0.012) |
| **All women** (equation 5) | 0.342*** | 0.286*** | 0.351*** | 0.414*** | 0.656*** |
| | (0.001) | (0.001) | (0.002) | (0.003) | (0.007) |
| **Participants** (equation 6) | 0.014*** | 0.012*** | 0.021*** | 0.037*** | 0.082*** |
| | (0.002) | (0.001) | (0.004) | (0.001) | (0.005) |

*p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses. The first row shows the marginal wage rate elasticity for women that work while the second row shows the elasticity for working and non-working women.

## 5 Conclusions

Earlier studies on the labor supply of middle-aged to elderly women have been mostly focused on the US and on European countries and to a much lesser extent on Latin American countries. Hence, the purpose of this study is to analyze the labor supply response of this population to changes in the marginal wage rate in Mexico. The results suggest that older women in these age cohorts react more to a change in the marginal wage, which is in line with studies based in developed countries (see Mroz 1987; French 2005), suggesting that older individuals have larger elasticities than their younger counterparts. Furthermore, elasticities seem to decrease when compared to the elasticities of prime-aged women in Mexico. Gómez and Campos-Vázquez (2010) report labor supply elasticities for Mexican women in their prime years that range between 0.65 and 1.52. The elasticities reported in the present study are smaller and assume values between 0.34 and 0.65.

I also find that the wage elasticity of labor supply is larger for older women than for middle-aged women. The results also show that the choice of model matters for the magnitude of the elasticities measured among the participants, although the qualitative results are quite similar. In addition, the elasticities suggest that the participation decision is more sensitive to changes in the marginal wage rate than the hours of work among the participants.[24] The latter is interesting in the sense that this part of the population can be seen as a labor supply reserve, which can contribute to alleviating some of the pressure on the social welfare system in Mexico. Policy-makers could tailor policies to increase the marginal wage rate of older women to incentivize non-participants to join the labor market. Eventually, tax collection could increase and assist Mexican social welfare in depending less on government debt.

The results in this study should be read with caution due to the limitations of the data. First, the data does not report non-labor income, and the severity of this omitted variable problem is difficult to assess. I have tried to reduce this problem by including variables that are likely to correlate with non-labor income such as age, marital status, and the number of children. The data also lacks information on work experience, which is potentially useful in estimating the wage equation. In the future, richer datasets may be available to solve these issues.

[24] This interpretation suggests that changes in the marginal wage rate could increase the extensive margin of the labor supply and incentivize women to work past the age of retirement. It is important to note that this interpretation comes from a static labor supply model; however, a dynamic model could also suggest that favorable marginal tax treatment of older workers delays retirement and increases life-cycle labor supply (Gustafsson, 2021).

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## Appendix

**Table A1: Labor Force Participation.**

| Age Group | 50–70 | 50–55 | 56–60 | 61–65 | 66–70 |
|---|---|---|---|---|---|
| Age | –0.188*** | –0.109*** | –0.211*** | –0.298*** | –0.222*** |
| | (0.008) | (0.014) | (0.031) | (0.086) | (0.049) |
| Education years | 0.286*** | 0.288*** | 0.301*** | 0.332*** | 0.175*** |
| | (0.014) | (0.019) | (0.015) | (0.106) | (0.054) |
| Children | –0.181*** | –0.215*** | –0.198*** | –0.207*** | –0.103*** |
| | (0.011) | (0.027) | (0.029) | (0.081) | (0.011) |
| Married | –2.133*** | –1.856*** | –2.601*** | –7.954*** | –2.149* |
| | (0.104) | (0.097) | (0.303) | (2.816) | (1.204) |
| Constant | 10.767*** | 6.498*** | 12.631*** | 19.163*** | 12.246*** |
| | (0.485) | (0.789) | (1.783) | (5.461) | (4.257) |
| Prob > Chi[2] | 0.0000 | 0.0000 | 0.0000 | 0.0362 | 0.0000 |
| Sigma_u | 1,426 | 1,264 | 1,624 | 1,795 | 1,821 |
| Rho | 0,671 | 0,615 | 0,725 | 0,763 | 0,768 |
| Observations | 242,066 | 120,686 | 63,581 | 36,845 | 20,954 |

*p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses. All specifications include year and quarter controls. The table shows the estimates of a random effects probit regression in Stata (xtprobit). The table also shows that rho is different from zero, which indicates that the panel-variance component is important and that the panel estimator is different from the pooled estimator.

