A Welfare Analysis of the Negative Income Tax with Nonlinear Labor Supply Estimation*

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Abstract

This paper conducts a social welfare analysis of the negative income tax (NIT), explicitly allowing for nonlinear labor supply responses with respect to the take-back rate, i.e., the rate at which NIT transfer payments are reduced per additional dollar of income. We derive a theoretical model which yields a notion of social welfare as function of the take-back rate that we calibrate using data from two NIT experiments that were conducted in the US in the 1970s. We find (i) that both the theoretical model and the empirical estimates suggest that the labor supply with respect to the take-back rate is nonlinear; (ii) that the social welfare optimizing take-back rates strongly differ between models calibrated with nonlinear versus linear labor supply functions; and (iii) that the welfare optimizing take-back rate lies between 65% and 69% for most tested parameterizations. However, due to poor data quality, the validity of the empirical findings is limited.

Keywords: Negative income tax, social welfare, nonlinear labor supply
JEL classification: H21, I30, J20, J30

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1. Introduction

Standard social welfare analysis often uses a single parameter, typically an elasticity, to quantify key behavioral responses to policy changes. This "sufficient statistics approach" (Chetty, 2009), however, may produce results that strongly differ from approaches that explicitly allow for variation in elasticities across different policy levels. A striking example is provided by Kasy (2018), who analyzes optimal coinsurance rates for health insurance using data from the RAND health insurance experiment. Allowing for arbitrary variation in health care expenditure elasticities across different coinsurance rates, he finds a welfare maximizing coinsurance rate of 18%, whereas the sufficient statistics approach yields an optimal rate of 50%.

In this paper, we use a similar approach to that of Kasy (2018) to analyze the negative income tax (NIT), a transfer scheme that aims at reducing poverty. The NIT provides families without any income with a transfer equal to the guaranteed income level G. The NIT transfer, however, linearly declines in family income at the take-back rate t up until a break-even point where the transfer becomes zero (see, e.g., Saez, 2002). In our analysis, we focus on the role of t to answer the research question: which level of t is social welfare maximizing? To this end, we first theoretically derive a notion of social welfare that takes into account the families' allocation decision regarding their disposable time which can either be used for work (which earns labor income that is used for consumption, but also reduces the NIT transfer) or leisure. Our notion of social welfare describes the trade-off between the policy maker's two objectives that both depend on the magnitude of the take-back rate t: (i) maximizing private utility, which is achieved by reducing t, i.e., all other things equal, increasing the NIT transfer, and (ii) minimizing government spending for the NIT, which is achieved by increasing t, assuming all other things equal. The key behavioral relationship in our model is the one between t and the labor supply, as a marginal increase in t induces a decrease in labor supply, which in turn diminishes the mechanical savings effect regarding the transfers. Unlike previous theoretical analyses of the NIT (see, e.g., Saez, 2002), we do not rely on the aforementioned sufficient statistics approach that summarizes key behavioral relationships using a single elasticity parameter. Instead, we derive simple expressions of the labor supply and social welfare that are functions of t. In a next step, we empirically estimate the labor supply function using data from two NIT experiments that were conducted in the US in the 1970s. In these experiments, treated families were assigned to different NIT plans, i.e., different combinations of G and t. Controlling for G and a number of family-specific controls, we find that families assigned to higher take-back rates supply less labor in terms of hours worked, as predicted by our theoretical model. Furthermore, also in line with the theory model, the empirical labor supply function is concave for most of the observed range of t. However, considering the full available range of t, this result does not hold. Finally, we plug the estimated labor supply function into our notion of social welfare. For most of the tested parameterizations, our findings suggest that the welfare optimizing take-back rate is quite large, lying between approximately 65% and 69%. However, due to poor data quality of the NIT experiment data, the validity of these empirical findings is limited. Furthermore, we find that the social welfare optimizing take-back rates strongly differ depending on whether we allow for nonlinearities in the labor supply estimation or not.

Besides the aforementioned contribution to the theoretical literature regarding the welfare analysis of the NIT, we add to two strands of the empirical literature. First, we contribute to the large body of studies estimating labor supply responses to government-run transfer programs. Regarding the NIT experiments, a comprehensive list of studies is provided by Widerquist (2005), who summarizes previous labor supply response estimates as being varying in size.[1] Most of the previous estimations using the NIT experiment data regress labor supply on changes in the net wage rate that are induced by the introduction of the

[1]The lack of an agreed acceptable level of work-disincentive also had effects on the policy debate surrounding the NIT in the US (Widerquist, 2005). In the end, the NIT was not introduced. Instead, the US opted for the Earned Income Tax Credit regime, which, up to a certain threshold, matches each dollar of earned income with a certain transfer, but pays nothing in the case of zero income (Saez, 2002). As pointed out by Saez (2002), however, many transfer programs in European countries work like the NIT.

NIT, often distinguishing different subgroups, such as husbands, wives, or single female heads (Robins, 1985). In contrast, our estimation approach of the labor supply response focuses on the direct effects of different levels of the take-back rate on aggregated family labor supply. The evaluation of labor supply responses also plays a large role in the context of randomized control trials (RCTs) that provide targeted transfers. A recent example is Verho et al. (2022) who study the work-disincentive effect of participants in an RCT conducted in Finland that replaced minimum unemployment benefits with an unconditional income of the same size. They find that the days in employment did not statistically change during the first year. Banerjee et al. (2017) provide a comprehensive re-evaluation of data from seven RCTs of cash transfers in six developing countries. They do not find systematic evidence of a work-discouragement effect. Second, we add to the growing literature in public finance that estimates behavioral effects for different levels of policy variables rather than relying on a single aggregating estimate. Besides the aforementioned study by Kasy (2018), a recent example can be found in Fuest et al. (2022) who study the profit shifting behavior of multinational firms. They show that profit elasticities depend nonlinearly on the magnitude of countries' tax rates and argue that taking these nonlinearities into account is key for obtaining accurate profit shifting estimates.

The remainder of the paper is structured as follows. Section 2 theoretically derives our notion of social welfare. Section 3 describes the estimation strategy as well as the data. The results of our empirical labor supply and social welfare estimations are presented in Section 4. Finally, Section 5 concludes.

2. Theory

2.1. Household Optimization Problem

We start out by describing the decision problem of the family that is subject to the NIT. The theory builds on standard intensive labor supply models in the context of income taxation as discussed in, e.g., Hausman (1985) or Keuschnigg and Wamser (2024).[2] The key decision that the family has to make is the one concerning the allocation of the available time $T > 0$ between hours worked $L \in (0, T)$, that are compensated at the wage rate $w > 0$,[3] and hours used for leisure F. Hence, leisure is given by $F = T - L$. The opportunity cost of leisure is the labor income that could have been earned instead. The total income of the family states as follows:

$$Y = wL + I + S + P = wL + I + S + \max\{G - t(wL + I) - S,\ 0\}. \tag{1}$$

The labor income is given by wL. $I \geq 0$ denotes unearned income, such as interest, dividends, or capital gains. $S \geq 0$ gives the total public assistance that the family receives, including, e.g., Aid to Families with Dependent Children (AFDC). We treat both I and S as exogeneously given. Finally, $P = \max\{G - t(wL + I) - S,\ 0\}$ denotes the NIT payment, with $G > 0$ denoting the guaranteed income level and $t \in (0, 1)$ denoting the take-back rate. Note that while labor income and unearned income are taxed at t, the welfare income S is taxed at 100%, which means that the NIT payment effectively replaced the multitude of different welfare programs during the US experiments (Mathematica Policy Research, Inc. [MPR], 1980). For the remainder of this section, we assume that the family receives some strictly positive NIT payment P in the optimum, i.e., $G > t(wL + I) + S$.[4] Furthermore, we set unearned income to zero, i.e., $I = 0$. This assumption is plausible in the context of the US NIT experiments of the 1970s that we use for our empirical analysis below, as the samples consist of poor families with no or negligibly small unearned income.[5] Finally, we introduce the "keep-rate" k, which we define as $1 - t$. The use of the keep-rate rather than the take-back rate is solely due to practical reasons regarding the formulation of the social

[2] Note that the model is kept simple, as the goal is to obtain a notion of social welfare function that can be directly estimated and that allows for nonlinearities in the labor supply. For a more rigorous theoretical analysis of the NIT, see Aboudi et al. (2014) or Saez (2002).

[3] We assume that families are price takers and take the wage rate as given.

[4] We further assume that also after marginal changes in exogenous model parameters, in particular changes in t, the family still receives some strictly positive NIT transfer.

