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Inequality when effort matters^{*}

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Abstract

It is sometimes argued that poorer people choose to work less, implying less welfare inequality than suggested by observed incomes. Social policies have also acknowledged that efforts differ, and that people respond to incentives. Prevailing measures of inequality (in outcomes or opportunities) do not, however, measure incomes consistently with personal choices of effort. The direction of bias is unclear given the heterogeneity in efforts and preferences. Data on the labor supplies of single American adults suggest that adjusting for effort imposing common preferences attenuates inequality, although the effect is small. Allowing for preference heterogeneity consistently with behavior suggests higher inequality.

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1. Introduction

Disparities in levels of living reflect to some degree differences in personal efforts. While views differ greatly on how much effort matters, as compared to advantageous circumstances, it is clear that many people believe that effort plays some role. In a 2014 opinion poll of the American public, about one third of respondents viewed poverty as stemming from a lack of effort by poor people while a similar proportion believed that the rich were rich because they worked harder (PEW Research Center, 2014).

Furthermore, it is widely agreed that inequalities stemming from effort do not have the same ethical salience as those stemming from circumstances beyond an individual's control. This view has influenced social policies. For example, antipoverty policies in America and elsewhere have often identified the "undeserving poor" as those who are judged to be poor for lack of effort.² "Bad behaviors" are seen by some observers to be a source of exaggerated concerns about inequality.³ Those who take the alternative view—that it is really differing circumstances that ultimately divide the "rich" from the "poor" —tend to find the inequality far more troubling, and are more demanding of a policy response, than do those who think it is largely about personal choices. (In the same PEW Research Center poll, about 50% of respondents felt that circumstances/advantages were the main reason for poverty and inequality.) Yet here too it is often acknowledged that behavioral responses, such as through work effort, are germane to the design of social policies even when the bulk of inequality stems from differing circumstances.⁴

It is thus striking that most prevailing measures of inequality ignore such differences. The measures treat two people with the same income (or consumption) equally even if one of them must work hard to obtain that income while the other is idle. This concern has been raised before in the literature on the measurement of inequality in outcomes, where it has been argued that conventional measures in the space of observed incomes overstate the true inequality in welfare.⁵

² This is an old idea, but in modern times it became prominent in Katz's (1987) critique of American antipoverty policy. See Ravallion (2014) on the history of economic thought on antipoverty policy. Also see Gans's (1995, ch.1) discussion of the history of derogatory labels for poor people.

³ For example, Stein (2014) argues that: "There is an immense amount of income inequality here and everywhere. I am not sure why that is a bad thing. Some people will just be better students, harder working, more clever, more ruthless than other people." Stein goes on to claim that long-term poverty reflects "poor work habits." Also see the debate between Eichelberger (2014) and Williamson (2014) on the proposition that "poor people are lazy."

⁴ See the seminal formulation of the problem of redistribution with incentive constraints in Mirrlees (1971). Kanbur et al. (1994) extend this model to accommodate poverty reduction as the objective.

⁵ On the theoretical implications for inequality measurement see Allingham (1972) and Stiglitz (2009).

Nor are differences in preferences addressed by standard measures, recognizing that the cost of effort (the utility loss) almost surely depends on personal circumstances. Thus there is a disconnection between the social-policy debates on inequality and prevailing measurement practices.

In the recent literature on inequality of opportunity (INOP) one finds an explicit recognition of the role of effort in determining incomes. The usual theoretical starting point is Roemer's (1998) argument that income depends on both circumstances and personal efforts, such as labor supply.⁶ (Examples of relevant circumstances are parental income and parental education.) Income inequalities due to differing efforts are not seen as having ethical or policy salience.⁷ Motivated by Roemer's formulation, there have been a number of attempts to measure INOP.⁸ However, while "effort" figures prominently in the theory, it has been largely ignored in the empirical studies of INOP. The disconnect remerges. By this approach, equality of opportunity is deemed to prevail if observed incomes do not vary with observed circumstances.⁹ This can be called the "reduced-form approach" (in that differing efforts are implicit, in so far as effort is influenced by circumstances). Proponents argue that this provides a lower bound to the extent of INOP given incomplete data on circumstances.¹⁰ In recent years, the approach has been applied across many countries at all levels of development.¹¹

This paper explores the implications for the measurement of inequality (in either outcomes or opportunities) of an explicit accounting for heterogeneity in personal efforts and preferences. Some concept of individual welfare is implicit in any assessment of whether one person is better off than another. This is taken for granted in measuring "real income," such as when deflating nominal incomes for cost-of-living differences or adjusting for demographic

⁶ While Roemer's formulation has been influential, it is not the only approach. For a more general treatment (containing Roemer's model as a special case) see Fleurbaey and Schokkaert (2012).

⁷ It is arguably a big step to say that we should not be concerned about inequalities stemming from different efforts if only because such inequalities today can generate troubling inequalities of opportunity tomorrow.

⁸ Contributions include Van de gaer et al. (2001), Bourguignon et al. (2007), Paes de Barros et al. (2009), Trannoy et al. (2010), Ferreira and Gignoux (2011), Ferreira et al. (2011), Hassine (2012), Marrero and Rodriguez (2012), Singh (2012) and Brunori et al. (2013). Also see the broader discussions in Pignataro (2011), Roemer (2014), Roemer and Trannoy (2015) and Ferreira and Peragine (2015).

⁹ This is sometimes called "ex-ante" equality; "ex-post" equality requires equal reward for equal effort; see the discussion in Fleurbaey and Peragine (2009). For example, if someone starting out with a disadvantage in terms of her ability to generate income can make up the difference by hard work then one would surely be reluctant to say that there is no remaining inequality of opportunity; while the income difference according to circumstances may have vanished (no ex ante inequality), the difference in welfare remains (ex post inequality). This paper will also focus on the ex-ante concept.

¹⁰ See Ferreira and Gignoux (2011) for a clear statement of this argument.

¹¹ Ferreira and Peragine (2015) claim that the method has been applied to at least 40 countries.

heterogeneity using equivalence scales. But it is logically no less compelling when welfare depends on effort. While there may be constraints (such as labor-market frictions) on the scope for freely choosing one's effort, it appears that a significant degree of choice can be exercised by most people. Presumably the reason that those who think that income inequality is largely due to different efforts are not so troubled by that inequality is that they think there is little or no underlying inequality in welfare; the inequality reflects personal choices.¹² The paper examines the theoretical foundations and empirical robustness of prevailing methods of measuring inequality amongst adults when effort is deemed to matter to welfare.¹³ The empirical application uses data on the labor supply and incomes of single adults in the U.S. in 2013.

The nub of the matter is that the way inequality is being assessed in practice does not use a valid money-metric of welfare when effort matters.¹⁴ As long as people care about effort, observed incomes do not identify how welfare varies and so they are a questionable basis for assessing inequality of outcomes or opportunities. One possible fix is the idea of a "standard income."15 Here one measures income as if every able-bodied adult worked some standard number of hours, such as a full-time job. Assuming that everyone is free to work as much or as little as they like, if someone has an observed income below the poverty line but could in principle avoid this by working full time then, by the standard income approach, she is not deemed to be poor. (Of course, the welfare interpretation is different if the person is physically unable to work full time, or is rationed in the labor market such that she cannot find the stipulated standard amount of work.) However, like observed incomes, standard incomes are not a valid money metric of welfare.¹⁶ For whatever reason, the standard income idea has attracted little attention amongst economists measuring inequality.

Recognizing that people take responsibility for their efforts, given their circumstances, leads one to ask how a true money-metric of welfare-reflecting the disutility of effort-varies.

¹³ Of course, effort is only one aspect of the debates about inequality numbers; for example, there are also issues about price indices and equivalence scales. Note also that practitioners are on safer ground in measuring inequality amongst children for whom personal effort is not yet an issue. Here the concern is about inequality among adults. ¹⁴ Other issues, both conceptual and practical, have been raised about INOP measurement. See Kanbur and Wagstaff

¹² This is an instance of a more general point that is well understood in welfare economics, namely that inequality of income need not imply inequality of welfare. Heterogeneity in preferences further complicates matters.