Table A1 presents the results of the participation equation (1). The table shows that all estimates are statistically significant. The estimated effects of Age, Children, and Married have a negative sign. Therefore, the probability of a female participating in the labor force decreases with age, the number of children, and being married. On the other hand, the estimated effects of education suggest that having more years in education increases the probability of joining the labor force.

**Table A2: Log-gross wage Regression.**

| Age Group | 50–70 | 50–55 | 56–60 | 61–65 | 66–70 |
|---|---|---|---|---|---|
| Age | –0.004*** | –0.002 | –0.001 | –0.002 | –0.012 |
| | (0.000) | (0.002) | (0.003) | (0.004) | (0.007) |
| Education years | 0.102*** | 0.109*** | 0.098*** | 0.090*** | 0.085*** |
| | (0.000) | (0.008) | (0.001) | (0.001) | (0.003) |
| Inverse Mills | 0.082*** | 0.142*** | 0.065*** | 0.016*** | 1.023** |
| Ratio | (0.003) | (0.005) | (0.005) | (0.002) | (0.010) |
| Constant | 2.400*** | 2.196** | 2.252 | 2.451 | 3.013 |
| | (0.033) | (0.088) | (0.172) | (0.293) | (0.521) |
| $R^2$ | 0.367 | 0.378 | 0.353 | 0.351 | 0.297 |
| Sigma_z | 0.249 | 0.181 | 0.196 | 0.198 | 0.261 |
| Sigma_u | 0.281 | 0.242 | 0.252 | 0.269 | 0.301 |
| Rho | 0.412 | 0.375 | 0.381 | 0.401 | 0.435 |
| Observations | 136,533 | 76,757 | 35,485 | 15,471 | 5,820 |

*p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses. All specifications include year and quarter controls. The table shows the estimates of a random effects regression in Stata (xtreg). The table also shows that rho is different from zero, which indicates that the panel-variance component is important and that the panel estimator is different from the pooled estimator.

Table A2 presents the results of the log-gross wage equation (2). Due to the data limitations, the equation follows a simple human capital model, where wage is regressed based on an individual's age and education years (Blundell et al. 2001). The equation also controls for selection by including the inverse Mill's ratio. The inverse Mill's ratio is obtained from the participation equation (1), and the ratio represents the covariance between the error terms in the participation and wage equations. Table A2 shows that the effect of Age is only statistically significant for the 50–70 group. On the other hand, the effect of Education is statistically significant and positive. The log gross wage increases with education years, but the increase is smaller for older cohorts. The effect of the inverse Mills ratio is also positive and statistically significant, implying that women with the greatest earning potential are relatively more likely to be observed in the labor market. The latter suggests the presence of selection bias if non-participants are not included in the labor supply model. Hence, I follow the estimation methodology presented in section 3.

**Table A3: First stage regression for the marginal wage rate**

| Age Group | 50–70 | 50–55 | 56–60 | 61–65 | 66–70 |
|---|---|---|---|---|---|
| **Participants** | | | | | |
| Log $W^M$ | 0.915*** | 0.907*** | 0.916*** | 0.918*** | 0.904*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| Age | 0.000** | -0.000 | 0.000*** | 0.001*** | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Children | 0.002*** | 0.002*** | 0.003*** | 0.002*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Married | –0.006*** | –0.000*** | –0.005*** | 0.003*** | 0.004*** |
| | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| Constant | 0.042*** | 0.089*** | 0.028*** | –0.008 | 0.085*** |
| | (0.001) | (0.004) | (0.007) | (0.013) | (0.019) |
| Observations | 136,533 | 76,757 | 35,485 | 15,471 | 5,820 |
| Prob > Chi2 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| **All women** | | | | | |
| Log $W^M$ | 0.918*** | 0.908*** | 0.916*** | 0.919*** | 0.915*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Age | 0.000*** | 0.000 | 0.000*** | 0.001*** | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Children | 0.002*** | 0.003*** | 0.003*** | 0.002*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Married | –0.003*** | 0.000*** | –0.002*** | 0.009*** | 0.007*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | 0.036*** | 0.084*** | 0.008 | –0.058*** | 0.071*** |
| | (0.001) | (0.003) | (0.005) | (0.007) | (0.009) |
| Observations | 242,066 | 120,686 | 63,581 | 36,845 | 20,954 |
| Prob > $Chi^2$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

