The effect of child support on fathers' labor supply*

Pinchuan Ong

National University of Singapore

Institutional and data appendices available HERE.

February 23, 2024

Child support frequently increases with the noncustodial fathers' incomes. I study the effect on their work incentives. For identification, I exploit the end of child support when the children involved reach emancipation age. Empirically, child support paid drops to near zero on emancipation; fathers correspondingly increase their work hours and annual earnings. Formally, each 10 percentage point increase in the child support rate leads to an 8–11 percent decrease in labor supply conditional on working. I find weaker extensive margin responses. In a structural model, I map these estimates to the intertemporal elasticity of labor supply (Frisch elasticity). JEL: J12, J22.

*NUS Business School, National University of Singapore, 15 Kent Ridge Drive, Singapore 119245. ong.pinchuan@nus.edu.sg. I am deeply indebted to Matthew Notowidigdo, Seema Jayachandran, and Diane Schanzenbach for their insightful guidance and advice throughout the process of writing this paper. I thank Matthias Doepke, Ivan Canay, Robert Miller, Richard Blundell, Alexandre Mas, Basit Zafar, Douglas Webber, Shing-Yi Wang, Andrew Goodman-Bacon, Hilary Hoynes, Heather Royer, participants of the Northwestern Applied Microeconomics Lunch group, and two anonymous referees for valuable feedback and suggestions at various points of this project. This paper would not have been possible without all the data collection efforts that went into the PSID, NLSY, BHPS, UKHLS, HILDA, SHP, and SIPP; I thank all parties involved for these important datasets, and for making the data easily available. Research reported in this paper received financial support from the NUS Start-up Grant A-0003845-00-00.

1 Introduction

Divorce and nonmarital births are common in most modern economies. To ensure that the children involved have an adequate standard of living while keeping public spending manageable, all developed countries have formal systems in place that oblige the noncustodial parent to make child support payments towards these children. These systems affect many people, and payments can be large. For example, in the US, one quarter of families with children are single parent families (OECD, 2014), and support-paying noncustodial parents pay 13 percent of family income in child support on average. This amount is comparable to their effective tax rate of 8 percent.[1]

This paper estimates the effect of child support on noncustodial fathers' incentives to work.[2] Given how many people are affected, and that the affected population involved tends to be economically vulnerable, much work has been done to understand the impact of child support on the outcomes of the child (see e.g. Amato and Gilbreth, 1999; Walker and Zhu, 2009; Rossin-Slater, 2017; Noghanibehambari et al., 2022). Separately, because child support payments often increase with fathers' incomes, we might expect it to reduce their work incentives, similar to how taxes affect labor supply and taxable income (Feldstein, 1995; Blundell et al., 1998; Feldstein, 1999; Saez et al., 2012; Blundell et al., 2016). This means that we need to understand the effects of child support on the noncustodial parents in order to understand its full implications for welfare and policy (Foerster, 2022).

To obtain a causal estimate, I exploit the fact that child support payments usually stop once all the children involved are old enough to become legally independent. This is known as the age of emancipation of the children in some jurisdictions, a term which I adopt in this paper. Using five longitudinal datasets spanning four countries, I construct a sample of fathers who have to pay child support based on their marital and fertility histories, and compare their labor supply before and after their last eligible children achieve the emancipation age. An increase in work post-emancipation indicates that these fathers cut back their pre-emancipation labor supply in response to having to pay child support.

In the sample I examine, as the last child eligible for support achieves the emancipation age, the amount of child support paid as a fraction of income decreases to almost zero. At the same time, fathers increase their labor supply by 3 percent compared to before emancipation. The effect is mainly driven by the intensive margin (annual work hours or earnings conditional on working or earning respectively), with a smaller and sometimes statistically insignificant effect on the extensive margin (positive work hours or earnings). The estimates are robust

[1] Estimated using the Current Population Survey 2010–2016 (Flood et al., 2017).

[2] Child support payments can also go from noncustodial mothers to custodial fathers, but these arrangements are less common, and I restrict the analysis to noncustodial fathers for data reasons.

to using specific years relative to emancipation (in particular, excluding college-going years), changes in sample, excluding some control variables or additionally controlling for child age, and changes in the way that variables used for identification are constructed.

Intuitively, identification of the labor supply response relies on child age being exogenous to the incentives to work. This would be violated if child emancipation has a direct effect on time availability or taste for non-working time. To investigate this, I examine a "placebo sample" of fathers without child support obligations. I find that these fathers do not work more on emancipation of their youngest children. Furthermore, a time-use analysis of US married fathers reveals that pre-emancipation time that was spent with their children likely goes towards personal and with-spouse leisure and self-care, and not towards more work activities. These analyses are consistent with child support being the reason for the labor supply increase on emancipation for the main sample of support-paying fathers. I formalize this in a robustness specification using a difference-in-differences regression.

The estimated response has a structural interpretation as an intertemporal labor supply elasticity (Frisch elasticity). In particular, we expect it to be free of income effects. The response is a labor supply elasticity because child support affects the fathers' effective wages: of each dollar of income earned, a certain percentage is paid in support and cannot be used for consumption.[3] In general, there would be a substitution effect—an increase in the effective wage makes work more desirable—and an income effect—the increased effective wage makes the father feel richer, which reduces work incentives. Specific to my setting, the child emancipation variation that I exploit is highly predictable, which is the key requirement for the labor supply elasticity to be a Frisch elasticity (Keane, 2022).[4] Based on this, I estimate a Frisch elasticity ranging from 0.7 to 0.9 on the intensive margin and 0.1 (statistically insignificant at the 5 percent level) to 0.3 on the extensive margin. If we took into consideration the possibility that the fathers care about (or dislike) the consumption of the support-receiving children and mothers, the implied Frisch elasticity ranges between 0.6 and 1.1.

This paper contributes to two strands of literature, the first being a literature that looks at the effect of child support payments on labor supply. Good estimates of the labor supply response matter for welfare calculations—alimony and child support are both transfers from

[3]I use the term effective wage to refer to the amount of goods that can be consumed per hour of leisure foregone (equivalently, per hour of labor supplied). This is the relevant relative price when defining labor supply elasticities, and can differ from the real market wage (compensation by employers in amount of goods per hour of labor supplied) in the presence of taxes or child support.

[4]Intuitively, a future effective wage increase leads to a negative income effect in the future, but since the fathers anticipate this in advance, the agent works less (and saves less) even before the change happens. This smoothing of the income effect over time implies that it can be handled (to first order) with simple fixed effects.

the noncustodial to the custodial parent, but in a dynamic model of divorce and labor supply, Foerster (2022) finds that the latter is more efficient primarily because it induces smaller work disincentives.[5] From a policy perspective, child support is a nonnegligible part of the custodial parents' incomes (Cancian et al., 2003), and since the noncustodial parents have to earn in order to pay support, many worry about possible disemployment effects (Pirog and Ziol-Guest, 2006; Carasso et al., 2016; Cancian et al., 2013). In fact, previous work has shown that stricter child support enforcement (e.g. incarceration penalties) are successful in forcing noncustodial parents to work, which suggests that the parents must be reducing their labor supply to avoid child support in the first place (Schroeder and Doughty, 2009; Zatz and Stoll, 2020).

Research on how child support affects labor supply face two main difficulties: it is difficult to find a source of exogenous variation, and most datasets are not powered towards looking at divorce and child support issues, especially if we need to link the father's data to the child. Earlier work finds little effect for fathers (Freeman and Waldfogel, 1998; Holzer et al., 2005) and a small negative effect or no effect for mothers (Graham and Beller, 1989; Graham, 1990; Hu, 1999), but the evidence here is mainly correlational. More recent studies apply more robust statistical methods, with most of the work done on maternal labor supply (Cuesta and Cancian, 2015; Fisher, 2017; Rossin-Slater and Wüst, 2018; Barardehi et al., 2020; Friday, 2021). To my knowledge, only one paper produces a quasi-experimental estimate for fathers—Rossin-Slater and Wüst (2018) use a simulated instrument based on income and children at the time of separation and find no labor supply effects in Danish administrative data. While I use self-reported data that is less comprehensive, my identifying variation (emancipation) is easier to understand than the simulated instrument. There is also a difference in interpretation—my estimate is better interpreted as a pure leisure-labor substitution response to the effective wage change, while theirs would also include an income effect that acts in the opposite direction.[6]

Because child emancipation is highly anticipatable, this paper also contributes to a large literature estimating the Frisch elasticity of labor supply (MaCurdy, 1981; Altonji, 1986; Altuğ and Miller, 1990; Pistaferri, 2003; Ziliak and Kniesner, 2005; Keane, 2011; Blundell et al., 2016; Keane, 2022). The Frisch elasticity is an important parameter used in calibrating macroeconomic and dynamic public finance models, which makes it relevant for understanding business cycle dynamics and computing the welfare cost of government intervention

[5] This paper is more generally related to work on the institution of divorce (Peters, 1986; Gray, 1998; Friedberg, 1998; Chiappori et al., 2002; Walker and Zhu, 2006; Wolfers, 2006; Stevenson, 2008; Voena, 2015; Altindag et al., 2017; Grossbard-Schectman, 2019; Foerster, 2022; Bansak et al., 2021).

[6] While responses that include income effects are also important, welfare calculations or structural models generally require elasticities that are free of income effects.

(Golosov et al., 2011; Reichling and Whalen, 2012). The main difficulty in estimation is in finding a setting where agents can predict their effective wage in advance, while avoiding endogeneity issues in estimation. Recent work have exploited tax reforms in Iceland (Bianchi et al., 2001; Sigurdsson, 2019; Stefánsson, 2019) and Switzerland (Martinez et al., 2021) that result in one year of tax-free income, noting that these tax holidays are highly publicized and salient. Unfortunately, exploitable tax reforms happen infrequently. This paper contributes to the literature by identifying a novel setting in which the effective wage change is highly predictable and salient. The main advantage of this setting is that anticipatable child support changes are found in many countries. Furthermore, the change in support on cessation is large, which helps overcome issues related to optimization frictions (Chetty, 2012).

The paper proceeds as follows. Section 2 describes the relevant elements of child support policies, the datasets, and the empirical specifications used to estimate the labor supply response of the noncustodial fathers. Section 3 presents the results and related issues. Section 4 discusses the model to interpret the results as a Frisch elasticity and discusses the estimates. Section 5 concludes.

2 Institutional setting, data, and empirical specification

2.1 Institutional setting

A key feature of my empirical strategy is that it is broadly applicable in many datasets: in principle, I get a causal estimate as long as I have enough information on marriage and fertility. This is important in overcoming data limitations; most datasets are small once I restrict to support-eligible parents. In this paper, I use data from several countries, selected based on panel data availability and the presence of key institutional features. To my knowledge, panel datasets that include clear information on child support payments by the *noncustodial parent* exist in the US, UK, Australia, Switzerland, and Canada. Of these, access to the Canadian dataset is restricted, and hence was not included for this study.[7] In this section, I provide a summary of important features of countries involved in this paper; details of each country's laws are provided in the online institutional details appendix.

Across all countries, there are two ways in which child support cases begin. In the majority of cases, child support starts when a couple with children divorce. Here, child

[7] Three other countries, Germany, Russia and South Korea, have panel datasets that include information on transfers to children. However, the wording in the surveys are more suggestive of transfers to current children in the family or children from the current marriage living elsewhere rather than from a previous marriage. Germany, additionally, was excluded because child support there is "lumpy"—it is set as constant amounts within income bands, which makes detection of the leisure-labor substitution more complex.

support is usually determined as part of the divorce proceedings. In other words, when the judge determines who gets which assets, she also determines who gets custody of the child, and the amount of child support. The second type of child support cases are those in which the parents were never married. In these cases, the custodial parent has the additional step of determining involvement of the other parent. Child support payments are then determined by the courts or institution with authority based on formulas similar to divorce cases. The distinction between divorce and nonmarital cases does not pose a problem in my setting, and I combine both groups in my analysis.

In the countries I consider, support amounts are stipulated according to rules that use the fathers' income. The formulas used are public information, and hence fathers know what to expect. In the UK and Australia, these formulas are rigid rules that the authorities must follow; in the US and Switzerland, judges are allowed to deviate from these guidelines, but deviation requires explanation (instituted as a federal requirement in the US). Deviations can be endogenously determined, which necessitates the use of an instrument in this paper.

There is some heterogeneity across jurisdictions in the way that child support is set, the first being whether to consider the mother's income in the formula (a frequently debated issue). Forty-two US states (Venohr, 2013), Australia, and some cantons of Switzerland consider both father's and mother's incomes, while others set child support amount as a percentage of the father's income.[8] In all cases, child support obligations increase with the father's income. Because of this, I use the child support rate—the amount of child support divided by the father's income—as the main regressor for interpretation. In jurisdictions that determine child support as a percentage of the father's income, the interpretation of child support as a rate is clear. In jurisdictions that uses both father and mother income in computing child support, the interpretation of child support as a rate is approximate, with the approximation being perfect if child-rearing expenditure (a parameter used in computation) increases linearly in the parents' income with an intercept of zero. In practice, Cancian and Costanzo (2019) show that the two different computation methods yield modest differences in child support for most families in Wisconsin, which suggests that the approximation is good in most cases.

Since working more potentially attracts more child support payments in future, we expect child support to induce a substitution away from work. This threat of higher future

[8] In Wisconsin (which uses only the payer's income), for example, a father without shared custody pays 17%, 25%, or 29% of gross income for one, two, or three children respectively. In jurisdictions that use both parents' incomes, a child-rearing expenditure amount that increases with total parental income and number of children is first computed, and then the father pays his share of total income multiplied by the expenditure. There is usually some subsistence amount built into the formulas to ensure a minimal consumption level for either parent, and shared parenting time (on the payer's part) generally reduces the child support amount. Venohr and Williams (1999) and Venohr (2013) provide comprehensive overviews of the systems that exist.

payments relies on the child support determinations—usually presented to parents as dollar amounts—being updated when circumstances change in later years. In Australia and the UK, annual updating is essentially automatic. In the US and Switzerland, updating happens when either the father, the mother, or a child support agency reviews the case. To help keep child support amounts current, US federal laws require parents with formal child support to be notified of their right to review every three years, and the review is automatic when the parents are on welfare.[9] Infrequent updating makes it harder to detect the substitution away from work using year-on-year changes in child support. Partly because of this, I use long-run variation in this paper by comparing all periods before with all periods after child emancipation—a father might be able to increase his income without attracting the notice of his ex-wife or authorities in the next year, but doing the same for all years until child emancipation becomes increasingly difficult.

The amount that fathers eventually pay (or whether they pay at all) is potentially endogenous, which motivates the need for an instrument. The instrument that I use exploits the end of child support when the child reaches the emancipation age. That child support ends when the child is emancipated is publicly known and easily understood by the fathers. The emancipation age varies across jurisdictions, ranging from 16 in the UK to 21 in a few US states. Payments are usually allowed to continue past emancipation age if the child is still in high school, and a few jurisdictions allow payments through college; this weakens the first stage of the instrumental variables (IV) regression but would not directly bias the estimated effect of child support on labor supply. A potential souce of endogeneity is that child college-going may directly affect the fathers' labor supply (e.g. through college fees that are not attributed to child support). I hence investigate robustness to this in several ways.

