Heterogeneity in Labor Supply Responses to Tax Changes

Evidence From a Structural Discrete Choice Model

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Abstract

The present thesis analyzes heterogeneity in labor supply responses to tax changes. My utilized tool for investigating this topic is the microsimulation model LOTTE-Arbeid, which is developed by the Research Department of Statistics Norway. The model is estimated on cross-sectional data of Norwegian households and delivers output in terms of labor supply elasticities.

The findings contribute new, meaningful subgroups within the simulated labor supply responses to tax changes. I compare the results to that of related international literature, and further analyze heterogeneity across subgroups with econometric models.

Preface

I would like to express my gratitude towards my supervisor, Trine Engh Vattø. Without her insightful observations and expertise, writing this thesis would have been impossible.

I would also like to thank my dear friend, Blaise, for sharing enthusiasm in the topic as well as creative inputs.

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Chapter 1

Introduction

Economics is, inter alia, about the optimal allocation of resources. However, often is the case, that the social decision-maker can only influence outcomes indirectly. This is also the situation we face when selecting tax rates; the ultimate revenue of the government will depend not only on the actual rates in a linear fashion, but will also be influenced by the micro-level decisions that workers make. Workers, who will dynamically react to changes in taxation by adjusting their labor supply, through the decision of how much leisure time to convert into wage-paying labor.

My fascination with this topic comes from the paradoxical nature of taxation; society depends on labor market participation for its value creation, yet increased income taxes might distort labor supply negatively.

Consider the well-known implications of the Laffer curve, where a too high tax rate will ultimately reduce government revenue as the workers lose their monetary incentives towards working - some individuals may even try to signal that they are poor, to gain more benefits[1]. Tax is also a highly debated topic and the opinions are divided. It concerns everyone, and knowing how to shape an efficient tax system is a complex task.

Redistribution is a key task of a government, but not at the cost of losing a critical amount of economic output. It is therefore important to know the magnitude of

[1]As first discussed by Nobel Memorial Prize in Economic Sciences laureate, James Alexander Mirrlees (Mirrlees, 1971).

distortion in the labor supply caused by the current tax system.

In this thesis, I aim to uncover insights on the tax responsiveness of workers. My research question is *to which extent are labor supply elasticities heterogeneous across different characteristics?* I will answer the problem by quantifying the responses and analyzing the results' variability across multiple characteristics.

I employ the microsimulation model LOTTE-Arbeid to estimate labor supply responses to tax changes. The model is developed by the Research Department at Statistics Norway and has so far been utilized to examine differences between single men, single women, and couples, in the Norwegian population. I extend the analysis by dividing the population into more complex groups and run regressions to investigate the significance of these through the inclusion of analytically selected interaction terms.

LOTTE-Arbeid is a structural model, which means that it separates preferences and policy parameters, such that the former is invariant with respect to the latter. Provided that preferences are properly specified, this separation makes the model suited for ex-ante evaluations of policy changes, as various changes can be considered within the same model framework (Aaberge & Colombino, 2015). Moreover, this modeling concept is appropriate for analysis on heterogeneity, as it allows preference parameters to be modified by individual characteristics.

Two alternative approaches also commonly utilized in the analysis of how labor supply is influenced by tax policies, are quasi-experiments and discontinuity in budget constraints. Both of these rely on observing the effect of an actual policy on income. The former uses first difference estimators and the latter estimates responses in the labor supply by observing the budget constraint, before and after a tax rate change. In comparison to structural models, these are less versatile.

Even though these models can provide interesting insights on the effects of the very tax reform that they are derived from, they are less appropriate for predictive purposes since there is no separation between preferences and policy parameters (Thoresen & Vattø, 2015). Furthermore, the parameters reflect the average of a diverse population, making these models less flexible in terms of analysis of heterogeneity as well.

I follow the structure of Mastrogiacomo et al. (2017a), who used a structural model to research labor supply heterogeneity in the Netherlands and compare the results of the two models. More specifically, I evaluate how elasticities vary with marital status, parental status, sex, length of education, wage rate, age, and the number of children. As the underlying data differ as well, the dynamics of the different groups enable the comparison of Norwegian and Dutch societies, at least in terms of behavioral responses to tax changes.

My main findings from the comparison of the two models are:

- Marital status has opposite effects on labor supply elasticities in the two countries. In Norway, the single population is relatively inelastic compared with couples, whereas in the Netherlands the opposite is the case.
- In Norway, single parents are more responsive than single non-parents, but parents in couples are less responsive than couples without children. In the Netherlands, parents are always more responsive than non-parents, and the effect of having children seems rather strong compared with the Norwegian results.
- In both countries, females are more elastic relative to men, and the difference between the sexes is larger among couples than singles.

By analyzing the mean of selected variables across elasticity deciles, and running linear regressions, I aim to assess the model in a simplified manner and reflect on the relative importance variables have on labor supply elasticity.

The structure of the thesis is as follows: in chapter 2, I present the microsimulation model LOTTE-Arbeid and explain how it is derived from a combination of economic theory and household data. In chapter 3, I detail the method by which elasticities are obtained in the framework of LOTTE-Arbeid. In chapter 4, I present the results from the model simulations, as well as regressions. In chapter 5, I compare my findings with those of Mastrogiacomo et al. (2017a). In chapter 6, I present an extended analysis of the relationships between labor supply elasticity and individual characteristics, where I use different regression models to investigate these. The thesis is concluded in chapter 7.

Chapter 2

The Behavioral Microsimulation model "LOTTE-Arbeid"

2.1 Overview

LOTTE-Arbeid is a microsimulation model which takes into account that tax changes generate behavioral responses, and in this way enables researchers to analyze the net impacts of policies on government revenue. The model is part of the LOTTE-system, which was developed by the Research Department of Statistics Norway in the 1970s, intending to estimate how individual income tax policies affect government revenue and distribution of income.

Initially, LOTTE did only estimate the direct effects of tax changes. In other words, how much government revenue changes with given ceteris paribus changes in the individual income taxes. Later, it has been extended with the modules LOTTE-Konsum and LOTTE-Arbeid, which evaluate the effects of indirect taxation and labor supply responses to tax changes, respectively (J. Dagsvik, Kornstad, Jia, & Thoresen, 2008).

LOTTE-Arbeid is estimated using cross-sectional data of Norwegian households, from Statistics Norway's Labor Force Survey (AKU) and Income Statistics. The version I use in this thesis, contains preference parameters of the households which are estimated based on AKU data from 2014. The model is built on standard economic theory such as a utility maximization constrained by a budget and total time available, where consumption and leisure (labor) are the decision variables. Yet, it departs from the traditional schoolbook approach in three important ways.

First, LOTTE-Arbeid is a discrete labor choice model, meaning that individuals can choose between a finite number of working levels, rather than choices resulting from a continuous function, which is the common approach in textbooks[2]. This feature lets the model integrate complex tax and benefit systems, that make budgets break with the regular convexity and continuity conditions. For this reason, the discrete choice modeling approach has increased in popularity over the last years. Not to mention, it can also be argued that this representation of the choice set reflects the labor market more realistically, as real-world workers do not have an infinite amount of choices (J. K. Dagsvik, Jia, Kornstad, & Thoresen, 2013).

Second, the stochastic property of the model accounts for unobservable heterogeneity in preferences and job opportunities. Hence, it makes sense to interpret "job type" as the decision variable, since individuals optimize utility not only with respect to leisure (labor), but also with respect to different unobservable job attributes, such as job location, responsibility, or career opportunities (J. Dagsvik, Kornstad, Jia, & Thoresen, 2008).

Third, the model explicitly takes into account institutional restrictions on the availability of jobs. It does so by including a term that specifies the fraction of jobs that are available in the market, and this fraction is allowed to vary between individuals. For example, there are more full-time jobs than part-time jobs, and more jobs available for those with higher education. Thus, both individual characteristics and restrictive features of the labor market determine the probability distribution of labor supply in this model (J. Dagsvik, Kornstad, Jia, & Thoresen, 2008).

Heterogeneity among households is accounted for in several ways. By dividing individuals into three groups, LOTTE-Arbeid allows for different estimated preference parameters across these groups. The three groups are couples, single men and single women, whose primary occupation is wage earner. The groups have similar utility representations, but the values of the parameters are allowed to differ by observable

[2] Also known as the Hausmann approach.

individual characteristics, such as age and the number of children. Unobserved heterogeneity is captured in a stochastic term in the utility specification.

The wage rate is assumed to be a function of observable personal characteristics, such as experience and time spent in education, as well as unobserved characteristics captured in a stochastic error term. The stochastic part of the wage equation results in a probability distribution function of wage, making results reflect a more realistic picture of the wage distribution. In this way, a controlled level of randomness is introduced across the wage of individuals with equivalent observable characteristics.

In the following sections, I provide a stepwise explanation of the method in which LOTTE-Arbeid is developed. In section 2.2 I present the theoretical framework and explain how this conveniently results in a multinomial logit model for labor supply. Then, in section 2.3, I describe the model estimation, which consists of estimating the parameters of the wage regression and the parameters of utility functions.

2.2 Theoretical Framework

2.2.1 Utility Maximization Given Budget

For simplicity, start by considering utility maximization for one individual. The utility of this person can be represented by the sum of a deterministic utility function and a stochastic term.

$$U(C, L, Z|X)^* = U(C, L|X) + v(Z) \tag{1}$$

Where $U(\cdot)^*$ represents the individual's true utility, $U(\cdot)$ is a deterministic function and $v(\cdot)$ is the stochastic term. The deterministic term in (1) is allowed to vary across observable personal characteristics, X. The input variables are consumption, C, and leisure, L, which are also observable in the data.

$v(\cdot)$ captures unobserved preferences over job attributes, Z, as well as measurement errors of the variables in X, and optimization errors of the individual (Creedy & Kalb, 2005). Since the stochastic term captures preferences over variables other than consumption and leisure (labor) that determine a person's job choice, "job type" can be considered as the decision variable. A change in labor supply thus represents a change in "job" (J. K. Dagsvik et al., 2013).

Utility is bounded by a time constraint and a budget constraint, which are captured by equations (2) and (3), respectively.

$$T = H + L \tag{2}$$

$$C = H \times W + I - t(H \times W, I) = f(H \times W, I) \tag{3}$$

Where T represents total time available, H is the number of working hours, L is hours of leisure, C is consumption, W is wage rate, and I captures other types of income.

Labor income is wage rate times the number of hours worked. Examples of other income sources are benefit transfers from the government, capital income, or income from self-employed work[3]. $t(\cdot)$ represents the tax function, which captures details in the tax and benefits system[4]. It follows that $f(\cdot)$ represents a function transforming gross income to net income.

The budget constraint in (3) specifies that consumption equals disposable income. The budget constraint is binding as LOTTE-Arbeid is a static model where there is no scope for individuals' savings or borrowing decisions.

Since labor supply is the variable of interest, $(T–H)$ can be substituted for L in the utility function. Similarly, C can be substituted with the budget constraint, such that utility becomes a maximization problem with respect to working hours only. This results:

$$U_i^* = U_i(H_i|X) + v_i \tag{4}$$

Where U_i^* represents the individual's true utility, U_i the deterministic utility, and v_i the stochastic part. The notation i indicates the level of working hours.

LOTTE-Arbeid assumes that men choose between seven different levels of working hours, and women choose between eight levels, which means that couples can choose between 7×8 combinations. Men have one less hour alternative as they

[3]Primarily self-employed individuals are excluded from the model.

[4]LOTTE-Arbeid is connected to LOTTE-Skatt, such that taxes for each possible labor supply choice of each individual can be computed.

cannot opt out of the labor market in this framework. The reason for this is that men not participating in the labor market are poorly represented in the data, making modeling of this group problematic.[5]

2.2.2 A Probability Distribution of Labor Supply

v_i is assumed to follow an extreme value type I distribution, which is a common assumption for two reasons; it has been found useful in applications involving extreme values, and it is highly tractable (Creedy & Kalb, 2005). The convenience of the extreme value distribution will be made clear in the following sections.

The specification of the error distribution implies that error terms across hour choices are assumed to be independent, a property which is referred to as independence of irrelevant alternatives (IIA). This means that the relative preference over two alternatives does not depend on whether a third-choice alternative is included or not (Creedy & Kalb, 2005). For example, if an individual prefers job type 1 and job type 2 equally much, then adding a third alternative will not suddenly make the individual prefer type 1 more than type 2.

Since the probability distribution of v_i is specified, the probability that a certain hour level is preferable over the other alternatives can be calculated. More specifically, let (4) be the utility obtained through i hours of work. Then, in order for the individual to prefer working i hours, this utility has to exceed the utilities obtained from the other hour levels, $j \neq i$.