*p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses. All specifications include year and quarter controls. The table shows the estimates of the first stage of the iv tobit regression in Stata (iv tobit) with clustered standard errors. Log $W^M$ denotes the log-marginal wage rate had an individual worked the mean weekly hours.

Table A3 presents the first-stage results of equation (5) when the instrument is the log-marginal wage at means. The table shows that the instrument has a statistically significant effect on the log-marginal wage rate for all cohorts in both groups: all participants and all women.

Table A4 presents the first-stage results of equation (5) when the instrument is the log-marginal wage at 40 hours. The table shows that the instrument has a statistically significant effect on the log-marginal wage rate for all cohorts in both groups: all participants and all women.

## Table A4: Labor Supply IV at 40 hours.

| Age Group | 50-70 | 50-55 | 56-60 | 61-65 | 66-70 |
|---|---|---|---|---|---|
| **Participants** | | | | | |
| Log $W^{40}$ | 0.819*** | –0.074 | 1.191*** | 1.928*** | 3.316*** |
| | (0.058) | (0.081) | (0.116) | (0.179) | (0.384) |
| Age | –0.269*** | –0.116*** | –0.232*** | –0.467*** | –0.351** |
| | (0.008) | (0.031) | (0.054) | (0.087) | (0.148) |
| Children | –0.406*** | –0.431*** | –0.404*** | –0.391*** | –0.327*** |
| | (0.021) | (0.029) | (0.039) | (0.053) | (0.079) |
| Married | –2.441*** | –2.595*** | –2.422*** | –2.192*** | –1.806*** |
| | (0.094) | (0.121) | (0.187) | (0.296) | (0.499) |
| Constant | 51.638*** | 46.604*** | 49.036*** | 60.066*** | 48.176*** |
| | (0.543) | (1.618) | (3.193) | (5.568) | (10.216) |
| Prob > $Chi^2$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Observations | 136,533 | 79,757 | 35,485 | 15,471 | 5,820 |
| **All women** | | | | | |
| Log $W^{40}$ | 8.101*** | 7.927*** | 8.768*** | 10.434*** | 14.087*** |
| | (0.103) | (0.142) | (0.215) | (0.344) | (0.733) |
| Age | –1.556*** | –0.0752*** | –1.574*** | –2.738*** | –2.647*** |
| | (0.014) | (0.053) | (0.098) | (0.158) | (0.264) |
| Children | –2.453*** | –2.507*** | –2.403*** | –2.492*** | –2.115*** |
| | (0.032) | (0.047) | (0.064) | (0.089) | (0.133) |
| Married | –12.506*** | –10.384*** | –13.901*** | –18.149*** | –22.435*** |
| | (0.177) | (0.225) | (0.361) | (0.579) | (0.961) |
| Constant | 92.709*** | 48.926*** | 95.077*** | 160.729*** | 142.103*** |
| | (0.911) | (2.871) | (5.775) | (10.017) | (18.167) |
| Prob > $Chi^2$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Observations | 242,066 | 120,686 | 63,581 | 36,845 | 20,954 |

*p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses. All specifications include year and quarter controls. The table shows the estimates of the first stage of the ivtobit regression in Stata (ivtobit) with clustered standard errors. Log $W^{40}$ denotes the log-marginal wage rate had an individual worked the mean weekly hours.