2.2 Data

I use five panel datasets covering 4 countries to estimate the labor supply responses of fathers to child support obligations. The five datasets are the Panel Study of Income Dynamics (PSID) in the US; the National Longitudinal Survey of Youth 1979 (NLSY) in the US; the British Household Panel Survey combined with its successor the UK Household Longitudinal Study (BHPS+); the Household, Income and Labour Dynamics in Australia (HILDA) dataset; and the Swiss Household Panel (SHP). For consistency in treatment, I harmonize the method of construction of all variables across all five datasets as much as possible. Details of the data and cleaning procedures are provided in the online data appendix.

[9] A related issue for the US is that some courts require a large-enough change in income from the last time of support determination before updating the amount.

My identification strategy requires information on which children are eligible for child support, and their ages. I construct these variables based on the timings of marriages and child births for each father. To improve identification of eligibility, I exclude the child if she lives mostly with the father during the years in which she is eligible, or if she has died (if information is available). Marital histories are provided as derived variables in the PSID, NLSY, and HILDA, and fertility histories are provided as derived variables in the former two; in all other cases, I construct the relevant histories based on retrospective questionnaires (usually asked up to once per person), supplemented with marital status and family relationship information from each wave.

My main regressor of interest is the child support rate, computed as the child support amount paid by the total individual before-tax income of the father. Income includes earnings from work and income from other sources if recorded in the data, since this is generally the income base for computations of child support. The resulting child support rate computed has large outliers; to reduce their influence, I winsorize the rate at the first and ninety-ninth percentiles separately for each dataset.

In principle, a child support rate exists even if the father is not earning income. As such, I impute the child support rate if it is missing. For each individual, I impute using the previous observed value for observations before emancipation of the youngest eligible child, half of the previous observed value in the year of emancipation, and the median for observations after emancipation. To avoid periods of education and retirement, I do not extrapolate beyond the first and last observed child support rate of the father. Imputation serves two purposes: it increases the sample size slightly (by about 1 percent), and it allows estimation of a response along the extensive margin.

I use all male observations between the ages of 26 and 59 for which information on marriage start and end dates are available, subject to a few dataset-specific restrictions and the following restrictions applied across all datasets. (Dataset-specific restrictions are described in the subsection for each dataset in the online data appendix.) First, I use only fathers who have at least one eligible child below emancipation age in at least one wave; this restriction is motivated by the strategy of following these fathers and observing their reactions to emancipation of the children. Second, I drop fathers who have ever had to pay child support for more than 4 children because these fathers are likely to be atypical. Third, I exclude years before the fathers are supposed to pay child support; these are years before divorce or nonmarital births. Fourth, for simplicity, I exclude years before and including the last observed positive change in the number of eligible children; this can occur because of multiple divorces, and the restriction ensures that there is only one year in which emancipation age is reached. Fifth, I exclude observations for which the youngest eligible child is younger than

5; empirically, I observe that the average child support rate is lower at those ages, which likely reflects noise in the data that affects child age construction.

Appendix Table A1, columns 1 to 3, show summary statistics for all men in the datasets versus the sample of fathers I examine. Fathers in the sample are less educated, work and earn less, marry earlier, and have children earlier. That said, the IV estimates of labor supply in this paper implicitly place more weight on fathers who are non-delinquent in payments, because these fathers are instrument compliers (Imbens and Angrist, 1994). Appendix Table A1, columns 4 and 5, accounts for this by weighting fathers based on their observed pre-emancipation child support rate. Differences between complying fathers and all men become smaller.

2.3 Empirical specification

I estimate the response of fathers to having to pay child support using the IV specification

$$\begin{aligned} y_{it} &= \psi_i + \zeta_{d(i)t} + \boldsymbol{Z}'_{it}\boldsymbol{\alpha}_{d(i)} + \gamma s_{it} + \varepsilon_{it} \\ s_{it} &= \tilde{\psi}_i + \tilde{\zeta}_{d(i)t} + \boldsymbol{Z}'_{it}\tilde{\boldsymbol{\alpha}}_{d(i)} + \tilde{\gamma}_{d(i)} IV_{it} + \nu_{it}, \end{aligned} \tag{1}$$

where s_{it} is the child support rate of individual i in year t, and IV_{it} takes a value of one if the father's youngest eligible child is older than or at the emancipation age of his jurisdiction, half in the year before emancipation, and zero for years before.[10] I consider two intensive-margin and two extensive-margin outcomes for y_{it}: respectively, the log of annual work hours, the log of annual labor earnings, whether the father worked any positive hours, and whether he had any positive labor earnings. The main coefficient of interest, γ, is the response of the father to a percentage point increase the child support rate. We expect this to be negative: fathers cut back their labor supply in response to having to pay child support.

My estimation strategy combines the five datasets $d(i)$ to improve statistical power. Individual fixed effects (ψ_i and $\tilde{\psi}_i$) and year-dataset fixed effects ($\zeta_{d(i)t}$ and $\tilde{\zeta}_{d(i)t}$) are included in all specifications, and a vector of covariates $\boldsymbol{Z}_{it}$ is included in my main specification. $\boldsymbol{Z}_{it}$ includes age-education fixed effects and the log of the father's wage these are known to affect labor supply (MaCurdy, 1981; Altonji, 1986), and furthermore, father age is likely to be correlated with child age. Because wage is unlikely to be correlated with the age of the youngest eligible child after conditioning on the age-education and time fixed effects, I

[10]The year prior is emancipation is the relevant year of change because support is determined based on past year income. I use half to account for the annual nature of the data—in the previous year, there is a 50 percent chance that the survey occurred fewer than 12 months before emancipation age, in which case increases in earnings would no longer attract higher child support liabilities. Results are robust to dropping the year before emancipation instead of using a probabilistic value.

impute missing log wage values with a constant number and include a dummy variable in parallel to reduce arbitrary loss in data. I cluster standard errors at the individual level to allow for arbitrary correlation of errors within individuals.

The key identifying assumption is that, conditional on the fixed effects and control variables, factors that could influence the fathers' incentives to work are uncorrelated with the youngest eligible child achieving the emancipation age. Note that the empirical strategy in Equation (1) exploits long-run variation in child support by comparing all periods after emancipation with all periods before (given the restrictions in Section 2.2) using an event study design. Using long-run variation is more appropriate if we worry that events around the emancipation age might induce responses by the fathers, or if we worry that fathers need time to react to the end of child support. Section 3.4 explores robustness to using specific years relative to emancipation among other issues.

The only coefficient that is not heterogeneous across datasets in Equation (1) is the main coefficient of interest, γ. In particular, this implies that there are five instruments in the first stage, one for each dataset. While combining the five instruments might give a more powerful first stage, using five instruments is a more accurate reflection of the differences in institutional factors and survey question wording. All IV results shown in this paper are based on two-stage least squares (2SLS).

The estimated labor supply response can be interpreted as a response that is common across all datasets. This assumes no heterogeneity in the responses across datasets or countries, and is known as the fixed treatment effects model or full pooling equilibrium model in the meta-analysis literature (Borenstein et al., 2010; Meager, 2018). Alternatively, the estimated response can be interpreted as a weighted average of the dataset-specific responses, induced by differences in questionnaire wording or institutional factors. In Appendix B, I show that the weights are a function of the size of the dataset, the strength of the first stages (the $\tilde{\gamma}_{d(i)}$'s), and the variation of the instrument within each dataset after partialling out the covariates.

The meta-analysis literature also provides formal estimators that summarize dataset-specific treatment effects when there is heterogeneity in responses across datasets. Known as the random treatment effects model or the no pooling equilibrium model in the literature, the main difference for the estimated average is that the random treatment effects estimators asymptote towards a simple average of the dataset-specific estimates as the degree of heterogeneity across datasets increases. Along with the estimated average, random treatment effects models are usually used in order to understand the variance of the heterogeneity across datasets. Given the few number of datasets used in this paper, I abstract from this. The most important implication of this is that estimates from this study are limited in their generality (Borenstein et al., 2009, p. 83–84); despite the fact that I use five datasets in this paper, we should exercise the same level of caution regarding external validity as we would for results from any one single study.

In a few sections below, it is useful to consider the reduced form specification

$$y_{it} = \psi_i + \zeta_{d(i)t} + \boldsymbol{Z}'_{it}\boldsymbol{\alpha}_{d(i)} + \tilde{\tilde{\gamma}} IV_{it} + \varepsilon_{it}, \tag{2}$$

with $\tilde{\tilde{\gamma}}$ interpretable as the labor supply effect of emancipation of the youngest child eligible for child support. A "true" reduced form specification that corresponds to Equation (1) would require five equations, one for each dataset; the only difference between this specification and the "true" specification is that $\tilde{\tilde{\gamma}}$ is averaged across datasets.

3 Results

3.1 First stage

Figure 1 shows the average rate paid by fathers in each year relative to emancipation of the youngest eligible children. In the years before the change in the effective wage (marked by the vertical dashed line), fathers pay an average of 7.8 percent of their income in child support, a figure lower than statutory rates reported in each country. (Statutory rates differ across jurisdictions and number of children supported, but are generally above 10%.) This is mainly due to two factors. First, fathers are frequently delinquent in their payments—in the US, only about 60 percent of child support obligation amounts are actually paid (Grall, 2018). Second, some non-eligible children might be misclassified as eligible, since identification of eligibility in the data is based on the timing of births and marriages. Unfortunately, the data does not allow the two factors to be distinguished. After emancipation age, the average rate drops to an average of 1.6 percent in the ten years after emancipation.

Table 1 formally shows that the first stage is strong in four out of five of the datasets, and is strong overall.[11] On average, crossing the threshold corresponds to a 5 percentage points drop in the support rate. The first stage F-statistic is somewhat weaker for Switzerland. There are two reasons for this. First, the Swiss sample is much smaller than the rest. Second, most of the youngest eligible children are in vocational education in the Swiss sample, and vocational education is heterogeneous in length according to the course of study (not observed in the data). This in turn induces heterogeneity in the age at which support payments end, since payments are required while the child is in vocational education. Results are robust to

[11] Appendix Figure A1 shows the first stage for each dataset graphically.

excluding Switzerland.

3.2 Labor supply response to child support

Figure 2, panel A shows the average annual number of work hours by fathers in each year relative to emancipation of the youngest eligible children, after partialling out individual and age fixed effects.[12,13] In the years before the child achieves the emancipation age, after adjusting for individual and age effects, employed fathers worked 1,960 hours anually on average; in the years after, they worked 2,010 hours. Panel B shows the analogous plot for the average annual earnings of fathers. In the years before the change in the effective wage, employed fathers earned 49,600 dollars annually on average; in the years after, they earned 51,600 dollars. Hence, emancipation of the youngest eligible child is associated with an increase of labor supply of around 3 to 4 percent. Furthermore, residualized work hours and earnings appear to be relatively constant before and after emancipation respectively, which suggests that the effect is constant at different time horizons. This is reassuring on two counts: first, it supports the use of long-term variation rather than focusing on the years just around emancipation, and second, it lessens the concern that the result is due to events that happen just around emancipation. Appendix Table A2 provides formal estimates of the reduced form specification (2).

Table 2, panel A, columns 1 to 4 show estimates of the intensive-margin labor supply response based on an ordinary least squares (OLS) regression of Equation (1), with log work hours as the dependent variable in columns 1 and 2 and log earnings as the dependent variable in columns 3 and 4. Intensive margin responses vary widely, with hours-based estimates smaller than those based on earnings. Columns 5 to 8 of the same panel show that corresponding estimates for the extensive margin are small and not statistically significantly different from zero. These OLS estimates are biased for at least two reasons. First, measurement error in the child support rate likely attenuates the estimate.[14] Second, child support could be correlated with factors that affect incentives to work over time, or other institutional factors like the ability of fathers to (illegally) avoid support payment.

[12] Life cycle profiles make interpretation of non-residualized figures difficult (Appendix Figure A2). Nonetheless, work hours exhibit similar increases around the emancipation age. Earnings appears to be continuous across emancipation age, indicating that identification relies more on fixed effects.

[13] Analogous dataset-specific figures are less precise, and are shown in Appendix Figure A3.

[14] A related consideration is division bias (Borjas, 1980). Because the child support rate is computed by dividing support amounts by total income—which comprises mainly of earnings—measurement error in earnings induces a negative correlation between earnings and the support rate. This is consistent with the earnings-based estimates in columns 3 and 4 being more negative than the hours-based estimates in columns 1 and 2. The presence of measurement error reinforces the need for the instrument.

Causal estimates based on the IV specification (1) are shown in Table 2, panel B.[15] Including all controls, a 10 percentage point increase in the child support rate leads to an 8 to 11 percent decrease in labor supply of fathers on the intensive margin. The response on the extensive margin is weaker; a 10 percentage point increase in the child support rate leads to a 1 (not statistically significant) to 3 percent decrease in he probability that the father works. The similarity in estimates across the first four columns suggests that fathers either have little control over their wage or do not respond on this margin.[16]

Appendix Table A3 reports estimates for the US, as well as estimates separately for each dataset. For the US, which makes up almost half of the fathers in the combined dataset, the estimate based on log of work hours is negative and statistically significant, and estimates based on other outcomes are qualitatively similar to estimates in Table 2 panel B. Examining each dataset separately leads to large standard errors, although point estimates are negative in general.

3.3 Falsification

My identification strategy requires that the emancipation of the children living outside the fathers' households does not directly affect the labor supply of the fathers. For example, if fathers maintain contact with these children who live outside their household, and if child college-going frees up time for work activities, the estimated response would be biased towards finding an effect. I perform two falsification exercises that help reassure that the results are not driven by this. Both rely on the same idea: if taste shifters were correlated with child age, I should see a similar change in labor supply when *any* youngest child is emancipated, and in particular, when the youngest child from an intact marriage is emancipated.

For the first falsification test, I restrict attention to the subsample of fathers who are supposed to pay child support for at least one child, but whose youngest children are never eligible. Barring errors due to imperfect identification of children and marriages, these youngest children are born within marriages that are intact at the time of observation, and have older half-siblings who *are* eligible. Table 3, panel B estimates the reduced form specification (2) with the addition of an indicator variable for emancipation of the youngest ineligible child. (Panel A repeats the reduced form estimates from the main sample to facilitate comparison). Estimates are imprecise because the sample is smaller, but point estimates suggest that the emancipation of the ineligible child has negligible effect compared

[15] Appendix Figure A4 shows the counterpart of Figure 2 based on these four outcomes (i.e. split by intensive and extensive margins).

[16] Estimates based on log earnings are slightly larger than those based on log work hours, but we cannot reject that the two are the same, given standard errors.

to emancipation of the child eligible for support.