[5] See descriptive statistics below in Section 3.2 or Widerquist (2005).

welfare function. The budget constraint in (1) then simplifies to

$$Y = G + kwL. \tag{2}$$

It is important to note that since our model is static and therefore does not allow for savings, consumption equals total income Y. Given that the NIT is a policy instrument that is designed to target low-income households and given that the transfers from the NIT experiment typically do not raise families' disposable incomes much above the poverty line (see, e.g., discussion of the NIT experiments that were conducted in the US in the 1970s below), this assumption seems plausible. Finally, we assume that the family's preferences for consumption Y and leisure F are captured by the Cobb–Douglas utility function

$$U(Y, F) = U(Y, T - L) = Y^{\alpha}(T - L)^{1-\alpha}. \tag{3}$$

α and $1 - \alpha$ are the utility elasticities of consumption and leisure, respectively, which we take as given, with $\alpha \in (0, 1)$.[6] We proceed to formulate the utility maximization problem of the household (with λ denoting the Lagrange multiplier and $V(\cdot)$ denoting the indirect utility function):

$$V(k, w, \alpha, T, G) = \max_{Y,L} \left[Y^{\alpha}(T - L)^{1-\alpha} + \lambda(G + kwL - Y) \right]. \tag{4}$$

Solving the first-order conditions corresponding to (4), we obtain the Marshallian labor supply:

$$L^* = L(k, w, \alpha, T, G) = \alpha T - \frac{G(1 - \alpha)}{kw}. \tag{5}$$

[6]Note that $\alpha \in (0, 1)$ implies homogeneity of degree one, i.e., multiplying both Y and F by the same factor $a > 0$ leads to an increase in utility by the same factor. Formally: $U(aY, aF) = aU(Y, F)$ (see, e.g., Mas-Colell et al., 1995).

For our analysis, we are particularly interested in the response of L^* with respect to marginal changes in the keep-rate k. The Marshallian labor supply in (5) implies that L^* is strictly increasing in k, as

$$\frac{\partial L^*}{\partial k} = \frac{G(1-\alpha)}{k^2 w} > 0. \tag{6}$$

Note that this result implies that the substitution effect is larger than the income effect. The substitution effect states that less leisure is consumed as a result of an increase in the after-tax wage rate kw, i.e., the opportunity cost of leisure. Consequently, the labor supply $L = T - F$ increases. The income effect, on the other hand, suggests that the labor supply decreases as kw increases, as the household can maintain its original consumption level Y with a labor supply level that is lower than the initial one.[7]

A key result of our theoretical model is that the labor supply response is *nonlinear*. More precisely, the second derivative of (5) with respect to the keep-rate k implies concavity:

$$\frac{\partial^2 L^*}{\partial k^2} = \frac{-2G(1-\alpha)}{k^3 w} < 0. \tag{7}$$

This means that the labor supply response induced by a marginal increase in k is smaller when k is comparatively high already. Consequently, this finding suggests that characterizing the complete labor supply function with a single parameter – as often done in simple sufficient statistics welfare formulas – is not feasible in our setup.

The family's consumption in the optimum is given by:

$$Y^* = Y(k, w, \alpha, T, G) = G + kwL^* = \alpha(kwT + G). \tag{8}$$

It can easily be seen that the first derivative of Y^* with respect to k is also strictly positive: $\partial Y^*/\partial k = \alpha w T > 0$. This is due to (i) the fact that the family increases its labor supply

[7]For an in-depth discussion of the substitution and income effects, see Keuschnigg and Wamser (2024).

in response to an increase in k (see (6)) and thereby increases its labor income; and (ii) a mechanical increase in the NIT transfer due to an increase in k.

Finally, the indirect utility function is obtained by plugging (5) and (8) into (4):[8]

$$\begin{aligned} V^* = V(k, w, \alpha, T, G) &= (G + kwL^*)^\alpha (T - L^*)^{1-\alpha} \\ &= [\alpha(kwT + G)]^\alpha \left[(1-\alpha)\left(T + \frac{G}{kw}\right)\right]^{(1-\alpha)}. \end{aligned} \tag{9}$$

The derivation of V^* with respect to k states as follows:

$$\frac{\partial V^*}{\partial k} = \frac{(1-\alpha)}{k} Y^{*\alpha} (T - L^*)^{-\alpha} L^*. \tag{10}$$

Given the assumptions regarding ranges of the parameters and choice variables, it follows that $\partial V^*/\partial k > 0$. A proof of this result as well as a detailed derivation of (10) are provided in Appendix 1. Invoking the Envelope Theorem, it can be shown that changes in the choice variables (i.e., L, Y, and λ) as response to a marginal change in k have no effect on V^* in the optimum. Instead, the derivative of V^* with respect to k equals its direct derivative (see, e.g., Mas-Colell et al., 1995 or Keuschnigg and Wamser, 2024). A brief demonstration of the Envelope Theorem is provided in Appendix 2.

2.2. NIT Payment

We now turn to the government side. Using the family's optimal labor supply choice L^* from above, we can compute the NIT payment that the government makes to the family:[9]

$$P^* = G - (1-k)wL^* - S. \tag{11}$$

[8]Note that the term $\lambda^*(G + kwL^* - Y^*)$ in (4) becomes zero, as the budget constraint is satisfied with equality in the optimum.

[9]Keep in mind that we assume that $P > 0$ always holds.

A marginal change in k has two effects on the magnitude of P^*. (i) A mechanical effect that can simply be computed by holding the family's labor supply fixed at L^*. It amounts to wL^*. Note that this effect is always strictly positive, i.e., it increases the NIT payment, as both $w > 0$ and $L^* > 0$. (ii) A behavioral effect, which results from the family adjusting its labor supply in response to the change in k. In detail, this change amounts to $-(1-k)w(\partial L^*/\partial k)$. As $k \in (0,1)$, $w > 0$, and $\partial L^*/\partial k > 0$ (see (6) above), this behavioral effect is strictly negative, i.e., reduces the NIT payment. Adding up the mechanical and the behavioral effects, we obtain the partial derivative of (11) with respect to k:

$$\frac{\partial P^*}{\partial k} = wL^* - (1-k)w\frac{\partial L^*}{\partial k} = w\left(\alpha T - \frac{G(1-\alpha)}{k^2 w}\right). \tag{12}$$

The last equality is obtained by inserting the value function for L^* (see (5)) as well as its derivative with respect to k (see (6)). The labor supply response of the household at k plays an important role for the magnitude of (12), with a strong response, i.e., a steeply upward sloping labor supply curve, being beneficial for the government. Note that our model does not suggest any particular sign for (12); in theory, payments could decrease as result of an increase in k. This is the case when the behavioral effect outweighs the mechanical effect. In our empirical application below, however, this special case does not play a role.

2.3. Social Welfare Function

Finally, we define social welfare as a function of k that the policy maker seeks to maximize. Similar to Kasy (2018), we define social welfare as the difference between household utility (see (9)) and the transfer payment (see (11)), both of which are value functions of the take-back rate k and all other exogenous parameters. For the sake of notational simplicity we shall henceforth denote the value function of the labor supply depicted in (5) with $L^* = L(k)$.

Formally, the social welfare function states as follows:

$$
\begin{aligned}
SW(k) &= V^* - P^* \\
&= (G + kwL(k))^\alpha (T - L(k))^{1-\alpha} - [G - (1-k)wL(k) - S].
\end{aligned} \tag{13}
$$

Note that while both our notion of social welfare as well as the one proposed by Kasy (2018) account for nonlinear behavioral responses, there are two key aspects in which they differ. First, we explicitly model the household's trade-off between consumption and leisure under the assumption of Cobb-Douglas preferences. In Kasy (2018), the individual chooses a level of health care expenditure while being confronted with a given coinsurance rate. However, the trade-off the individual faces in this setup, i.e., staying/becoming healthy versus reducing out-of-pocket costs and thereby increasing, e.g., other consumption, is not theoretically modeled. Instead, the only assumption that is made by Kasy (2018) is that maximized private utility changes linearly with respect to the coinsurance rate. In our setup, the indirect utility function is a nonlinear function of the policy parameter of interest k, see (10).[10] Second, the social welfare function used by Kasy (2018) assumes that the policy maker sets a marginal value of an additional dollar transferred to the sick relative to the cost of an additional dollar of expenditure for the health insurance provider, which is assumed to be larger than one. Without this parameter, the social welfare function in Kasy (2018) essentially collapses. In contrast, our setup does not necessitate invoking such a parameter.

As mentioned above, the policy maker sets the keep-rate such that social welfare is maximized. We denote the maximizing level of the keep-rate as k^*. The first-order condition is

$$
SW'(k^*) = \left.\frac{\partial V^*}{\partial k}\right|_{k=k^*} - \left.\frac{\partial P^*}{\partial k}\right|_{k=k^*} = 0. \tag{14}
$$

[10]Note that if one would assume quasilinear preferences for our problem with consumption Y entering utility linearly, the indirect utility function would also change linearly with respect to k. However, we believe that assuming Cobb-Douglas preferences with diminishing marginal utility with respect to both consumption and leisure is more adequate.