Let us assume a fixed level of U_i^*. An individual prefers hour level i over hour level j, if:

$$\begin{aligned} U_i^* &\geq U_j^* \\ U_i + v_i &\geq U_j + v_j \\ v_j &\leq U_i - U_j + v_i \qquad \forall\, j \neq i \end{aligned} \tag{5}$$

Based on the cumulative distribution function of v_i, the inequality in (5) is satisfied

[5]Unemployed and individuals receiving disability benefits are excluded from the model's data sample, as only "voluntary" non-participation is modeled.

with probability:

$$\begin{aligned} Pr(U_i^* \geq U_j^*) &= Pr(v_j \leq U_i - U_j + v_i) \\ &= F(U_i - U_j + v_i) \end{aligned} \tag{6}$$

For a given value of v_i, equation (6) represents the probability that hour level i produces higher utility than hour level j. In other words, (6) is the conditional probability that U_i^* is higher than U_j^*.

For an individual to choose hour level i, the inequality in (5) must hold for all hour levels $j \neq i$ at the same time. Since the distributions of the error terms are independent, all the conditional probabilities corresponding to the one in (6) can be multiplied, for all $j \neq i$, to get the probability that hour level i generates the highest utility of the possible hour levels, given v_i. To get the marginal distribution of hour level i, v_i must be integrated:

$$p_i = \int_{-\infty}^{\infty} \left[\prod_{j \neq i} F(U_i - U_j + v_i) \right] f(v_i)\, dv_i \tag{7}$$

Equation (7) represents the probability that an individual prefers working i hours rather than any of the other hour levels. By inserting for the probability distribution function and the cumulative distribution function (from here on out: PDF and CDF) in this equation, followed by some manipulations, results the multinomial logit model:

$$p_i = \frac{e^{U_i}}{\sum_{j=0}^{k} e^{U_j}} \tag{8}$$

Where i is the hour level to be evaluated, and k represents the number of hour levels that the individual can choose between.[6]

See from equation (8) that the probability distribution of hours worked can be obtained by inserting for measured utility, instead of integrating the product of the conditional CDFs as in (7). This result comes from the assumption of an extreme value distributed stochastic term in the utility, and it simplifies the estimation of the model substantially.

[6] See Creedy and Kalb (2005) for a detailed explanation.

2.2.3 Labor Market Restrictions

So far, I have only considered the individual's preferences and disregarded features of the labor market that restrict the availability of jobs. Equation (8) reflects an unrealistic scenario where the individual can choose between all jobs in the market. In reality, there is only a subset of jobs that hire i hours, and only a subset of those is actually achievable for the individual. In equation (8) this feature can be incorporated by also summing over the available jobs at hour level i.

$$p_i = \sum_{z \in B(i)} \frac{exp(U_i)}{\sum_{j \in K} \sum_{z \in B(i)} exp(U_j) + exp(U_0)} = \frac{exp(U_i)m(i)}{exp(U_0) + \sum_{j \in K} exp(U_j)m(j)} \tag{9}$$

Where $B(i)$ represents the subset jobs that are available for the individual and z are the jobs in this subset. $m(i)$ is the number of jobs in the subset. Hence, the probability that the individual will work i hours is weighted by the fraction of jobs hiring at this level. This fraction depends on the features of the labor market as well as the characteristics of the individual.

Note that labor market constraints and preferences can only be distinguished by the functional from restrictions. Both the preference parameters and the parameters of the labor market constraints are estimated simultaneously.[7]

2.3 Parameter Estimation

2.3.1 Data Used for Model Estimation

The model is built on data from Statistics Norway's Labor Force Survey, that registers employees' working hours and monthly wages (Wage statistics, or AKU), as well as Income Statistics that contain information on individual characteristics such as annual income, marital status, parental status, level of education etc. The Labor Force Survey collects data on all employees in the public sector, and 50 – 60% of the employees in the private sector. The two datasets are combined using unique identification numbers of the individuals (Thoresen & Vattø, 2015).

[7]See J. K. Dagsvik et al. (2013) for a detailed explanation.

Preference parameters are assumed to be relatively unchanging over time. The model version that I utilize in this thesis has parameters that are estimated from 2014 data. Variables that determine disposable income in the individual's budget constraint are, however, updated in 2018.

2.3.2 Estimated Parameters of the Wage Regression

The data consists of both employed and unemployed individuals, where only females are considered in the latter group. As mentioned before, the population of unemployed men is small and unrepresentative, making it convenient to omit this group from the model estimation. The inclusion of unemployed women allows elasticities on the extensive margin for this group to be estimated. In other words, to which extent individuals choose to enter or leave the labor market. Without unemployed females, one could only estimate elasticities along the intensive margin, namely, how much labor supply changes given that an individual already works.

As there is no observed wage rate for the unemployed individuals the model uses an estimation on wage, which is a second-degree polynomial regression on length of education, experience, and experience squared, where *experience = age - length of education - 7*.

$$log\bar{w} = X^1\beta + \eta \tag{10}$$

Equation (10) represents the wage regression. $\bar{w}$ is the average wage rate, X^1 is the matrix of explanatory variables, and β is the coefficient matrix. η is a normally distributed error term capturing the effect of non-observable variables that have an impact on the average wage rate.

Estimation of elasticities starts with thirty random draws of the η in the wage regression for each individual. For each draw, the resulting wage level is substituted into the multinomial logit model and the PDF of every individual's labor supply is derived. From this distribution, the expected labor supply of each individual can be obtained. Since every individual has thirty wage levels and thus thirty probability distributions of hour levels, they have thirty expected values of labor supply. The average over these thirty values represents the expected labor supply of an individual.

By using 30 random draws of the normally distributed error term in the wage regression, the model accounts for a more complex reality. In chapter 3, I describe the following steps in the estimation of labor supply elasticities.

The wage regression estimates the wage rate of both working and non-working individuals. This is partly to have the same basis of the two groups, making the comparison more clear-cut. Another argument is that there may be some measurement errors of the wage rates on the individual level. These can be diminished if a wage regression is used instead, which generates consistent wages for all observations.

2.3.3 Estimated Parameters of the Utility Functions

The parameters in the utility function can be estimated by using data and the so-called maximum likelihood method. The maximum likelihood method can be employed after making an assumption of the underlying probability distribution that our data is constructed from. The concept of the method is summarized in its name; the estimated parameters are those that maximize the likelihood of observing our data.

More specifically, labor supply is assumed to follow a multinomial logit distribution, also, the probabilities of choosing different hour levels are independent. Thus, the probability of making some specific observations can be written as the product of each individual's probability of working the hour levels that were observed. Equation (11) represents this probability:

$$Pr(H_{i1}, \ldots, H_{iN}) = p_{i1}p_{i2}\ldots p_{iN} = \prod_{n=1}^{N} \frac{e^{U_{in}}}{\sum_{j=1}^{k} e^{U_{j_n}}} \tag{11}$$

Where N reflects the number of observations, or individuals, and k is the number of hour levels.

After inserting for the observed choices and characteristics of the individuals in equation (11), the parameters are left as the only unknown values. These are found by maximizing the logarithm of (11). Logarithmizing makes the product into a sum and solving gets easier (Creedy & Kalb, 2005).

The remaining question is which type of function should represent the deterministic part of the utility. Some common model choices are translog, quadratic, or a Box-

Cox transformed utility. However, there are several other possibilities (Löffler, Peichl, & Siegloch, 2018).

The choice depends on how well the different functions satisfy standard theory assumptions about preferences, such as decreasing marginal utility in consumption. Solving the maximum likelihood estimators for different models, one can check which function has the most appropriate representation of preferences. The quality of the discrete choice model is that quasiconcavity, a requirement for the existence of optimum points in a maximization problem, does not have to be satisfied everywhere. As long as the function is quasiconcave in the observed labor supply points, the model is sufficiently good.

LOTTE-Arbeid uses a Box-Cox utility representation of the deterministic utility function, of both single men, single women and couples. Single men and women have a utility function of the form

$$\begin{aligned} log v^s(C,H) &= \alpha_2 u(C) + \beta(X)u(L) \\ &= \alpha_2 \frac{(C-C_0)^{\alpha_1}-1}{\alpha_1} + \beta(X)\frac{(L-L_0)^{\alpha_3}-1}{\alpha_3} \end{aligned} \tag{12}$$

where C is consumption, L is leisure and C_0 and L_0 are the respective lower limits on these variables. The parameters α_2, α_3 and β are fixed, and the latter is modified by the variables the natural base logarithms of age, age squared and number of young and older children[8], which are captured in X. Younger children are defined as aged 7 and below, whereas older children are those aged 8 to 17.

Couples are assumed to maximize a shared household utility function, that is to say, they are assumed to pool their incomes and determine consumption and labor supply simultaneously. The utility function is similar to the one in (12), but it has three additional terms capturing interaction between the different variables.

$$\begin{aligned} log v^c(C,H) = {} & \alpha_2 u(C) + \beta_f(X_f)u(L_f) + \beta_m(X_m)u(L_m) \\ & + \gamma_f u(C)u(L_f) + \gamma_m u(C)u(L_m) + \gamma u(L_f)u(L_m) + vgb \end{aligned} \tag{13}$$

Equation (13) represents the utility function of couples, and f and m denote female and male, respectively. The functions $u(\cdot)$ represent similar Box-Cox utility functions as the ones presented in (12), where consumption, C and leisure, L, are the input variables.

[8] Adult children are no longer considered as children in the same household.

Chapter 3

Simulating Labor Supply Elasticities

To obtain measures of labor supply elasticities from a structural discrete choice model like LOTTE-Arbeid, one simulates the responses to an hourly wage increase. The elasticity is defined as the percentage change in expected labor supply, for each percentage change in the wage rate. The responsiveness is evaluated at the individual level in order to look into the heterogeneous effects of labor supply responses.

In the following two sections I detail the steps on how labor supply elasticities are obtained from the estimated model. I start by describing how elasticities of individuals are simulated in section 3.1. Then, in section 3.2, I explain how these individual elasticities together with data on individual-specific characteristics are utilized to obtain insights into heterogeneity in labor supply responses.

3.1 Simulating Individual's Labor Supply Elasticities

Recall from section 2.3.2 that the estimation of labor supply elasticities starts with 30 random draws from each individual's wage regression, and that the expected labor supply of an individual is represented by the mean of 30 expected values of labor supply.

The next step is simulating a change in an exogenous variable that affects individuals' labor income. This can be the income tax schedule, benefits related to work, or wage rates. In this thesis, I study heterogeneity in labor supply elasticities with respect to the net wage rate.

The behavioral effects of a change in the wage rate indirectly reflect peoples' responses to income tax changes, as variation in the net wage rate can either stem from an altered gross wage rate or a reduction in a flat income tax rate. Typically, individuals' responsiveness to taxes is reported as labor supply elasticities or earnings elasticities to compare the responsiveness across different contexts.

The expected working hours of each individual are simulated similarly as above for the alternative case, where wages are increased. Then individual elasticities are calculated as the percentage change in each individual's expected labor supply. In practice, it is common to simulate a ten percent increase in wage rates and divide the expected working hours response by ten to ensure some response in labor supply.

$$\epsilon_n = \frac{E_n^1[h] - E_n^0[h]}{E_n^0[h]} * 100/10 \tag{14}$$

Where index n represent individual n, and $E_n^0[h]$ and $E_n^1[h]$ represent expected labor supply before and after changes in wage rates, respectively. The fraction is multiplied by 100 to get elasticities in terms of percentages, and it is divided by 10 to get elasticities as measures of the % change in expected labor supply per 1 % change in the wage rate.

The labor supply elasticity, or the total elasticity, is commonly interpreted as the sum of two types of elasticities, namely the extensive margin elasticity and the intensive margin elasticity (Mastrogiacomo et al., 2017a). The former measures labor market participation responses, being the extent to which individuals choose to enter or leave the labor market. The latter measures the extent to which working individuals choose to work more or less.

The extensive elasticity is calculated from the change in the probability that individual i chooses to work, and the intensive follows as the total elasticity minus the extensive. The formulas are presented in equations (15) and (16):

$$\epsilon_n^{ext} = \frac{(1 - p_1) - (1 - p_0)}{(1 - p_0)} * 100/10 \tag{15}$$

$$\epsilon_n^{int} = \epsilon_n - \epsilon_n^{ext} \tag{16}$$

Where the extensive elasticity is described by equation (15) and the intensive by (16). p_0 represents the probability that individual n chooses not to work before the change in wage rate, and p_1 represents the corresponding probability after the change in the wage rate.

3.2 Labor Supply Elasticities of Subgroups

To analyze the heterogeneity of responses to changes in wage rates, the population is divided into groups based on common characteristics. They can, for example, be grouped based on sex or marital status. Then, the average elasticity for each group presents a measure of aggregate responses within the different groups. If, for instance, individuals are grouped by sex, the results reflect how females and males typically respond when they experience a change in the wage rate.

So far, LOTTE-Arbeid has investigated groups of single women, single men, and couples. Besides sex and marital status, the data that the model is derived from contains information on other variables such as individuals' age and length of education, as well as the number of children in different age groups. This enables us to investigate how these characteristics correlate with labor supply elasticities.

Heterogeneity in labor supply responses across these and other subgroups is the topic of the following chapter.