^{(2014),} Fleurbaey and Schokkaert (2012), Atkinson (2015, Chapter 1), Ravallion (2016, Chapter 5). ¹⁵ This is the term used by Kanbur and Keen (1989). A similar idea is the full-time equivalent income (or salary) but this terminology is not used here as it risks confusion with the concept of equivalent income adopted later in the paper, following King (1983). ¹⁶ For a demonstration of this point see Kanbur and Keen (1989).

It has long been known that one can in principle measure income in a welfare-consistent way, as the monetary equivalent of utility.¹⁷ However, the implications for inequality are far from obvious. Those who claim that high (low) incomes largely reflect high (low) effort will expect to see a systematic positive relationship between effort and income, which will attenuate the welfare disparities suggested by observed incomes. Against this view, people in disadvantaged circumstances may be encouraged to make greater effort to compensate. Alongside these vertical differences, there may also be heterogeneity in work effort at given income, reflecting differences in (inter alia) wage rates and preferences. When two people with the same observed income make different efforts to derive that income then adjusting for the disutility of effort implies higher inequality between them. This "horizontal" effect mitigates the systematic effect on welfare inequality of vertical differences stemming from a positive relationship between income and mean effort. Indeed, one can readily construct examples in which mean effort is a non-decreasing function of income but the horizontal heterogeneity in effort at given income implies unambiguously higher inequality in the welfare space for a range of preference parameters.¹⁸ The paper elaborates these points and illustrates their relevance to assessments of the extent of inequality and poverty in America.

Two responses can be anticipated. First, the concern identified here applies to any situation in which income is used to measure welfare, which also depends on personal choices that matter independently of income. That is true. A focus on measuring INOP is nonetheless justified given that this has been the main place (in theory at least) where effort has been acknowledged as a source of inequality that needs to be treated differently to inequalities stemming from circumstances.

Second, one might be uncomfortable with the welfarist perspective, in which personal utilities are the basis for judgements about inequality and social welfare. However, it would surely be hard to defend a view that (on the one hand) people take responsibility for their effort but (on the other hand) the degree of their effort has no bearing on how their welfare should be

¹⁷ There have been a number of applications of the idea of money-metric utility to distributional analysis, including King (1983), Jorgenson and Slesnick (1984), Blundell et al. (1988), Apps and Savage (1989), Kanbur and Keen (1989). Also see the discussions in Slesnick (1998) and Fleurbaey and Maniquet (2011, Chapter 1).

¹⁸ For example, suppose that there are three income levels y = (1,1,2), with corresponding efforts x = (0,1,1) and that welfare is $y - \alpha x$ where $0 < \alpha < 1$. Then the Lorenz curve for $y - \alpha x$ shifts out relative to that for y for the poorest third but is unchanged for the upper third. (The two income-poorest are re-ranked.) For all measures satisfying the usual transfer axiom, inequality is no lower for welfare over this range of the preference parameter.

assessed. Rejecting the view that utility is the sole metric of welfare does not justify ignoring the differences in the efforts taken to make a living.

The next section discusses how effort has been treated in the literature on measuring inequality of opportunity. Section 3 draws out some theoretical implications of behavioral responses for measuring inequality of outcomes or opportunities, allowing better circumstances to either encourage or discourage effort. Section 4 looks at a simple parametric model, which is implemented on U.S. data. A concluding discussion is found in Section 5.

2. Measuring inequality when effort matters

In motivating existing measures of income inequality (whether in outcomes or opportunities) one might start by assuming that utility depends solely on income, and is some inter-personally constant function of income. Effort may matter for income, but there will be no interior solution for effort; everyone will work as hard as is humanly possible. While circumstances may still influence a person's maximum effort, this model is clearly unrealistic. It also too simple to capture the way effort has been widely seen as a matter of personal choice and responsibility in policy debates. For example, the stereotype of the "undeserving poor" is not that they are working as much as time permits, but this is still too little.

Instead, utility is taken here to be a function of effort (denoted x_i for person i=1,...,n) as well as total personal income (y_i), entering negatively and positively respectively.¹⁹ The relevant income concept for welfare is normally taken to be net of taxes. Here we can "solve out" by treating them as a function of gross income. There is heterogeneity in preferences, represented by a parameter α_i . (For example, preferences over income and effort may well depend on household size and demographic composition, and factors such as disability.) Combining these assumptions we can write the utility function as $u(y_i, x_i, \alpha_i)$.

Income depends on circumstances (c_i) as well as effort:

$$y_i = y(x_i, c_i) \tag{1}$$

The function *y* is taken to be increasing in both arguments. (The heterogeneity in preferences does not directly influence incomes, but may do so indirectly via effort.) Define:

¹⁹ Effort is bounded, but this is not made explicit for now since attention is confined to interior solutions for effort. (In the parametric model in section 4 a time constraint will be explicit.)

$$\widetilde{u}(x_i, c_i, \alpha_i) \equiv u[y(x_i, c_i), x_i, \alpha_i]$$

It is assumed that:²⁰

$$\widetilde{u}_{xx}(x_i, c_i, \alpha_i) = u_y y_{xx} + y_x^2 u_{yy} + 2y_x u_{yx} + u_{xx} < 0$$

Effort is taken to be a matter of personal choice. The interior solution for effort requires that:

$$\widetilde{u}_{x}(x_{i},c_{i},\alpha_{i}) = u_{y}(y_{i},x_{i},\alpha_{i})y_{x}(x_{i},c_{i}) + u_{x}(y_{i},x_{i},\alpha_{i}) = 0$$
(2)

The chosen effort (solving (1) and (2)) depends on circumstances and preferences, which we can write as $x_i = x(c_i, \alpha_i)$.²¹

The empirical approach to INOP measurement that has emerged in the literature focuses on an estimate of the reduced-form equation for income, solving out effort. Treating effort as a personal choice, the reduced-form equation can be written as:²²

$$\widetilde{y}(c_i, \alpha_i) \equiv y[x(c_i, \alpha_i), c_i]$$
(3)

The corresponding regression specification in the literature typically takes the form:

$$y_i = \beta_0 + \beta_1 c_i + \varepsilon_i \tag{4}$$

Where ε is treated as a zero-mean error term uncorrelated with circumstances ($E(\varepsilon_i | c_i) = 0$).

The heterogeneity in preferences is relegated to the error term. (Of course, in practice ε also includes measurement errors.)

The bulk of the applied literature on measuring INOP has studied the conditional mean of income given circumstances, as usually measured by the linear projection for y based on (4), namely $\hat{E}(y_i|c_i) = \hat{\beta}_0 + \hat{\beta}_1 c_i$ where the expectation is taken over the distribution of ε .²³ The R² for the estimated regression model in (4) is interpreted as the share of inequality attributed to unequal observed circumstances. The primary focus of the rest of this paper is the validity of

²⁰ Subscripts for person *i* are dropped in places to simplify the notation. I assume twice differentiability when convenient. Subscripts are used for partial derivatives, in obvious notation. When convenient for the exposition I also treat c and e as continuous scalars (such as parental income and labor supply respectively), but they are vectors in reality and with discrete elements.

²¹ Notice that this model is static, in that all effort is a current choice. In a dynamic model one might postulate that there are also current gains from past efforts, which are taken as exogenous to choices about current effort. (An example is past effort at school versus current labor supply given schooling.) The present paper confines attention to a static model. ²² This is explicit in Bourguignon et al. (2007), Trannoy et al. (2010) and Ferreira and Gignoux (2011), but implicit

in most of the literature.

 $^{^{23}}$ Instead of a regression, some studies of INOP use a cross-tabulation of mean y by groups of people defined according to their c's. This is not an important difference in this context.

using observed incomes for measuring income inequality when effort is a personal choice variable.

3. Inequality of what? Observed versus welfare-equivalent incomes

In their review of the theory and methods of measuring INOP, Ferreira and Peragine (2015) claim that "...the existence of effort variables, observed or unobserved, is entirely immaterial [to the measure of inequality] since [equation 4] is a reduced-form equation, where any effect of circumstances on incomes through their effects on efforts is already captured by the regression coefficients." (My clarifications in brackets.)