For the second falsification test, I examine fathers whose oldest children are born at least one year after the fathers' last marriages, and whose last marriages are intact at the last interview. Barring errors due to imperfect identification of children and marriages, these fathers do not have to pay child support for any of their children. Table 3, panel C show that these fathers do not work more on emancipation of these children. In panel D and Figure 3, I show propensity score reweighted estimates based on the procedure in DiNardo et al. (1996) to make the sample more comparable to the main sample. The graph for work hours appears flat around emancipation, while the graph for earnings exhibits a slight decline starting from emancipation. Nonetheless, all estimated effects are statistically insignificant and small in magnitude.

What, then, are non-divorced fathers doing after their yongest children reach emancipation age? Table 4 reports results from an analysis of the American Time Use Survey (ATUS). In the first three panels, I match each married father in the ATUS to the age of his spouse's last-born child in the Current Population Survey (CPS) fertility module, and regress time spent on whether the child is emancipated or not (and controls). Reassuringly, comparing married fathers with children above emancipation age to those with unemancipated children, we see that the first group of fathers do not work statistically-significantly more even as they spend less time with the children (panel A). Instead, fathers with children above emancipation age spend more time alone or in activities that involve their spouses but not the children (panel B). In panel C, we see that these are mainly leisure or self-care activities. Apparently, the time that is freed up from spending less time with children goes into personal or couple leisure as opposed to working.

Neither the ATUS nor the CPS collects the fertility histories of men, which precludes using the same strategy to analyze the time use of divorced fathers (since we do not know the ages of children living outside the household). Instead, I use information on child support payments (available since 2010) to estimate the direct (non-child support-induced) effect of emancipation on work time of child support-paying divorced fathers. This is shown in panel D of the table. On average, these fathers spend 26 minutes a day with their non-household children. Assuming that their time-use pattern follows that of non-divorced fathers, we expect these divorced fathers to work 8 more hours annually after child emancipation (statistically insignificant). This point estimate would explain 11% of the reduced form estimate in Table 3, panel A.

3.4 Robustness specifications

Table 5 focuses again on the main sample of fathers to report robustness tests of the estimated response to various changes in model specifications. In the table, each cell shows the estimated response with the change specified at the start of the row. First, as the youngest eligible children approach emancipation age, fathers might expect that they could increase labor supply without an accompanying increase in amount paid in future once the child is emancipated. Also, child college-going might directly affect the fathers' labor supply. To address these concerns, the first row excludes the three years before the youngest eligible child reaches emancipation age, and the second row additionally excludes the four years after emancipation (the college-going years). The estimated responses remain similar.

The identifying variation in this paper comes from comparing all years before emancipation with all years after. The third and fourth rows of Table 5 show that the estimates are robust to the time-to-emancipation by, respectively, excluding and restricting the sample to the eleven years around emancipation. Estimates are similar in these two rows, and standard errors imply that we cannot reject that they are different. The fifth row estimates regression discontinity specifications by including linear trends in the age of the youngest eligible child in the sample from the previous row. (The year before emancipation is excluded.) Point estimates are again relatively similar.

The sixth row excludes wage from the list of control variables, since one could think of it as being a "bad control" (Angrist and Pischke, 2009). The seventh row excludes observations with imputed support rates. The eighth row uses an alternative imputation method, since imputing based on a father's support rates in other years might generate errors that are correlated with the emancipation instrument (since this also varies across time for each father). Specifically, the alternative imputation method uses the average child support rates of age bands 5 to 9, 10 to 14, 15 to 17, 18 to 20, 21 to 25, 26 and older. The ninth row excludes divorces that occur after the youngest eligible child turns 10, to address concerns about possible endogenous choice in the timing of divorce. The tenth row excludes Switzerland from the sample, since the first stage in the SHP is relatively weaker. Estimates are similar to the estimates in the main specification.

Fathers are often delinquent in their child support payments. This does not pose an identification problem per se, since individual fixed effects control for the unobserved propensity that a father chooses to not pay (or pay less) when given the chance. However, like fertility (see e.g. Rossin-Slater and Wüst, 2018), delinquency is a possible margin of response to child support obligations, and we might wonder if it interacts with the labor supply margin. The eleventh row probes this issue by excluding fathers who did not make a child support payment more than 50 percent of the time before emancipation. Assuming that the nonpayment is due to delinquency—plausible given the weak extensive margin response that I find—the remaining fathers are those that are more diligent in payment. Intensive margin estimates are smaller than my main estimates, suggesting that fathers who are more likely to be delinquent are also more likely to cut back on their labor supply. That said, the estimates are still statistically significant, implying that even the more diligent fathers cut back on labor supply in response to child support.

As discussed briefly in Section 2.1, there is some variation in the emancipation age of children across jurisdictions, and hence time-to-emancipation is not solely a function of child age. This provides another opportunity to control for child age effects in a manner that is different from examining a placebo group. The twelfth row does this by including fixed effects for the age of youngest child eligible for support in two-year bins.[17] Estimates in this row hence abstract away from the effect of important life events that happen at similar ages in different countries. (E.g. children often go to college at the same ages in developed countries.) Estimates are similar to the estimates in the main specification, although the more demanding specification means that they are less precise.

My main estimates exploit the emancipation of the youngest eligible child because the event study design allows simple and visual checks (including a falsification test), and because the biggest changes in the child support rates occur at that the zero-to-one child margin.[18] We might additionally want to exploit variation from the emancipation of slightly older children. Indeed, Figure 1 exhibits a slight drop in the child support rate up to three years before emancipation, which is consistent with emancipation of slightly older children. (Among fathers with two eligible children, the median age difference between the two children is 3 years.) In the thirteenth row, I explore using all variation in this figure to obtain more precise estimates. To do this, I compute the leave-self-out average support rate at every year relative to emancipation, and construct the instrument as the log of one less this average. Point estimates are similar to that in the main specification, and standard errors do not improve appreciably, suggesting that emancipation of the youngest child accounts for most of the available variation.

Finally, in the fourteenth row, I estimate an instrumented difference-in-differences specification, using fathers with no child support obligations from Section 3.3 as the control group for fathers in my main sample (the treatment group). The specification in this row elaborates Equation (1):

[17] Estimates using one-year bins are similar but less precise, such that only the effect on the log of annual work hours is statistically significant at the 10 percent level.

[18] Expenditures in the number of children are often non-linear, which is why the support rate for two children is often not twice as large as that for one child.

$$y_{it} = \psi_i + \zeta_{d(i)T(i)t} + \boldsymbol{Z}'_{it}\boldsymbol{\alpha}_{d(i)T(i)} + \eta_{d(i)}\text{Post}_{it} + \gamma \log(1 - s_{it}) + \varepsilon_{it} \tag{3}$$

$$\log(1 - s_{it}) = \tilde{\psi}_i + \tilde{\zeta}_{d(i)T(i)t} + \boldsymbol{Z}'_{it}\tilde{\boldsymbol{\alpha}}_{d(i)T(i)} + \tilde{\eta}_{d(i)}\text{Post}_{it} + \tilde{\gamma}_{d(i)}\text{Post}_{it}T_i + \nu_{it},$$

where T_i is one if the father is treated, and Post_{it} takes a value of one if the father's youngest eligible (if treated) or ineligible (if control) child is older than or at the emancipation age of his jurisdiction, half in the year before emancipation, and zero for years before. The effects of control variables are allowed to differ across treatment-control group status $T(i)$ to account for possible differences across fathers. The estimated coefficients remain similar.[19]

In Appendix Table A5, I report results for several other outcomes that might be of interest. Column 1 shows that the response of food consumption to the child support rate is negative but not statistically significant. Hence, paying child support does not induce cutbacks in consumption that are statistically significant. Column 2 shows that the response of salaried employee income with respect to the child support rate is similar to that of my main estimates.[20] Columns 3 to 5 examine other intensive margins of interest—whether the father is working a second job, the annual weeks worked, and the number of hours worked per week. All point estimates are negative, but only the log annual weeks worked is statistically significant.

With a few modifications, the estimation strategy in this paper can be modified to estimate the effect of receiving child support for mothers of eligible children. Appendix C reports that the labor supply of mothers does not change when their youngest eligible children reach emancipation age. Instrument relevance, however, is weaker than that for the fathers (although the F statistic for the first stage is still above conventionally-used levels for the intensive margin), and hence results should be treated with caution.

4 The Frisch elasticity interpretation of the results

Because the child emancipation age is predictable, and because child support affects the effective wage of the father, the labor supply response to child support (a reduced form parameter) is interpretable as a Frisch elasticity (a structural parameter). Despite its importance for macroeconomic models and welfare computations, settings with predictable changes in the effective wage (that are also observed by the econometrician) are hard to come by, which makes the contribution of this estimate to the literature important. In this

[19] Appendix Table A4 shows that the estimates for the US are robust to the same specification changes.

[20] I do not report the corresponding response for self-employment income because too few fathers earn this income in the datasets for an analysis.

section, I describe a model to interpret the results as a Frisch elasticity and discuss the estimates.

4.1 The model

The model I use is adapted from MaCurdy (1981) and related papers. At time period 0, father i solves

$$\max_{\{c_{it},a_{i,t+1},h_{it}\}_{t=0,1,\ldots,\text{all states}}} \hat{E}\left[\sum_{t=0}^{T}\beta^t\left[u\left(c_{it}\right)-\frac{e^{\boldsymbol{Z}_{it}'\boldsymbol{\alpha}+U_{it}}}{1+\frac{1}{\gamma}}h_{it}^{1+\frac{1}{\gamma}}\right]|\Phi_{i0}\right] \tag{4}$$

$$\text{s.t. } c_{it}+\frac{1}{1+r}a_{i,t+1}=a_{it}+w_{it}h_{it}-S_{it},\quad \forall t,\ \text{states}, \tag{5}$$

$$S_{i,t+1}=s_{it}w_{it}h_{it},\quad \forall t,\ \text{states}, \tag{6}$$

where c is consumption, a is assets, h is work hours, w is the market wage rate, β is the impatience parameter, and r is the interest rate. Utility is time separable, and separable in consumption and work hours. $\boldsymbol{Z}_{it}$ (a vector with associated coefficient vector $\boldsymbol{\alpha}$) and U_{it} are observed and unobserved factors that affect the father's incentives to work (work taste shifters). Equation (4) also incorporates an assumption that the father does not value the child or mother's consumption, since they do not live with the father.

The budget constraint (5) that the father faces is typical, except that the father has to pay an amount S in child support, with the amount determined in Equation (6) as the product of previous period earnings and child support rate s_{it}. s_{it} depends on the age of the youngest eligible child, among other factors unobserved to the econometrician. $\hat{E}\left(\cdot|\Phi_{it}\right)$ is father i's subjective expectation given the information set Φ_{it}. Φ_{it} is known to the father at time t, includes the wage, support rate, and taste shifters, and follows a stochastic process that depends only on past information. In particular, this rules out dependence of future wages (which are in $\Phi_{i,t+1}$) on current choice of labor supply (Altuğ and Miller, 1998; Imai and Keane, 2004; Blundell et al., 2016).

In this model, the Frisch elasticity, $\frac{\partial \log h_{it}}{\partial \log w_{it}}\Big|_{\lambda_{it}}$ where λ_{it} is the marginal utility of wealth in period t, is γ. Furthermore (derivations are in Appendix D.1):[21]

$$\log h_{it} = \gamma \log \lambda_{i0} + \gamma t \log \frac{1}{\beta(1+r)} + \gamma \log(1-\dot{s}_{it})$$
$$+ \gamma \log w_{it} - \gamma \boldsymbol{Z}'_{it}\boldsymbol{\alpha} - \gamma U_{it} + \gamma \sum_{\tau=1}^{t} \log(1+\epsilon_{i\tau}) \tag{7}$$
$$\approx \psi_i + \zeta_t - \gamma \dot{s}_{it} + \gamma \log w_{it} - \gamma \boldsymbol{Z}'_{it}\boldsymbol{\alpha} + \varepsilon_{it}, \tag{8}$$

where, in Equation (7) (first equality), $\dot{s}_{it} \equiv \frac{s_{it}}{(1+r)}$, λ_{i0} is the marginal utility of wealth in period 0 and $\epsilon_{i,t+1} \equiv \beta(1+r)\frac{\lambda_{i,t+1}}{\lambda_{it}} - \hat{E}\left[\beta(1+r)\frac{\lambda_{i,t+1}}{\lambda_{it}}|\Phi_{it}\right]$ is the innovation to the ratio of marginal utility of wealth (henceforth, shocks to MU) that is not predicted in advance by the father. The child support rate is attenuated by a rate-of-return factor because child support payments respond to labor supply increases with a lag.[22] For ease of interpretation, Equation (8) collects the time-invariant, individual-invariant, and unobservable terms in $\psi_i \equiv \gamma \log \lambda_{i0}$, $\zeta_t \equiv \gamma t \log \frac{1}{\beta(1+r)}$, and $\varepsilon_{it} \equiv -\gamma U_{it} + \gamma \sum_{\tau=1}^{t} \log(1+\epsilon_{i\tau})$, respectively. Additionally, the equation implements the approximation $\log(1-\dot{s}_{it}) \approx -\dot{s}_{it}$. This approximation captures the relationship between child support and the effective wage: each percentage point increase in the child support rate reduces the effective wage by one log point. Comparing Equation (8) with the first line of Equation (1), we see that the intensive-margin estimates reported in Section 3 are approximately equal to the negative of the Frisch elasticity.

Examining ε_{it}, we see that causal interpretation of the Frisch elasticity can be broken down into the two terms that it comprises. Exogeneity of the instrument with respect to U_{it} is the usual uncorrelated assumption that was the focus of Sections 3.3 and 3.4—unobserved shifters of the taste for work should be uncorrelated with the instrument (emancipation of the child in my setting). Exogeneity with respect to $\sum_{\tau=1}^{t} \log(1+\epsilon_{i\tau})$ is specific to the Frisch elasticity interpretation—it is required to remove income effects from the estimate. Appendix D.2 describes the full set of assumptions needed for this. In particular, we need a strong assumption that fathers have rational expectations regarding changes in their marginal utility. The advantage of the highly predictable emancipation instrument is that concerns regarding rational expectations are mitigated.

[21] A technical assumption required for this and a subsequent step is that $|\epsilon_{it}| < 1$, so that I can take logs and perform a Taylor expansion.

[22] Intuitively, the benefit of delaying the "tax" by each additional year is an additional year's worth of interest obtained by saving or investing this amount.

4.2 Frisch elasticity estimates and discussion

The formal estimates of the Frisch elasticity based on Equation (7) (which uses the effective wage) are shown in Table 2 panel C. Estimates are similar to the negative of those in Table 2 panel B, as expected. Frisch elasticities range from 0.7 to 0.9 on the intensive margin, and 0.1 (statistically insignificant) to 0.3 on the extensive margin. In a recent meta-analysis, Elminejad et al. (2023) report quasi-experimental averages of 0.6 for the intensive margin (based on 8 studies) and 0.2 for extensive margin (based on 14 studies) respectively.[23] Hence, Frisch elasticity estimates based on child support in this paper are consistent with quasi-experimental estimates in the literature, with intensive margin estimates coming in slightly higher.