Chapter 4

Results

In this chapter, I present the results on elasticities of subgroups within the three groups of LOTTE-Arbeid, single women, single men, and couples. In the first three sections, I divide the population into similar groups to those of Mastrogiacomo et al. (2017a), such that the results later, in chapter 5, can be evaluated through a comparison with the elasticities of the Dutch population.

Mastrogiacomo et al. divide households into four main groups, depending on marital and parental status. When evaluating how elasticities vary with different individual characteristics, single women and men are pooled together as one group of singles. On the contrary, women and men in couples are separated when investigating how elasticities vary with characteristics. The Norwegian results on singles are discussed in section 4.1, and section 4.2 considers the results on Norwegian couples.

Mastrogiacomo et al. present results on behavioral responses for the extensive and the intensive margin, for both women and men. As unemployed men are omitted from the data in LOTTE-Arbeid, the extensive margin elasticities cannot be evaluated for the Norwegian men. However, 4.3 presents the results on these elasticities for females.

In contrast to the Dutch paper, I also present elasticities of single men and women when these are separated into two individual groups. I do this in section 4.4.

Throughout this chapter, the tables depict mean elasiticites of labor supply for subgroups, while the standard deviations of these groups are displayed in parentheses.

In contrast to standard deviations, coefficients of variation enable better comparability between groups. As there is a significant magnitude of difference between the different groups' mean elasticities, the mean-relative sizes of the average deviations might be informative in certain cases. For this reason, I also include the same tables with coefficients of variation instead of standard deviations, in the appendix as tables A.1,A.2, A.3, and A.4.

4.1 Elasticities of Singles

Table 1 summarizes total labor supply elasticities of different subgroups within the single population of LOTTE-Arbeid. The population is divided into two main groups, one consisting of singles who do not have children and one consisting of single parents. The two groups are further divided into subgroups of different sexes, education levels, wage rates, ages, as well as groups that are divided after the age of the youngest child.

I do not consider all the variables that are discussed in the paper of Mastrogiacomo et al. I disregard elasticities of immigrants versus natives, as the LOTTE data does not contain information on these variables. Neither do I evaluate how elasticities vary with skill level.

Similar to Mastrogiacomo et al, I divide education into two levels, where the lower level has a limit of thirteen years of education and anyone who has education above this threshold is allocated to the group of higher educated individuals.

I also divide wage rates into quartiles, but the groupings of age and children are different from the Dutch paper's. LOTTE-Arbeid includes individuals between age 26 and age 62, while the Dutch model has individuals between age 20 and age 57. It is therefore not possible to divide age into identical groups, but only similar ones as in Mastrogiacomo et al. I divide age into three groups, more specifically terciles.

As for the grouping of children, LOTTE-Arbeid has one group for children aged 7 and below, and one group for children aged 8 to 17, whereas Mastrogiacomo et al.

divide children into three groups, one for children aged 3 and below, one for children aged 4 to 11 and the third group for those aged 12-17.

In table 1, singles without children on average have a smaller elasticity (0.13) than single parents (0.17). This is the case throughout all subgroups, except for males whose elasticity is slightly lower for parents compared with those who do not have children.

In both groups of singles, women have a quite large elasticity relative to men. The difference is 0.16 in the group of non-parents and 0.18 in the group of parents.

Table 1: Labor Supply Elasticities of Singles

Variables	Without children	With children
All	0.13 (0.46)	0.17 (0.26)
Female	0.21 (0.34)	0.21 (0.27)
Male	0.05 (0.55)	0.03 (0.18)
Lower education	0.15 (0.31)	0.20 (0.27)
Higher education	0.11 (0.62)	0.12 (0.26)
First wage quartile	0.26 (0.36)	0.29 (0.28)
Second wage quartile	0.12 (0.34)	0.17 (0.21)
Third wage quartile	0.07 (0.30)	0.11 (0.21)
Fourth wage quartile	0.09 (0.70)	0.10 (0.30)
First age tercile	0.09 (0.35)	0.19 (0.26)
Second age tercile	0.13 (0.62)	0.15 (0.21)
Third age tercile	0.19 (0.35)	0.16 (0.32)
Youngest child 0-7	-	0.21 (0.33)
Youngest child 8-17	-	0.15 (0.23)

The table includes mean elasticities for different subgroups of the single Norwegian population. The numbers inside the parentheses represent standard deviations.

Looking at the other subgroups, lower educated singles have higher elasticities than higher educated singles, both in the group of parents and in the group of non-parents.

Wage level seems to have a similar impact on responsiveness as education level, namely that higher wage rates are associated with lower elasticities. For parents, elasticities are monotonically decreasing in wage rate, whereas for non-parents, the elasticity decreases in the first three quartiles before it increases slightly in the fourth quartile.

These results might reflect the fact that higher educated individuals on average have a higher wage rate than lower educated individuals[9].

When it comes to the relationship between age and elasticity, the results are less univocal. In the group of single non-parents, elasticity is monotonically increasing in age, while in the group of single parents this relationship is better described as having a U-shape. In the latter group, the first age tercile has the highest elasticity.

One potential explanation for the differences between the groups of parents and the group of non-parents can be that people typically have young children when they belong to the first age tercile (age 26-35). According to table 1, parents whose youngest child is in preschool age, tend to respond more to changes in labor income than parents whose youngest child is in the older group.

Lastly, the difference between the coefficients of variation reflects that there is a larger variation among non-parents (3.44) than in the group of parents (1.59), yet the variation is quite high in both groups. This indicates that there are other factors than parental status which play significant roles in determining singles' labor supply elasticity.

Evaluating subgroups, there are overall high dispersions as coefficients of variation exceed 1 in all groups, except in the parents' first wage quartile (0.95). In both the group of non-parents and parents the male subgroups stand out, as the coefficient of variation is as high as 12.12 in the group of men without children, and 5.32 in the group of fathers. Within the group of non-parents, there are particularly large variations in the second, third and fourth wage quartiles, as well as in the second age tercile. The fourth wage quartile of parents also constitutes a scattered group.

The high variations across subgroups indicate that the characteristics in consideration are weak predictors of elasticity when evaluating the groups separately.

[9] The connection between these variables is rather complicated. I provide a deeper analysis of correlated variables using OLS models with interaction terms in chapter 6.

4.2 Elasticities of Couples

Comparing results on labor supply elasticities for couples, parents have a lower elasticity (0.36) than non-parents (0.46), as opposed to the results found on singles. Elasticities of couples are on average higher than the elasticities of singles. A possible reason can be that couples value spending leisure time with their partner.

However, it must be noted, that the model suffers from sampling bias caused by the exclusion of unemployed males: in this way, couples in the model always have at least one source of income, which could allow for more flexibility regarding leisure. The relationship between partner's financial status and the individual's elasticity is analyzed further in chapter 6.

Mastrogiacomo et al. do not discuss average elasticities for couples in the case where women and men are pooled together in one group. Table 2 summarizes the different labor supply elasticities of men and women separately, results which are comparable to the findings of Mastrogiacomo et al. Again, the numbers inside the parentheses represent standard deviations. Coefficients of variation are presented in table A.2, in appendix.

In table 2, both men and women with children have a lower average elasticity than men and women without children. This result is somewhat similar to the finding on singles, although the difference between parents and non-parents is larger in the group of couples.

The difference between the sexes is larger in the group of couples, compared with the group of singles. The elasticity of females without children exceeds that of their male partners with 0.36, and the difference between mothers and fathers is 0.32.

Moving to education levels, the results are not consistent with that of singles. More specifically, higher educated individuals in couples are more elastic than lower educated individuals in couples, except in the group of female parents.

Table 2: Labor Supply Elasticities of Individuals in Couples

	Without children		Parents	
Variables	Female	Male	Female	Male
All	0.64 (1.37)	0.28 (1.29)	0.52 (0.91)	0.20 (0.84)
Lower education	0.63 (0.97)	0.25 (0.91)	0.55 (0.91)	0.16 (0.94)
Higher education	0.65 (1.72)	0.33 (1.72)	0.51 (0.92)	0.23 (0.76)
First wage quartile	0.67 (0.65)	0.21 (0.28)	0.52 (0.90)	0.15 (0.73)
Second wage quartile	0.56 (1.20)	0.28 (1.27)	0.50 (0.75)	0.17 (0.57)
Third wage quartile	0.56 (0.56)	0.27 (0.95)	0.50 (1.00)	0.22 (1.07)
Fourth wage quartile	0.78 (2.30)	0.37 (2.02)	0.56 (1.00)	0.27 (0.90)
First age tercile	0.42 (0.44)	0.17 (0.42)	0.45 (0.97)	0.15 (0.81)
Second age tercile	0.73 (1.92)	0.37 (1.54)	0.49 (0.84)	0.21 (0.95)
Third age tercile	0.80 (1.32)	0.32 (1.58)	0.62 (0.91)	0.25 (0.72)
Youngest child 0-7	-	-	0.48 (0.89)	0.18 (0.85)
Youngest child 8-17	-	-	0.54 (0.92)	0.22 (0.83)

The table includes mean elasticities for different subgroups of Norwegian couples.

The numbers inside the parentheses represent standard deviations.

Also, the wage rate has a different impact on individuals in couples than it has on single individuals. The highest elasticities are in the fourth wage quartile in all couple groups, which is the exact opposite of the result on singles, where the highest responsiveness is in the first wage quartile.

In the groups of females in couples, the second-highest elasticity is in the first wage quartile, and the relationship between elasticity and wage rate seems to follow a U-shape. The elasticity of male parents increases monotonically in wage, whereas for male non-parents the pattern appears more ambiguous, although it appears to be an increasing tendency from first to fourth quartile.

In the context of singles, there seems to be a connection between how the level of education and wage rates affect an individual's responsiveness. This connection is less intuitive in the context of couples, yet the highest wage quartile and the highest education level are both associated with the highest elasticity.

Among age groups of the workers in couples, the elasticity is monotonically increasing in age in all groups, except in the group of males without children. In this group the elasticity is highest in the second age tercile, followed by the third tercile.

Single non-parents also have a monotonically increasing relationship between elasticity and age. In contrast, comparing single parents with parents in couples brings the opposite result, as single parents are more elastic in their early ages.

As suggested in the previous section, it is reasonable to believe that the age of parents and the age of children are correlated from the way elasticity changes in a similar manner across age groups of parents as it does across age groups of the youngest child.

Even though age seems to have an opposite effect on the elasticity of individuals in couples than it has on singles, the correlation between the age of children and the age of parents seems applicable to the context of couples as well. The reason for this is that these parents are more elastic when their youngest child is in the older age group.

Evaluating the coefficients of variation, there is a higher variation among non-parents than it is in the group of parents, a result that resembles the finding on the group of singles.

Moreover, the dispersion in the pooled group of couples is also large, which indicates that there are variables other than marital status which impact labor supply elasticity. Except in the first wage quartile of female non-parents, the coefficients of variation are larger than one in all subgroups, and there is reason to believe that the stand-alone characteristics alone are poor predictors of elasticity.

4.3 Extensive and Intensive Margin Elasticities of Females

Table 3 summarizes the extensive and intensive margin elasticities of females in all groups, as well as the respective standard deviations. See appendix, table A.3, for coefficients of variation.

Starting with singles, the differences between the two marginal elasticities are not particularly high in this group. On average, the extensive marginal elasticity is somewhat larger, but across subgroups, opposite results can be found. Namely, that the intensive marginal elasticity is larger than the extensive.

More specifically, the responsiveness along the extensive margin dominates in the group of lower educated individuals, whereas the intensive margin elasticity is more important for the higher educated people. This result also holds for wage quartiles, where extensive margin elasticities are higher in the two first wage quartiles, and the intensive margin elasticity is larger among individuals whose wage rate is higher.

When it comes to age groups, results are more dissimilar in the groups of singles. Among non-parents, the extensive margin elasticity dominates in the second and third tercile, while in the group of mothers the intensive margin elasticity dominates in the first and second tercile, and elasticities are approximately equal in the third age tercile. The extensive margin elasticity of mothers is higher in both age groups of children.

Moving over to couples, the results differ substantially. Throughout all subgroups, the intensive margin elasticity is considerably larger than the elasticity along the extensive margin. The extensive elasticities are similar across singles and couples, hence marital status mainly has an impact on responsiveness along the intensive margin. From this, it can be argued that the gap between singles and couples' intensive elasticity is an important reason why there are higher elasticities among couples, in addition to the difference in men's elasticities between the groups of singles and couples.

One reason why couples are more responsive along the intensive margin can be that couples always have at least one labor income since unemployed men are not considered.

The mean coefficients of variation are smaller than one only for the extensive margin elasticities of couples. Across subgroups of couples, the fourth wage quartile of parents stands out as the sole subgroup having a coefficient of variation that is larger than one at the extensive margin.