As the following argument will make clear, the robustness of the reduced-form model in (4) is questionable when effort is a matter of personal choice. This also has bearing on the measures obtained for inequality of outcomes. The extent to which circumstances are observed is not the issue here and this problem can be ignored for now; *c* is taken here to be fully observed. The problem lies elsewhere, in how one measures "income" given that effort is a choice. The problem is found in both the traditional inequality measures based on the distribution of observed incomes y_i (*i*=1,...,*n*) and in the recent literature on measuring INOP based on estimates of $E(y_i|c_i)$. And once this problem is recognized it is far from clear what the measures obtained in this literature are telling us about inequality.

When measuring inequality or poverty we typically aim to assure that the monetary metric of welfare is "real," which is normally identified by consistency with a model of utility. This is implemented using cost-of-living indices and equivalence scales or (more generally) equivalent income functions.²⁴ The appeal of welfare consistency is no less obvious when effort matters.²⁵ We are presumably concerned with how welfare varies with circumstances. However, on noting that utility is $u(\tilde{y}(c_i, \alpha_i), x_i, \alpha_i)$ it is immediately evident that $\tilde{y}(c_i, \alpha_i)$ is only a valid monetary metric of welfare if everyone has the same preferences and effort is constant or does not matter to welfare. These must be deemed extremely strong assumptions. Consider preferences first. If circumstances alter preferences then the reduced-form approach is not going

²⁴ The equivalent income function was introduced by King (1983).

²⁵ Although largely ignored in the literature on measuring INOP this point has been understood for some time in the context of empirical welfare measurement when labor supply gives disutility. Early contributions include Blundell et al. (1988) and Apps and Savage (1989). On micro approaches to modelling labor supply see Blundell et al. (2007).

to properly reflect INOP. An obvious example is disability; there is no reason to believe that the welfare effect of disability is evident in its income effect, as presumed by standard measures of INOP. Nor would the effect of (say) age on the personal (physical and psychic) costs of effort be necessarily evident in incomes. Second, even with homogeneous preferences ($\alpha_i = \overline{\alpha}$, say, for all *i*), if we take effort seriously as a source of disutility then it is plain that $\tilde{y}(c_i, \overline{\alpha})$ will not rank people consistently with their welfare.

When utility depends on income and effort, the welfare-consistent measure of income is the <u>equivalent income</u>, y_i^* obtained by solving:

$$u[y_i^*, \overline{x}, \overline{\alpha}] = u[\widetilde{y}(c_i, \alpha_i), x(c_i, \alpha_i), \alpha_i]$$
(5)

Here \bar{x} is a fixed reference level of effort (which can be taken to depend of fixed reference levels of both circumstances and the preference parameter, \bar{c} and $\bar{\alpha}$).²⁶ On inverting the utility function (with the inverse function w.r.t. income denoted u^{-1}) it is evident from (5) that y_i^* is an inter-personally constant and strictly increasing function of utility, which we can write as:²⁷

$$y_i^* = u^{-1}[u(\tilde{y}(c_i, \alpha_i), x(c_i, \alpha_i), \alpha_i); \bar{x}, \bar{\alpha}] = f(c_i, \alpha_i)$$
(6)

This formulation assumes that utilities are level comparable between people with different α_i 's (reflecting, for example, different household demographics). Theoretical objections have been raised to such interpersonal comparisons of welfare although they are routine in measuring inequality and poverty (though not always explicit).²⁸ Alternatively one might prefer to only evaluate the utility of given income and effort at fixed preference parameters, $\alpha_i = \overline{\alpha}$. Both approaches will be allowed in the empirical work.

Whether there is more or less inequality in the equivalent income space than for observed incomes depends on the properties of the utility function and how both efforts and preferences vary across the population. We cannot determine the outcome solely by looking at how effort varies with observed income, as in the reduced-form approach to measuring INOP. For example (and this case will be salient empirically), one might find that mean effort (forming an

²⁶ As is well recognized in the literature on welfare measurement, only by setting fixed reference prices can we derive a valid money-metric of utility (see, for example, King, 1983). However, the point also holds for heterogeneity in effort or other non-income dimensions of welfare.

²⁷ In obvious notation and subsuming $\overline{x}, \overline{\alpha}$ in the definition of the equivalent-income function f.

²⁸ An influential critique was by Robbins (1935). In modern terms, see the discussion in Fleurbaey and Maniquet (2011).

expectation over the distribution of the preference parameters) rises with income, yet the variance in effort and preferences entails higher inequality of equivalent income than observed income. Since nothing very general can be said in theory, the effect on measured inequality of adjusting observed income for effort will be treated as an empirical question to be taken up later in this paper.

Without further restrictions on preferences, a standard inequality measure calculated using a distribution of equivalent incomes need not fall in response to equalizing redistributions of money incomes, as pointed out by Blackorby and Donaldson (1988). There are correctives for this problem in the literature.²⁹ Here it will also be treated as an empirical question about the relationship between equivalent income and money income.

While not much more can be said in theory about the effect of effort on overall inequality, we can say more about how inequalities of opportunity in the equivalent-income space compare to the income space. There are two sources of differences between the two income metrics: heterogeneity in circumstances and heterogeneity in preferences. The former is of primary interest from the perspective of measuring INOP. To focus on the former for the expository purpose of this discussion, I now set $\alpha_i = \overline{\alpha}$. However, the contribution of heterogeneity in preferences will be considered in Section 4.

Better circumstances yield higher equivalent income. (Applying the envelope theorem it is readily verified that $f_c = y_c u_{\tilde{y}} / u_{y^*} > 0$.) On applying the implicit function theorem to equation (2) and differentiating we have:

$$x_{c} = \frac{-u_{y}y_{xc} - y_{c}(u_{xy} + y_{x}u_{yy})}{\tilde{u}_{xx}}$$
(7)

The sign of this expression cannot be determined based on the assumptions so far. Better circumstances (meaning that $y_c > 0$) could either encourage or discourage effort. However, it would seem reasonable to assume that if better circumstances discourage effort then there is a limit to this effect such that $\tilde{y}_c > 0$, i.e., $x_c > -y_c / y_x$.

²⁹ Blackorby and Donaldson (1987) recommend the use of "welfare ratios," whereby money incomes are normalized by the poverty line, defined as a point on the consumer's cost function, at a reference utility level. Alternatively, one can select the (arbitrary) reference values in the equivalent income function to assure that the problem is avoided empirically, as done by Ravallion and van de Walle (1991).

The issue is then to compare how much the two income metrics respond to differing circumstances, as required for assessing the extent of INOP. Evidently $y_i^* \ge (\le) \tilde{y}_i$ as $x(\bar{c}, \bar{\alpha}) \ge (\le) x(c_i, \bar{\alpha})$ (given that effort gives disutility). We can identify two cases:

Case 1: Poorer circumstances encourage effort ($x_c < 0$). (Sufficient conditions are that $u_{xy} \le 0$, $y_{xc} \le 0$ and $u_{yy} < 0$.) Then $y_i^* \ge (\le) \tilde{y}_i$ as $\overline{c} \le (\ge) c_i$. Panel (1) in Figure 1 illustrates this case under linearity. We see a steeper "circumstances gradient" in equivalent income.

Case 2: Poor circumstances discourage effort $(x_c > 0)$. (Sufficient conditions are that $y_{xc} > 0$ and $u_{xy} + y_x u_{yy} > 0$.) Then $y_i^* \ge (\le) \tilde{y}_i$ as $\bar{c} \ge (\le) c_i$. Here we find that measurement in the income space overstates inequality of opportunity, based on how equivalent income varies with circumstances, as illustrated in panel (2) of Figure 1.

These stylized cases are deterministic. In the stochastic formulation with an error distribution—reflecting (*inter alia*) heterogeneity in preferences unexplained by observed circumstances—Case 1 does not imply that measuring inequality based on observed incomes understates inequality based on equivalent incomes, with the opposite in Case 2. The error distributions around the two income measures as functions of circumstances may well be different, such that (for example) inequality turns out to be higher for equivalent incomes in Case 2. That is an empirical issue to which we turn next. As we will see, heterogeneity in preferences further clouds the picture.

4. Empirical implementation

The upshot of these observations is that the behavioral responses to circumstances through choice of effort remain material to the interpretation of disparities in incomes between people in different circumstances and to the measures obtained for inequality or poverty of outcomes.