Using the expressions for the first derivatives of V^* and P^* with respect to k from above (see (10) and (12), respectively), we can rewrite (14) as a function of the Marshallian labor supply $L(k)$ and its first derivative with respect to k, $L'(k)$:

$$SW'(k^*) = \frac{(1-\alpha)}{k^*} \left(G + k^* w L(k^*)\right)^{\alpha} \left(T - L(k^*)\right)^{-\alpha} L(k^*) - wL(k^*) + (1-k^*) w L'(k^*) = 0. \tag{15}$$

Note that the first derivative of the social welfare function is conceptually similar to the notion of excess burden as described in, e.g., Keuschnigg and Wamser (2024) in the context of income taxation. This becomes apparent when we think about a marginal decrease in k, which is identical to an increase in the take-back rate t:[11] An increase in t reduces utility (see (10)), which reduces overall social welfare (see (13)). However, the increase in t mechanically lowers the NIT payment, which is beneficial for overall welfare, as the government has more money at its disposal for other purposes that increase welfare. In this sense, from a social welfare perspective, a lower NIT payment is similar to an increase in income tax revenue. The degree to which the lower NIT payments make up for the decrease in private utility hinges on the behavioral response of the household, or, more precisely, the magnitude of the substitution effect at t. In case the household is strongly decreasing its labor supply in response to a marginal increase in t, i.e., a reduction in the after-tax wage rate $(1-t)w$, the mechanical decrease in the NIT payment is largely canceled out. Our notion of the excess burden states how much of the loss in utility cannot be offset by the decrease in the NIT payment. They key innovation compared to other standard formulas of social welfare and excess burden is that we do not rely on a single elasticity parameter characterizing the curvature of the labor supply function. Instead, we account for the response intensity at each level of k. In the remainder of the paper, we use data from the US NIT experiments to estimate $L(k)$, explicitly allowing for nonlinearities. Then, we use the estimate of $L(k)$ to estimate (13) for different levels of k to determine the welfare optimizing keep-rate k^*.

[11] Keep in mind that $k = 1 - t$.

3. Empirical Approach

3.1. Estimation Strategy

The key ingredient for the estimation of the social welfare function for different levels of the take-back rate k is the labor supply $L(k)$, see (13). With all exogenous model parameters at hand, one could simply calculate $L(k)$ using (5). However, we are interested in an empirical estimate of the labor supply, $\hat{L}(k)$, that accounts for behavioral responses that cannot be captured by our simple model. In doing so, we accept potential deviations between $\hat{L}(k)$ the purely model-based $L(k)$. In the following, we describe the estimation strategy for obtaining $\hat{L}(k)$ using data from two NIT experiments that were conducted in the US in the 1970s. In these experiments, families were assigned to different NIT plans consisting of combinations of take-back rates ($k = 0.30$, $k = 0.40$, $k = 0.50$, or $k = 0.60$) and guaranteed income levels G, which amounted to either 75%, 95%, 100%, 120%, or 140% of the respective family's poverty line (see MPR, 1980; Robins, 1985; Widerquist, 2005). In addition to the families in the NIT plans, the experiments observed a number of families in the control group with $k = G = 0$. We predict the marginal effects of the different take-back rates on the labor supply of the families using the following linear estimation equation:[12]

$$\begin{aligned} \textit{Labor supply}_{iq} &= \beta_{0.3}\mathbb{1}(k_{iq} = 0.3) + \beta_{0.4}\mathbb{1}(k_{iq} = 0.4) + \beta_{0.5}\mathbb{1}(k_{iq} = 0.5) + \beta_{0.6}\mathbb{1}(k_{iq} = 0.6) \\ &\quad + \kappa G_{iq} + \gamma \textit{No treatment}_{iq} + \boldsymbol{\phi X_i} + \boldsymbol{\psi X_{iq}} + \boldsymbol{\zeta X_{iq-1}} + \theta_y + \varepsilon_{iq}. \qquad (16) \end{aligned}$$

[12] Note that our labor supply estimation differs from most previous studies using the same NIT experiment data in that these studies typically conduct the estimation at the individual level, often times focusing on and comparing the labor supply responses of different groups such as husbands, wives, or single female heads of households. See Robins (1985) or Widerquist (2005) for overviews of such studies. Note that in our context, estimating the labor supply at the individual level would complicate the analysis, as, e.g., the labor supply of the husband is a function of his wife's labor supply and vice versa. Controlling for the respective spouse's labor supply, however, would lead to endogeneity issues. Furthermore, since the NIT payments are administered at the family level, either way some sort of (non-trivial) aggregation from the individual response to the family level response would still be necessary in such a setup.

The indices i and q denote family and experimental quarter, respectively.[13] The dependent variable $Labor\ supply_{iq}$ gives the sum of hours worked by all members of family i on all regular jobs in the given quarter q. Following Kasy (2018), we estimate the marginal effects of different take-back rates using dummy variables, denoted by $\mathbb{1}(k_{iq} = k)$. The corresponding OLS coefficients are denoted by the β_k's. The marginal effect of the guaranteed income level G_{iq} is given by κ. Note that for the families in the control group, G_{iq} is equal to zero in all quarters. $No\ treatment_{iq}$ is an indicator variable that is equal to unity if a family was in the control group, i.e., was never eligible for any NIT payment. To ensure that the estimation of the β_k's and κ is not contaminated by families that are treated with an NIT plan, however, do not receive NIT payments as their income is too high,[14] we assign families that did not receive any NIT payments in the previous quarter $q-1$ to the control group in q. The underlying rationale of this assignment of certain observations to the control group is that the magnitudes of the keep-rate and the guaranteed income level are only relevant when a strictly positive NIT payment is expected. Not making this adjustment would lead to a systematic bias in the estimation of the β_k's and κ, as one would expect more generous plans (i.e., plans with high k and high G) to have a higher share of families receiving payments than less generous ones (i.e., plans with low k and low G). We further control for a set of time-constant variables, contained in $\boldsymbol{X_i}$, as well as sets of contemporary and lagged variables, contained in $\boldsymbol{X_{iq}}$ and $\boldsymbol{X_{iq-1}}$, respectively. The corresponding coefficients for the variables in $\boldsymbol{X_i}$, $\boldsymbol{X_{iq}}$, and $\boldsymbol{X_{iq-1}}$ are collected in the vectors $\boldsymbol{\phi}$, $\boldsymbol{\psi}$, and $\boldsymbol{\zeta}$, respectively. These additional variables control for factors that potentially influence the labor supply other than the NIT variables and include, e.g., the pre-experimental average wage rate across the different working family members, the pre-experimental quarterly total labor income, the number of adults, the number of minors, the gender of the family head, or the received

[13]The experimental quarters denote the months since the enrollment of the family, with the first quarter comprising the first, second, and third month after the enrollment month (Mathematica Policy Research, Inc. [MPR] and Social & Scientific Systems, Inc. [SSS], 1980). Therefore, the experimental quarters generally do not align with the calendar quarters, i.e., January to March, April to June, etc.

[14]For details on the calculation of the NIT payments, see Section 2.1.

welfare income. In particular controlling for pre-experimental income as well as the family size and composition is crucial, as the assignment of the different NIT plans was not random but instead was based on the Conlisk-Watts assignment model (Conlisk and Watts, 1979). This method aims to reduce the expected costs of the experiment, i.e., the sum of NIT payments, and therefore favors families with high pre-tax income and small families in the assignment of generous plans, i.e., plans with high k and high G.[15] As pointed out by Keeley and Robins (1978), controlling for the Conlisk-Watts assignment variables is the only way to correct for the bias from the non-random assignment, even though the inclusion of additional control variables may reduce the reliability of the estimates (Keeley, 1981). In addition to the family-specific control variables we control for year fixed effects, which are denoted by θ_y, with y indicating the calendar year. Note that since each unique NIT plan was tested only at one of the two sites,[16] we pool over the two locations, i.e., do not include site fixed effects. Further note that since a family's NIT plan did not change over the course of the experiment, we do not include family fixed effects. However, we cluster our standard errors at the family level to account for non-independence between the different quarters. Finally, ε_{iq} denotes the error component. Similar to Kasy (2018), we de-mean all covariates except for the $\mathbb{1}(k_{iq} = k)$'s and the $No\ treatment_{iq}$ dummy. Since our model does not include a constant, this allows for the interpretation of the β_k's in (16) as the average labor supply corresponding to the given coinsurance rate for a hypothetical family that has control variables that are equal to the respective sample means.

Regarding the labor supply estimation, there is an important aspect that deserves some special attention, namely the distinction between intensive and extensive margin responses (Heckman, 1993). Unlike Saez (2002), our theoretical model – for the sake of simplicity – focuses exclusively on intensive margin responses and rules out non-participation in the labor market by assumption. Given that we consider the aggregated labor supply of a family rather

[15] Note that family size is relevant for the magnitude of NIT payments, as G is calculated by multiplying a constant factor with the family-specific poverty line, with the latter being higher for large families. For more details on the calculation of the poverty line, see Section 3.2.

[16] More details on this are provided below in Section 3.2.

than of an individual and given that our observations correspond to rather long three month time periods, this assumption does not seem completely implausible. In fact, only 16.78% of family-quarter observations in the final sample report zero hours worked. Nevertheless, we want to clarify that the empirical estimates of the labor supply are the result of a combination of responses along both margins.