This result implies that the individual characteristics explain labor supply elasticities along the extensive margin of couples rather well. As for the intensive margin,

Table 3: Mean Extensive Intensive Elasticities of Selected Groups of Females

	Singles				Couples			
	Without children		With children		Without children		With children	
	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive
All	0.12 (0.18)	0.09 (0.26)	0.11 (0.17)	0.10 (0.17)	0.13 (0.11)	0.51 (1.36)	0.12 (0.10)	0.40 (0.90)
Lower education	0.19 (0.21)	0.10 (0.07)	0.16 (0.20)	0.10 (0.07)	0.16 (0.11)	0.48 (0.96)	0.15 (0.10)	0.40 (0.91)
Higher education	0.04 (0.09)	0.09 (0.37)	0.05 (0.09)	0.09 (0.25)	0.11 (0.10)	0.54 (1.70)	0.11 (0.10)	0.40 (0.90)
First wage quartile	0.21 (0.23)	0.10 (0.08)	0.20 (0.22)	0.11 (0.07)	0.18 (0.12)	0.49 (0.65)	0.15 (0.10)	0.36 (0.89)
Second wage quartile	0.13 (0.19)	0.10 (0.31)	0.14 (0.18)	0.09 (0.06)	0.13 (0.09)	0.43 (1.19)	0.11 (0.09)	0.39 (0.73)
Third wage quartile	0.07 (0.13)	0.09 (0.36)	0.06 (0.12)	0.08 (0.05)	0.12 (0.10)	0.44 (0.51)	0.11 (0.10)	0.39 (0.99)
Fourth wage quartile	0.05 (0.10)	0.09 (0.17)	0.05 (0.10)	0.11 (0.32)	0.11 (0.10)	0.66 (2.29)	0.11 (0.11)	0.45 (0.95)
First age tercile	0.07 (0.15)	0.09 (0.42)	0.13 (0.18)	0.09 (0.06)	0.10 (0.09)	0.31 (0.40)	0.12 (0.09)	0.33 (0.96)
Second age tercile	0.12 (0.17)	0.08 (0.06)	0.10 (0.16)	0.08 (0.06)	0.14 (0.10)	0.59 (1.92)	0.12 (0.10)	0.37 (0.82)
Third age tercile	0.17 (0.20)	0.11 (0.13)	0.11 (0.16)	0.11 (0.29)	0.17 (0.12)	0.63 (1.32)	0.13 (0.11)	0.49 (0.89)
Youngest child 0-7	-	-	0.14 (0.18)	0.11 (0.24)	-	-	0.12 (0.10)	0.35 (0.88)
Youngest child 8-17	-	-	0.10 (0.16)	0.09 (0.12)	-	-	0.12 (0.10)	0.42 (0.90)

The numbers inside the parentheses represent standard deviations.

however, elasticities seem to be relatively poorly explained by the characteristics separately, both for couples and singles. This interpretation can also be applied to the extensive margin elasticities of singles.

4.4 Separating Single Women and Men

Mastrogiacomo et al. pool single men and women in one group when investigating how singles' labor supply elasticities vary with different individual characteristics. However, it is also interesting to find out whether there are any particular differences between the two sexes within this group. In table 4, I separate males and females and present their respective elasticities and standard deviations. See appendix, table A.4, for coefficients of variation.

Women are considerably more responsive than men, in any subgroup, and on average children do not make a large impact on the results. Women have more or less the same mean elasticity in the groups of non-parents and parents (0.21), while the elasticity of male parents is slightly lower (0.03) than the corresponding result on non-parents (0.05).

Men and women have opposite results when it comes to education level, in the sense that lower educated females are more elastic than females with higher education, and the opposite is the case for men. As the results presented in table 1 indicate, the effect of education level on women's elasticities is sufficiently strong to make the average elasticity in the pooled group of singles follow a similar pattern as the one for females only.

When it comes to wage quartiles, the results show that females tend to be less responsive the higher is their wage rate. The only exception is the slight increase in elasticity going from third to the fourth quartile in the group of single mothers. Male non-parents on the other hand, have a substantially higher elasticity in the fourth quartile, relative to other quartiles. The elasticity of fathers is somewhat stable across all wage quartiles.

Table 4: Labor Supply Elasticities of Single Men and Women

	Singles			
	Without children		With children	
	Female	Male	Female	Male
All	0.21 (0.34)	0.05 (0.55)	0.21 (0.27)	0.03 (0.18)
Lower education	0.29 (0.28)	0.03 (0.26)	0.26 (0.26)	0.03 (0.20)
Higher education	0.13 (0.39)	0.08 (0.86)	0.14 (0.28)	0.04 (0.14)
First wage quartile	0.32 (0.30)	0.04 (0.42)	0.30 (0.28)	0.02 (0.01)
Second wage quartile	0.23 (0.39)	0.02 (0.08)	0.23 (0.24)	0.05 (0.32)
Third wage quartile	0.16 (0.40)	0.02 (0.09)	0.14 (0.17)	0.02 (0.01)
Fourth wage quartile	0.14 (0.22)	0.10 (1.00)	0.16 (0.35)	0.04 (0.16)
First age tercile	0.16 (0.46)	0.03 (0.15)	0.22 (0.24)	0.04 (0.27)
Second age tercile	0.20 (0.23)	0.07 (0.86)	0.18 (0.21)	0.03 (0.13)
Third age tercile	0.29 (0.29)	0.04 (0.41)	0.22 (0.35)	0.03 (0.02)
Youngest child 0-7	-	-	0.25 (0.32)	0.06 (0.34)
Youngest child 8-17	-	-	0.19 (0.24)	0.03 (0.09)

The numbers inside the parentheses represent standard deviations.

Single women without children get more responsive with age, whereas single men with similar parental status are the most responsive in the middle age group. In the group of single mothers, the middle age group is associated with the lowest elasticity, and the results on fathers are again relatively stable. Both single mothers and fathers are more responsive when their youngest child is in the ages below 7.

Comparing coefficients of variation across groups, on average and in all subgroups, men without children have considerably higher values compared with females without children. In the group of parents, there is also on average higher variation among males than females, but across subgroups, the variation is higher among females in the first wage quartiles, third wage quartiles, and the third age tercile.

Chapter 5

Comparison to a Previous Study on Heterogeneity

When comparing results on elasticities from LOTTE-Arbeid with results from the structural discrete choice model of Mastrogiacomo et al, it is important to keep in mind that not only are the model populations different but the models are also estimated using slightly different methods.

LOTTE-Arbeid is estimated using cross sectional data from one time period, and coefficients are determined by the method of maximum likelihood. The Dutch model is derived from panel data covering the years 1999–2005, and the parameter estimation benefited from a major tax reform that was implemented in 2001. Moreover, it explicitly accounts for heterogeneity between households with and without children in that it has separate utility functions for these households. LOTTE-Arbeid, on the other hand, pools these households together such that singles with and without children share the same utility function. The same holds for couples.

As for the wage estimations, the Norwegian model uses a wage regression to estimate the wage rates of both workers and unemployed individuals. Mastrogiacomo et al. only use a regression to impute gross hourly wages for the non-workers.

According to Löffler et al. (2018), who performed a meta-analysis on structural labor supply models, results on labor supply responses to tax changes are very sensitive to the treatment of hourly wages. More specifically, they found that the choice between predicting wage rates for non-workers only or for the full sample, may in fact double the estimated labor supply elasticity, increasing the average own-wage elasticity in their analysis from 0.23 to 0.46. In contrast, different specifications of the utility functions and the choice sets do not systematically affect results.

Lastly, as the two models are estimated in different countries, and any differences in the results may also reflect the fact that the tax systems are not identical. Therefore, a comparison of the two models' results is not a fully-fledged validation of LOTTE-Arbeid, but rather an interesting reflection on the different models' results.

5.1 Singles

Table 1, which pools single men and women, shows that Norwegian singles without children have a smaller elasticity (0.13) than single parents (0.17) and that females in both groups are quite responsive relative to men. This pattern is consistent with the findings of Mastrogiacomo et al. However, the total elasticities of the Dutch population are generally higher, and the extent to which sex and children affect elasticities differ between the two models. The results from the Dutch model can be found in the appendix, figure B.1.

Dutch singles without children have a total elasticity equal to 0.35, whereas single parents have an elasticity almost double as high, equal to 0.61. Having children has a much larger effect on average elasticity in the Dutch model than in the Norwegian.

In fact, evaluating all subgroups in the Dutch single population, the elasticities are always higher for parents versus non-parents. This contrasts with the results of LOTTE-Arbeid, where men with children on average have a slightly lower elasticity than men without children, and the elasticity of females is more or less the same in both groups. Also, for the third age quartile average elasticity is lower for singles with children.

In the groups of single parents, the difference between men and women is similar in the two models, close to 0.17. Among singles without children, however, the difference between men and women is relatively large in the Norwegian model, approximately 0.17 compared with 0.06 in the Dutch model.

Looking at the other subgroups, the results of LOTTE-Arbeid on education levels are similar to those of Mastrogiacomo et al, namely that lower educated singles have higher elasticities than higher educated singles, for both parent and non-parent singles.

Elasticities across wage quartiles also share similarities with the Dutch model as elasticities follow a decreasing trend in wage level. More specifically, Mastrogiacomo et al. find that elasticities decrease monotonically with wage level both among singles without children and among single parents.

The results in table 1 show that this is also the case for single parents in the LOTTE population. For singles without children, this pattern is found in the first three quartiles, before the elasticity increases again in the fourth quartile.

When it comes to age terciles, elasticities are quite different between the Norwegians and the Dutch. The responsiveness presented by Mastrogiacomo et al. decreases monotonically with age in both groups of singles. In the LOTTE population, the opposite is the case for singles without children, while elasticities for single parents seem to have a U-shaped relationship with age, as the second age tercile has the lowest responsiveness. For single parents, the results are consistent with the Dutch; elasticities are higher for parents whose youngest child is in the youngest age group.

5.2 Couples

In table 2, both male and female parents have lower average labor supply elasticities than men and women without children, a finding that holds throughout the table, with the first age tercile of females as an exception. This result contrasts with Mastrogiacomo et al. where parents are more responsive than non-parents across all subgroups. The Dutch results on couples can be found in the appendix, under figure B.2 and B.3.

Similar to the Dutch, the Norwegian model also finds that females in couples are more responsive than men in couples. The differences between the sexes' elasticities are quite large for both groups of Norwegian couples, 0.36 for those without children and 0.31 for parents. In the Dutch population, these differences are 0.14 and 0.31, respectively.

Analyzing the two models' results on singles, the Dutch population is substantially more responsive than the Norwegian. The opposite is the case when comparing the groups of couples, where the Dutch population is generally less responsive than the Norwegian.

An explanation for this can be that marital status seems to have opposite effects on the two populations. More specifically, Norwegian couples have considerably higher elasticities than Norwegian singles, while the reverse is true for the Dutch population.

In LOTTE-Arbeid higher educated individuals tend to be more responsive than lower educated individuals, except in the group of female parents. This contrasts with the Dutch results where the higher education level is associated with lower elasticities, in all subgroups.

When it comes to wage quartiles, the two models' results are somewhat similar. Starting with the Norwegian, four groups have the highest elasticity in their last quartile. Among the females, individuals in the first wage quartile are the second most responsive, and the relationship between elasticity and wage rate seems to have some kind of U-shape.

For male parents, the relationship between wage rate and elasticities is monotonically increasing, whereas for males without children this relationship seems to have a more arbitrary shape. The results found on the female Dutch population resemble the pattern found across wage quartiles in the female Norwegian population, although in the group of Dutch female parents the highest elasticity is found in the first wage quartile and not the fourth. The elasticity of Dutch males is decreasing in wage, opposite of our finding on Norwegian fathers.

Elasticities across all groups of couples in the Norwegian population, except in the group of males without children, present a monotonically increasing relationship with age. The deviating group of male non-parents seems to have a concave relationship between age and responsiveness. The Dutch results also show monotonically increasing elasticity in age for couples without children.

For parents, elasticities are moving in the opposite direction. Regarding the age of the youngest child, the results of the two models show opposite relationships. In the Norwegian population, parents whose youngest child is in the group of older children seem to be more responsive than parents with the youngest child in the preschool age. Dutch parents, however, are more responsive when their youngest child is in the youngest group.

5.3 Extensive and Intensive Elasticities

Mastrogiacomo et al. find that across all female groups, extensive elasticities are larger than intensive elasticities. In other words, the fraction of individuals who enter the labor market contribute more to the total expected change in labor supply, than the fraction of individuals who alter their already positive labor supply.

The results can be found in appendix, where figure B.1 presents elasticities of singles and figure B.2 and figure B.3 present the elasticities of couples without and with children, respectively. Table 3 summarizes these elasticities of the females in LOTTE-Arbeid.

The differences between the extensive and intensive elasticities of the Norwegian singles are not particularly large in the group of singles. On average, the extensive elasticity is slightly larger than the intensive, but in certain subgroups, intensive elasticities are higher than extensive.

In the group of couples, on the other hand, the intensive elasticities are substantially larger than the extensive elasticities, both on average and across subgroups. This is the exact opposite of the Dutch results.

Comparing the average results of the two populations, the Dutch population is more responsive than the Norwegian along the extensive margin. This indicates that unemployed Dutch women are incentivized by pecuniary measures in the labor market to a larger degree than the women in Norway.