The following empirical example illustrates the sensitivity of inequality measures to including an allowance for heterogeneous efforts and preferences. I focus solely on effort through labor supply, giving the standard consumption-leisure choice model. The utility function is assumed to have the Cobb-Douglas functional form.

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In common with the prevailing approaches in the literature to measuring INOP based on how observed incomes vary with circumstances, any direct welfare effects of circumstances that are not evident in income or labor supply are ignored.³⁰ This limitation is likely to be especially salient for disabilities and demographic effects on welfare (due to differing numbers of children and family sizes). In recognition of this concern, the analysis here is only done for a specific family type, namely single-person households, and excludes those with any (self-reported) disability. Thus a number of thorny issues of inter-household distribution, setting equivalence scales and making inter-personal welfare comparisons between those with and without disabilities are swept aside for the present purpose.

While acknowledging the limitations of these calculations, they serve to demonstrate that allowing for the disutility of effort can give a quite different picture of inequality to that suggested by prevailing methods.

Data: The data are from the Annual Social and Economic Supplement of the Current Population Survey (CPS) for the U.S. for 2014 (with reference to incomes for 2013).³¹ The analysis is confined to the roughly 6,000 single-person households in the 2014 CPS.

Labor supply is measured by average hours of work per week in 2013.³² The mean is 39 hours (with a median is 40 hours). The range in hours worked is from nearly zero to 99 hours. Table 1 provides some key summary statistics and Figure 2 plots log hours worked per week in the last year against log total pre-tax income.³³ Mean labor supply for those with an income under \$20000 (the poorest 16%) is 30 hours, while it falls to 26 hours for those living under \$15,000 (the poorest 8%) (Table 1). We see that mean (log) labor supply rises with income up to a certain point then levels off for the upper 30% or so (Figure 2).

³⁰ This relates to the long-standing problem of inferring welfare from observed demand or supply behavior in markets. Suppose that effort maximizes $u[f(y_i, x_i), d_i]$ subject to $y_i = y(x_i, d_i)$ where d_i represents disability (an element of c_i more generally). However, the observed solutions, $x_i = x(d_i)$, also maximize $f(y_i, x_i)$ and so they cannot identify $u[f(y_i, x_i), d_i]$ as the unique maximand. Early expositions of this point in the context of making welfare comparisons across different household types for the purpose of setting equivalence scales include Pollak and Wales (1979) and Browning (1992).

³¹ The CPS data were accessed through the University of Minnesota's <u>IPUMS-CPS</u> site.

³² This is obtained by multiplying reported weeks of work in the last year by reported average hours of work per week then dividing by 52.

 $^{^{33}}$ Recall that pre-tax income (y) is the relevant concept in the model in Section 2 in which taxes are solved-out, assuming that they are some function of y. Also note that the CPS does not ask for taxes paid so imputations of uncertain reliability are required.

While there is an income gradient in labor supplies, it does not appear to be large enough to plausibly account for much of the income disparities. For example, the average hourly wage rate of those with income less than \$20,000 is \$8.26. Ten hours extra work at this wage rate would only make up 10% of the gap between the average income of this group and the overall mean income.³⁴ Looked at a different way, this group of workers would have to work almost 100 hours per week extra to reach mean income—equivalent to three full-time jobs. (Table 1 gives these calculations for various income cut-offs.)

While the income gradient in hours of work does not seem especially steep, the pattern suggests that the partial effect of adjusting for effort as forgone leisure will go some way toward attenuating overall inequality in observed incomes. However, the large variance in labor supply at given income, especially at middle income levels evident in Figure 2 also comes into play. This "horizontal" effect is inequality increasing.

To see the net effect, consider the following measure of standard income. Suppose that all those working less than the average hours were able to make up the gap at their current average wage rate; there is no change for those working at or above the average hours. Thus standard income is defined as:

$$y_i^s \equiv w_i \max(x^s, x_i) + \pi_i \tag{8}$$

Here the wage rate is w_i while there unearned income (independent of effort) is π_i . The standard for labor supply is denoted x^s and is set at 39 hours. The assumption that the current wage can be maintained is questionable; to make up the hours, some may well have to switch to lower-paying jobs or incur prohibitively high personal costs of supplying the extra effort. So this simulation could well over-estimate the impact, especially on poverty.

Figure 3 plots the standard income against observed income (both in logs). There are some large proportionate gains, although they are spread through the bulk of the income range. The first two rows of Table 2 give inequality and poverty measures for observed incomes and the standard incomes. The full-time worker simulation brings down all three inequality measures, and both poverty measures. Figure 4 gives the Lorenz curves; there is not strict Lorenz dominance, although the overlap does not happen until the 98th percentile.

³⁴ The overall mean weekly income of the sample is \$1048, while the mean weekly income of those living below \$20,000 per annum is \$245.

When we come to incorporate effort in a welfare-consistent measure of income, this horizontal effect will again become important although then it will also interact with preferences. The net effect on measured inequality is thus an empirical issue to which we turn after describing the parametric model to be used.

Parametric model: In implementing an empirical model of income as a function of circumstances and effort the literature has often assumed a functional form that is additively-separable between effort and circumstances. However, it would clearly be questionable to assume that the marginal returns to circumstances are independent of effort. Indeed, in thinking about the economics one is drawn to postulate that the returns to effort (the wage rate when effort is simply labor supply) depend on circumstances—creating a natural interaction effect.

To consider the implications further, let us write equation (1) for individual *i* as:

$$y_i = w(c_i)x_i + \pi(c_i) \ (i=1,...,n)$$
 (9)

The notation now recognizes explicitly that the wage rate and unearned income depend on circumstances, denoted $w(c_i)$ and $\pi(c_i)$ respectively. The values of $w(c_i)$ and $\pi(c_i)$ are the key parameters of effort choice, which is taken to maximize a utility function of the form:

$$u(y_i, x_i, \alpha_i) = \ln y_i + \alpha_i \ln(t - x_i)$$
(10)

where *t* is the total time available for leisure or work (so that $t - x_i$ is leisure time). The (log) equivalent income is:

$$\ln y_i^* = \ln y_i + \alpha_i \ln(t - x_i) - k$$
(11)

where *k* is the fixed reference. Optimal labor supply requires that $\alpha_i = w(c_i)(t - x_i) / y_i$; the latter is called here the leisure ratio (the ratio of the imputed value of leisure to income).

The limitations to what can be inferred about INOP from the reduced-form relationship between observed incomes and circumstances alone can be seen clearly if one compares the implied elasticities to differences in circumstances. Solely for expository purposes, let us treat *c* as a continuous scalar. Then it is readily verified that:

$$\frac{\partial \ln y_i^*}{\partial \ln c_i} = s_{wi} \frac{\partial \ln w(c_i)}{\partial \ln c_i} + s_{\pi i} \frac{\partial \ln \pi(c_i)}{\partial \ln c_i}$$
(12.1)

$$\frac{\partial \ln y_i}{\partial \ln c_i} = \left(\frac{\alpha_i + s_{wi}}{1 + \alpha_i}\right) \frac{\partial \ln w(c_i)}{\partial \ln c_i} + \left(\frac{s_{\pi i}}{1 + \alpha_i}\right) \frac{\partial \ln \pi(c_i)}{\partial \ln c_i}$$
(12.2)

Here $s_{wi} = w(c_i)x_i / y_i$ and $s_{\pi i} = \pi(c_i) / y_i$ are earned and unearned income shares respectively. In both cases the income elasticity w.r.t. circumstances is a weighted mean of the corresponding elasticities for the wage rate and unearned income.³⁵ When either $w(c_i)/\pi(c_i)$ is a constant or $\alpha_i = 0_i$ observed income and equivalent income have the same elasticities with respect to circumstances. More generally the two elasticities differ. The difference in weights depends on the preference parameter. As the value attached to leisure rises (higher α_i), observed income progressively shifts its weight from unearned income to earned income, while the weights for equivalent income remain unchanged at given income shares. This is intuitive; the more highly leisure is valued, the more observed income disparities undervalue inequality in unearned income from the point of view of welfare.