An intensive-margin estimate of 0.7–0.9 is generally consistent with arguments in the macroeconomics literature as well. In particular, Rogerson and Wallenius (2013) argue that a Frisch elasticity of 0.75 and above is needed to explain the retirement decision of individuals. The macroeconomics literature discusses various reasons that estimates based on microdata could be biased downwards. Chetty (2012) notes that estimates based on small shocks induce optimization frictions that attenuate the estimate. This is less of a concern for my estimates because the drop in child support at emancipation is large and salient, and I use predictable long-run variation so fathers would have ample time to adjust their labor supply decisions. Domeij and Floden (2006) point out that credit constrained individuals in the sample cannot shift their labor supply intertemporally, which would induce negative income effects in the estimates. This, again, is less of a concern here, because credit-constrained fathers are more likely to be delinquent in payments and would not be instrument compliers (Imbens and Angrist, 1994). (Indeed, when I exclude fathers with initial wealth below the median among all fathers, estimates remain similar to those based on the full sample.) Imai and Keane (2004) and Keane and Wasi (2016) demonstrate that ignoring human capital accumulation attenuates estimates, since this ignores the possibility that working also increases future wages. For the age range of fathers in my dataset, the bias could be such that the actual Frisch elasticity is twice as large (Wallenius, 2011). Finally, Frisch elasticity estimates in this paper could be biased downwards if fathers need to accumulate precautionary savings due to risks that they cannot insure against (Low, 2005).

Specific to the child support context, another possible source of bias for Frisch elasticity estimation is the extent to which the father cares about the consumption of the mother or the child out of his child support payments. Intuitively, if the father resents the fact that the mother benefits from child support, the main estimates could be a reflection of this unwill-

[23] Correcting for publication bias yields 0 to 0.25 for the intensive margin and 0 to 0.2 for the extensive margin.

ingness to let the mother benefit at his expense. The true Frisch elasticity (intertemporal response of hours work to the *effective wage*) is then smaller than that reported above. Conversely, if the father values child or mother consumption, the true Frisch elasticity is larger than that reported above.

In Appendix D.3, I present a model that incorporates an assumption that the father likes or dislikes consumption out of his child support payments. The model requires calibration of three additional parameters—the child's share of total family consumption, set at 0.3 based on Lino et al. (2017), and the degrees to which the father likes or dislikes consumption out of child support (respectively, $\kappa^*_{\mathfrak{m}}$ and $\kappa^*_{\mathfrak{c}}$). Intuitively, emancipation induces a labor supply response, which is then split between "resentment/liking" and "dislike for work" based on the parameterization of the model.[24]

Appendix Table A6 shows the estimated Frisch elasticity at various values of $\kappa^*_{\mathfrak{m}}$ and $\kappa^*_{\mathfrak{c}}$.[25] As the intensity of like for child or mother consumption out of child support increases, the estimated Frisch elasticity increases. When the father likes both mother and child consumption out of child support 30 percent as much as his own family's consumption, the true Frisch elasticity rises to 1.1. When the father dislikes the mother's consumption out of child support 30 percent as much as he likes his own family's consumption, the true Frisch elasticity drops to 0.6. Hence, incorporating preferences over consumption of the mother or child leads to intensive-margin Frisch elasticities of 0.6–1.1.

5 Conclusion

In this paper, I estimate the labor supply response of fathers to having to paying child support. For identification, I exploit the fact that fathers are frequently not legally required to make payments after all eligible children achieve the emancipation age of the jurisdiction. I find that fathers work more after the children reach the emancipation age, implying that they cut back their pre-emancipation labor supply in response to having to pay child support. The post-emancipation increase in labor supply is unlikely to be directly attributable to events around child emancipation itself, since fathers without child support obligations (a falsification group of fathers) simply increase leisure or self-care activities instead of work activities, and the results are similar based on various robustness specifications that relate to this. My results imply that a 10 percentage point increase in the child support rate leads

[24] I calibrate these parameters because there is insufficient data to estimate them. Even combining datasets, only about one-fifth of father-years have corresponding observations for the mother.

[25] In Appendix D.4, I show that the statutory support rate of around 10 to 15 percent per child implies that $\kappa^*_{\mathfrak{c}}$ should be below 0.25. I bound $\kappa^*_{\mathfrak{m}}$ by symmetry, reflecting an assumption that the father would not dislike mother consumption more than he likes child consumption.

to an 8 to 11 percent decrease in labor supply of fathers on the intensive margin, and a 1 (statistically insignificant) to 3 percent decrease on the extensive margin.

Because child emancipation is highly predictable, estimates in this paper are better interpreted as a pure leisure-labor substitution effect from having to pay child support (i.e. they are free of income effects that act in the opposite direction of the substitution effects). Formally, they map to estimates of a Frisch elasticity of labor supply in a model. Based on this, the intensive-margin Frisch elasticity is 0.7 to 0.9, and the extensive-margin Frisch elasticity is 0.1 (statistically insignificant) to 0.3. Taking into account the possibility that the fathers care about (or dislike) the consumption of the support-receiving children and mothers, I find that the intensive-margin Frisch elasticity ranges between 0.6 and 1.1.

The intensive-margin earnings-Frisch elasticity of 0.9 estimated in this paper is the intertemporal child support analog of the elasticity of taxable income with respect to the net of tax share in Feldstein (1999). The pre-emancipation support rate in the 5 datasets is 7.8 percent, and the average earnings is $49,600 in 2016 US dollars. Applying Feldstein's deadweight loss formula gives a welfare loss of $160 per father. In the four economies considered, about 5.9 million mothers received child support in 2016, so assuming that there is a paying father for each receiving mother, the total deadweight loss from fathers cutting back their labor supply is $906 million. This number is a lower bound on the deadweight loss for two reasons. First the formula is sensitive to the support rate used, and the pre-emancipation support rate estimated in this paper is attenuated by misclassification of child eligibility. Second, these calculation ignores interactions with the tax system, which would raise deadweight loss.

Data acknowledgements:

[PSID] The collection of data used in this study was partly supported by the National Institutes of Health under grant number R01 HD069609 and R01 AG040213, and the National Science Foundation under award numbers SES 1157698 and 1623684.

[NLSY] The NLSY79 survey is sponsored and directed by the U.S. Bureau of Labor Statistics and conducted by the Center for Human Resource Research at The Ohio State University. Interviews are conducted by the National Opinion Research Center at the University of Chicago.

[BHPS+] Understanding Society and BHPS are funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by NatCen Social Research and Kantar Public. The research data are distributed by the UK Data Service.

[HILDA] This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Survey was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to the Australian Government, DSS or the Melbourne Institute.

[SHP] This study has been realized using the data collected by the Swiss Household Panel (SHP), which is based at the Swiss Centre of Expertise in the Social Sciences FORS. The project is financed by the Swiss National Science Foundation.

References

Altindag, Duha T, John Nunley, and Alan Seals, "Child-custody reform and the division of labor in the household," *Review of Economics of the Household*, 2017, *15*, 833–856.

Altonji, Joseph G, "Intertemporal substitution in labor supply: Evidence from micro data," *Journal of Political Economy*, 1986, *94* (3, Part 2), S176–S215.

Altuğ, Sumru and Robert A Miller, "Household choices in equilibrium," *Econometrica: Journal of the Econometric Society*, 1990, pp. 543–570.

— **and** — , "The effect of work experience on female wages and labour supply," *The Review of Economic Studies*, 1998, *65* (1), 45–85.

Amato, Paul R and Joan G Gilbreth, "Nonresident fathers and children's well-being: A meta-analysis," *Journal of Marriage and the Family*, 1999, pp. 557–573.

Angrist, Joshua D and Jörn-Steffen Pischke, *Mostly harmless econometrics: An empiricist's companion*, Princeton university press, 2009.

Bansak, Cynthia, Shoshana Amyra Grossbard, and Ho-Po Crystal Wong, "Mothers' caregiving during COVID: The impact of divorce laws and homeownership on women's labor force status," Working Paper 14408, Institute of Labor Economics (IZA) 2021.

Barardehi, Ilyar Heydari, Patryk Babiarz, and Teresa Mauldin, "Child support, consumption, and labor supply decisions of single-mother families," *Journal of Family and Economic Issues*, 2020, *41*, 530–541.

Baum, Christopher F., Mark E. Schaffer, and Steven Stillman, "Enhanced routines for instrumental variables/generalized method of moments estimation and testing," *The Stata Journal*, 2007, *7* (4), 465–506.

Bianchi, Marco, Bjorn R Gudmundsson, and Gylfi Zoega, "Iceland's natural experiment in supply-side economics," *American Economic Review*, 2001, *91* (5), 1564–1579.

Blundell, Richard, Alan Duncan, and Costas Meghir, "Estimating labor supply responses using tax reforms," *Econometrica*, 1998, pp. 827–861.

_ , Monica Costa Dias, Costas Meghir, and Jonathan Shaw, "Female labor supply, human capital, and welfare reform," *Econometrica*, 2016, *84* (5), 1705–1753.

Borenstein, Michael, Larry V Hedges, Julian Higgins, and Hannah R Rothstein, "A basic introduction to fixed-effect and random-effects models for meta-analysis," *Research synthesis methods*, 2010, *1* (2), 97–111.

_ , _ , Julian PT Higgins, and Hannah R Rothstein, *Introduction to meta-analysis*, West Sussex, UK: John Wiley & Sons, 2009.

Borjas, George J, "The relationship between wages and weekly hours of work: The role of division bias," *The Journal of Human Resources*, 1980, *15* (3), 409–423.

Bureau of Labor Statistics, U.S. Department of Labor, "National Longitudinal Survey of Youth 1979 cohort, 1979-2014 (rounds 1–26)," 2017. Produced and distributed by the Center for Human Resource Research, The Ohio State University, Columbus, OH.

Cancian, Maria and Molly A Costanzo, "Comparing income-shares and percentage-of-income child support guidelines," *Children and Youth Services Review*, 2019, *96*, 451–462.

_ , Carolyn J Heinrich, and Yiyoon Chung, "Discouraging disadvantaged fathers' employment: An unintended consequence of policies designed to support families," *Journal of Policy Analysis and Management*, 2013, *32* (4), 758–784.

_ , Daniel R Meyer, and Hwa-Ok Park, "The importance of child support for low-income families," Report prepared for the Bureau of Child Support, Wisconsin Department of Workforce Development, University of Wisconsin 2003.

Carasso, Adam, Harry Holzer, Elaine Maag, and C Eugene Steuerle, "The next stage for social policy: Encouraging work and family formation among low-income men," Discussion Paper No. 28, Urban Institute 2016.

Chetty, Raj, "Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply," *Econometrica*, 2012, *80* (3), 969–1018.

Chiappori, Pierre-Andre, Bernard Fortin, and Guy Lacroix, "Marriage market, divorce legislation, and household labor supply," *Journal of political Economy*, 2002, *110* (1), 37–72.

Cuesta, Laura and Maria Cancian, "The effect of child support on the labor supply of custodial mothers participating in TANF," *Children and Youth Services Review*, 2015, *54*, 49–56.

Department of Social Services and Melbourne Institute of Applied Economic and Social Research, "The Household, Income and Labour Dynamics in Australia (HILDA) Survey, GENERAL RELEASE 16 (Waves 1-16)," 2018. http://dx.doi.org/10.4225/87/VHRTR5.

DiNardo, John, Nicole M Fortin, and Thomas Lemieux, "Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach," *Econometrica*, 1996, *64* (5), 1001–1044.

Domeij, David and Martin Floden, "The labor-supply elasticity and borrowing constraints: Why estimates are biased," *Review of Economic dynamics*, 2006, *9* (2), 242–262.

Elminejad, Ali, Tomas Havranek, Roman Horvath, and Zuzana Irsova, "Intertemporal substitution in labor supply: A meta-analysis," *Review of Economic Dynamics*, 2023, *51*, 1095–1113.

Feldstein, Martin, "The effect of marginal tax rates on taxable income: a panel study of the 1986 Tax Reform Act," *Journal of Political Economy*, 1995, *103* (3), 551–572.

_ , "Tax avoidance and the deadweight loss of the income tax," *Review of Economics and Statistics*, 1999, *81* (4), 674–680.

Fisher, Hayley, "The impact of child support on the household income and labour supply of payee lone mothers," *Economic Record*, 2017, *93* (301), 189–213.

Flood, Sarah M., Liana C. Sayer, and Daniel Backman, "American Time Use Survey data extract builder: Version 3.1 [dataset]," 2022. College Park, MD: University of Maryland and Minneapolis, MN: IPUMS, https://doi.org/10.18128/D060.V3.1.

Flood, Sarah, Miriam King, Steven Ruggles, and J. Robert Warren, "Integrated Public Use Microdata Series, Current Population Survey: Version 4.0 [dataset]," 2017. Minneapolis, MN: University of Minnesota. https://doi.org/10.18128/D030.V4.0.

Foerster, Hanno, "Untying the knot: How child support and alimony affect couples' decisions and welfare," Working Paper, Boston College 2022.

Freeman, Richard B. and Jane Waldfogel, "Does Child Support Enforcement Policy Affect Male Labor Supply?," in Irwin Garfinkel, Sara S. McLanahan, Daniel Meyer, and Judith Seltzer, eds., *Fathers Under Fire: The Revolution in Child Support Enforcement*, NY: Russell Sage Foundation, 1998, chapter 4.

Friday, Cameron, "The impact of child support income on the labor supply of its recipients," Working Paper, Vanderbilt University 2021.

Friedberg, Leora, "Did unilateral divorce raise divorce rates? Evidence from panel data," *The American Economic Review*, 1998, *88* (3), 608–627.

Giles, David EA, "Instrumental variables regressions involving seasonal data," *Economics Letters*, 1984, *14* (4), 339–343.

Golosov, Mikhail, Maxim Troshkin, and Aleh Tsyvinski, "Optimal dynamic taxes," Working Paper 17642, National Bureau of Economic Research 2011.

Graham, John W, "Child support and mothers' employment," *Contemporary Economic Policy*, 1990, *8* (1), 95–109.

_ **and Andrea H Beller**, "The effect of child support payments on the labor supply of female family heads: An econometric analysis," *Journal of Human Resources*, 1989, pp. 664–688.

Grall, Timothy, "Custodial Mothers and Fathers and Their Child Support: 2015," Current Population Reports P60-262, U.S. Census Bureau 2018.

Gray, Jeffrey S, "Divorce-law changes, household bargaining, and married women's labor supply," *The American Economic Review*, 1998, *88* (3), 628–642.

Grossbard-Schectman, Shoshana, *On the Economics of Marriage*, New York, NY: Routledge, 2019.

Holzer, Harry J, Paul Offner, and Elaine Sorensen, "Declining employment among young black less-educated men: The role of incarceration and child support," *Journal of Policy Analysis and Management*, 2005, *24* (2), 329–350.

Hu, Wei-Yin, "Child support, welfare dependency, and women's labor supply," *Journal of Human Resources*, 1999, pp. 71–103.