Among the couples, the Norwegians are much more responsive than the Dutch along the intensive margin. As for the singles, the intensive elasticities are equal in the two populations when comparing non-parents. In the group of parents, however, the

Dutch are slightly more elastic along the intensive margin than the Norwegians.

When it comes to the subgroups, Norwegian singles can not be compared with Dutch singles, as there are no separate results on men and women in the latter.

In the Dutch population, the intensive elasticity is relatively stable across the different subgroups.

The extensive elasticities vary more than intensive ones. This means, that the variables in consideration predict responses of employed Dutch women rather well, but that there are omitted variables that are significant in predicting the responses of the unemployed.

In the Norwegian population, the opposite is observed; namely that the intensive elasticity varies more across subgroups than the extensive elasticity. The Norwegian model, therefore, seems to predict the labor supply responsiveness of the unemployed population better than it does for the employed population.

Chapter 6

A Regression Analysis of Heterogeneity

In the previous chapters, I detailed how Norwegian couples on average are more elastic than singles and that parental status seemingly has a larger effect on individuals in couples than it has on singles. The results further suggest that there is a correlation between wage rates and education levels, and a correlation between the age of the parents and the age of the youngest child.

There are signs that some relationships between labor supply elasticity and other variables follow certain patterns, which makes it plausible to assume that the variables have a specific impact on elasticity. On the other hand, large coefficients of variation indicate that the grouping of the population is insufficient when aiming to predict labor supply responses. It is therefore interesting to ask how the precision would change after dividing into even more specific subgroups, e.g., females in couples who are in the first wage quartile and at the same time have low education and her youngest child is 16 years old.

In this chapter, I, therefore, analyze the relationship between the key variables in greater detail, using econometric tools. I start with discussing results from correlation matrices, in section 6.1, where I show a lack of direct relationships between variables. In section 6.2, I present the mean of selected variables over the elasticity deciles, which shows in a simplistic way how certain characteristics change drastically across the deciles, while others are more or less the same. In section 6.3, I utilize OLS models, extended with interactions and polynomial terms, to show the relative significance of the variables. Regressions provide a way to analyze the average effect of variables on the labor supply responses in a sort-of multidimensional way, compared to the grouped tables presented in earlier chapters.

6.1 Correlation Between Variables

Table A.5 in appendix presents a correlation matrix of labor supply elasticity and variables describing individuals' sex, marital and parental status, years of education, wage rate, age, as well as whether they have children in the younger and older age group. The results are the Pearson correlation coefficients, and measure the linear correlation between the different variables. The values range from -1 to 1, where the former implies perfect negative correlation and the latter implies perfect positive correlation.

The coefficients describing the relationship between elasticity and the other variables are close to zero, implying that independently, the individual characteristics are poor predictors of labor supply responsiveness. Of all variables, marital status and sex have the highest correlation with elasticity, but the two relationships still appear rather weak.

Evaluating the correlation between the individual characteristics, there is little evidence of strong relationships, as almost all values are less than 0.30. There are only a few numbers that stand out.

The correlation between wage rate and education level (0.62) presents a moderate relationship between the two variables. This to some degree confirms our suspicion in section 4.1, where elasticity follows a similar pattern across wage quartiles as it does across education levels.

The wage rate also has a moderate correlation with sex (0.59), where higher wage rates are expected among males than females. The relationship between marital and parental status (0.42) also stands out as relatively strong, where being in a couple is positively correlated with being a parent. Lastly, there is a negative correlation between the age of workers and having young children (-0.37), i.e., older workers are less likely to have young children.

The relationship between age and having older children is weak (-0.05), which might reflect the fact that as parents get older their children become adults and are no longer considered as children in the model. The correlations between being a parent and having children in the younger (0.50) and older (0.85) age groups are also rather strong, but this is as expected from the specification of "being a parent", where a worker is a parent if it has at least one child in either of the age groups.

From the results presented in the previous sections, labor supply elasticity appears to have a non-linear relationship with the different variables. Patterns change when going from singles to couples and women to men. It is, therefore, reasonable to believe that the correlation coefficients presented in table A.5 contain limited information about the true relationships between the different variables.

A better representation could be the matrix of Spearman correlation coefficients. In contrast to the Pearson coefficients, the Spearman coefficients measure the strength and direction of a monotonic association, linear or non-linear, between two variables. The coefficients also rank between -1 and 1, where the former implies a perfect, monotonically decreasing relationship and the latter implies a perfect, monotonically increasing relationship. The Spearman coefficients are presented in table A.7 in Appendix.

Again, there are mostly low values of correlation, implying that most variables have weak direct relationships. Also, the few pairs of variables that have relatively high correlations are the same, except with two additions. The associations between elasticity and marital status (0.56), as well as elasticity and sex (-0.44) are no longer presented as weak, but instead moderate. Thus, marital status and sex might be good explanatory variables of elasticity anyway.

The correlations from table A.5 and table A.7, as well as the high coefficient of variation values of tables 1 and 2 imply it is worth to investigate further by dissecting some of these groups. The tools that could be utilized are limited by the available variables and the scope of this thesis.

6.2 Elasticity Deciles

So far, the topic of discussion has been how the mean elasticities differ between groups. In table 5, I would instead like to display how key variables change between the different elasticity deciles. In this way, I can analyze which characteristics vary or stay similar along the elasticity values.

Table 5: Mean of Selected Variables Across Elasticity Deciles

Elasticity deciles		Marital status	Parental status	Sex	Education	Wage	Age	Labor supply
1	-1.36 - 0.015	0.04	0.11	0.93	0.18	283.44	41.02	37.35
		(4.62)	(2.83)	(0.27)	(2.13)	(0.13)	(0.25)	(0.09)
2	0.015 - 0.04	0.01	0.17	0.64	0.48	295.2	41.83	36.50
		(10.08)	(2.22)	(0.75)	(1.04)	(0.20)	(0.27)	(0.04)
3	0.04 - 0.05	0.02	0.22	0.10	0.62	272.93	42.43	35.13
		(7.69)	(1.89)	(2.99)	(0.78)	(0.14)	(0.26)	(0.02)
4	0.05 - 0.08	0.83	0.70	0.88	0.35	309.52	43.37	37.34
		(0.45)	(0.65)	(0.38)	(1.36)	(0.12)	(0.22)	(0.04)
5	0.08 - 0.09	0.95	0.58	0.96	0.58	348.02	48.07	37.78
		(0.23)	(0.85)	(0.20)	(0.85)	(0.14)	(0.18)	(0.04)
6	0.09 - 0.18	0.94	0.50	0.59	0.70	332.98	48.40	36.10
		(0.26)	(1.01)	(0.83)	(0.66)	(0.18)	(0.18)	(0.05)
7	0.18 - 0.25	0.96	0.67	0.08	0.67	281.27	44.36	33.33
		(0.21)	(0.70)	(3.36)	(0.7)	(0.14)	(0.19)	(0.03)
8	0.25 - 0.40	0.85	0.59	0.13	0.48	271.01	45.47	31.02
		(0.42)	(0.83)	(2.54)	(1.05)	(0.19)	(0.21)	(0.09)
9	0.40 - 0.65	0.56	0.42	0.23	0.37	276.41	48.00	26.39
		(0.88)	(1.17)	(1.81)	(1.31)	(0.22)	(0.20)	(0.14)
10	0.65 - 39.96	0.85	0.43	0.17	0.46	274.86	49.64	17.99
		(0.42)	(1.15)	(2.25)	(1.07)	(0.18)	(0.18)	(0.37)
	Total	0.60	0.44	0.47	0.49	294.56	45.26	32.89
		(0.82)	(1.13)	(1.06)	(1.02)	(0.19)	(0.22)	(0.20)

The numbers inside the parentheses represent coefficients of variation.
Marital and parental status take the value of 1 in case an individual is married or has at least one child.
Education is another binary variable, 1 in case an individual has at least 13 years of education.
Δwage is the difference in hourly wage between partners in NOK. Sex takes the value of 1 for males.
Labor supply is the hours spent with work in a week. Hourly wage and annual income in NOK.

Unsurprisingly, the two-digit elasticities are obtained mostly by individuals working part-time, who have more room to increase their labor supply. It is possible, that these people are less highly educated, which could explain why the hourly wages are peaking in lower elasticity deciles.

Age seems to be more consistent, as all deciles feature people with more or less the same average wage. The seemingly ambiguous effect of age on elasticity will be discussed in greater detail in the following section.

The appendix contains table A.8, with the couple's financial variables and their means (and coefficients of variation) along the complete sample's elasticity decile limits.

Having kids seems to be a feature of the most inelastic (closest to zero) deciles, while the variable of sex shows, how males tend to dominate these most inelastic groups too. For couple's, income does no longer have the same implied U-shape as for the whole population, a result that motivated the interaction terms in the regressions analysis of the next section.

6.3 Econometric Analysis

6.3.1 Simple OLS

The econometric models simplify the much more complex nature of LOTTE-Arbeid but provide a trivial tool to analyze its dynamics. The goal of this analysis is to show the relative importance of the variables used in the simulation, as well as to point out some weaknesses of its results.

The matrix of explanatory variables can be grouped into non-financial characteristics and financial regressors. Non-financial variables include parental status, education, marital status, age, and sex. Financial variables describe an individual's incentives towards working.

For couples, financial variables also include the salaries of partners: as the model assumes the partners share their utility function and budget, it is reasonable to assume, that the higher earner in the pair will increase their labor supply more. $\Delta wage$ captures this incentive difference between the couples. It is zero for both singles and married people who have equal earnings.

The first model, displayed in table 6, was using all variables at hand and fitting parameters using the ordinary least squares method. The discrete variables have all been modified to be binary vectors. For the sake of simplicity, the children variables have been combined into a single binary variable, which takes the value of 1 in case the individual has any children, 0 otherwise.

Some of the variables, most notably education, own hourly wage, and having children, are insignificant, which means that the range of their standard error is too wide relative to the sign of their coefficients. However, I made use of them later, by interacting these variables with others. The significant results are displayed in the summary tables.

Wage and working hours are assumed to have decreasing returns to scale, hence both variables are the natural base logarithms of the original values in the regressions. In this way, despite relying on OLS estimations, I can put a little non-linearity into the model. The improved p-values in the case of these variables implied that the logs were indeed improving the fitness of the observations.

The interpretation of the coefficients is, for instance, an additional 1000 NOK difference of wage between married partners, results in a 0.7201 increase in elasticity. This is somewhat counter-intuitive, as it implies, a person with a richer partner will have higher elasticity, and increase their labor supply more.

The idea behind taking the natural base logarithm of certain variables is to deal with potential outliers and to implement a certain degree of decreasing returns to scale. In the case of these variables, the coefficients' interpretation becomes the average effect an additional percentage of income, wage, or partner's income has on elasticity.

Perhaps more interesting than the actual values of the coefficients, is their sign. For instance, being married increases elasticity, while being male decreases it. The reason for including both hourly wage and income is to account indirectly for working hours (which is a variable directly related to the dependent variable of elasticity); an individual with low wage but high income has a high labor supply and vice versa.

Table 6: Baseline Model

Elasticity	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
maritalstatus	0.3099	0.04	8.09	0.00	0.23	0.39
parentalstatus	-0.0213	0.02	-1.33	0.18	-0.05	0.01
sex	-0.1606	0.02	-6.87	0.00	-0.21	-0.11
education	0.0274	0.02	1.25	0.21	-0.02	0.07
age	0.0512	0.01	1.13	0.00	0.03	0.07
$ln(wage)$	0.0932	0.08	1.14	0.25	-0.07	0.25
$ln(income)$	-0.0267	0.00	-13.94	0.00	-0.03	-0.02
$\Delta wage$	0.7201	0.11	6.59	0.00	0.51	0.93
$ln(partner's\, inc.)$	-0.0031	0.00	-1.12	0.26	-0.01	0.00
constant	-0.2382	0.43	-0.56	0.58	-1.07	0.60

R^2 = 0.059. In marital status, parental status, education and sex, the value of 1 denotes being married, having at least one child, having at least 13 years of education, and being male respectively. Δwage is the difference between the partner's and the individual's hourly wage in thousand NOKs.

6.3.2 Extended OLS

Researchers often rely on using interaction terms, when there is reason to believe that the variables themselves would not show a direct causal relationship, but allowing for different slopes for regressors across the value of another variable brings significant results even using simple, linear models (Bernhardt & Jung, 1979).

First, I allow (log)wage to have different coefficients based on having at least 13 years of education or not. The result is only a little different but highly significant coefficients on wage. However, the wages are much higher values than the rest of the dummies.

Another tweaking is the addition of polynomials terms. The logic of using polynomial terms is that it allows us to interpolate closer to the true shape of the relationship of age to elasticity, relative to a simple linear equation. It is not assumed that a squared variable would have an intuitive interpretation, but only that the regressor has a reverse U-shaped effect on elasticity (Friedrich, 1982).

It is reasonable to assume that age has a non-monotonic impact on elasticity because individuals with adult offspring are not considered to be parents in the model. As *age* and age^2 have opposite sign coefficients, the idea about the shape is proven correct.