Comparison of the two empirical income measures: There are a number of possible scenarios of interest for the parameters and data. A benchmark case can be configured to be deliberately conservative about the impact of adjusting for effort on measured inequality. It may be expected that the presence of the relatively few low labor supplies in Figure 2 will exaggerate the extent of inequality in equivalent incomes. To address this concern the following analysis is restricted to those households who worked for money at least one day (8 hours) per week on average over 2013. This cuts out about 200 households.³⁶ The available time for work or leisure is set at 100, leaving out about 10 hours per day. This also seems conservative.

In one scenario, preferences are assumed to be constant, with α_i set at the sample mean of $w(c_i)(t-x_i)/y_i$ for all *i*. This is instructive, but it does not allow for the preference heterogeneity that has long been emphasized in some quarters. In a second scenario, the preference parameter is allowed to vary. One possibility is to assume that everyone in the survey has freely chosen their ideal labor supply, and to set $\alpha_i = w(c_i)(t-x_i)/y_i$ for all *i*. This is questionable given the existence of labor-market frictions, whereby some survey respondents had too little leisure, and some too much, relative to their ideals. Setting the parameter to accord exactly with the leisure ratios in the survey data thus produces an implausibly large variance coming from the high levels of log leisure, which are given a high weight in the Cobb-Douglas

 $^{^{35}}$ Note that for both (12.1) and (12.2) the weights sum to unity.

³⁶ As noted, those reporting any disability affecting work or any difficulty (seeing, hearing, remembering, mobility, personal care) are excluded from the main analysis reported here. 5% of the sample reported a disability affecting their work.

specification. The spread of leisure ratios is evident in Figure 5. For example, for 170 observations the implied leisure term in equation (10) added over 20 to log income! While the spread of empirical leisure ratios undoubtedly reflects labor-market frictions, measurement errors may also be playing a role.

Some degree of smoothing of the empirical leisure ratios is clearly needed. For this purpose, the idiosyncratic preferences were set at the predicted values based on a regression of $\ln[w(c_i)(t - x_i)/y_i]$ on a quadratic function of the log wage rate, log unearned income (with their interaction) and a vector of observed circumstances from the CPS related to gender, age, race, place of birth, whether parents were born in the U.S. (Unfortunately, the data source does not include other information about parents, such as their education.) Age enters as the deviation from the median of 49 years. The left-out group for the dummy variables comprises white, native-born, males of 49 years of age with parents born in the U.S.; 25% of the sample is in this group. The Appendix gives the regression used to estimate the predicted value of the leisure ratio. Figure 5 gives the densities of the predicted leisure ratio, showing how this trims the extreme values.

We can now calculate the equivalent incomes. Figure 6 gives the kernel density functions for both log equivalent income and log observed income. Panel (a) is for common preferences. Then we see that equivalent incomes have a similar mode but lower variance, although there is still a fairly close alignment of the density functions. Panel (b) allows idiosyncratic preferences, with the preference parameter set at the predicted values of the leisure ratio, as described above. The effect of the adjustment for effort is then to add noticeably thicker tails.

The densities in Figure 6 relate to marginal distributions. The heterogeneity in effort creates dispersion in the equivalent income measures for given observed incomes. This conditional variance in effort is evident in Figure 7, which plots log equivalent income against log observed income. Again, results are given for the case of common preferences (panel a) and for idiosyncratic preferences (panel b). Figure 7 also gives the regression lines, which have slopes that are significantly less than unity in both cases though steeper for idiosyncratic preferences. ³⁷ In other words, the adjustment for effort tends to raise (lower)

³⁷ The regression coefficients are 0.832 (s.e.=0.007) and 0.565 (s.e.=0.021) for common preferences and idiosyncratic preferences respectively.

equivalent incomes for the poor (rich). However, the idiosyncratic-preferences case generates much greater dispersion of equivalent incomes at given observed income.

Both equivalent incomes are correlated with standard incomes, again using a full-time job as the standard, although the correlation is higher for common preferences; in logs one finds that r=0.883 using common preferences, as compared to 0.404 using idiosyncratic preferences. Figure 8 gives the scatter plots. While standard income seems a reasonably good predictor of equivalent income with common preferences, this cannot be said about idiosyncratic preferences.

As noted in Section 3, the curvature (if any) in the relationship between observed incomes and equivalent incomes is of interest. This was tested using the RESET test on the linear regression of equivalent income on observed income using the squared values of fitted residuals. The test did not reject linearity for either the constant preferences specification (prob.=0.131) or idiosyncratic preferences specification (prob.=0.712). This was also the case when I include a control for labor supply.³⁸

Table 2 also provides the same inequality indices for the two equivalent-income measures while Figure 9 gives the Lorenz curves. When one imposes common preferences, the level of inequality falls after adjusting for effort; the effect is not large and nor is there Lorenz dominance, although the intersections are at the extremes (the poorest percentile for common preferences and the upper three percentiles for the idiosyncratic preferences). By contrast, inequality measures rise with the switch to the welfare-consistent income measure with idiosyncratic preferences. The thicker lower tail of equivalent incomes evident in Figure 6(b) implies that poverty rates rise for a broad interval of lines; Table 2 gives poverty rates for two illustrative poverty lines (*z*). Since we have seen from Figure 2 that mean effort conditional on income rises with income, it is plain that the higher inequality in equivalent income in the idiosyncratic-preferences case stems from the aforementioned variance in effort at given income, given that those consuming more leisure are deemed to value it more with idiosyncratic preferences.

To throw some light on the <u>structure</u> of INOP, Table 3 gives regressions of log observed income and log equivalent income against the same set of variables describing circumstances as used in predicting the leisure share. Again, results are given for both common preferences and idiosyncratic preferences. The regressions with common preferences look fairly similar to those

³⁸ The RESET tests then gave prob.=0.786 and 0.522.

for observed incomes. Nonetheless, there are a number of differences for specific circumstances. The female income differential falls appreciably when one adjusts for labor supply, though it remains significant.³⁹ The curvature in the relationship with age remains, but the turning point rises to 71 years, as compared to 58 years for observed incomes. There are small differences in the effects of race and place of birth. Recall that in setting common preferences, the sample mean of $w(c_i)(t-x_i)/y_i$ was used. Sensitivity tests indicated that higher values (tested at one and two standard deviations above the mean) tended to further attenuate the gender and race effects, while increasing the effects of either being foreign born or having a foreign-born mother.

When one allows for idiosyncratic preferences, the regressions change even more. The relationship with age switches curvature between the two income concepts, but the turning point is outside the range of the data; equivalent income declines with age within the data range. The effect of being female is now positive, as is the effect of being African American, Asian or Hispanic. Significantly negative effects emerge for those born in South-East Asia, South-West Asia, Central or Eastern Europe, and Africa. There is positive effect of being foreign born and having a foreign-born mother.

Some of these effects may well be confounded by differences in unemployment rates by gender or race, and labor-market discrimination. All one can reasonably conclude from these calculations is that the claims made about INOP based on observed incomes may well be far from robust to allowing for heterogeneity in both effort and preferences.

Notice that the R^2 rises appreciably when one switches to idiosyncratic preferences. Recall, however, that the preference parameter (the leisure ratio) is predicted based (in part) on circumstances. If one uses the actual leisure ratio rather than the predicted value the R^2 falls appreciably, as can be seen from column (4) in Table 3. There is a marked loss of overall explanatory power for this set of circumstances. Most circumstances related to race and place of birth become insignificant. To some extent this reflects the aforementioned problem of extreme values in the leisure ratio. However, the observation warns against concluding that INOP is greater when one allows for idiosyncratic preferences.

³⁹ The data do not include work done within the home, though this is probably similar by gender in the sample of single adults.

5. Conclusions

A not uncommon view historically, which one still hears today, is that high incomes are simply the reward for greater effort, and poverty reflects laziness. Critics of this view point instead to structural and institutional factors relevant to poverty and inequality. However, even accepting that effort choice is a key factor, it is far from obvious that allowing for a disutility of effort implies less inequality in terms of either outcomes or opportunities.