Imai, Susumu and Michael P Keane, "Intertemporal labor supply and human capital accumulation," *International Economic Review*, 2004, *45* (2), 601–641.

Imbens, Guido W. and Joshua D. Angrist, "Identification and Estimation of Local Average Treatment Effects," *Econometrica*, 1994, *62* (2), 467–475.

Keane, Michael P, "Labor supply and taxes: A survey," *Journal of Economic Literature*, 2011, *49* (4), 961–1075.

_ , "Recent research on labor supply: Implications for tax and transfer policy," *Labour Economics*, 2022, *77*, 102026.

_ **and Nada Wasi**, "Labour supply: The roles of human capital and the extensive margin," *The Economic Journal*, 2016, *126* (592), 578–617.

Lino, M, K Kuczynski, N Rodriguez, and T Schap, "Expenditures on Children by Families, 2015," Technical Report, U.S. Department of Agriculture, Center for Nutrition Policy and Promotion 2017. Miscellaneous Publication No. 1528-2015.

Low, Hamish W, "Self-insurance in a life-cycle model of labour supply and savings," *Review of Economic dynamics*, 2005, *8* (4), 945–975.

MaCurdy, Thomas E, "An empirical model of labor supply in a life-cycle setting," *Journal of political Economy*, 1981, *89* (6), 1059–1085.

Martinez, Isabel Z, Emmanuel Saez, and Michael Siegenthaler, "Intertemporal labor supply substitution? Evidence from the Swiss income tax holidays," *American Economic Review*, 2021, *111* (2), 506–546.

Meager, Rachael, "Understanding the average impact of microcredit expansions: A Bayesian hierarchical analysis of seven randomized experiments," *American Economic Journal: Applied Economics*, 2018.

Noghanibehambari, Hamid, Farzaneh Noghani, and Nahid Tavassoli, "Child support enforcement and child mortality," *Applied Economics Letters*, 2022, *29* (5), 391–402.

Organisation for Economic Co-operation and Development, "OECD Family database," Technical Report, OECD, Paris 2014.

Panel Study of Income Dynamics, public use dataset, 2017. Produced and distributed by the Institute for Social Research, University of Michigan, Ann Arbor, MI.

Peters, H Elizabeth, "Marriage and divorce: Informational constraints and private contracting," *The American Economic Review*, 1986, *76* (3), 437–454.

Petersen, Kaare Brandt and Michael Syskind Pedersen, "The matrix cookbook," Technical Report, Technical University of Denmark 2012. Retrieved Nov 7, 2018, from `http://www2.imm.dtu.dk/pubdb/views/publication_details.php?id=3274`.

Pirog, Maureen A and Kathleen M Ziol-Guest, "Child support enforcement: Programs and policies, impacts and questions," *Journal of Policy Analysis and Management*, 2006, *25* (4), 943–990.

Pistaferri, Luigi, "Anticipated and unanticipated wage changes, wage risk, and intertemporal labor supply," *Journal of Labor Economics*, 2003, *21* (3), 729–754.

Pronzato, Chiara Daniela, "British Household Panel Survey Consolidated Marital, Cohabitation and Fertility Histories, 1991-2009 [computer file]. 3rd Edition," January 2011. University of Essex. Institute for Social and Economic Research, [original data producer(s)]. Colchester, Essex: UK Data Archive [distributor]. SN: 5629, http://dx.doi.org/10.5255/UKDA-SN-5629-1.

Reichling, Felix and Charles Whalen, "Review of estimates of the Frisch elasticity of labor supply," Working Paper 2012-13, Congressional Budget Office 2012.

Rogerson, Richard and Johanna Wallenius, "Nonconvexities, retirement, and the elasticity of labor supply," *American Economic Review*, 2013, *103* (4), 1445–1462.

Rossin-Slater, Maya, "Signing up new fathers: Do paternity establishment initiatives increase marriage, parental investment, and child well-being?," *American Economic Journal: Applied Economics*, 2017, *9* (2), 93–130.

_ **and Miriam Wüst**, "Parental responses to child support obligations: Evidence from administrative data," *Journal of Public Economics*, 2018, *164*, 183–196.

Saez, Emmanuel, Joel Slemrod, and Seth H Giertz, "The elasticity of taxable income with respect to marginal tax rates: A critical review," *Journal of Economic Literature*, 2012, *50* (1), 3–50.

Schroeder, Daniel and Nicholas Doughty, "Texas non-custodial parent choices: Program impact analysis," technical report, The University of Texas at Austin 2009.

Sigurdsson, Jósef, "Labor Supply Responses and Adjustment Frictions: A Tax-Free Year in Iceland," 2019. Available at SSRN: https://ssrn.com/abstract=3278308.

Stefánsson, Arnaldur, "Labor supply response to a tax holiday: The take-home from a large and salient shock," Working Paper, Uppsala University 2019.

Stevenson, Betsey, "Divorce law and women's labor supply," *Journal of Empirical Legal Studies*, 2008, *5* (4), 853–873.

University of Essex. Institute for Social and Economic Research, NatCen Social Research, Kantar Public, "Understanding Society: Waves 1-7, 2009-2016 and Harmonised BHPS: Waves 1-18, 1991-2009. [data collection]. 10th Edition," 2018. UK Data Service. SN: 6614, http://doi.org/10.5255/UKDA-SN-6614-11.

Venohr, Jane C, "Child support guidelines and guidelines reviews: State differences and common issues," *Family Law Quarterly*, 2013, *47* (3), 327–352.

_ **and Robert G Williams**, "The Implementation and Periodic Review of State Child Support Guidlines," *Family Law Quarterly*, 1999, *33*, 7.

Voena, Alessandra, "Yours, Mine, and Ours: Do Divorce Laws Affect the Intertemporal Behavior of Married Couples?," *American Economic Review*, 2015, *105* (8), 2295–2332.

Walker, Ian and Yu Zhu, "Child support and partnership dissolution," *The Economic Journal*, 2006, *116* (510), C93–C109.

_ **and** _ , "Child support and educational outcomes: Evidence from the British Household Panel Survey," 2009. Available at SSRN: `https://ssrn.com/abstract=1414930`.

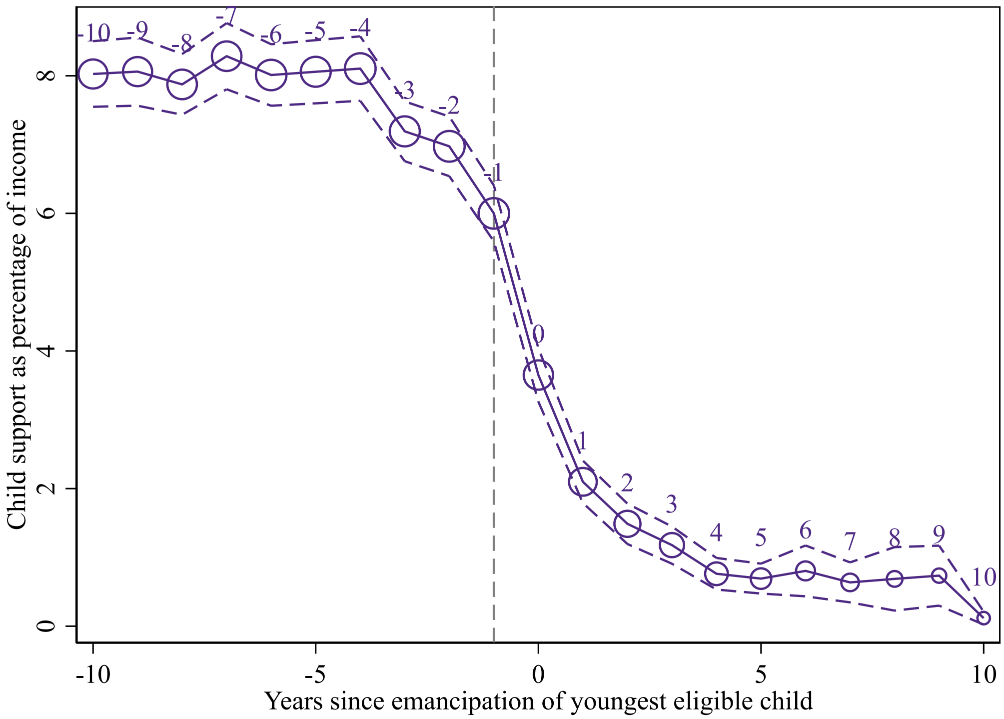
Wallenius, Johanna, "Human capital accumulation and the intertemporal elasticity of substitution of labor: How large is the bias?," *Review of Economic Dynamics*, 2011, *14* (4), 577–591.

Wolfers, Justin, "Did unilateral divorce laws raise divorce rates? A reconciliation and new results," *American Economic Review*, 2006, *96* (5), 1802–1820.

Zatz, Noah D and Michael A Stoll, "Working to avoid incarceration: Jail threat and labor market outcomes for noncustodial fathers facing child support enforcement," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 2020, *6* (1), 55–81.

Ziliak, James P and Thomas J Kniesner, "The effect of income taxation on consumption and labor supply," *Journal of Labor Economics*, 2005, *23* (4), 769–796.

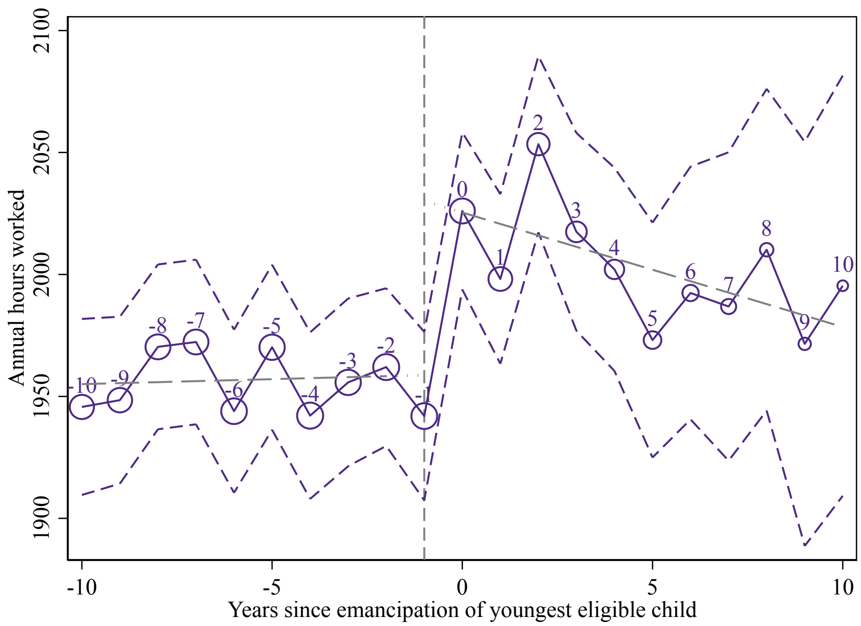
Figure 1: Average child support rate in each year relative to emancipation



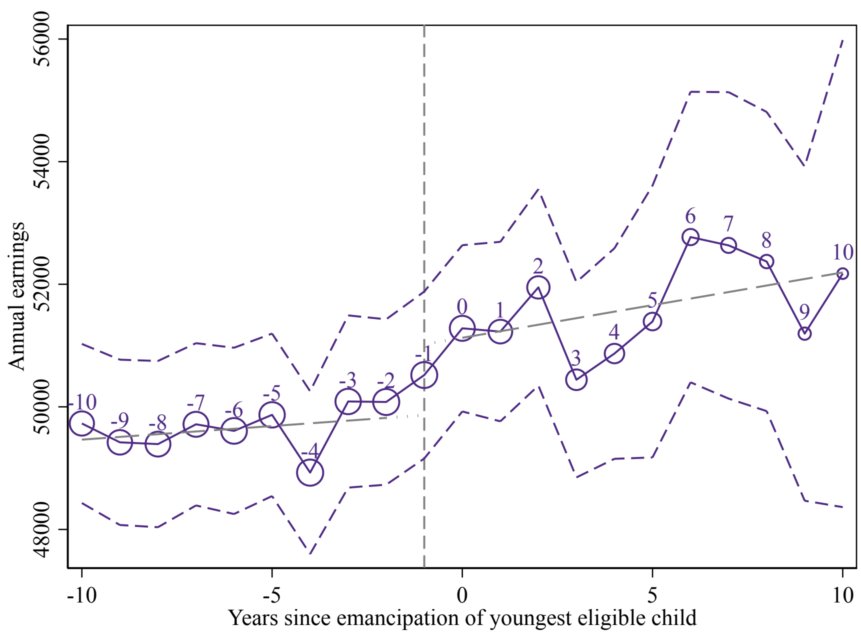
Notes: The sample comprises all father-years with non-missing child support rates. Each point on the figure is the average support rate in the year relative to emancipation of the youngest eligible child. Marker size is proportional to number of observations of each cell. Dashed line shows 95% confidence interval of the estimated mean. Vertical dashed line marks the year before emancipation.

Figure 2: Average residualized work hours and earnings among fathers in each year relative to emancipation

(a) Work hours



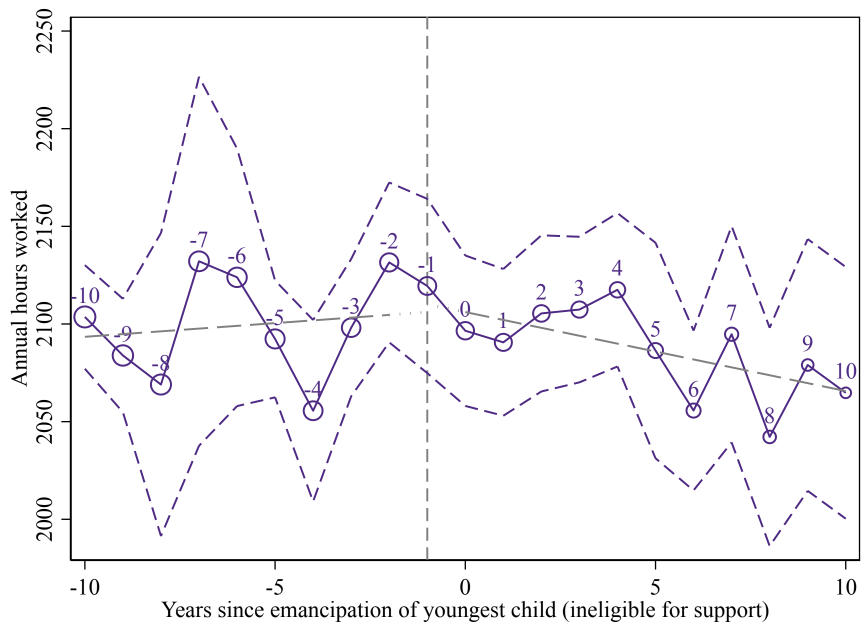
(b) Earnings



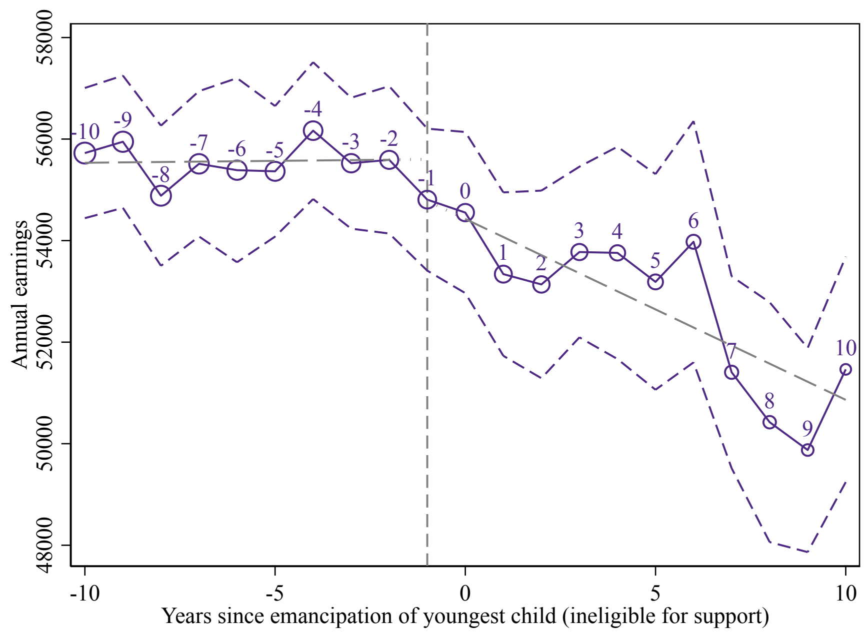
Notes: The sample comprises all father-years with non-missing child support rates. Each point on each figure is the average residualized annual work hours or earnings (including zero hours or dollars) in the year relative to emancipation of the youngest eligible child, after individual and age fixed effects are partialled out from the outcome. Marker size is proportional to number of observations of each cell. Dashed line shows 95% confidence interval of the estimated mean. Vertical dashed line marks the year before emancipation. Horizontal dashed lines are fitted linear predictions before and after the year before emancipation respectively.