From frequency tables, it is noticeable that the partner's income has a similar U-shaped effect: the individual with a higher and lower income of the partner will both have, on average, a higher elasticity of labor supply. Therefore, I have also tweaked this variable with the second-degree polynomial.

The results of polynomial additions can be seen in the appendix, as table C.1. Note, that the two second-degree polynomial terms have opposite signs, implied a reverse U-shape for age, and a U-shape for partner's income. The latter variable is magnified to trillion NOK, in order to have a larger coefficient. As mentioned earlier, these variables do not have intuitive interpretations, just account for the shape of these distributions.

Next, I consider that financial variables might have heterogeneous effects based on some of the non-financial variables. With allowing interaction between the continuous and binary variables, the variables will have different slopes, depending on the value of the binary variables.

The summary of this extension is shown in table C.2. Only the most significant interaction terms are used. Income and partner's income have different slopes based on being male and having higher education while having children will have a second slope for partner's income.

The significance of a partner's income interacted by higher education might be a result of highly educated people marrying individuals with similar education. The effect of being a parent is more straightforward: having children might impact the importance of who is earning more in the couple when they choose their labor supplies.

Finally, I tried to account for how being married, having a child, or being male affect elasticity in a heterogeneous manner. With the addition of further interaction terms on these binary variables, I can account, for example, for the difference in the effect being married has between males and females.

The results of this model are displayed in table C.3. Yet again, only the most significant combination of interactions is displayed. The triple interaction term between being married, having higher education, and the sex dummy is the least significant, however, its presence in the model improves the significance of the two-term interactions. The marginal effect of variables becomes complicated in this model, but the interpretation of an interaction term is, for example, that being married and having higher education at the same time, will further increase the elasticity of labor supply by 0.1464 on average, relative to individuals who are only married or have higher education.

The consistently low R-squared values tell us that the overall fitness of the models is lacking. Even though the resulting elasticities are the output of a model, it is an especially complex one, designed to analyze human behavior. As such, the R squared values are more informative about the relative performance of the models, rather than a quantifying proof of “all models being poor”.

The fitting is especially poor in the case of outlier high elasticities. As visible in the residual plot, the model systematically underestimates in their cases. Table 5 shows the high variety in estimated elasticities.

To account on some level for these outliers, I ran the same regression with quintile specific constant terms, based on the level of initial, pre-policy labor supplies. This is in a way a quasi-quantile regression, as the ratio of labor supplies, before and after the wage increase, defines the elasticity, our dependent variable.

The model can be further improved by allowing some of the other variables to take different slopes, depending on the labor supply quintiles. However, this would lead to over-fitting, and the analysis would lose its purpose, which is in a way the validation of the elasticity simulation itself.

The lowest quintile working hours group of individuals working less than 29.30 hours is captured with the constant term, as they are the reference group. As the negatively large coefficients of the other groups implies, the reference group’s elasticity is much larger on average.

Table 7: Quintile Specific Intercepts

Elasticity	Coef.	Std. Err.	t	P>∣t∣	[95% Conf. Interval]	
sex	-0.3164	0.26	-1.23	0.22	-0.82	0.19
age	-0.1263	0.08	-1.56	0.12	-0.28	0.03
age^2	0.0130	0.01	1.42	0.16	-0.01	0.03
$sex \times age$	0.3139	0.12	2.57	0.01	0.07	0.55
$sex \times age^2$	-0.0376	0.01	-2.74	0.01	-0.06	-0.01
$ln(wage)$	0.4034	0.05	7.91	0.00	0.30	0.50
$\Delta wage$	0.1941	0.12	1.64	0.10	-0.04	0.43
$parent \times pinc$	-0.0329	0.01	-2.40	0.02	-0.06	-0.01
$parent \times pinc^2$	0.0017	0.00	2.93	0.00	0.00	0.00
$partner's\,inc.$	0.0440	0.01	3.45	0.00	0.02	0.07
$partner's\,inc.^2$	-0.0020	0.00	-3.50	0.00	0.00	0.00
$maritalstatus$	0.2767	0.02	11.55	0.00	0.23	0.32
$marital \times sex$	-0.2315	0.03	-7.08	0.00	-0.30	-0.17
$labor\,supply\,quintiles$						
2. 29.30 - 33.93	-0.8564	0.02	-41.59	0.00	-0.90	-0.82
3. 33.93 - 35.68	-0.8660	0.02	-40.52	0.00	-0.91	-0.82
4. 35.68 - 37.83	-1.1394	0.03	-40.96	0.00	-1.19	-1.08
5. 37.83 - 74.02	-1.2236	0.03	-41.11	0.00	-1.28	-1.17
$constant$	-1.1181	0.30	-3.78	0.00	-1.70	-0.54

R^2 = 0.1954. In marital status, parental status, education and sex, the value of 1 denotes being married, having at least one child, having at least 13 years of education, and being male respectively. Partner's income is in 1 million NOK, partner's income squared in 1 trillion NOK. Labor supply is the hours spent with work in a week. Δwage is the difference between the partner's and the individual's hourly wage in thousand NOKs.

Sex making a difference in the coefficients of age, might imply some time lost asymmetrically between males and females due to having children. Similarly, parent making a difference in partner's income shows the difference cross-income elasticity makes depending on having children, while the interaction term between married and sex allows for a different intercept for married and unmarried males and females.

The residual plots, figures D.1 and D.2, for the baseline and the quintile model respectively, show that the predictions largely improve for the higher four quintiles. This proves a certain problem with the elasticity results, that I have briefly mentioned earlier.

As the residual plots show, that the distribution of estimates clearly depends on groups of the initial labor supplies. The quintile-specific intercepts make these differences even more obvious, as visible in figure D.2. Individuals with very low (or very high) working hours, will have an extremely large range (or very small range) to increase their labor supply. This results in potential outliers, whose elasticity values distort the mean elasticities across the groups they are more prominently present in. This way, when discussing a group having a larger (or smaller) mean elasticity than others, it is possibly caused by such people.

Another interesting result is the fifth quintile, the subset of the population working high hours initially. These people even decrease their working hours after the wage increase. It is likely, that in the case of these people, their spouses will increase their labor supply, and negative elasticities are a result of the pooled income (and discrete choice set) of couples.

Chapter 7

Conclusion

Mastrogiacomo et al. find that marital status makes a rather significant impact on the difference between men and women's labor supply elasticities in the Netherlands. Elasticities of single men and women are quite similar, but men in couples have much smaller elasticities than women in couples.

Regarding parental status, households with children are almost twice as responsive as households without children. Single parents have the highest elasticity, and particularly those with children in the preschool age. Households with the youngest child in the group of 12 to 17 year old's are the least elastic.

In all groups, elasticities are higher for lower educated individuals, and elasticities are monotonically decreasing in wage rate, except for female partners with children whose elasticity is the highest in the fourth wage quartile.

Lastly, responsiveness along the extensive margin dominates the intensive margin elasticities across all groups.

The results from LOTTE-Arbeid also reflect an impact of marital status on the difference between men's and women's labor supply elasticities. The difference between the sexes is larger in the group of couples compared with the group of singles, a result which resembles the Dutch.

In contrast to the Dutch results, parental status does not seem to have a particularly large effect on labor supply responsiveness of the Norwegian households, and the effect is opposite in the group of singles compared with the effect on couples.

Having children seems to increase the responsiveness of singles, whereas the effect is reversed on couples.

Norwegian singles are the most responsive when their youngest child is below 7 years old's. Couples whose youngest child is in this group are less responsive than couples who have older children.

Singles with lower education respond more to changes in wage rate than singles with higher education. The findings on couples are opposite, except in the group of mothers which share similar results to those of singles.

The effect of wage rates on the Norwegian elasticities is less univocal than it is in the Netherlands. Like the Dutch results, elasticities are monotonically decreasing in wage among Norwegian singles, except for the slight increase from the third to the fourth quartile of non-parents. However, the results on couples are quite different.

Individuals in couples are the most responsive in the fourth wage quartile. Females' elasticity seems to have a U-shaped relationship with wage rates, while elasticities of males show increasing tendencies going from first to fourth wage quartile.

Singles without children become more responsive with age. Parents in the same group are the most responsive in the youngest age group, and the relationship between elasticity and age follows a U-shape. Except for male partners without children, individuals in couples also become more elastic the older they get. The former group is the most elastic in the third age tercile, and the least in the first tercile.

Finally, the extensive margin elasticity dominates the intensive in the group of single females, although the difference is not large. In the group of females in couples, the intensive elasticity dominates the extensive, and quite substantially.

With regressions, I aimed to show which variables are good estimators of elasticity, and which ones require the interaction of other variables for significant effect. When creating tables, only a handful of variables are taken into account to show their effect. OLS enables the parallel comparison of these effects. The signs of the coefficients can be interpreted as an overall decreasing or increasing average effect across a given variable.

Perhaps the greatest concern with estimations for labor supply is the lack of knowledge about the reason why an individual chooses to work less or more. The workers with lower working hours are potential outliers in estimated elasticities, as they have more room to increase their labor supply, while people who work more than 60 hours per week will be deterministically inelastic.

Another critique of this method is the use of utility functions and trying to account for neo-classical optimization theory, even though this results in the addition of many arbitrary decisions by the researchers. Utility maximization is a vague concept, and certainly unrealistic in many ways. Instead, a model could rely on purely the earnings and change in earnings of individuals, from which labor elasticities can be calculated by disintegrating earnings into labor supply.

The analysis is flawed to conclude causality, as the dependent variable itself is the outcome of a complex simulation relying on some of the data. However, the models show how elasticities depend heterogeneously on financial status.

Finally, a somewhat missing component of the results is to what extent are outliers present in the individual groups, as presented in the tables of chapter 4. As shown, the individuals with lower working hours can be very sensitive to changes in their own wage, which results in people who work up to 40% more.

The distribution of individuals with potentially outlier-like high elasticity values distort the grouped means asymmetrically. Perhaps, policies should also take into account the initial working hours of individuals, carefully paying attention not to overburden them, but incentivizing a full workload for everyone.

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Appendix A

Omitted Tables

Table A.1: Mean Labor Supply Elasticities of Selected Groups of Singles

Variables	Without children	With children
All	0.13 (3.44)	0.17 (1.59)
Female	0.21 (1.62)	0.21 (1.31)
Male	0.05 (12.12)	0.03 (5.32)
Lower education	0.15 (2.00)	0.20 (1.34)
Higher education	0.11 (5.66)	0.12 (2.11)
First wage quartile	0.26 (1.40)	0.29 (0.95)
Second wage quartile	0.12 (2.95)	0.17 (1.24)
Third wage quartile	0.07 (4.13)	0.11 (1.89)
Fourth wage quartile	0.09 (7.96)	0.10 (3.20)
First age tercile	0.09 (3.87)	0.19 (1.39)
Second age tercile	0.13 (4.82)	0.15 (1.41)
Third age tercile	0.19 (1.89)	0.16 (1.97)
Youngest child 0-7	-	0.21 (1.56)
Youngest child 8-17	-	0.15 (1.54)

The numbers inside the parentheses represent coefficients of variation.

Table A.2: Mean Labor Supply Elasticities of Individuals in Couples

	Without children		With children	
Variables	Female	Male	Female	Male
All	0.64 (2.13)	0.28 (4.54)	0.52 (1.76)	0.20 (4.16)
Lower education	0.63 (1.53)	0.25 (3.60)	0.55 (1.66)	0.16 (5.75)
Higher education	0.65 (2.65)	0.33 (5.13)	0.51 (1.83)	0.23 (3.35)
First wage quartile	0.67 (0.97)	0.21 (1.31)	0.52 (1.74)	0.15 (4.93)
Second wage quartile	0.56 (2.14)	0.28 (4.47)	0.50 (1.48)	0.17 (3.42)
Third wage quartile	0.56 (1.00)	0.27 (3.50)	0.50 (2.02)	0.22 (4.81)
Fourth wage quartile	0.78 (2.96)	0.37 (5.47)	0.56 (1.76)	0.27 (3.31)
First age tercile	0.42 (1.04)	0.17 (2.48)	0.45 (2.15)	0.15 (5.32)
Second age tercile	0.73 (2.63)	0.37 (4.21)	0.49 (1.71)	0.21 (4.43)
Third age tercile	0.80 (1.65)	0.32 (4.94)	0.62 (1.48)	0.25 (2.89)
Youngest child 0-7	-	-	0.48 (1.87)	0.18 (4.85)
Youngest child 8-17	-	-	0.54 (1.70)	0.22 (3.79)

The numbers inside the parentheses represent coefficients of variation.