If one takes seriously the idea that effort comes at a cost to welfare then prevailing methods of measuring inequality—including those found in the recent literature on inequality of opportunity—are not using a valid monetary measure of welfare. However, the likely heterogeneity in effort and preferences must also be brought into the picture. It may be granted that average effort rises with income (at least over some range), but there is also a variance in effort at given income, and preferences clearly vary as well. The implications for assessments of inequality stem from both the vertical differences (in how mean effort varies with income) and the horizontal differences (in how effort varies at given income). Once this point is acknowledged, it is not clear what existing measures tell us about inequality. The paper has provided an elaboration of this concern and an illustration of the potential implications of heterogeneity in effort and preferences using data on labor supply and incomes for the U.S.

It is unclear on *a priori* grounds what can usefully be inferred about inequality without adjusting for effort in a welfare-consistent way. The challenge remains of how to do better. There are both empirical and conceptual issues. The implications of taking effort seriously for inequality measurement depend crucially on the behavioral responses to unequal opportunities, and not all of those responses are readily observable. Measures with a clearer welfare-economic interpretation call for data on efforts, for which existing surveys are limited to a subset of the many dimensions of effort. And the longstanding challenges faced in making inter-personal comparisons of welfare across heterogeneous people cannot be avoided in this context.

While acknowledging these limitations, the paper has provided some illustrative calculations for American working singles. A positive income gradient in labor supply is evident in the data. This gradient accounts for very little of the income gap between the poorest third (say) and the overall mean. If one calculated standard incomes such that all workers had at least the average employment of 39 hours per week (at their present wage rate) then inequality and

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poverty measures would fall. The contribution of the lower employment of poor workers to poverty rates is notable; for example, while 17% of workers have an observed income under \$20,000 this would fall to 12% if those workers supplied the average number of hours per week of all workers although this may well be an overestimate. However, the fact that poorer workers work less appears to contribute rather little to total inequality in observed incomes.

Imposing common preferences at the average revealed disutility of effort, one finds that allowing for heterogeneous efforts yields only a modest drop in the measured level of inequality. Nor does it make much difference in the structure of inequality, as indicated by correlations with a set of observed circumstances related to gender, age, race and place of birth, although larger differences in the structure of inequality emerge with a stronger preference for leisure.

Allowing for idiosyncratic preferences changes the picture. It is unclear just how far one would want to go in allowing for differing preferences. Here the paper has not insisted that every individual in the survey data is at their personal optimum, as some may well be working less than desired, and some more. A regression-based "smoothing" of the data allows for differing preferences associated with wages, unearned incomes and the same set of circumstances. On doing so, the paper finds substantially higher measures of inequality and poverty and some notable differences in the structure of inequality emerge. These distributional effects do not stem from the relationship between mean effort and income but rather from the horizontal heterogeneity in effort and how this is magnified by the preference heterogeneity. This source of horizontal inequality swamps the tendency for mean labor supply to rise with income.

Whether one accepts the assumptions underlying these methodological changes is an open question. However, it is clear from this study that it should not be presumed that allowing for effort in a way that is broadly consistent with behavior would substantially attenuate the disparities suggested by standard data sources on income inequality. Indeed, one can even defend the opposite claim when an allowance is made for heterogeneity in preferences.

Figure 1: The circumstances gradient of income for alternative metrics and alternative behavioral responses at given preferences

(1) Poor circumstances encourage effort

(2) Poor circumstances discourage effort







Figure 2: Labor supply plotted against total income for U.S. single adults in 2013

<u>Note</u>: The regression line is the "nearest neighbor" smothered scatter plot using a locally-weighted quadratic function. The overall quadratic regression (with White standard errors in parentheses) is: $\ln x_i = -6.873 + 1.712 \ln y_i - 0.069 \ln y_i^2 + \hat{\varepsilon}_i \quad R^2 = 0.206; n = 5863$



Figure 3: Plot of standard incomes against observed incomes

<u>Note</u>: The standard incomes are calculated by assuming that all those working less than average hours were to work average hours at the same wage rate as at present.



Figure 4: Lorenz curves for observed incomes and "full-employment" standard incomes

Figure 5: Kernel densities of the log leisure ratio







(a) Common preferences



Figure 7: Plot of log equivalent income against log observed income

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Figure 8: Plot of log equivalent income against log standard income



Figure 9: Lorenz curves for the three income concepts



Income cut-off (<i>z</i>)	% of sample	Mean hours of work per week (\overline{h}_z)	Mean wage rate (\$/hour) (\overline{w}_z)	Mean income (\$/week) (\overline{y}_z)	% of income gap covered by working average hours per week $(\frac{100(39.26 - \overline{h}_z)\overline{w}_z}{(1048.26 - \overline{y}_z)})$	Extra hours per week to reach mean income $(\frac{1048.26 - \overline{y}_z}{\overline{w}_z})$
10,000	4.03	23.66	5.62	119.15	9.44	165.32
15,000	8.31	26.35	7.10	177.20	10.52	122.68
20,000	15.11	29.56	8.26	244.96	9.97	97.25
25,000	22.67	31.64	9.38	304.60	9.61	79.28
30,000	29.66	33.00	10.28	354.90	9.28	67.45
35,000	38.20	34.50	11.40	411.69	8.52	55.84
Median	50.00	35.81	12.92	487.84	7.95	43.38
Maximum	100.00	39.26	24.09	1048.26	n.a.	0.00

Table 1: Summary statistics

Note: The median is \$42,010. Means are calculated for all sample points up to z.

Table 2: Inequality and poverty measures for U.S. working singles without disabilities

		Inequality inde	X	Pover	ty rate
	Gini	Mean log	Robin	z=\$15,000	z=\$20,000
		Deviation	Hood		
		(MLD)			
Observed incomes	0.402	0.296	0.284	0.083	0.165
Standard income using mean	0.387	0.262	0.275	0.046	0.115
hours as the standard.					
Equivalent incomes with	0.385	0.272	0.272	0.072	0.139
common preferences set at					
mean leisure ratio					
Equivalent incomes with	0.460	0.444	0.328	0.140	0.190
idiosyncratic preferences					
based on predicted leisure ratio					

<u>Note</u>: The standard incomes are calculated by assuming that all those working less than the mean hours of 39 per week were to work those hours at the same wage rate as at present. The equivalent incomes are explained in the text. The Gini index is half the average absolute difference between all pairs of incomes, expressed as a proportion of the mean. MLD is given by the mean of the log of the ratio of the overall mean income to individual income. Robin Hood index is the fraction of total income that one would need to take away from the richer half and give to the poorer half to assure equality.