In a second step, to be able to compute and evaluate the social welfare function not only at the observed k's but at all k's in the range $[0.30, 0.60]$, we apply a cubic spline monotonic interpolation approach (Dougherty et al., 1989; Forsythe et al., 1977; Hyman, 1983). Unlike conventional cubic splines, this method ensures that the slope of the labor supply curve is monotonically increasing. Of course, this requires that the β_k estimates that are passed to the spline are monotonically increasing as well, i.e., $\beta_{0.3} \leq \beta_{0.4} \leq \beta_{0.5} \leq \beta_{0.6}$. As can be seen in Section 4.1, this is the case in our analysis. Another feature of the spline is that the interpolated line passes right through observed data points, i.e., the β_k's. The main advantage of cubic spline monotonic interpolation lies in its simplicity, in particular in comparison to machine learning based algorithms that are usually more computationally intensive, require tedious (and often times arbitrary) tuning of hyperparameters (see, e.g., Hastie et al., 2009), and usually do not work with categorical variables (Potdar et al., 2017). On the downside, compared to some machine learning algorithms such as the Gaussian Process Priors used by Kasy (2018) that allow for the computation of confidence bounds, the interpolated line obtained with cubic splines does not allow to make statements about statistical uncertainty.

In a third and final step, the estimated labor supply curve is plugged into the social welfare function (13). Other exogenous parameters that are needed for the computation of social welfare as function of k, i.e., G, T, w, or S, are calibrated using the data from the NIT experiments. The utility elasticities of consumption and leisure, α and $1 - \alpha$, are varied in the empirical analysis to simulate different family preferences.

3.2. *Data, Sample, and Parameterization*

As mentioned above, the data used for the empirical analysis stem from the NIT experiments that were conducted in different areas of the United States between 1968 and 1980.[17] The implementation of the experiments was the result of political debate surrounding the NIT in the context of the "war on poverty" that President Lyndon Johnson's called for in his state of the union address in 1964. Advocates of the NIT, including most prominently the Office of Economic Opportunity, which was established by the US Congress to administer the war on poverty, were confronted with the criticism that NIT programs could promote idleness. While a reduction of the labor supply in response to the NIT is in line with economic theory (see Section 2), reliable empirical estimates regarding the magnitude of the work-disincentive effect were not available at the time. As a result, the NIT experiments were implemented to obtain the necessary information to settle the debate (Hum and Simpson, 1993).

For our analysis, we use the "Cross-Site Analysis File", which includes records for the New Jersey, the Gary (Indiana), and the Seattle/Denver Income Maintenance Experiments (SIME/DIME) and was provided by the Data and Information Services Center (DISC) at the University of Wisconsin-Madison.[18] The Cross-Site Analysis File provides relevant variables for the different experiments in a common format using the same concepts and definitions for the construction of the variables (MPR and SSS, 1980). In detail, it provides information on each individual enrolled in the experiment as head of a family for the 12 experimental quarters as well as for the four quarters preceding the start of the NIT treatment.[19] Note that since

[17]Note that additionally to the NIT experiments conducted in the US, there was also an experiment conducted in Manitoba, Canada between 1975 and 1978, the so-called "Manitoba Basic Annual Income Experiment" or "Mincome" (Widerquist, 2005). However, due to data availability, we only consider the US experiments.

[18]Note that the fourth US experiment, the Rural Income-Maintenance Experiment (RIME) which was conducted in Iowa and North Carolina from 1970 to 1972 (Widerquist, 2005) is not included in the Cross-Site Analysis File and therefore is not part of our analysis.

[19]Note that due to infrequency of interviews and attrition, not all families are covered in each quarter. Regarding the survey method of interviews, there is evidence of systematic misreporting of labor supply (Greenberg et al., 1981; Greenberg and Halsey, 1983). Since the periodic interviews are the only data available to us, we cannot correct for this bias, however, we want the reader to be aware that the results presented in this paper may possibly be biased due to misreporting.

we also control for pre-experimental variables, we exclude experimental observations where the number of family heads does not coincide with the one of the quarter before the start of the treatment, as this suggests that either a marriage or a divorce happened (MPR and SSS, 1980) and the pre-experimental variables therefore lose validity as controls.[20] We convert all monetary variables to 1971 dollars using consumer price based annual inflation rates that we obtain from the World Bank's *World Development Indicators* database. Since several variables that we need for our analysis are not provided for the New Jersey experiment, we only use data from the Gary and the Seattle/Denver experiments.[21]

The Gary experiment was carried out between 1971 and 1974 and initially comprised a total of 1,799 households. It included only black families, with the majority of them being single-headed (54%). The requirements for participation were that the head of the family was between 18 and 58 years old and that the family income was below 240% of the poverty line in the year of enrollment. The NIT plans that were tested in Gary were combinations of the guaranteed income levels G of either 75% or 100% and keep-rates k of 0.40 or 0.60 (Robins, 1985; Widerquist, 2005). Note that the assignment of treatment in all experiments was based on information obtained from a couple of interviews that were conducted before enrollment (MPR, 1980). Compared to the Gary experiment, the Seattle/Denver experiments, for which we observe the time span 1971 to 1975,[22] exhibited a much larger sample size of initially 4,800 households. The households in the Seattle/Denver experiments were primarily black (43%), followed by an almost equally big share of white households (39%), and a comparatively small share of Latino households (18%). The share of single-headed families amounted to

[20]Interestingly, the families in the NIT experiments exhibited a substantial number of divorces, which in itself is a research subject. Widerquist (2005) provides an extensive list of papers regarding this topic.

[21]The variables that are missing for New Jersey include, e.g., the quarterly experimental payments or family social security income (MPR and SSS, 1980).

[22]Note that for 71% of the households, the treatment was planned – and communicated – to last three years, which is also the treatment duration of the Gary experiment. For the other households in of the sample, the treatment duration was longer, either five years (25%) or 20 years (4%). However, the experiments were cancelled in 1980, such that the maximum treatment duration only amounted to 9 years. For our analysis, we only use the first three years of treatment, irrespective of the communicated total duration. We are aware that the labor supply response may differ depending on the communicated duration of treatment, however, due to a lack of variation in treatment duration across sites and therefore NIT plans, we do not control for this in our analysis.

39%. For eligibility, the households' income had to be below 325% of the respective poverty line in the year of enrollment. The plans that were tested in the Denver/Seattle experiments were combinations of the guaranteed income levels G of either 95%, 120%, or 140% and keep-rates k of 0.30 or 0.50 (Robins, 1985; Widerquist, 2005).[23]

The variables from the Cross-Site Analysis File that we use for our labor supply estimation are the following. The dependent variable, labor supply in hours in the given quarter ($Labor\ supply_{iq}$), is calculated as the sum of a family's heads' hours worked on all regular jobs. In an alternative specification of our model, we use the labor income ($Labor\ income_{iq}$) rather than the labor supply as dependent variable. Labor income is defined as the total of gross wages earned by a family's heads on all regular jobs in the respective quarter. As mentioned above, we code indicator variables for each of the four keep-rates k used in the experiment, which are denoted by $\mathbb{1}(k_{iq} = k)$. We also control for the guaranteed income level G_{iq} which states the NIT transfer in the absence of any family income. Note that since the Cross-Site Analysis File only provides G as the share of the respective family's poverty line, we use poverty thresholds tables for the year 1971 which we obtain from the US Census Bureau to calculate the actual thresholds using the relevant information on the families.[24] The indicator $No\ treatment_{iq}$ is equal to unity if a family is in the control group, in which case all $\mathbb{1}(k_{iq} = k)$'s as well as G_{iq} are equal to zero. As discussed above, besides the actual control group of the experiment, we also assign families that are assigned to an NIT plan but did not receive any transfers in the previous quarter to the control group of the current quarter. As final NIT related variable, we control for the NIT payments that the family received in the previous quarter ($NIT\ payment_{iq-1}$). Next, we control for family size, distinguishing the number of adults ($Persons\ 18\ or\ older_{iq}$) as well

[23]Note that additionally flexible keep-rates that depended on the household's income were tested in Seattle/Denver. However, we exclude households treated with such flexible rates, as our setup is using indicator variables to control for different levels of the keep-rate, which does not allow us to sensibly control for continuous variation in k (see Section 3.1). Furthermore, note that flexible keep-rates on the right-hand side of our labor supply estimation equation would be endogenous due to simultaneity, as they depend on income and are therefore correlated with the labor supply.

[24]Note that we converted all monetary variables to 1971 dollars before.

as minors ($Persons\ 17\ or\ younger_{iq}$). We further control for the gender of the head of the family ($Female\ head_{iq}$),[25] as well as the family type. Regarding the latter, we distinguish two-headed families ($Two\ heads_{iq}$), one-headed families with at least one dependent under 18 years old ($One\ head,\ dependents_{iq}$), and one-headed families without dependents ($One\ head,\ dependents_{iq}$). Since the NIT plans were not assigned randomly, but dependent on family size and pre-experimental income (Conlisk and Watts, 1979; Widerquist, 2005), we also control for the average quarterly family labor income across the four pre-experimental quarters ($Labor\ income\ pre-exp_i$). We furthermore control for a family's pre-experimental wage rate ($Wage\ rate\ pre-exp_i$), which we calculate as the weighted mean of all hourly wage rates of a family's heads, with the weights reflecting the share of total family hours worked by the given individual. Note that using wage figures during the treatment quarters would be endogenous, as family members of treated families might be reluctant to accept low paying jobs, effectively making the wage rate a treatment outcome itself.[26] The idea behind controlling for pre-experimental wage is to account for the families' value in the labor market. Finally, we control for families' income sources outside of labor income, namely the previous period's non-labor income ($Non-labor\ income_{iq-1}$), which includes interest and rent income (i.e., the I in the theoretical model in Section 2), total welfare income ($Welfare\ income_{iq-1}$), and social security income ($Social\ security\ income_{iq-1}$). The final sample includes a total of 30,307 family-quarter observations. Descriptive statistics on all variables are depicted in Table 1.