Table A.3: Extensive Intensive Elasticities of Selected Groups of Females

	Singles				Couples			
	Without children		With children		Without children		With children	
Variables	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive
All	0.12 (1.50)	0.09 (2.89)	0.11 (1.55)	0.10 (1.70)	0.13 (0.85)	0.51 (2.67)	0.12 (0.83)	0.40 (2.25)
Lower education	0.19 (1.13)	0.10 (0.70)	0.16 (1.22)	0.10 (0.68)	0.16 (0.69)	0.48 (2.03)	0.15 (0.71)	0.40 (2.27)
Higher education	0.04 (2.25)	0.09 (4.23)	0.05 (1.82)	0.09 (2.68)	0.11 (0.88)	0.54 (3.19)	0.11 (0.92)	0.40 (2.28)
First wage quartile	0.21 (1.08)	0.10 (0.74)	0.20 (1.10)	0.11 (0.66)	0.18 (0.66)	0.49 (1.33)	0.15 (0.68)	0.36 (2.45)
Second wage quartile	0.13 (1.40)	0.10 (3.14)	0.14 (1.29)	0.09 (0.69)	0.13 (0.69)	0.43 (2.78)	0.11 (0.81)	0.39 (1.88)
Third wage quartile	0.07 (1.97)	0.09 (4.06)	0.06 (1.83)	0.08 (0.67)	0.12 (0.83)	0.44 (1.16)	0.11 (0.88)	0.39 (2.56)
Fourth wage quartile	0.05 (1.84)	0.09 (1.96)	0.05 (1.82)	0.11 (3.06)	0.11 (0.88)	0.66 (3.47)	0.11 (1.05)	0.45 (2.14)
First age tercile	0.07 (2.23)	0.09 (4.57)	0.13 (1.39)	0.09 (0.71)	0.10 (0.82)	0.31 (1.27)	0.12 (0.77)	0.33 (2.88)
Second age tercile	0.12 (1.50)	0.08 (0.77)	0.10 (1.60)	0.08 (0.69)	0.14 (0.74)	0.59 (3.24)	0.12 (0.90)	0.37 (2.19)
Third age tercile	0.17 (1.17)	0.11 (1.16)	0.11 (1.54)	0.11 (2.59)	0.17 (0.72)	0.63 (2.08)	0.13 (0.88)	0.49 (1.84)
Youngest child 0-7	-	-	0.14 (1.28)	0.11 (2.17)	-	-	0.12 (0.80)	0.35 (2.49)
Youngest child 8-17	-	-	0.10 (1.62)	0.09 (1.40)	-	-	0.12 (0.89)	0.42 (2.14)

The numbers inside the parentheses represent coefficients of variation.

Table A.4: Labor Supply Elasticities of Single Men and Women

	Without children		With children	
	Female	Male	Female	Male
All	0.21 (1.62)	0.05 (12.12)	0.21 (1.31)	0.03 (5.32)
Lower education	0.29 (0.97)	0.03 (10.89)	0.26 (1.01)	0.03 (6.37)
Higher education	0.13 (3.06)	0.08 (10.25)	0.14 (1.93)	0.04 (3.56)
First wage quartile	0.32 (0.96)	0.04 (11.48)	0.30 (0.94)	0.02 (0.67)
Second wage quartile	0.23 (1.67)	0.02 (4.08)	0.23 (1.03)	0.05 (6.04)
Third wage quartile	0.16 (2.55)	0.02 (4.28)	0.14 (1.19)	0.02 (0.46)
Fourth wage quartile	0.14 (1.56)	0.10 (9.67)	0.16 (2.17)	0.04 (3.50)
First age tercile	0.16 (2.88)	0.03 (5.73)	0.22 (1.09)	0.04 (6.35)
Second age tercile	0.20 (1.16)	0.07 (12.5)	0.18 (1.17)	0.03 (4.15)
Third age tercile	0.29 (1.00)	0.04 (9.60)	0.22 (1.60)	0.03 (0.64)
Youngest child 0-7	-	-	0.25 (1.31)	0.06 (5.64)
Youngest child 8-17	-	-	0.19 (1.28)	0.03 (3.51)

The numbers inside the parentheses represent coefficients of variation.

Table A.5: Pearson Correlation

	Elasticity	Sex	Couple	Parent	Education	Wage	Age	Child 0-7	Child 8-17
Elasticity	1.00								
Sex	-0.14	1.00							
Couple	0.14	0.07	1.00						
Parent	0.03	-0.03	0.42	1.00					
Education	0.01	-0.04	0.16	0.17	1.00				
Wage	-0.04	0.59	0.28	0.13	0.62	1.00			
Age	0.09	0.05	0.20	-0.23	-0.09	0.26	1.00		
Child 0-7	-0.01	0.01	0.24	0.50	0.11	-0.01	-0.37	1.00	
Child 8-17	-0.02	0.03	0.35	0.83	0.11	0.15	-0.05	0.11	1.00

Table A.6: Summary Statistics for Selected Variables

Variable	Mean	St. Dev	Min	Max
Elasticity	0.30	0.90	-1.36	39.96
Extensive elasticity	0.12	0.14	-0.20	0.63
Intensive elasticity	0.29	0.86	-1.36	39.83
Marital status	0.60	0.49	0	1
Parental status	0.44	0.50	0	1
Sex	0.47	0.50	0	1
Education	13.44	2.98	6	19
Wage rate	294.78	55.14	166.98	517.31
Age	45.27	10.05	26	62
No. of kids 0-7	0.23	0.57	0	5
No. of kids 8-17	0.57	0.88	0	5
Labor income	746,370.60	1,818,876	0	0
Disposable income	1,023,975	3,673,164	0	0
Labor supply	32.47	7.62	0	74.02

Income variables in million NOK.

Table A.7: Spearman Correlation

	Elasticity	Sex	Couple	Parent	Education	Wage	Age	Child 0-7	Child 8-17
Elasticity	1.00								
Sex	-0.44	1.00							
Couple	0.56	0.07	1.00						
Parent	0.22	-0.03	0.42	1.00					
Education	0.04	-0.03	0.16	0.17	1.00				
Wage	-0.13	0.59	0.27	0.13	0.62	1.00			
Age	0.23	0.05	0.18	-0.27	-0.10	0.24	1.00		
Child 0-7	0.12	-0.01	0.24	0.50	0.12	-0.01	-0.39	1.00	
Child 8-17	0.19	-0.02	0.35	0.83	0.11	0.15	-0.09	0.11	1.00

Table A.8: Mean of Selected Variables for Couples Across Elasticity Deciles

Elasticity deciles		Y. kids	O. kids	Sex	L. Supp	$\Delta Wage$	P's inc.	Wage	Inc.
1	-1.36 - 0.01	0.19	0.53	0.5	36.35	5.97	1,365,463	328.36	1,565,861
		(2.06)	(0.96)	(1.01)	(0.31)	(16.69)	(1.82)	(0.16)	(2.18)
2	0.02 - 0.04	0.12	0.53	0.65	37.97	-14.11	666,871	321.89	1,799,644
		(2.82)	(0.97)	(0.76)	(0.04)	(-4.34)	(0.74)	(0.11)	(1.97)
3	0.04 - 0.05	0.41	0.72	0.9	38.52	-35.19	573,727	303.69	1,407,265
		(1.21)	(0.63)	(0.35)	(0.04)	(-1.72)	(1.08)	(0.16)	(2.02)
4	0.05 - 0.08	0.4	0.57	0.99	37.93	-48.65	488,881	315.04	866,432
		(1.23)	(0.86)	(0.07)	(0.01)	(-1.22)	(1.35)	(0.1)	(2.05)
5	0.08 - 0.09	0.22	0.48	1.00	38.00	-68.77	511,915	351.95	1,048,819
		(1.88)	(1.04)	(0.06)	(0.03)	(-1.04)	(1.23)	(0.12)	(2.03)
6	0.09 - 0.18	0.14	0.44	0.62	36.3	-28.44	749,835	336.95	1,275,368
		(2.49)	(1.13)	(0.78)	(0.04)	(-3.37)	(2.59)	(0.17)	(2.28)
7	0.18 - 0.25	0.26	0.54	0.09	33.4	65.91	1,021,450	281.62	677,050
		(1.69)	(0.92)	(3.28)	(0.03)	(1.14)	(2.09)	(0.14)	(2.03)
8	0.25 - 0.40	0.32	0.48	0.16	31.56	69.21	1,028,321	271.62	758,282
		(1.45)	(1.03)	(2.31)	(0.05)	(1.37)	(2.00)	(0.2)	(3.05)
9	0.40 - 0.65	0.2	0.48	0.42	28.63	21.15	1,015,519	301.13	879,989
		(2.03)	(1.04)	(1.19)	(0.08)	(5.05)	(2.48)	(0.22)	(1.76)
10	0.65 - 39.96	0.15	0.4	0.19	17.73	69.55	1,645,530	283.73	706,173
		(2.39)	(1.24)	(2.09)	(0.39)	(1.35)	(1.91)	(0.16)	(1.99)
	Total	0.24	0.49	0.5	32.33	10	914,368	307.18	900,477
		(1.78)	(1.03)	(1.00)	(0.23)	(10.25)	(2.24)	(0.18)	(2.28)

The numbers inside the parentheses represent coefficients in variation.

Young kids denote having children below the age of 7, Old kids similarly, children 8-17.

Δ wage is the difference in hourly wage between partners in NOK. Sex takes the value of 1 for males.

Labor supply is the hours spent with work in a week. Hourly wage and annual income in NOK.

Appendix B

Results from Mastrogiacomo et al. (2017a)

Labour supply elasticities: singles without and with children

	Singles without children			*Singles parents*		
	Total	*Extensive*	*Intensive*	*Total*	*Extensive*	*Intensive*
All	0.35	0.27	0.08	0.61	0.43	0.18
Male	0.32	0.24	0.08	0.46	0.33	0.13
Female	0.38	0.29	0.09	0.63	0.44	0.18
Lower educated	0.73	0.60	0.13	0.98	0.71	0.25
Higher educated	0.25	0.17	0.07	0.48	0.32	0.15
Native	0.32	0.23	0.08	0.56	0.38	0.17
Immigrant	0.56	0.47	0.09	0.78	0.58	0.20
First wage quartile	0.67	0.52	0.14	1.05	0.76	0.27
Second wage quartile	0.42	0.33	0.09	0.87	0.62	0.24
Third wage quartile	0.26	0.19	0.07	0.55	0.36	0.19
Fourth wage quartile	0.16	0.11	0.05	0.41	0.28	0.12
Age 20–28	0.43	0.32	0.11	1.01	0.74	0.26
Age 29–40	0.27	0.20	0.07	0.70	0.49	0.20
Age 41–57	0.35	0.27	0.07	0.52	0.36	0.16
Youngest child 0–3	–	–	–	1.03	0.84	0.18
Youngest child 4–11	–	–	–	0.63	0.43	0.18
Youngest child 12–17	–	–	–	0.51	0.33	0.17

Figure B.1: Results from Mastrogiacomo et al. (2017a)
Table includes mean elasticities for different subgroups.

Labour supply elasticities couples without children

	Male own			*Female cross*			*Female own*			*Male cross*		
	Total	*Ext.*	*Int.*	*Total*	*Ext.*	*Int.*	*Total*	*Ext.*	*Int.*	*Total*	*Ext.*	*Int.*
All	0.07	0.07	0.00	−0.03	−0.01	−0.02	0.25	0.21	0.05	−0.03	−0.01	−0.02
Lower educated	0.10	0.10	0.00	0.03	0.05	−0.02	0.41	0.35	0.05	0.00	0.01	−0.01
Higher educated	0.06	0.06	0.00	−0.04	−0.02	−0.02	0.22	0.16	0.05	−0.04	−0.02	−0.02
Native	0.06	0.06	0.00	−0.03	−0.01	−0.02	0.25	0.20	0.05	−0.03	−0.01	−0.02
Immigrant	0.18	0.19	0.00	0.03	0.04	−0.02	0.27	0.22	0.05	−0.03	−0.01	−0.01
First wage quartile	0.08	0.08	0.00	0.01	0.02	−0.01	0.25	0.21	0.04	−0.01	0.00	−0.01
Second wage quartile	0.07	0.07	0.00	−0.01	0.00	−0.02	0.24	0.18	0.05	−0.03	−0.01	−0.02
Third wage quartile	0.07	0.07	0.00	−0.03	−0.01	−0.02	0.24	0.19	0.05	−0.04	−0.02	−0.02
Fourth wage quartile	0.06	0.06	0.00	−0.07	−0.04	−0.03	0.29	0.23	0.06	−0.03	−0.02	−0.02
Age 20–28	0.04	0.04	0.00	0.00	0.01	−0.01	0.11	0.06	0.05	−0.04	−0.02	−0.02
Age 29–40	0.05	0.05	0.00	−0.02	0.00	−0.02	0.14	0.08	0.06	−0.06	−0.04	−0.02
Age 41–57	0.08	0.08	0.00	−0.04	−0.02	−0.03	0.40	0.33	0.07	−0.01	0.00	−0.01

Figure B.2: Results from Mastrogiacomo et al. (2017a) 1

Table includes mean elasticities for different subgroups.