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							Log eq	quivalent ir	lcome	Log e	quivalent ii	ncome
				Log equ	uivalent i	income	(idiosyn	cratic pref	erences	(idiosy1	ncratic pref	erences
	Log ol	bserved ir	ncome	(comm	on prefer	ences)	using pre	dicted leisı	ure ratio)	using a	ctual leisur	e ratio)
	Coeff.	SE	Prob.	Coeff.	SE	Prob.	Coeff.	SE	Prob.	Coeff.	SE	Prob.
Constant	10.842	0.019	0.000	10.749	0.020	0.000	10.148	0.025	0.000	9.907	0.117	0.000
Female	-0.107	0.021	0.000	-0.042	0.020	0.036	0.446	0.027	0.000	0.477	0.132	0.000
Age-49*	0.694	0.075	0.000	0.867	0.077	0.000	-1.354	0.099	0.000	-1.472	0.475	0.002
(Age-49) squared*	-0.040	0.046	0.000	-0.019	0.005	0.000	0.011	0.060	0.080	0.118	0.029	0.000
Race: Black	-0.224	0.026	0.000	-0.166	0.024	0.000	0.407	0.036	0.000	0.286	0.166	0.086
Race: Black mixed	-0.142	0.117	0.223	-0.077	0.103	0.452	0.577	0.157	0.000	0.402	0.698	0.564
Race: Am. Indian	-0.261	0.086	0.002	-0.209	0.078	0.008	0.158	0.124	0.202	0.122	0.676	0.857
Race: Asian	0.152	0.069	0.028	0.144	0.064	0.025	0.334	0.096	0.001	0.727	0.524	0.165
Race: Other	-0.083	0.097	0.389	-0.095	0.085	0.268	-0.201	0.107	0.061	-0.350	0.511	0.493
Hispanic	-0.162	0.037	0.000	-0.123	0.036	0.001	0.379	0.048	0.000	0.399	0.241	0.098
Born US Oth.Terr.	-0.138	0.247	0.577	-0.173	0.222	0.438	-0.719	0.283	0.011	-1.459	1.178	0.215
Born Central Am.	-0.724	0.197	0.000	-0.697	0.173	0.000	0.000	0.230	1.000	0.231	1.167	0.843
Born Caribbean	-0.435	0.203	0.032	-0.458	0.180	0.011	-0.316	0.239	0.187	-0.481	1.158	0.678
Born S. America	-0.311	0.215	0.149	-0.371	0.195	0.057	-0.839	0.256	0.001	-1.422	1.171	0.225
Born N. Eur.	0.229	0.235	0.331	0.140	0.207	0.499	-0.388	0.305	0.203	-0.975	1.198	0.416
Born Western Eur.	-0.052	0.276	0.850	-0.161	0.245	0.513	-0.607	0.285	0.033	-0.377	1.713	0.826
Born C-East Eur.	-0.249	0.206	0.226	-0.323	0.181	0.074	-0.660	0.253	0.009	-1.422	1.107	0.199
Born East Asia	-0.314	0.212	0.139	-0.300	0.188	0.110	0.225	0.254	0.375	0.165	1.301	0.899
Born SE Asia	-0.548	0.228	0.016	-0.615	0.211	0.004	-0.684	0.264	0.010	-1.145	1.244	0.358
Born SW Asia	-0.143	0.226	0.526	-0.237	0.213	0.267	-0.816	0.280	0.004	-1.389	1.327	0.295
Born Middle East	0.096	0.267	0.719	-0.082	0.256	0.749	-0.615	0.317	0.053	-0.018	1.647	0.992
Born Africa	-0.185	0.204	0.365	-0.320	0.183	0.080	-1.154	0.248	0.000	-1.157	1.261	0.359
Foreign born	0.260	0.187	0.165	0.321	0.165	0.052	0.622	0.216	0.004	0.733	1.077	0.496
Foreign: Dad	0.106	0.059	0.073	0.087	0.056	0.123	-0.081	060.0	0.368	-0.187	0.401	0.641
Foreign: Mom	0.158	0.074	0.034	0.174	0.064	0.007	0.264	0.095	0.005	0.765	0.696	0.272
Foreign: Both	0.132	0.056	0.018	0.117	0.051	0.023	-0.134	0.073	0.064	-0.357	0.337	0.289

Ν	5633	5633	5633	5633
\mathbb{R}^2	0.088	0.069	0.151	0.016
S.E. of regression	0.750	0.738	0.986	4.736
Mean dep. var.	10.610	10.610	10.610	10.610
F-statistic	21.740	16.525	39.891	3.563
Prob (F-statistic)	0.000	0.000	0.000	0.000
<u>Note</u> : White standard	errors (SE). * coefficients scaled	up by 100.		