Finally, we estimate the other parameters needed for the welfare analysis. For the wage rate w, we simply use the sample mean of the pre-experimental wage rate ($Wage\ rate\ pre-exp_i$), depicted in Table 1. We also parameterize the guaranteed income level G in the theoretical model using the sample mean of G_{iq}, however, we exclude observations where $G_{iq} = 0$ from our calculations, yielding $G = 1142.76$ dollars. The total public assistance

[25] Note that the head of the family is considered female if there is no male head.

[26] Of course, the wages in the pre-experimental quarters may be contaminated by anticipation effects, though we deem this a comparatively smaller issue.

Table 1: ***DESCRIPTIVE STATISTICS***

The table depicts descriptive statistics on all the variables used for the empirical labor supply estimation. Definitions of the variables are provided in Section 3.2.

Panel A: Dependent variables			
	Observations	Mean	(sd)
$Labor\ supply_{iq}$	30,307	472.373	303.755
$Labor\ income_{iq}$	30,307	1500.315	1122.858
Panel B: Experimental treatment variables			
	Observations	Mean	(sd)
$\mathbb{1}(k_{iq} = 0.3)$	30,307	0.166	0.372
$\mathbb{1}(k_{iq} = 0.4)$	30,307	0.083	0.276
$\mathbb{1}(k_{iq} = 0.5)$	30,307	0.164	0.371
$\mathbb{1}(k_{iq} = 0.6)$	30,307	0.083	0.276
G_{iq}	30,307	567.255	631.516
$No\ treatment_{iq}$	30,307	0.504	0.500
$NIT\ payment_{iq-1}$	30,307	186.684	310.510
Panel C: Family control variables			
	Observations	Mean	(sd)
$Persons\ 18\ or\ older_{iq}$	30,307	2.112	0.895
$Persons\ 17\ or\ younger_{iq}$	30,307	2.221	1.562
$Female\ head_{iq}$	30,307	0.362	0.481
$Two\ heads_{iq}$	30,307	0.640	0.480
$One\ head,\ dependents_{iq}$	30,307	0.342	0.474
$One\ head,\ no\ dependents_{iq}$	30,307	0.018	0.134
$Labor\ income\ pre-exp_i$	30,307	1398.770	870.305
$Wage\ rate\ pre-exp_i$	30,307	2.892	1.128
$Non-labor\ income_{iq-1}$	30,307	6.036	42.882
$Welfare\ income_{iq-1}$	30,307	90.585	224.465
$Social\ security\ income_{iq-1}$	30,307	40.775	173.082

that a family receives, denoted by S in the theoretical model, is parameterized by simply adding up the sample means of total welfare income ($Welfare\ income_{iq-1}$) and social security income ($Social\ security\ income_{iq-1}$) depicted in Table 1. The parameterization of T, i.e., the available time that is split up into work time L and leisure F, is somewhat more complicated. The reason for this is that it is not observable in the data and may in theory differ between individuals, depending on their circumstances. We therefore make an assumption, which is that each worker has a total of 60 hours at his or her disposal per week. Multiplying this figure with the sample mean of the number of adults per family (2.112; see Table 1) and accounting for the fact that a quarter has 12 weeks, we arrive at a $T = 1520.64$ hours. Finally, we need to make an assumption regarding the model parameter α in the Cobb-Douglas utility function, which defines both the utility elasticity of consumption and leisure. Rather than assuming a fixed value, we calculate the social welfare maximizing keep rate k^* for a range of α. Note, however, that we disregard $\alpha < 0.4$, as for this range we find that the slope of the indirect utility function V is not strictly monotonically increasing in k, which contradicts the theoretical model (see Section 2.1) and basic intuition. For the sake of illustration, we set $\alpha = 0.7$ for some graphical depictions of the indirect utility function as well as the social welfare function.

4. Results

4.1. Nonlinear Labor Supply Estimation

The results of our labor supply estimation are depicted in Table 2. We first focus on specification (1), which uses the families' total labor supply in a given quarter in hours ($Labor\ supply_{iq}$) as dependent variable. Note that this specification is also used as basis for our welfare analysis. A central result is that the labor supply corresponding to a hypothetical family which has control variables that are equal to the respective sample means is increasing in the keep-rate k. This finding is generally in line with the prediction of our

Table 2: ***PREDICTED AVERAGE LABOR SUPPLY AND LABOR INCOME FOR DIFFERENT KEEP-RATES***

The table presents OLS estimates. The dependent variable of specification (1) is the labor supply of family i in experimental quarter q, *Labor supply*$_{iq}$. The dependent variable of specification (2) is the total labor income of family i in experimental quarter q, *Labor income*$_{iq}$. Both models are estimated without constant and all independent variables except for the $\mathbb{1}(k_{iq} = k)$'s and $No\ treatment_{iq}$ are de-meaned. Robust standard errors are reported in parentheses (clustered at the family level). *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level. Definitions and descriptive statistics on all are provided in Section 3.2.

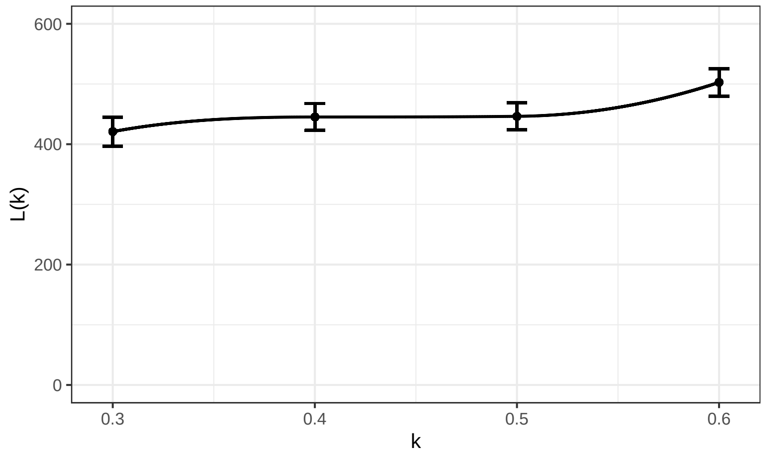
	(1)	(2)
$\mathbb{1}(k_{iq} = 0.3)$	420.919***	1295.262***
	(12.352)	(41.085)
$\mathbb{1}(k_{iq} = 0.4)$	445.200***	1313.494***
	(11.398)	(33.583)
$\mathbb{1}(k_{iq} = 0.5)$	446.289***	1399.793***
	(11.538)	(36.842)
$\mathbb{1}(k_{iq} = 0.6)$	502.634***	1475.266***
	(11.753)	(36.916)
G_{iq}	0.105***	0.445***
	(0.014)	(0.049)
$No\ treatment_{iq}$	497.283***	1635.510***
	(8.932)	(29.876)
$NIT\ payment_{iq-1}$	-0.360***	-1.207***
	(0.012)	(0.040)
$Persons\ 18\ or\ older_{iq}$	6.337	-1.820
	(4.073)	(13.175)
$Persons\ 17\ or\ younger_{iq}$	0.152	11.626
	(2.378)	(8.066)
$Female\ head_{iq}$	-144.413***	-522.334***
	(20.956)	(73.654)
$One\ head,\ dependents_{iq}$	35.302*	176.640**
(base: $Two\ heads_{iq}$)	(20.467)	(73.745)
$One\ head,\ no\ dependents_{iq}$	-32.326	-127.441
(base: $Two\ heads_{iq}$)	(31.151)	(100.406)
$Labor\ income\ pre-exp_i$	0.126***	0.458***
	(0.007)	(0.022)
$Wage\ rate\ pre-exp_i$	-54.196***	60.491***
	(8.138)	(19.622)
$Non-labor\ income_{iq-1}$	0.034	0.252
	(0.063)	(0.198)
$Welfare\ income_{iq-1}$	-0.332***	-1.103***
	(0.017)	(0.050)
$Social\ security\ income_{iq-1}$	-0.202***	-0.720***
	(0.021)	(0.065)
Year FEs	YES	YES
Adjusted R^2	0.830	0.829
Observations	30,307	30,307

theoretical model in Section 2. However, the fact that the increase in labor supply between $k = 0.50$ and $k = 0.60$ is larger than the increase between $k = 0.40$ and $k = 0.50$ contradicts the Marshallian labor supply function depicted in equation (5) in Section 2, which suggests that the optimal labor supply curve is concave, i.e., becomes flatter as k increases. The contradiction becomes more apparent in the graphical representation of the labor supply estimation as function of k, $\hat{L}(k)$, in Figure 1. Note that in the figure, the areas between the observed k's are imputed using a cubic spline monotonic interpolation approach (Dougherty et al., 1989; Forsythe et al., 1977; Hyman, 1983). Overall, we find that the difference in labor supply between the most generous keep-rate that was tested ($k = 0.60$) and the smallest keep-rate that was tested ($k = 0.30$) amounts to economically significant $503 - 421 = 82$ hours. Regarding our alternative specification in column (2) of Table 2 which analyzes labor income ($Labor\ income_{iq}$) instead of labor supply, we also find a positive relationship between the dependent variable and the different keep-rates. Note, however, that the labor income response does not exhibit the same pattern of differences between adjacent observed levels of k. This is due to the fact that – unlike in the theoretical model – wages are varying across families and time, which results in the labor supply and the labor income responses not being directly comparable.