Figure 3: Falsification sample: Average residualized work hours and earnings in each year relative to emancipation of youngest child among fathers who do not have child support obligations

(a) Work hours



(b) Earnings



Notes: The sample comprises all father-years for fathers who do not have child support obligations. Each point on each figure is the propensity-score weighted average residualized annual work hours or earnings (including zero hours or dollars) in the year relative to emancipation of the youngest child, after individual and age fixed effects are partialled out from the outcome. Propensity score weights are the the weights used in the Table 3 panel D. Marker size is proportional to propensity-score weight and number of observations of each cell. Dashed line shows 95% confidence interval of the estimated mean. Vertical dashed line marks the year before emancipation. Horizontal dashed lines are fitted linear predictions before and after the year before emancipation respectively.

Table 1: Effect of emancipation of the youngest eligible child on the child support rate

	Dependent variable: Child support rate					
	PSID (USA)	NLSY (USA)	BHPS+ (GBR)	HILDA (AUS)	SHP (CHE)	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
Post-emancipation	-0.038***	-0.061***	-0.035***	-0.043***	-0.051***	-0.045***
	(0.0045)	(0.0059)	(0.0039)	(0.0028)	(0.013)	(0.0021)
Observations	5,257	5,102	4,126	10,155	1,626	26,266
No. of fathers	1,066	726	544	1,171	255	3,762
Mean pre-threshold CS rate	0.07	0.12	0.06	0.06	0.16	0.08
F-statistic on instrument	74	110	80	227	15	464
Emancipation age	18–21	18–21	16	18	18	16–21

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample for each column is composed of all father-years in the dataset specified in the column title; country is indicated in parentheses. Child support rate (CS rate) is on a zero to one scale, and is computed as the ratio of the child support amount paid to the income of the father. Post-emancipation is an indicator variable that takes a value of one if the youngest eligible child is at emancipation age or older, half in the year before emancipation, and zero if younger. All specifications include as control variables individual fixed effects, dataset-year fixed effects, age-education-dataset fixed effects, and the log of the hourly wage interacted with dataset indicators.

Table 2: OLS and IV estimates of the labor supply response to child support

	Dependent variable:							
	Log of work hours		Log of earnings		Has positive work hours		Has positive earnings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Ordinary least squares estimates of the labor supply response to child support								
Child support rate	-0.11**	-0.17***	-0.81***	-0.68***	0.039	0.021	-0.0031	-0.013
	(0.054)	(0.054)	(0.087)	(0.077)	(0.029)	(0.023)	(0.030)	(0.026)
Observations	23,571	23,563	24,234	24,227	26,487	26,480	26,639	26,632
No. of fathers	3,551	3,551	3,610	3,610	3,796	3,796	3,804	3,804
Mean hours/earnings/frac.	2258.1	2258.3	56539.3	56542.2	0.89	0.89	0.91	0.91
Panel B: Two stage least squares estimates of the labor supply response to child support								
Child support rate	-0.68***	-0.80***	-0.90**	-1.05***	-0.38**	-0.34***	-0.14	-0.075
	(0.23)	(0.24)	(0.38)	(0.34)	(0.16)	(0.12)	(0.15)	(0.13)
Observations	23,159	23,151	23,819	23,812	26,036	26,029	26,186	26,179
No. of fathers	3,506	3,506	3,564	3,564	3,748	3,748	3,756	3,756
Mean hours/earnings/frac.	2261.8	2262.0	56473.2	56476.1	0.89	0.89	0.91	0.91
First stage F-statistic	110	100	111	100	111	101	111	102
Panel C: Frisch elasticity estimates								
Log(1 − CS rate)	0.63***	0.74***	0.81**	0.94***	0.34**	0.31***	0.13	0.068
	(0.21)	(0.21)	(0.34)	(0.31)	(0.14)	(0.11)	(0.13)	(0.12)
Observations	23,155	23,148	23,816	23,810	26,032	26,026	26,182	26,176
No. of fathers	3,505	3,505	3,563	3,563	3,747	3,747	3,755	3,755
Mean hours/earnings/frac.	2261.8	2261.9	56474.2	56476.2	0.89	0.89	0.91	0.91
First stage F-statistic	105	95	105	95	105	96	105	97
Individual & year FEs	x	x	x	x	x	x	x	x
Other controls		x		x		x		x

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises all father-years. Work hours are the annual work hours of the father. Earnings are the annual gross income from work of the father, in 2016 US dollars; currency conversions are based on 2016 exchange rates. Child support rate (CS rate) is on a zero to one scale, and is computed as the ratio of the child support amount paid to the income of the father. Instruments used are the post-emancipation variable from Table 1 interacted with dataset indicators. Individual & year FEs are individual fixed effects and dataset-year fixed effects. Other controls are age-education-dataset fixed effects, and the log of the hourly wage interacted with dataset indicators.

Table 3: Falsification regressions

	Dependent variable:			
	Log of work hours	Log of earnings	Has positive work hours	Has positive earnings
	(1)	(2)	(3)	(4)
Panel A: Sample: Fathers with CS obligations (main sample)				
Post-emancipation of child support child	0.033***	0.048***	0.017***	0.0033
	(0.011)	(0.015)	(0.0056)	(0.0061)
Observations	23,666	24,285	27,357	27,563
No. of fathers	3,584	3,680	3,926	3,993
Mean hours/earnings/fraction	2261.7	56149.6	0.87	0.89
Panel B: Sample: Main sample with subsequent children				
Post-emancipation of child support child	0.050*	0.100**	0.039***	0.0039
	(0.029)	(0.041)	(0.015)	(0.014)
Post-emancipation of ineligible child	0.0017	-0.035	-0.026	0.010
	(0.032)	(0.043)	(0.016)	(0.018)
Observations	3,785	3,908	4,448	4,503
No. of fathers	556	574	614	632
Mean hours/earnings/fraction	2277.6	53383.4	0.86	0.87
Panel C: Sample: Fathers with no CS obligations (unweighted)				
Post-emancipation of ineligible child	-0.0033	-0.0096	-0.0021	0.00075
	(0.0059)	(0.0085)	(0.0031)	(0.0032)
Observations	108,852	110,079	117,251	118,674
No. of fathers	12,875	13,393	13,513	14,115
Mean hours/earnings/fraction	2296.5	69968.2	0.93	0.93
Panel D: Sample: Fathers with no CS obligations (weighted)				
Post-emancipation of ineligible child	-0.016	-0.0087	0.0030	0.0030
	(0.011)	(0.015)	(0.0056)	(0.0068)
Observations	108,852	110,079	117,251	118,674
No. of fathers	12,875	13,393	13,513	14,115
Mean hours/earnings/fraction	2285.5	59431.8	0.91	0.91

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. Panel A: The sample is the main sample from Table 2. Panel B: The sample is the main sample restricted to fathers whose youngest children are not eligible for child support. Panel C and D: The sample comprises all father-years for fathers whose oldest children are born at least one year after the fathers' last marriages, and whose last marriages are intact at the last interview. Post-emancipation of child support child and ineligible child are indicator variables equal to one if the indicated child is at emancipation age or older, half in the year before emancipation, and zero if younger. The child support child is the youngest child eligible for child support used in the main tables, and the ineligible child is the youngest child of the father. Dependent variables are those used in Table 2, and all control variables in that table are included. Weights in panel D are propensity score weights computed separately by dataset using the procedure in DiNardo et al. (1996). Propensity scores are based on a probit regression of being a father with an eligible child on the following covariates: indicators for birth year deciles fully interacted with a linear function in birth year, indicators for the education level, indicators for age at first birth in decades fully interacted with a linear function in the age at first birth, indicators for the number of children by age 30, the log of average earnings between 25 and 30, and the log of average work hours between 25 and 30. For each of the last two, missing values are imputed with a constant and an indicator variable is included in parallel.

Table 4: Effect of emancipation of the youngest child on time use of non-divorced fathers, and implications for divorced fathers

Dependent variable: Minutes per day spent on specified activity. Regressor: Post-emancipation. Observations: 2380.			
Panel A: Children and work			
A1 Activities with own children	-135.8***	A2 Working and work-related act.	7.00
	(18.6)		(20.7)
Panel B: Activities with the specified parties, excluding those that involve own children			
B1 Alone or with spouse	121.8***	B3 Friends and acquaintances	-0.36
	(22.2)		(8.08)
B2 Other family members	2.05	B4 Co-workers and customers	17.5
	(3.08)		(19.9)
Panel C: Activities alone or with spouse (and not involving own children), by specified category			
C1 Personal care	29.3***	C6 Working and work-related act.	-4.42
	(10.8)		(8.73)
C2 Eating and drinking	27.5***	C7 Org., civic, and religious act.	-1.02
	(4.94)		(3.17)
C3 Household activities	9.89	C8 Leisure and sports	59.5***
	(9.94)		(13.3)
C4 Purchasing goods and services	5.53	C9 Phone calls, mail, and e-mail	1.32
	(4.40)		(1.38)
C5 Caring for and helping others	-1.80	C10 Other activities	-3.60
	(3.56)		(3.84)
Panel D: Implied emancipation effect on increase in work time of child support-paying divorced fathers			
D1 Min. per day spent with own non-household <18 y.o. child among 196 such fathers			25.9***
			(8.19)
D2 Implied direct emancipation effect on work hours of such fathers (hours per year)			8.14
			(23.3)

Notes: Robust standard errors in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises married men aged 26 to 59 in the 2003–2019 ATUS with at least one child aged above 5 in panels A to C, and divorced men aged 26 to 59 in the 2010–2019 ATUS whose family pays child support in the CPS supplemental poverty measure module in panel D. Existence and age of a married father's child is inferred from the spouse's fertility history in the CPS fertility module (unmatched observations are discarded). Each cell in panels A to C shows the result from a separate regression of time spent in the specified activity (in minutes per day) on post-emancipation (defined analogously to Table 1), controlling for fixed effects for the ages of the father and spouse, his education level, and the year, calendar month, and day-of-week of the survey. An activity may have zero or more participants. Own children is constructed from the ATUS-defined categories "own household child", "own non-household child under 18", "other non-household family members under 18", and "other non-household family members 18 and older" (the last three are possible categories that adult or near-adult children might be in). Categories used in panel C are Bureau of Labor Statistics major categories, with "caring for and helping household members" combined with "caring for and helping non-household members" to get the category in C5. These two categories are not separately interpretable using the strategy for this table. Cell D1 shows the mean minutes per day that child support-paying divorced fathers spend on activities together with their own non-household children under 18. Cell D2 shows the direct effect of emancipation on these fathers in hours per year, computed as $-\text{A2} \div \text{A1} \times \text{D1} \div 60 \times 365$. Standard error is computed via the delta method.

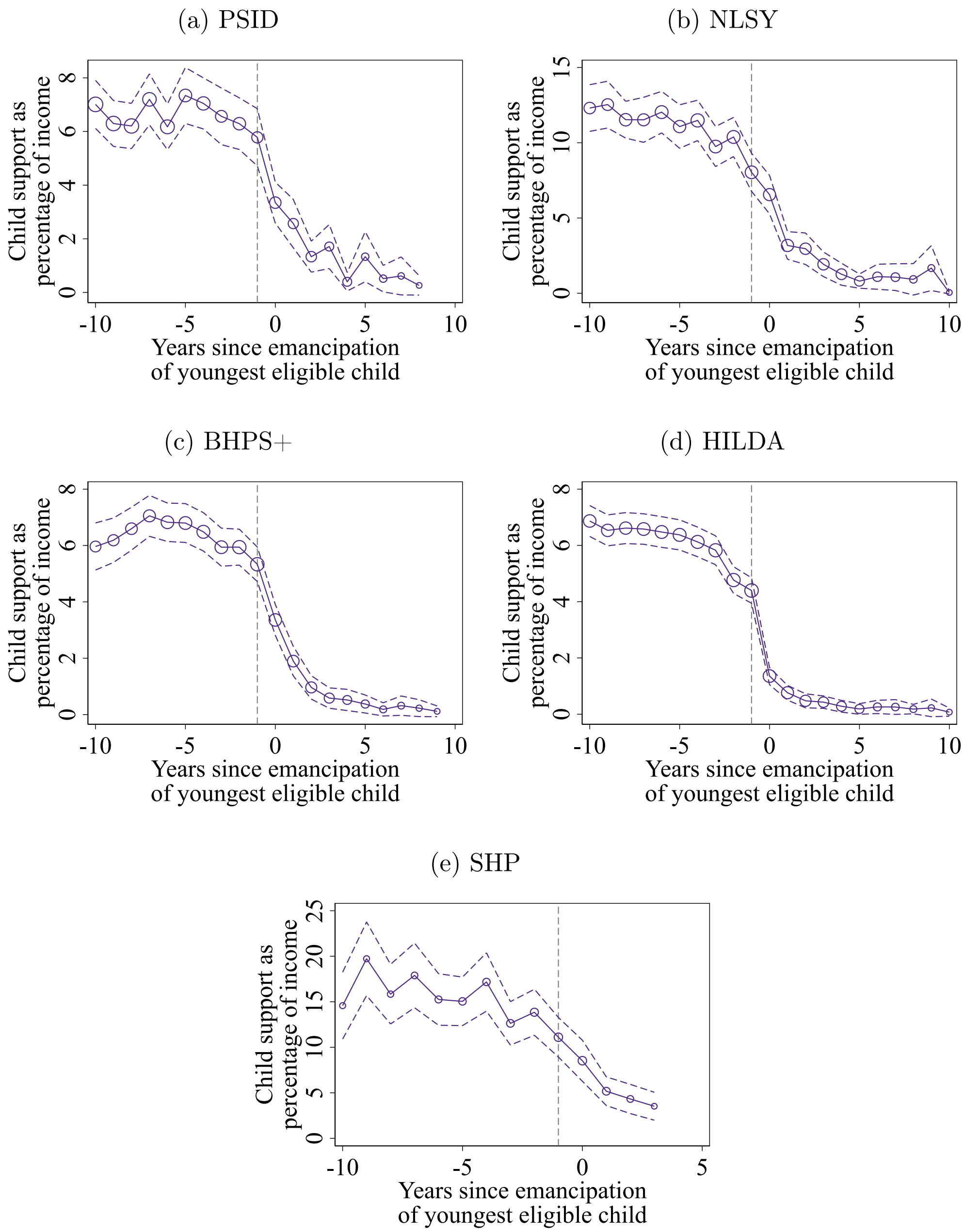
Table 5: Estimates of the labor supply response based on robustness specifications