Labour supply elasticities couples with children

	Male own			*Female cross*			*Female own*			*Male cross*		
	Total	*Ext.*	*Int.*	*Total*	*Ext.*	*Int.*	*Total*	*Ext.*	*Int.*	*Total*	*Ext.*	*Int.*
All	0.13	0.13	0.00	−0.18	−0.12	−0.06	0.44	0.34	0.10	−0.02	0.00	−0.02
Lower educated	0.25	0.24	0.01	−0.13	−0.07	−0.06	0.65	0.53	0.11	0.02	0.03	−0.01
Higher educated	0.11	0.11	0.00	−0.19	−0.13	−0.06	0.39	0.30	0.10	−0.04	−0.02	−0.02
Native	0.09	0.08	0.00	−0.20	−0.14	−0.06	0.40	0.30	0.09	−0.03	−0.01	−0.02
Immigrant	0.42	0.42	0.00	−0.08	−0.03	−0.05	0.57	0.45	0.11	−0.01	0.01	−0.02
First wage quartile	0.21	0.21	0.00	−0.15	−0.10	−0.06	0.57	0.45	0.11	0.01	0.02	−0.02
Second wage quartile	0.13	0.13	0.00	−0.16	−0.10	−0.05	0.43	0.33	0.10	−0.02	0.00	−0.02
Third wage quartile	0.11	0.11	0.00	−0.19	−0.13	−0.06	0.41	0.32	0.09	−0.04	−0.01	−0.02
Fourth wage quartile	0.09	0.09	0.00	−0.21	−0.15	−0.06	0.37	0.28	0.09	−0.04	−0.02	−0.02
Age 20–28	0.17	0.16	0.01	−0.22	−0.15	−0.07	0.51	0.40	0.11	0.01	0.02	−0.01
Age 29–40	0.14	0.14	0.00	−0.18	−0.12	−0.06	0.44	0.34	0.10	−0.03	−0.01	−0.02
Age 41–57	0.12	0.12	0.00	−0.18	−0.12	−0.06	0.42	0.32	0.09	−0.03	−0.01	−0.02
Youngest child 0–3	0.15	0.14	0.00	−0.20	−0.14	−0.06	0.43	0.33	0.10	−0.03	−0.01	−0.02
Youngest child 4–11	0.15	0.15	0.00	−0.16	−0.11	−0.05	0.46	0.36	0.10	−0.02	0.00	−0.02
Youngest child 12–17	0.10	0.10	0.00	−0.18	−0.13	−0.05	0.41	0.31	0.09	−0.02	0.00	−0.02

Figure B.3: Results from Mastrogiacomo et al. (2017a) 2

Table includes mean elasticities for different subgroups.

Appendix C

Omitted Models

Table C.1: Extension With Polynomial Terms

Elasticity	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
marital status	0.2458	0.02	14.25	0.00	0.21	0.28
parental status	-0.0052	0.02	-0.30	0.76	-0.04	0.03
sex	-0.1661	0.02	-6.91	0.00	-0.21	-0.12
education	0.0084	0.02	0.37	0.71	-0.04	0.05
age	-0.1356	0.07	-1.91	0.06	-0.27	0.00
age^2	0.0209	0.01	2.66	0.01	0.01	0.04
$ln(wage)$	0.1391	0.09	1.60	0.11	-0.03	0.31
$ln(income)$	-0.026	0.00	-13.54	0.00	-0.03	-0.02
$\Delta wage$	0.6273	0.11	5.72	0.00	0.41	0.84
$partner's\ income$	0.0332	0.01	4.53	0.00	0.02	0.05
$partner's\ income^2$	-0.0009	0.00	-4.10	0.00	0.00	0.00
constant	-0.1066	0.43	-0.25	0.80	-0.94	0.73

R^2 = 0.0604. In marital status, parental status, education and sex, the value of 1 denotes being married, having at least one child, having at least 13 years of education, and being male respectively. Partner's income is in 1 million NOK, partner's income squared in 1 trillion NOK. Δwage is the difference between the partner's and the individual's hourly wage in thousand NOKs.

Table C.2: Interactions Between Financial and Non-Financial Variables

Elasticity	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
marital status	0.2281	0.02	12.13	0.00	0.19	0.27
age	-0.1502	0.07	-2.12	0.03	-0.29	-0.01
age^2	0.0223	0.01	2.82	0.01	0.01	0.04
$ln(wage)$	0.1271	0.09	1.46	0.15	-0.04	0.3
$\Delta wage$	0.5167	0.11	4.53	0.00	0.29	0.74
sex	-0.7124	0.12	-5.97	0.00	-0.95	-0.48
education	-0.0468	0.05	-0.89	0.38	-0.15	0.06
$ln(income)$	-0.0302	0.00	-12.88	0.00	-0.03	-0.03
$partner's\ income$	0.1388	0.02	6.43	0.00	0.1	0.18
$partner's\ income^2$	-0.0059	0.00	-5.73	0.00	-0.01	0.00
$sex \times ln(income)$	0.0434	0.01	4.88	0.00	0.03	0.06
$sex \times pinc$	-0.1198	0.03	-3.68	0.00	-0.18	-0.06
$sex \times pinc^2$	0.0081	0.00	1.88	0.06	0.00	0.02
$education \times ln(income)$	0.0062	0.00	1.64	0.10	0.00	0.01
$education \times pinc$	-0.0702	0.02	-3.28	0.00	-0.11	-0.03
$education \times pinc^2$	0.0028	0.00	2.56	0.01	0.00	0.01
parental status	0.0115	0.02	0.61	0.54	-0.03	0.05
$parent \times pinc$	-0.0342	0.02	-2.02	0.04	-0.07	0.00
$parent \times pinc^2$	0.0024	0.00	43160	0.00	0.00	0.00
constant	0.0198	0.43	0.05	0.96	-0.82	0.86

R^2 = 0.0636. In marital status, parental status, education and sex, the value of 1 denotes being married, having at least one child, having at least 13 years of education, and being male respectively. Partner's income is in 1 million NOK, partner's income squared in 1 trillion NOK. Δwage is the difference between the partner's and the individual's hourly wage in thousand NOKs.

Table C.3: Complex Interactions Between Non-Financial Variables

Elasticity	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age	-0.1745	0.07	-2.46	0.01	-0.31	-0.04
age^2	0.0253	0.01	3.19	0.00	0.01	0.04
$ln(wage)$	0.1191	0.09	1.37	0.17	-0.05	0.29
$\Delta wage$	0.2900	0.13	2.21	0.03	0.03	0.55
sex	-0.6981	0.12	-5.8	0.00	-0.93	-0.46
$ln(income)$	-0.0275	0.00	-13.86	0.00	-0.03	-0.02
$sex \times ln(income)$	0.0431	0.01	4.77	0.00	0.03	0.06
$parental\ status$	0.0073	0.02	0.38	0.70	-0.03	0.04
$education$	-0.0709	0.03	-2.09	0.04	-0.14	0.00
$partner's\ income$	0.1491	0.02	6.49	0.00	0.10	0.19
$partner's\ income^2$	-0.0063	0.00	-5.88	0.00	-0.01	0.00
$parent \times pinc$	-24.3557	17.03	-1.43	0.15	-57.73	9.02
$parent \times pinc^2$	0.0017	0.00	2.30	0.02	0.00	0.00
$education \times pinc$	-0.1046	0.03	-4.15	0.00	-0.15	-0.06
$education \times pinc^2$	0.0041	0.00	3.38	0.00	0.00	0.01
$marital\ status$	0.2208	0.03	6.45	0.00	0.15	0.29
$marital \times education$	0.1464	0.04	3.38	0.00	0.06	0.23
$marital \times sex$	-0.1301	0.04	-3.1	0.00	-0.21	-0.05
$education \times sex$	0.0987	0.04	2.25	0.03	0.01	0.18
$marital \times edu. \times sex$	-0.0873	0.06	-1.54	0.12	-0.20	0.02
$constant$	0.1056	0.43	0.25	0.81	-0.73	0.94

$R^2 = 0.0653$. In marital status, parental status, education and sex, the value of 1 denotes being married, having at least one child, having at least 13 years of education, and being male respectively. Partner's income is in 1 million NOK, partner's income squared in 1 trillion NOK. Δwage is the difference between the partner's and the individual's hourly wage in thousand NOKs.

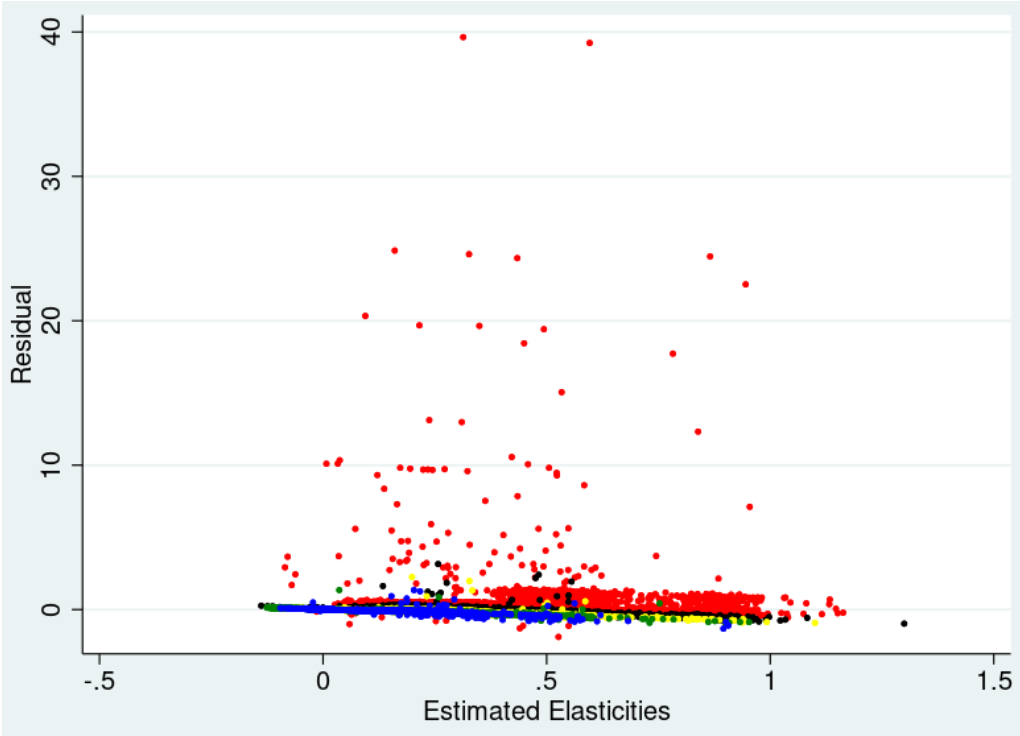

Figure D.1: Residual Plot of Baseline Model

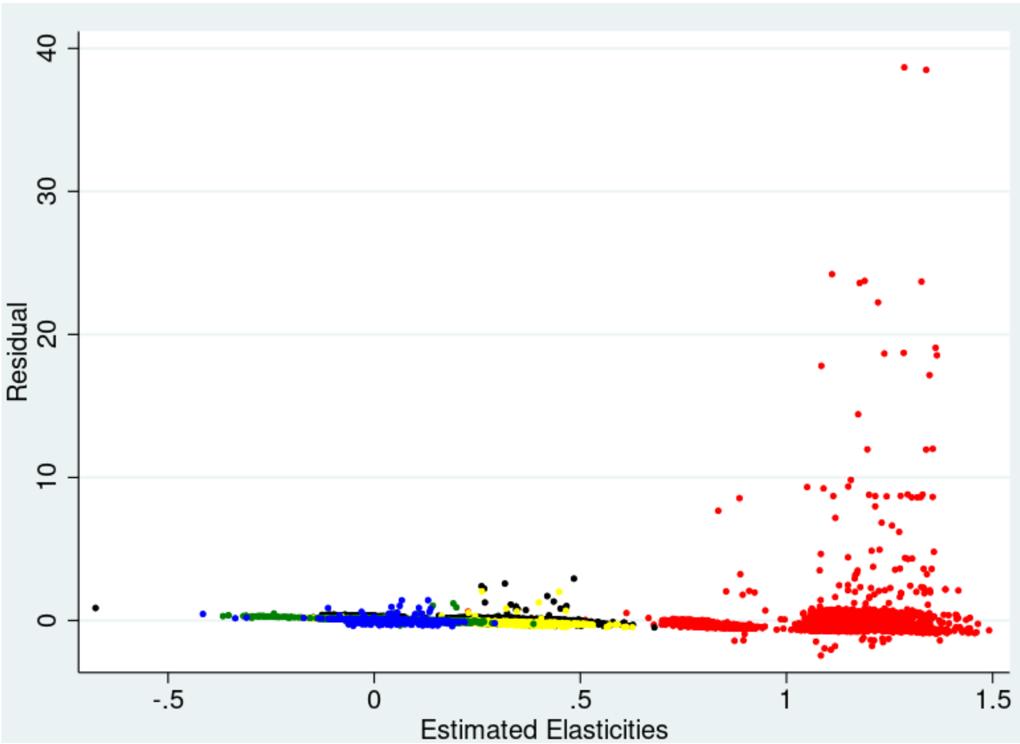

Figure D.2: Residual Plot of the Model With Quintile Specific Intercepts
Red dots denote observations from the first pre-policy labor supply quintile, black from second, yellow from third, blue from fourth, green from fifth.