Before we turn to the welfare analysis, let us briefly discuss the coefficient estimates on the other control variables. We find that labor supply is increasing in the guaranteed income level G_{iq}. This is surprising, given that our theoretical model predicts a negative relationship between labor supply and G_{iq} (see equation (5) in Section 2). However, in deciding on their labor supply for the current quarter, it can be argued that the actual received NIT payment from the previous quarter ($NIT\ payment_{iq-1}$), which also equals the NIT payment of the current quarter if the total family income remains unchanged, is the more relevant measure for families compared to G_{iq}, which states the transfer amount that is paid out only in the rare case where labor supply is equal to zero. The negative coefficient estimate on $NIT\ payment_{iq-1}$, which in absolute terms is three times as large as the estimate on G_{iq},

Figure 1: ***NONLINEAR LABOR SUPPLY ESTIMATION FOR DIFFERENT KEEP-RATES***

The figure depicts the nonlinear labor supply estimation for different keep-rates k. The black dots are the OLS coefficient estimates on different keep-rates k (see Table 2) and are depicted with corresponding 95% confidence intervals that are based on robust standard errors (clustered at the family level). The line connecting the OLS estimates is imputed using a cubic spline monotonic interpolation approach (Dougherty et al., 1989; Forsythe et al., 1977; Hyman, 1983).



matches the work-disincentive theory that more generous NIT plans reduce labor supply. Also in line with work-disincentive argument regarding the NIT is the positive coefficient on the indicator $No\ treatment_{iq}$, which suggest that untreated families exhibit a substantially higher labor supply. However, it has to be stressed that $No\ treatment_{iq}$ by definition is also equal to unity for families that are technically assigned to an NIT plan but did not receive any NIT payments in the previous period, as their total income exceeded the break-even threshold. Assuming that families with such high income also exhibit above average labor supply and assuming that their labor supply is somewhat constant across quarters, a part of the large coefficient on $No\ treatment_{iq}$ can be explained by a mechanical effect of high income earners being assigned to the control group.

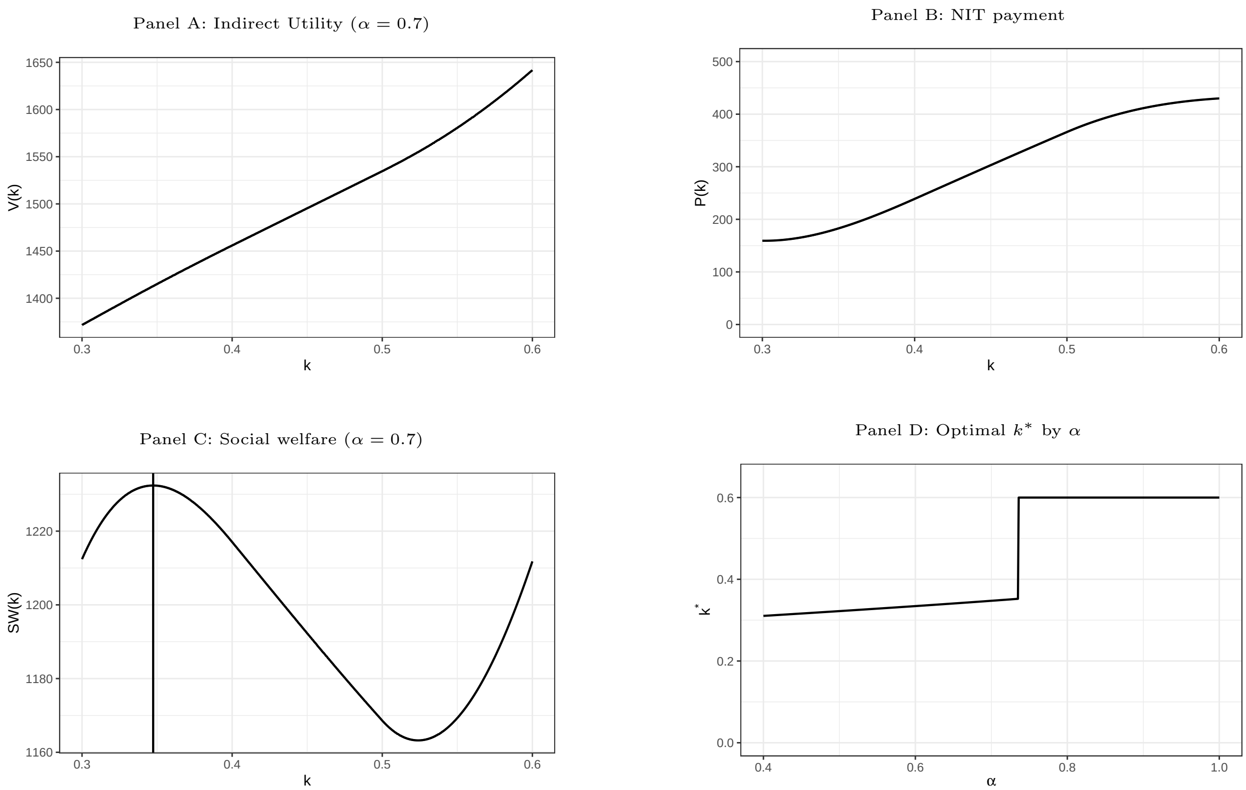
Regarding the family characteristics, the coefficients on the variables concerning the size and type of families suggest that families with a female head supply less labor and that labor supply is increasing with the amount of children. Furthermore, we find that families that received higher welfare and social security payments in the previous quarter work fewer hours on average – again, however, note that these effects may be in parts mechanical, as these payments often depend on and are decreasing in labor income. The coefficient on non-labor income is not significantly different from zero, which may be due to the fact that most families in the sample had no or negligibly little non-labor income and consequently the coefficient is identified from very little variation. As one would expect, we find that families with high pre-experimental income provide more labor on average. The negative coefficient on the pre-experimental wage rate, however, at first may seem surprising. A possible explanation may be that treated families could purposely reduce their labor supply to a level such that they become eligible for NIT payments. In this context, families with high wage rates need to reduce their labor supply to lower levels than families with low wage rates to obtain the same NIT transfer. Alternatively, the sign could be explained by the fact that high wage earners need to work less than low wage earners to generate the same income required to cover basic expenses. This latter mechanism is also valid for untreated families. A result that stands out in Table 2 is that the wage rate is the only control variable for which the coefficient estimate is both statistically significant from zero and differs in sign between our two model specifications. However, in the context of specification (2) which uses labor income rather than labor supply as dependent variable, the positive coefficient on the wage rate can simply be explained by the mechanical effect of income which is, holding work hours constant, increasing in the wage rate.

4.2. Optimal Social Welfare

We now turn to the analysis of social welfare, for which we use the nonlinear labor supply estimation $L^* = \hat{L}(k)$ that is depicted in Figure 1. We start out by analyzing the indirect utility function (using $\alpha = 0.7$), which is obtained by inserting $L^* = \hat{L}(k)$ into the first row of equation (9) (see Panel A of Figure 2). It can be seen that utility increases in the keep-rate k, which is in line with the theoretical model in Section 2. Moreover, the slope is almost perfectly linear, with only the section between $k = 0.50$ and $k = 0.60$ exhibiting a slightly steeper slope.

Figure 2: ***WELFARE ANALYSIS WITH NONLINEAR LABOR SUPPLY***

The figure depicts the welfare analysis based on the nonlinear estimation of the labor supply, $L^* = \hat{L}(k)$ depicted in Figure 1. Panel A depicts the indirect utility, which is obtained by plugging $L^* = \hat{L}(k)$ into (the first row of) (9). α is set to 0.7. Panel B depicts the NIT payment, which is obtained by plugging $L^* = \hat{L}(k)$ into (11). Panel C depicts the social welfare, which is obtained by plugging $L^* = \hat{L}(k)$ into (13). Note that the line depicted in Panel C gives the difference between the lines depicted in the Panels A and B. The vertical line depicts the social welfare maximizing keep-rate k^*, which is equal to 0.347 for setting $\alpha = 0.7$. Finally, Panel D depicts the welfare maximizing keep-rate k^* for different levels of α. For the parameterization of the other parameters, see Section 3.2.