		Dependent variable: Log of work hours	Log of earnings	Has positive work hours	Has positive earnings	First-stage F-statistic range
		(1)	(2)	(3)	(4)	(5)
0	Main estimates	-0.80***	-1.05***	-0.34***	-0.075	100–102
		(0.24)	(0.34)	(0.12)	(0.13)	
1	Exclude 3 years before emancipation	-0.56**	-0.84**	-0.33**	-0.0067	72–76
		(0.27)	(0.38)	(0.15)	(0.15)	
2	Exclude 3 years bef. to 4 years aft. eman.	-0.79**	-1.02**	-0.062	-0.076	41–43
		(0.38)	(0.49)	(0.17)	(0.18)	
3	Exclude 11 years around emancipation	-1.34**	-1.16	-0.053	-0.19	13–14
		(0.67)	(0.86)	(0.31)	(0.33)	
4	Include only 11 years around emancipation	-1.08**	-1.32**	-0.48*	0.13	38–41
		(0.47)	(0.66)	(0.25)	(0.29)	
5	Regression discontinuity specification	-0.93*	-1.51**	-0.53*	-0.11	30–33
		(0.51)	(0.73)	(0.28)	(0.31)	
6	Exclude wage as control variable	-0.83***	-1.05***	-0.15**	-0.0014	98–101
		(0.24)	(0.31)	(0.078)	(0.086)	
7	Exclude imputed support rate	-0.77***	-1.09***	N/A	N/A	94–95
		(0.24)	(0.36)			
8	Alternative imputation method	-0.73***	-1.09***	-0.39***	-0.090	100–108
		(0.24)	(0.35)	(0.13)	(0.14)	
9	Exclude divorces after child age 10	-0.78***	-1.22***	-0.32**	-0.11	71–74
		(0.28)	(0.41)	(0.15)	(0.16)	
10	Exclude Switzerland	-0.86***	-1.10***	-0.36***	-0.094	121–124
		(0.25)	(0.36)	(0.13)	(0.14)	
11	Excl. fathers who were delinq. on payments	-0.47**	-0.52*	-0.28***	0.095	136–143
		(0.19)	(0.27)	(0.10)	(0.11)	
12	Fixed effect for child age	-1.43**	-1.03	0.27	0.28	12–15
		(0.67)	(0.84)	(0.30)	(0.34)	
13	IV uses full support-age variation	-0.53**	-0.90***	-0.36***	-0.15	111–113
		(0.23)	(0.33)	(0.12)	(0.13)	
14	Difference-in-differences specification	-0.85***	-1.18***	-0.40***	-0.028	91–93
		(0.27)	(0.40)	(0.14)	(0.14)	

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. Each cell in the first four columns shows the result from a separate regression, and reports the robustness estimate corresponding to Table 2, columns 2, 4, 6 and 8. The last column shows the range of the F-statistic on the instruments in the first stage for the first four columns. Row 0: Estimates are the same as in Table 2. Row 1: The sample excludes three years before emancipation. Row 2: The sample excludes three years before to four years after emancipation. Row 3: The sample excludes 5 years before to 5 years after emancipation. Row 4: The sample uses only 5 years before to 5 years after emancipation. Row 5: The sample is that from Row 4, excluding the year before emancipation, and the specification additionally includes the running variable—age of the youngest eligible child less emancipation age plus one (to center the running variable around the year before emancipation)—and the running variable interacted with post-emancipation indicator, both interacted with dataset indicators. Row 6: The specification excludes log wage as a control variable. Row 7: The sample excludes observations for which the child support rate were imputed. Row 8: Missing child support rates are imputed (by dataset) using the average child support rates from observations with the youngest eligible children in the age bands 5–9, 10–14, 15–17, 18–20, 21–25, 26 and older. Row 9: The sample excludes observations for which the month of divorce occurs after the youngest eligible child turns 10. Row 10: The sample excludes the SHP. Row 11: The sample excludes fathers who did not pay child support in more than 50% of the waves before emancipation. Row 12: The specification includes fixed effects for the age of the youngest eligible child in two-year bins (not interacted with dataset indicators). Row 13: The instrument is $\bar{s}_{it} \equiv \sum_j \mathbb{1}\left[j \neq i, relage_{jt} = relage_{it}, d(j) = d(i)\right] s_{jt}$, the leave-self-out average of the child support rate s_{it} over all observations with the same child age relative to emancipation $relage_{it}$ and in the same dataset $d(i)$. Row 14: The sample additionally includes fathers from Table 4, panels C and D, and the specification used is the difference-in-differences specification described in the text.

A Appendix tables and figures

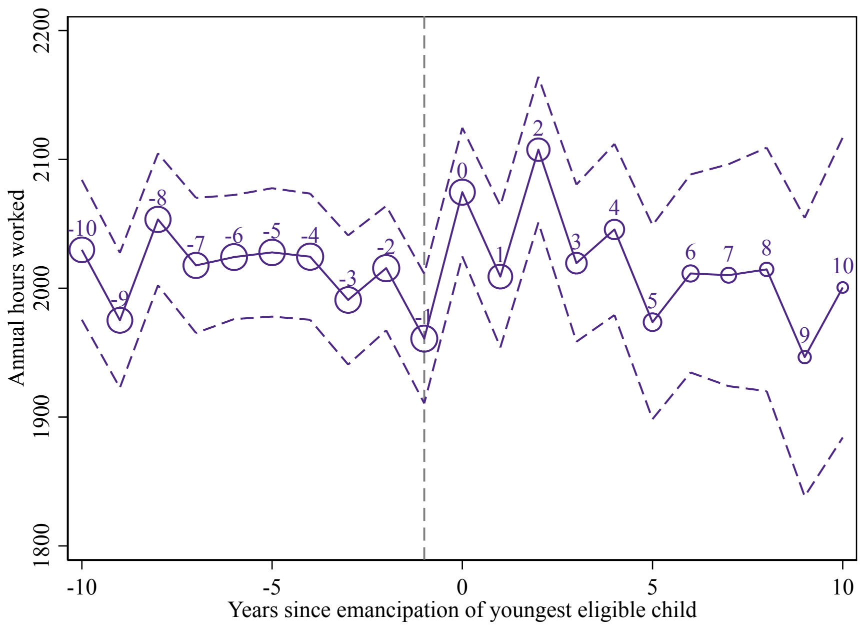
Appendix Figure A1: Average child support rate in each year relative to emancipation, by dataset



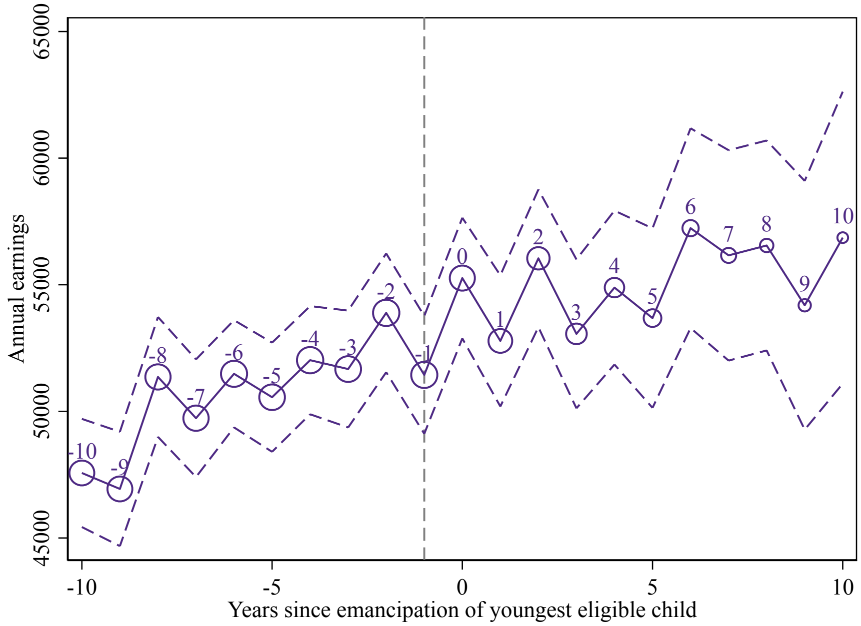
Notes: The sample comprises all father-years with non-missing child support rates. Each point on the figure is the average support rate in the year relative to emancipation of the youngest eligible child in the specified dataset. Marker size is proportional to number of observations of each cell. Dashed line shows 95% confidence interval of the estimated mean. Cells with fewer than 50 observations are not shown. Vertical dashed line marks the year before emancipation.

Appendix Figure A2: Average (non-residualized) work hours and earnings among fathers in each year relative to emancipation

(a) Work hours



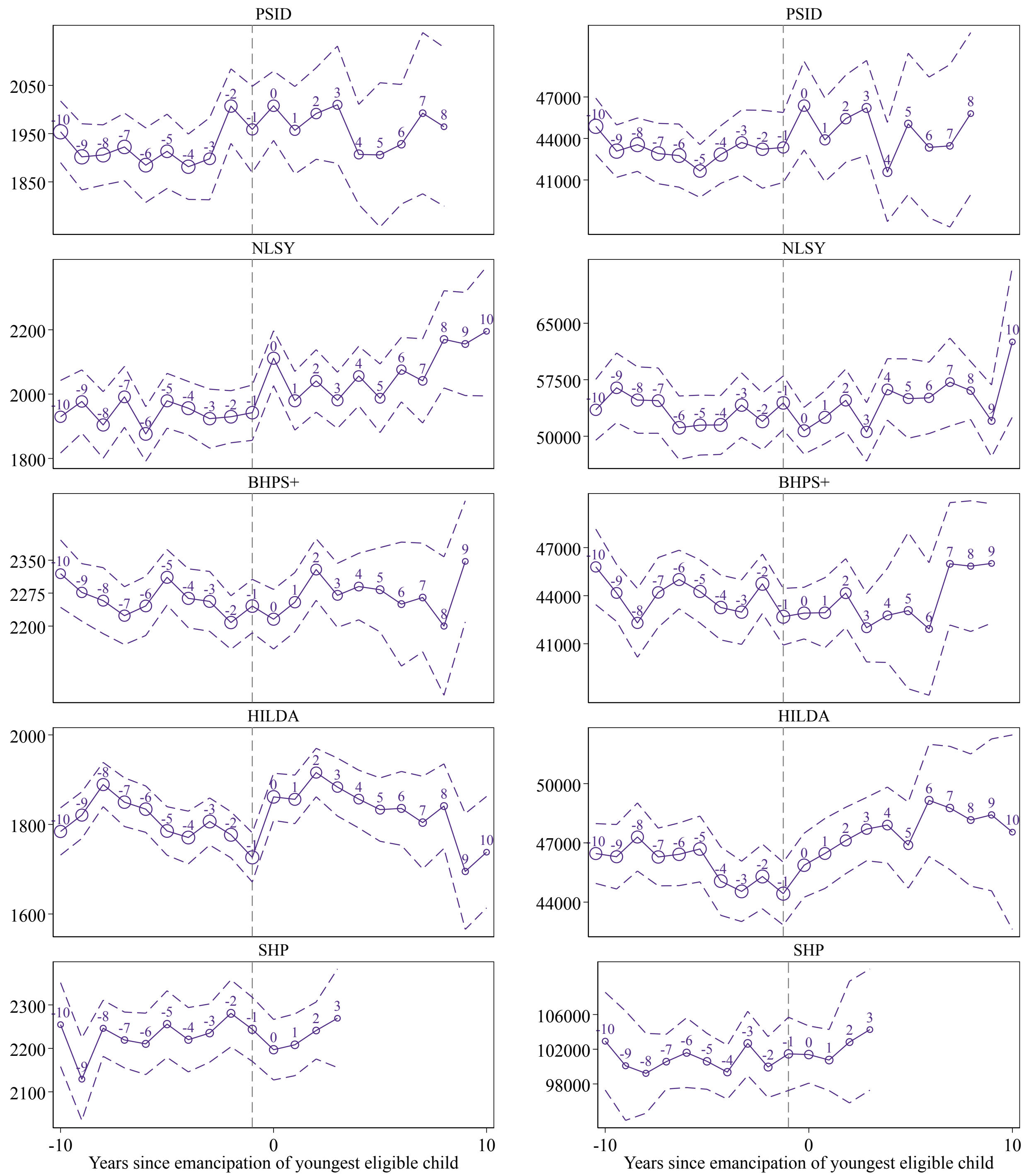
(b) Earnings



Notes: The sample comprises all father-years with non-missing child support rates. Each point on each figure is the average annual work hours or earnings (including zero hours or dollars) in the year relative to emancipation of the youngest eligible child. Marker size is proportional to number of observations of each cell. Dashed line shows 95% confidence interval of the estimated mean. Vertical dashed line marks the year before emancipation.