Coeff.SEProb.Constant 0.256 0.056 0.000 Log wage rate 0.150 0.031 0.000 Log wage rate squared -0.046 0.005 0.000 Log unearned income (+1) -0.073 0.009 0.000 Log unearned income squared -0.007 0.001 0.000 Log wage x log unearned income 0.036 0.002 0.000 Female 0.087 0.015 0.000 Age-49)* 0.000 0.058 0.992 (Age-49) squared* 0.024 0.003 0.000 Race: Black 0.075 0.019 0.000 Race: American Indian 0.061 0.066 0.355 Race: Asian 0.020 0.052 0.705 Race: Asian 0.020 0.052 0.705 Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born Central America 0.037 0.123 0.762 Born Caribean -0.042 0.128 0.746 Born South America -0.161 0.164 0.325 Born Morthern Europe -0.161 0.164 0.352 Born Su Asia -0.055 0.142 0.698 Born SE Asia 0.036 0.136 0.789 Born SE Asia -0.028 0.048 0.569 Foreign born 0.084 0.160 0.472 Foreign born 0.042 0.039 0.282 NS633R ² </th <th></th> <th>Lo</th> <th>g leisure ratio</th> <th>)</th>		Lo	g leisure ratio)
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Log wage rate squared-0.0460.0050.000Log unearned income (+1)-0.0730.0090.000Log unearned income squared-0.0070.0010.000Log wage x log unearned income0.0360.0020.000Female0.0870.0150.000Age-49*0.0000.0580.992(Age-49) squared*0.0240.0030.000Race: Black0.0750.0190.000Race: Black0.0870.0840.303Race: American Indian0.0610.0660.355Race: Other-0.0080.0580.885Hispanic0.0630.0260.015Born US Other Territories-0.1140.1520.452Born Central America0.0370.1230.746Born Northern Europe-0.1610.1640.325Born Western Europe-0.1260.1360.352Born East Asia0.0360.1360.789Born SE Asia-0.0360.1420.698Born SE Asia-0.1360.1360.789Born SE Asia-0.1360.1360.377Born Middle East-0.1360.1700.423Born SE Asia-0.0280.0480.569Foreign born0.0840.1160.472Foreign born0.0840.1160.472Foreign born0.0280.0480.569Foreign: Both-0.0420.0390.282N5633R²0.122 <t< td=""><td>Log wage rate</td><td>0.150</td><td>0.031</td><td>0.000</td></t<>	Log wage rate	0.150	0.031	0.000
Log unearned income (+1)-0.0730.0090.000Log unearned income squared-0.0070.0010.000Log wage x log unearned income0.0360.0020.000Female0.0870.0150.000Age-49*0.0000.0580.992(Age-49) squared*0.0240.0030.000Race: Black0.0750.0190.000Race: Black mixed0.0870.0840.303Race: American Indian0.0610.0660.355Race: Asian0.0200.0520.705Race: Other-0.0080.0580.885Hispanic0.0630.0260.015Born US Other Territories-0.1140.1520.452Born Cartibbean-0.0420.1280.746Born South America-0.1070.1380.438Born Northern Europe-0.1610.1640.325Born Western Europe-0.1260.1360.352Born East Asia0.0360.1360.789Born SW Asia-0.1440.1500.337Born Middle East-0.0550.1420.698Born SW Asia-0.1740.1330.192Foreign born0.0840.1160.472Foreign: Dad-0.0280.0480.569Foreign: Mom0.0230.0510.660Foreign: Both-0.0420.0390.282N5633R ² 0.122S.E. of regression0.529Mean dep. var.0.3	Log wage rate squared	-0.046	0.005	0.000
Log unearned income squared -0.007 0.001 0.000 Log wage x log unearned income 0.036 0.002 0.000 Female 0.087 0.015 0.000 Age-49* 0.000 0.058 0.992 (Age-49) squared* 0.024 0.003 0.000 Race: Black 0.075 0.019 0.000 Race: Black mixed 0.087 0.084 0.303 Race: American Indian 0.061 0.066 0.355 Race: Asian 0.020 0.052 0.705 Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born South America -0.0042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.126 0.136 0.352 Born East Asia 0.036 0.136 0.789 Born SW Asia -0.042 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign born 0.084 0.116 0.472 Foreign born 0.028 0.048 0.569 Foreign: Dad -0.028 0.048 0.569 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S	Log unearned income (+1)	-0.073	0.009	0.000
Log wage x log unearned income 0.036 0.002 0.000 Female 0.087 0.015 0.000 Age-49* 0.000 0.058 0.992 (Age-49) squared* 0.024 0.003 0.000 Race: Black 0.075 0.019 0.000 Race: Black mixed 0.087 0.084 0.303 Race: American Indian 0.061 0.066 0.355 Race: Asian 0.020 0.052 0.705 Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.128 0.746 Born South America -0.042 0.128 0.746 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.108 0.136 0.352 Born Suth America -0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign born 0.084 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 0.400 Mean dep. var. 0.348 F -statistic 25.962 Prob (F-statistic) 0.000 0.000	Log unearned income squared	-0.007	0.001	0.000
Female 0.087 0.015 0.000 Age-49* 0.000 0.058 0.992 (Age-49) squared* 0.024 0.003 0.000 Race: Black 0.075 0.019 0.000 Race: Black mixed 0.087 0.084 0.303 Race: American Indian 0.061 0.066 0.355 Race: Asian 0.020 0.052 0.705 Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Central or Eastern Europe -0.126 0.136 0.789 Born Set Asia 0.036 0.136 0.789 Born SE Asia -0.042 0.136 0.789 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.126 0.136 0.789 Born SW Asia -0.028 0.048 0.569 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-stat	Log wage x log unearned income	0.036	0.002	0.000
Age-49* 0.000 0.058 0.992 (Age-49) squared* 0.024 0.003 0.000 Race: Black 0.075 0.019 0.000 Race: Black mixed 0.087 0.084 0.303 Race: American Indian 0.061 0.066 0.355 Race: Asian 0.020 0.052 0.705 Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.163 0.136 0.352 Born East Asia 0.036 0.136 0.352 Born Set Asia -0.055 0.142 0.698 Born SW Asia -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 0.000 Mean dep. var. 0.348 F -statisticProb (F-statistic) 0.000 -0.000	Female	0.087	0.015	0.000
(Age-49) squared* 0.024 0.003 0.000 Race: Black 0.075 0.019 0.000 Race: Black mixed 0.087 0.084 0.303 Race: American Indian 0.061 0.066 0.355 Race: Asian 0.020 0.052 0.705 Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.161 0.164 0.352 Born Seat Asia 0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-statistic 25.962 $-prob(F-statistic)$ 0.000	Age-49*	0.000	0.058	0.992
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Race: Black mixed 0.087 0.084 0.303 Race: American Indian 0.061 0.066 0.355 Race: Asian 0.020 0.052 0.705 Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.108 0.153 0.480 Born Central or Eastern Europe -0.126 0.136 0.352 Born Set Asia 0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-statistic 25.962 $-prob(F-statistic)$ 0.000	Race: Black	0.075	0.019	0.000
Race: American Indian 0.061 0.066 0.355 Race: Asian 0.020 0.052 0.705 Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.161 0.164 0.352 Born Central or Eastern Europe -0.126 0.136 0.352 Born Se Asia 0.036 0.136 0.789 Born SY Asia -0.044 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-statistic 25.962 $Prob (F-statistic)$ 0.000	Race: Black mixed	0.087	0.084	0.303
Race: Asian 0.020 0.052 0.705 Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.126 0.136 0.352 Born Central or Eastern Europe -0.126 0.136 0.352 Born Se Asia 0.036 0.136 0.789 Born SY Asia -0.044 0.150 0.337 Born Middle East -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 0.529 Mean dep. var. 0.348 F -statistic 25.962 Prob (F-statistic) 0.000 -0.002 0.000	Race: American Indian	0.061	0.066	0.355
Race: Other -0.008 0.058 0.885 Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.126 0.136 0.352 Born Central or Eastern Europe -0.126 0.136 0.352 Born Se Asia 0.036 0.136 0.789 Born SW Asia -0.044 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 0.348 F-statistic 25.962 0.000 -0.000	Race: Asian	0.020	0.052	0.705
Hispanic 0.063 0.026 0.015 Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.108 0.153 0.480 Born Central or Eastern Europe -0.126 0.136 0.352 Born East Asia 0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 0.348 F-statistic 25.962 $prob (F-statistic)$ 0.000	Race: Other	-0.008	0.058	0.885
Born US Other Territories -0.114 0.152 0.452 Born Central America 0.037 0.123 0.762 Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.108 0.153 0.480 Born Central or Eastern Europe -0.126 0.136 0.352 Born East Asia 0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 0.488 F-statistic 25.962 -0.000 Prob (F-statistic) 0.000 0.000	Hispanic	0.063	0.026	0.015
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Born Caribbean -0.042 0.128 0.746 Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.108 0.153 0.480 Born Central or Eastern Europe -0.126 0.136 0.352 Born East Asia 0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 0.348 F-statistic 25.962 -796 Prob (F-statistic) 0.000 -746	Born Central America	0.037	0.123	0.762
Born South America -0.107 0.138 0.438 Born Northern Europe -0.161 0.164 0.325 Born Western Europe -0.108 0.153 0.480 Born Central or Eastern Europe -0.126 0.136 0.352 Born East Asia 0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 0.529 Mean dep. var. 0.348 -5.962 Prob (F-statistic) 0.000 -0.000	Born Caribbean	-0.042	0.128	0.746
Born Northern Europe-0.1610.1640.325Born Western Europe-0.1080.1530.480Born Central or Eastern Europe-0.1260.1360.352Born East Asia0.0360.1360.789Born SE Asia-0.0550.1420.698Born SW Asia-0.1440.1500.337Born Middle East-0.1360.1700.423Born Africa-0.1740.1330.192Foreign born0.0840.1160.472Foreign: Dad-0.0280.0480.569Foreign: Both-0.0420.0390.282N5633R²0.122S.E. of regression0.529Mean dep. var.0.348F-statistic25.962	Born South America	-0.107	0.138	0.438
Born Western Europe -0.108 0.153 0.480 Born Central or Eastern Europe -0.126 0.136 0.352 Born East Asia 0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-statistic 25.962 Prob (F-statistic) 0.000	Born Northern Europe	-0.161	0.164	0.325
Born Central or Eastern Europe -0.126 0.136 0.352 Born East Asia 0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-statistic 25.962 $Prob$ (F-statistic) 0.000	Born Western Europe	-0.108	0.153	0.480
Born East Asia 0.036 0.136 0.789 Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-statistic 25.962 $Prob$ (F-statistic) 0.000	Born Central or Eastern Europe	-0.126	0.136	0.352
Born SE Asia -0.055 0.142 0.698 Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 0.348 F-statistic 25.962 -7.962 Prob (F-statistic) 0.000 -7.000	Born East Asia	0.036	0.136	0.789
Born SW Asia -0.144 0.150 0.337 Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N5633 R^2 0.122 S.E. of regression 0.529 0.348 F-statistic 25.962 -0.000	Born SE Asia	-0.055	0.142	0.698
Born Middle East -0.136 0.170 0.423 Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N5633 R^2 0.122 S.E. of regression 0.529 0.348 F-statistic 25.962 25.962 Prob (F-statistic) 0.000	Born SW Asia	-0.144	0.150	0.337
Born Africa -0.174 0.133 0.192 Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N5633 R^2 0.122 S.E. of regression 0.529 -0.348 F-statistic 25.962 -0.000	Born Middle East	-0.136	0.170	0.423
Foreign born 0.084 0.116 0.472 Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N5633 R^2 0.122 S.E. of regression 0.529 -0.348 F-statistic 25.962 -0.000	Born Africa	-0.174	0.133	0.192
Foreign: Dad -0.028 0.048 0.569 Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 R^2 0.122 S.E. of regression 0.529 -0.048 -0.048 Mean dep. var. 0.348 -0.0348 F-statistic 25.962 -0.000	Foreign born	0.084	0.116	0.472
Foreign: Mom 0.023 0.051 0.660 Foreign: Both -0.042 0.039 0.282 N 5633 7 R ² 0.122 $5.5.$ of regression 0.529 Mean dep. var. 0.348 -5.962 Prob (F-statistic) 0.000	Foreign: Dad	-0.028	0.048	0.569
Foreign: Both -0.042 0.039 0.282 N5633R ² 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-statistic 25.962 Prob (F-statistic) 0.000	Foreign: Mom	0.023	0.051	0.660
N 5633 R^2 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-statistic 25.962 Prob (F-statistic) 0.000	Foreign: Both	-0.042	0.039	0.282
R ² 0.122 S.E. of regression 0.529 Mean dep. var. 0.348 F-statistic 25.962 Prob (F-statistic) 0.000	N	5633		
S.E. of regression0.529Mean dep. var.0.348F-statistic25.962Prob (F-statistic)0.000	R^2	0.122		
Mean dep. var.0.348F-statistic25.962Prob (F-statistic)0.000	S.E. of regression	0.529		
F-statistic25.962Prob (F-statistic)0.000	Mean dep. var.	0.348		
Prob (F-statistic) 0.000	F-statistic	25.962		
	Prob (F-statistic)	0.000		

Appendix: Regression used to predict the leisure ratio to allow for idiosyncratic preferences

Note: White standard errors (SE). * coefficients scaled up by 100.

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