Panel B of the same figure depicts the NIT payments based on the nonlinear labor supply estimation. It is obtained by plugging $L^* = \hat{L}(k)$ into equation (11). The shape of the NIT payment curve is a direct reflection of the curvature of L^* depicted in Figure 1: a strong labor supply increase associated with a marginal increase in k, as observable in the areas between $k = 0.30$ and $k = 0.40$ as well as between $k = 0.50$ and $k = 0.60$, counteracts the mechanical increase in the NIT payments substantially, which explains the flatness in these areas. A more moderate labor supply response, on the other hand, as seen between $k = 0.40$ and $k = 0.50$, is associated with a smaller reduction of the same mechanical increase in the NIT payments, which explains the steeper increase of the NIT payment curve in this range.

Finally, Panel C depicts our notion of social welfare as function of the keep-rate k. Social welfare is simply defined as the difference between the indirect utility (Panel A) and the NIT payment (Panel B) (see equation (13) in Section 2). Regarding the shape of the function, it stands out that social welfare is increasing only in the two areas with the smallest labor supply response, that is, at the bottom and the top of our observed range of k. In between these areas, social welfare is decreasing in k, which can be explained with the moderate labor supply response and its aforementioned relationship with the NIT payments. We find a local maximum at around $k^* = 0.347$, which is at the lower end of our observed range of k. However, we need to discuss two major caveats regarding the determination of k^*. First, we cannot rule out that there is a global maximum outside of the observed range $[0.30,\ 0.60]$. Second, the parameter α, which defines the utility elasticities of consumption and leisure, is a key determinant of the shape of the indirect utility function and therefore also the social welfare function. Due to data availability, there is nothing that can be done about the first point. However, the second point, i.e., the dependence of k^* on α, can easily be investigated in more detail. Panel D depicts for each α the corresponding social welfare maximizing level of k^*.[27] We find that up until about $\alpha = 0.736$ the corresponding optimal local maxima lie in the range between $k^* = 0.310$ and $k^* = 0.352$, with the k^* linearly increasing in α.

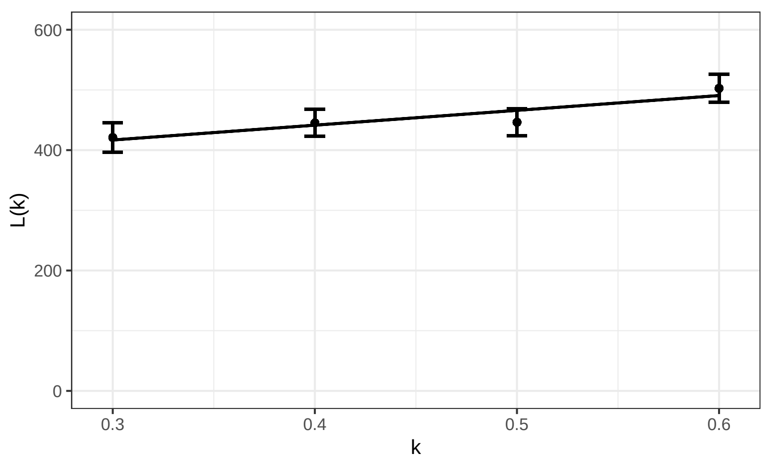
[27] Note again that we only consider $\alpha \geq 0.4$, as for $\alpha < 0.4$ the indirect utility function is not strictly monotonically increasing in k.

This small amount of variation in k^* within a rather large range of α shows that the finding with α fixed at 0.7 is quite robust in the sense that small deviations in α lead to similar optimal keep-rates k^*. However, at around $\alpha = 0.736$ there is a jump in k^*, which then has an optimal value of 0.60, i.e., the highest observed value of k in our analysis, for all α's above this threshold.

4.3. Comparison to Social Welfare Analysis with Linear Labor Supply

Figure 3: ***LINEAR LABOR SUPPLY ESTIMATION FOR DIFFERENT KEEP-RATES***

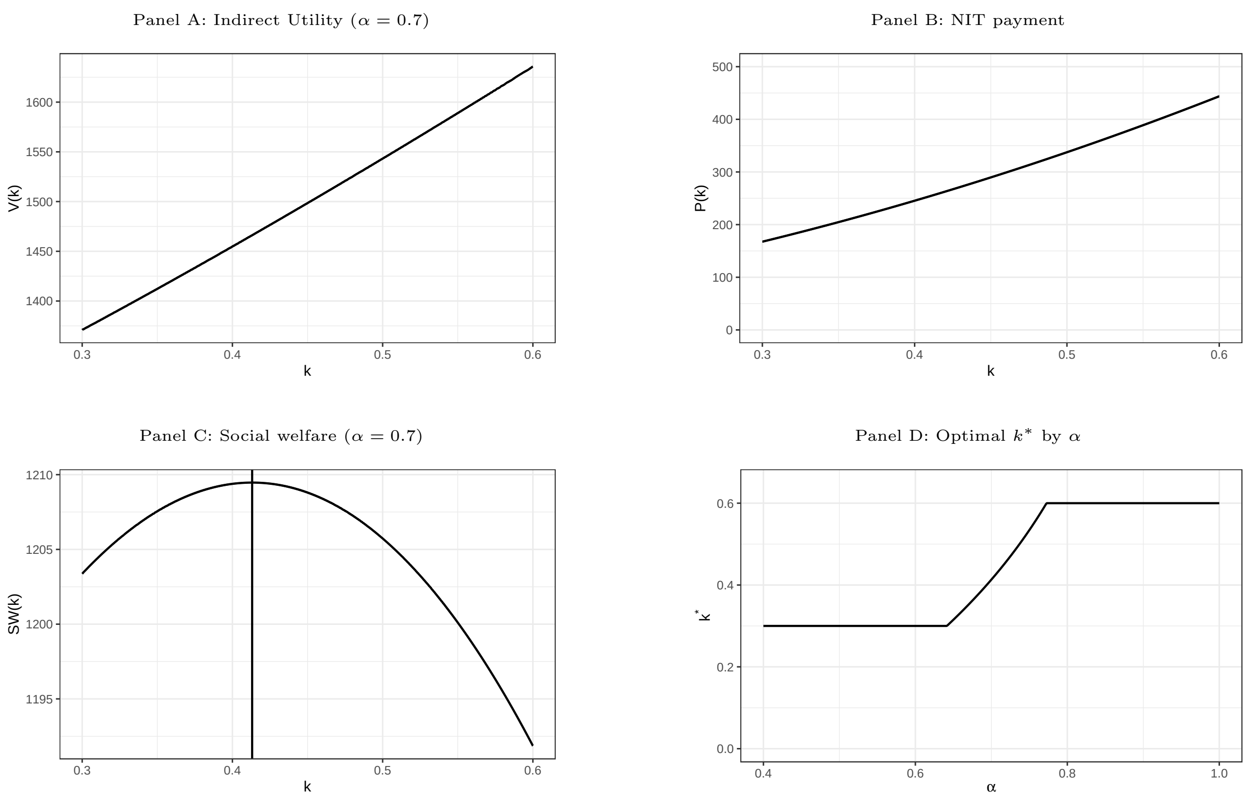
The figure depicts the linear labor supply estimation for different keep-rates k. The black dots are the OLS coefficient estimates on different keep-rates k (see Table 2) and are depicted with corresponding 95% confidence intervals that are based on robust standard errors (clustered at the family level). The line is fitted using an OLS regression with a constant.



In a last step of our analysis, to illustrate the importance of accounting for nonlinearities in the labor supply, we redo our welfare analysis on the basis of a linear labor supply function. This is supposed to mimic standard sufficient statistics welfare analysis where the curvature of the key behavioral response margin is summarized by a single parameter. In detail, the linear labor supply function is obtained by fitting a straight line between the four coefficients corresponding to the observed levels of k (see Table 2) using OLS. The result of this exercise is depicted in Figure 3. The linear estimate of $L^* = L(k)$ is then used to calculate indirect utility, the NIT payment, as well as social welfare using an otherwise iden-

Figure 4: *WELFARE ANALYSIS WITH LINEAR LABOR SUPPLY*

The figure depicts the welfare analysis based on the linear estimation of the labor supply, $L^* = \hat{L}(k)$ depicted in Figure 3. Panel A depicts the indirect utility, which is obtained by plugging $L^* = \hat{L}(k)$ into (the first row of) (9). α is set to 0.7. Panel B depicts the NIT payment, which is obtained by plugging $L^* = \hat{L}(k)$ into (11). Panel C depicts the social welfare, which is obtained by plugging $L^* = \hat{L}(k)$ into (13). Note that the line depicted in Panel C gives the difference between the lines depicted in the Panels A and B. The vertical line depicts the social welfare maximizing keep-rate k^*, which is equal to 0.413 for setting $\alpha = 0.7$. Finally, Panel D depicts the welfare maximizing keep-rate k^* for different levels of α. For the parameterization of the other parameters, see Section 3.2..



tical parameterization compared to above. The results are depicted in Figure 4. We find a, compared to the analysis using the nonlinear labor supply, similarly linearly shaped indirect utility function (Panel A). However, regarding the NIT payments (Panel B), we now find a perfectly linear curve, which is a stark contrast compared to the analysis with nonlinear labor supply. As discussed above, the curvature of the NIT payment function is directly corresponding to the labor supply function, which is now linear. Finally, Panel C depicts the social welfare, which is now a strictly concave function of k, with a local maximum at $k^* = 0.413$. Note that this social welfare maximizing k^* is substantially larger than the one in the analysis using nonlinear labor supply above, which amounts to 0.347. We further find that also for other levels of α the welfare-maximizing levels of k^* substantially differ between the different methods of computing labor supply (compare Panels D of Figures 2 and 4). Note also that the linear labor supply yields larger ranges of α for which either the minimum or the maximum observed values of k are optimal. This underlines the importance of accounting for nonlinearities in key behavioral responses to policy parameters and suggests that conventional social welfare analysis that disregards nonlinearities may potentially be very imprecise.

5. Conclusions

We conduct a welfare analysis of the NIT that explicitly allows for nonlinearities in the labor supply response to changes in the take-back rate. Our key finding is similar to that of Kasy (2018), which is that welfare optimizing levels of the policy parameter differ between analyses accounting for nonlinearities or not. We think that this finding should be considered in future research and in the interpretation of results from standard sufficient statistics analyses. However, regarding the magnitude of the optimal levels of the keep-rate, we refrain from formulating any policy implications. The reason for this is threefold, as (i) the external validity of the data is likely low, as the NIT experiments that are analyzed were conducted about 50 years ago; (ii) the data quality is poor, which is mainly due to the fact that treatment assignment was not random, that specific NIT plans were only tested in one of the two experiments considered, and that there was misreporting;[28] and (iii) only a limited number of guaranteed income levels and take-back rates was tested, with the latter only covering a range of 30 percentage points. Ideally, a potential future NIT experiment is conducted as RCT using a wider range of tested plans. The formulas derived in this paper could serve as basis for calculating social welfare with data from such an RCT.

[28]Note that the ambiguity in empirical results based on the NIT experiments data is a much discussed topic in the empirical NIT literature, see, e.g., Ashenfelter and Plant (1990), Hum and Simpson (1993), or Widerquist (2005).

Appendix 1. Proof that $\partial V^*/\partial k > 0$

In the following, we proof that $\partial V^*/\partial k > 0$. First, rewrite the indirect utility function as

$$V^* = Y^{*\alpha} \left(T - L^*\right)^{1-\alpha}. \tag{A.1}$$

Taking the first derivative of (A.1) with respect to k yields

$$\begin{aligned}\frac{\partial V^*}{\partial k} &= \alpha Y^{*\alpha-1} \frac{\partial Y^*}{\partial k} \left(T - L^*\right)^{1-\alpha} + Y^{*\alpha}(1-\alpha) \left(T - L^*\right)^{-\alpha} (-1) \frac{\partial L^*}{\partial k} \\ &= \underbrace{Y^{*\alpha}(T - L^*)^{-\alpha}}_{>0} \underbrace{\left[\alpha Y^{*-1} \frac{\partial Y^*}{\partial k} (T - L^*) - (1-\alpha) \frac{\partial L^*}{\partial k}\right]}_{\equiv Z}.\end{aligned} \tag{A.2}$$

Since we assume that $T > L > 0$ and $Y = G + kwL$ with $G > 0$, $k > 0$, and $w > 0$ (see Section 2.1), it follows that both consumption and leisure are always strictly positive and therefore $Y^{*\alpha}(T - L^*)^{-\alpha} > 0$. The sign of $\partial V^*/\partial k$ therefore equals the sign of Z. Using the results for Y^* and L^* as well as their first derivatives from Section 2.1, we can write Z as follows:

$$\begin{aligned}Z &= \alpha \frac{1}{\alpha(kwT + G)} \alpha w T \left[T - \left(\alpha T - \frac{G(1-\alpha)}{kw}\right)\right] - (1-\alpha) \frac{G(1-\alpha)}{k^2 w} \\ &= \frac{\alpha w T}{kwT + G} \left[(1-\alpha) \frac{kwT + G}{kw}\right] - (1-\alpha) \frac{G(1-\alpha)}{k^2 w} \\ &= (1-\alpha) \frac{\alpha T}{k} - (1-\alpha) \frac{G(1-\alpha)}{k^2 w} \\ &= \frac{(1-\alpha)}{k} \underbrace{\left[\alpha T - \frac{G(1-\alpha)}{kw}\right]}_{=L^*}.\end{aligned} \tag{A.3}$$

$(1-\alpha)/k > 0$, as we assume $\alpha, k \in (0, 1)$ (see Section 2.1). The hours worked in the optimum, L^*, must be strictly positive, too, as we assume $T > L > 0$. Therefore, $Z > 0$, and as a result, $\partial V^*/\partial k > 0$. ■

Appendix 2. Envelope Theorem

In the following, we demonstrate the Envelope Theorem that states that the effect of a marginal change in k on utility in the optimum equals its direct derivative.[29] Or, in other words, changes in the choice variables (i.e., Y, L, and λ) induced by the change in k do not affect utility in the optimum. For the sake of notational clarity, we restate the utility maximization problem from (4) using the placeholder $U(Y, T - L)$ for the Cobb-Douglas utility function:

$$V(k, w, \alpha, T, G) = \max_{Y,L} \left[U(Y, T - L) + \lambda(G + kwL - Y) \right]. \tag{A.4}$$

The first-order conditions from the utility maximization problem in (A.4) state as follows (with $U_Y = \partial U / \partial Y$ and $U_L = \partial U / \partial L$):

$$Y: \quad U_Y - \lambda \overset{!}{=} 0, \tag{A.5a}$$

$$L: \quad -U_L + \lambda kw \overset{!}{=} 0, \tag{A.5b}$$

$$\lambda: \quad G + kwL - Y \overset{!}{=} 0. \tag{A.5c}$$

Solving the first-order conditions yields value functions for the optimal labor supply Y^* and L^* (depicted in detail in Section 2.1) as well as the household's marginal, or shadow, value of income in the optimum (see, e.g., Mas-Colell et al., 1995):

$$\lambda^* = U_Y = \alpha Y^{*(\alpha-1)} (T - L^*)^{(1-\alpha)}. \tag{A.6}$$

[29] Note that we borrow the notation from Keuschnigg and Wamser (2024).

The indirect utility function can then be obtained by plugging the value functions for Y, L, and λ into (A.4):

$$V^* = V(k, w, \alpha, T, G) = U(Y^*, T - L^*) + \lambda^*(G + kwL^* - Y^*). \tag{A.7}$$

In a next step, we take the derivative of (A.7) with respect to k:

$$\frac{\partial V^*}{\partial k} = \lambda^* w L^* + \underbrace{(U_Y - \lambda^*)}_{=0 \text{ (see (A.5a))}} \frac{\partial Y^*}{\partial k} + \underbrace{(\lambda^* kw - U_L)}_{=0 \text{ (see (A.5b))}} \frac{\partial L^*}{\partial k} + \underbrace{(G + kwL^* - Y^*)}_{=0 \text{ (see (A.5c))}} \frac{\partial \lambda^*}{\partial k}. \tag{A.8}$$

The way we arranged the derivative shows that the second, third, and fourth terms are equal to zero as the optimality conditions (A.5a)-(A.5c) must be fulfilled. The partial derivative hence equals $\lambda^* w L^*$, which equals equation (10). The latter can be shown by substituting the value functions Y^* (see (8)), L^* (see (5)), and λ^* (see (A.6)) into (A.8) and (10):

$$\begin{aligned}
& \underbrace{\lambda^* w L^*}_{\text{(A.8)}} = \underbrace{\frac{(1-\alpha)}{k} Y^{*\alpha} (T - L^*)^{-\alpha} L^*}_{(10)} \\
\leftrightarrow \quad & \underbrace{\alpha Y^{*(\alpha-1)} (T - L^*)^{(1-\alpha)}}_{=\lambda^* \text{ (see (A.6))}} w = \frac{(1-\alpha)}{k} Y^{*\alpha} (T - L^*)^{-\alpha} \\
\leftrightarrow \quad & \alpha Y^{*(-1)} (T - L^*) w = \frac{(1-\alpha)}{k} \\
\leftrightarrow \quad & \alpha \frac{1}{\alpha(kwT + G)} \left(T - \alpha T + \frac{G(1-\alpha)}{kw} \right) w = \frac{(1-\alpha)}{k} \\
\leftrightarrow \quad & \frac{1}{(kwT + G)} \left(\frac{(1-\alpha)(kwT + G)}{kw} \right) w = \frac{(1-\alpha)}{k} \\
\leftrightarrow \quad & \frac{(1-\alpha)}{k} = \frac{(1-\alpha)}{k}. \ \blacksquare
\end{aligned} \tag{A.9}$$

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