Appendix Figure A3: Average residualized work hours and earnings among fathers in each year relative to emancipation, by dataset

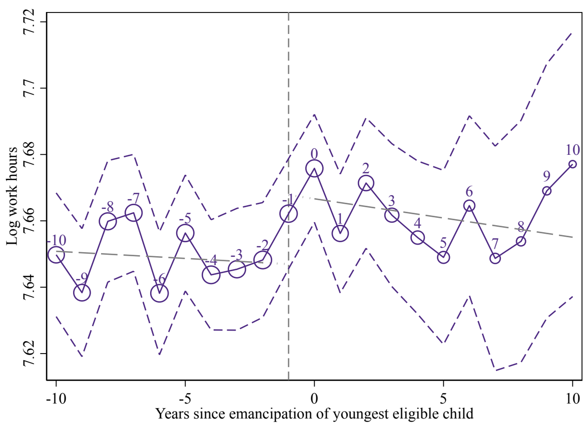
(a) Work hours (b) Earnings



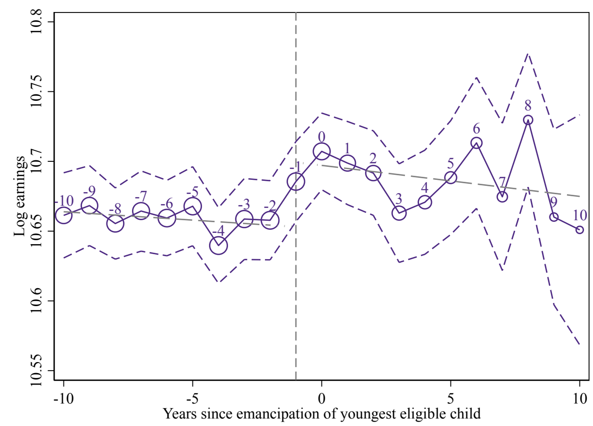
Notes: The sample comprises all father-years with non-missing child support rates. Each point on each figure is the average residualized annual work hours or earnings (including zero hours or dollars) in the year relative to emancipation of the youngest eligible child for observations in the specified dataset, after individual and age fixed effects are partialled out from the outcome. Marker size is proportional to number of observations of each cell. Dashed line shows 95% confidence interval of the estimated mean. Cells with fewer than 50 observations are not shown. Vertical dashed line marks the year before emancipation.

Appendix Figure A4: Average residualized work hours and earnings among fathers in each year relative to emancipation, by intensive and extensive margin

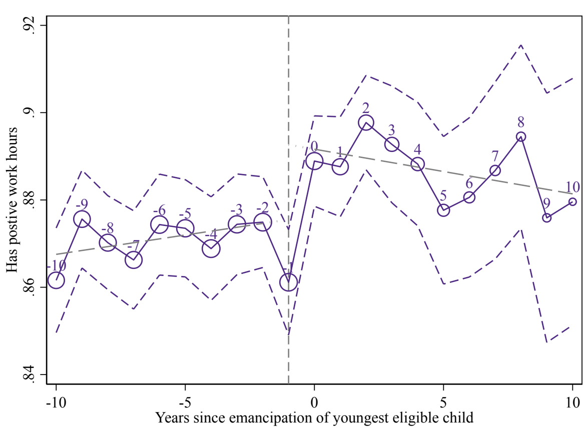
(a) Log work hours



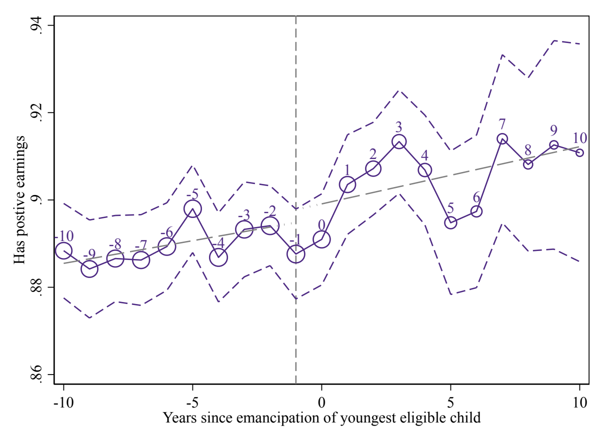
(b) Log earnings



(c) Positive work hours



(d) Positive earnings



Notes: The sample comprises all father-years with non-missing child support rates. Each point on each figure is the average residualized outcome in the year relative to emancipation of the youngest eligible child, after individual and age fixed effects are partialled out. The outcomes are, respectively, log annual work hours, log earnings, whether work hours is positive, and whether earnings is positive. Marker size is proportional to number of observations of each cell. Dashed line shows 95% confidence interval of the estimated mean. Vertical dashed line marks the year before emancipation. Horizontal dashed lines are fitted linear predictions before and after the year before emancipation respectively.

Appendix Table A1: Characteristics of fathers in the sample and for all men in the datasets

	All men in the five datasets	Unweighted		Weighted by child support rate	
		Statistics of main sample of fathers	Difference from all other men	Statistics of main sample of fathers	Difference from all other men
	(1)	(2)	(3)	(4)	(5)
Number of individuals with positive weights					
Full sample	50,929	5,470		3,589	
Observed before age 30	25,028	2,877		1,909	
Economic characteristics between ages 25 and 30					
Any work hours (%)	96	93	-3.4***	96	0.11
	[20]	[26]	(0.40)	[19]	(0.38)
Average hourly wage (USD/hour)	20	15	-5.3***	15	-4.9***
	[45]	[15]	(0.94)	[21]	(0.94)
Average annual earnings (USD)	41,000	34,500	-7,500***	39,100	-2,900***
	[28,100]	[23,200]	(560)	[22,900]	(560)
Average annual work hours	1,960	1,830	-150***	1,970	-9.8
	[768]	[865]	(16)	[750]	(15)
Demographic characteristics					
Birth year	1965	1968	3.0***	1966	1.4***
	[14]	[11]	(0.21)	[9.3]	(0.21)
Completed high school (%)	85	81	-5.2***	85	-0.60
	[36]	[40]	(0.51)	[36]	(0.51)
Has college education (%)	38	27	-13***	32	-7.3***
	[49]	[44]	(0.69)	[47]	(0.71)
Age at first marriage (if ever married)	25	24	-0.92***	24	-1.5***
	[10]	[9.4]	(0.17)	[9.3]	(0.17)
Age at birth of first child (if a father)	28	26	-2.8***	26	-2.2***
	[6]	[6]	(0.086)	[5]	(0.088)
Number of children by age 30	0.86	1.6	0.84***	1.5	0.77***
	[1.1]	[1.2]	(0.016)	[1.2]	(0.016)

Notes: Standard deviations reported in brackets below means, and standard errors reported in parentheses below difference estimates. The sample comprises all men aged 26 to 59, with the dataset-specific restrictions specified in the data appendix. Each observation is an individual. The main sample of fathers is the sample of fathers with support obligations used in the regressions. Column 4 shows estimates weighted by the pre-emancipation average child support rate, normalized so that the sum of weights is equal to the number of fathers. Columns 3 and 5 shows, respectively, unweighted and weighted estimates from a regression of the variable in the row title on an indicator of whether the father is in the main sample or not. In column 5, fathers in the main sample have the same weight as in column 4, while all other fathers have a weight of one. Dollar values are in 2016 US dollars.

Appendix Table A2: Reduced form effect of emancipation of the youngest eligible child on labor supply

	Dependent variable:			
	Log of work hours	Log of earnings	Has positive work hours	Has positive earnings
	(1)	(2)	(3)	(4)
Post-emancipation	0.033***	0.048***	0.017***	0.0033
	(0.011)	(0.015)	(0.0056)	(0.0061)
Observations	23,666	24,285	27,357	27,563
No. of fathers	3,584	3,680	3,926	3,993
Mean hours/earnings/fraction	2261.7	56149.6	0.87	0.89

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises all father-years. Work hours are the annual work hours of the father. Earnings are the annual gross income from work of the father, in 2016 US dollars; currency conversions are based on 2016 exchange rates. Post-emancipation is an indicator variable that takes a value of one if the youngest eligible child is at emancipation age or older, half in the year before emancipation, and zero if younger. All columns include all control variables from Table 2.

Appendix Table A3: Estimates of the labor supply response by dataset

	USA pooled	PSID (USA)	NLSY (USA)	BHPS+ (GBR)	HILDA (AUS)	SHP (CHE)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent variable: Log of work hours						
Child support rate	-1.23***	-1.09	-1.27***	-0.46	-0.47	0.0044
	(0.38)	(0.83)	(0.42)	(0.49)	(0.39)	(0.55)
Observations	9,527	4,923	4,604	3,830	8,234	1,560
No. of fathers	1,729	1,030	699	523	1,005	249
Mean hours	2,239	2,178	2,304	2,364	2,234	2,303
First stage F-stat.	90	68	111	83	222	16
Panel B: Dependent variable: Log of earnings						
Child support rate	-0.78	-0.91	-0.73	0.085	-1.85***	-0.21
	(0.48)	(0.87)	(0.57)	(0.58)	(0.68)	(0.58)
Observations	9,634	4,886	4,748	3,979	8,678	1,521
No. of fathers	1,739	1,025	714	537	1,043	245
Mean earnings	54,528	48,534	60,695	46,386	54,258	107,870
First stage F-stat.	89	66	111	86	227	13
Panel C: Dependent variable: Has positive work hours						
Child support rate	-0.064	-0.14	-0.041	-0.079	-0.86***	-0.12
	(0.15)	(0.20)	(0.18)	(0.15)	(0.28)	(0.22)
Observations	10,277	5,257	5,020	3,989	10,137	1,626
No. of fathers	1,789	1,066	723	533	1,171	255
Fraction with positive hours	0.93	0.94	0.92	0.96	0.82	0.96
First stage F-stat.	91	74	108	82	227	15
Panel D: Dependent variable: Has positive earnings						
Child support rate	-0.082	-0.038	-0.095	0.28	-0.21	0.18
	(0.15)	(0.19)	(0.19)	(0.28)	(0.29)	(0.18)
Observations	10,296	5,257	5,039	4,126	10,155	1,602
No. of fathers	1,789	1,066	723	544	1,171	252
Fraction with positive earnings	0.94	0.94	0.94	0.97	0.86	0.95
First stage F-stat.	94	74	114	80	227	15

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises all father-years. Work hours and earnings are the annual work hours and gross income from work respectively of the father. Child support rate is on a zero to one scale, and is computed as the ratio of the child support amount paid to the income of the father. Instruments used are the post-emancipation variable from Table 1 interacted with dataset indicators. All columns include all control variables from Table 2.

Appendix Table A4: Estimates of the labor supply response based on robustness specifications for the US

		Dependent variable:				First-stage F-statistic range
		Log of work hours	Log of earnings	Has positive work hours	Has positive earnings	
		(1)	(2)	(3)	(4)	(5)
0	Main estimates	-1.23***	-0.78	-0.064	-0.082	89–94
		(0.38)	(0.48)	(0.15)	(0.15)	
1	Exclude 3 years before emancipation	-1.27***	-0.84	-0.059	-0.021	62–68
		(0.44)	(0.58)	(0.18)	(0.17)	
2	Exclude 3 years bef. to 4 years aft. eman.	-1.10**	-0.50	0.12	0.019	50–54
		(0.53)	(0.64)	(0.20)	(0.21)	
3	Exclude 11 years around emancipation	-2.42**	-0.66	-0.23	-0.20	12–13
		(1.09)	(1.25)	(0.42)	(0.44)	
4	Include only 11 years around emancipation	-2.48**	-1.68	-0.31	-0.24	14–16
		(1.06)	(1.17)	(0.37)	(0.39)	
5	Regression discontinuity specification	-2.33*	-1.23	-0.59	-0.35	13–14
		(1.21)	(1.28)	(0.46)	(0.48)	
6	Exclude wage as control variable	-1.31***	-0.98**	-0.039	-0.087	85–92
		(0.38)	(0.45)	(0.13)	(0.12)	
7	Exclude imputed support rate	-1.07***	-0.79*	N/A	N/A	87–90
		(0.37)	(0.48)			
8	Alternative imputation method	-1.13***	-0.79	-0.15	-0.086	86–103
		(0.38)	(0.49)	(0.17)	(0.18)	
9	Exclude divorces after child age 10	-1.15**	-0.87	-0.025	-0.20	55–63
		(0.46)	(0.59)	(0.18)	(0.19)	
10	Excl. fathers who were delinq. on payments	-0.83***	-0.20	0.056	0.17	117–129
		(0.30)	(0.40)	(0.12)	(0.12)	
11	IV uses full support-age variation	-0.68*	-0.41	0.00045	-0.091	109–112
		(0.36)	(0.44)	(0.14)	(0.15)	
12	Difference-in-differences specification	-0.85***	-1.18***	-0.40***	-0.028	91–93
		(0.27)	(0.40)	(0.14)	(0.14)	

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. Each cell in the first four columns shows the result from a separate regression, and reports the robustness estimate corresponding to Table 2, columns 2, 4, 6 and 8. The last column shows the range of the F-statistic on the instruments in the first stage for the first four columns. Row 0: Estimates are the same as in Table 2. Row 1: The sample excludes three years before emancipation. Row 2: The sample excludes three years before to four years after emancipation. Row 3: The sample excludes 5 years before to 5 years after emancipation. Row 4: The sample uses only 5 years before to 5 years after emancipation. Row 5: The sample is that from Row 4, excluding the year before emancipation, and the specification additionally includes the running variable—age of the youngest eligible child less emancipation age plus one (to center the running variable around the year before emancipation)—and the running variable interacted with post-emancipation indicator, both interacted with dataset indicators. Row 6: The specification excludes log wage as a control variable. Row 7: The sample excludes observations for which the child support rate were imputed. Row 8: Missing child support rates are imputed (by dataset) using the average child support rates from observations with the youngest eligible children in the age bands 5–9, 10–14, 15–17, 18–20, 21–25, 26 and older. Row 9: The sample excludes observations for which the month of divorce occurs after the youngest eligible child turns 10. Row 10: The sample excludes fathers who did not pay child support in more than 50% of the waves before emancipation. Row 11: The instrument is $\bar{s}_{it} \equiv \sum_j \mathbb{1}\left[j \neq i, relage_{jt} = relage_{it}, d(j) = d(i)\right] s_{jt}$, the leave-self-out average of the child support rate s_{it} over all observations with the same child age relative to emancipation $relage_{it}$ and in the same dataset $d(i)$. Row 12: The sample additionally includes fathers from Table 4, panels C and D, and the specification used is the difference-in-differences specification described in the text.

Appendix Table A5: Elasticities of other outcomes with respect to the child support rate

	Dependent variable:				
	Log of food expenditure	Log of employee earnings	More than one job if working	Log of annual weeks worked	Log of weekly hours
	(1)	(2)	(3)	(4)	(5)
Child support rate	-0.49	-1.02***	-0.11	-0.40**	-0.17
	(0.38)	(0.33)	(0.23)	(0.20)	(0.22)
Observations	17,383	21,448	23,810	22,276	21,870
No. of fathers	2,637	3,373	3,553	3,308	3,288
Average levels	8.49	55.7	0.17	48.9	48.8
First stage F-stat.	120	95	100	122	122
Individual & year FEs	x	x	x	x	x
Other controls	x	x	x	x	x

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises all father-years. Column 1: The dependent variable is the log of annualized food expenditure of the father. Only the PSID, BHPS, and HILDA have information on food consumption and are used in these regressions. Column 2: The dependent variable is the log of annual income earned as salaried employees of the father. Column 3: The dependent variable is an indicator variable that takes a value of one if the father held two or more jobs in the year, and zero if the father held only one job. The observation is excluded if no jobs are recorded. Column 4: The dependent variable is the log of the annualized number of weeks worked. Column 5: The dependent variable is the log of the number of hours worked per week. The SHP does not contain weeks worked or hours per week information and is excluded from columns 4 and 5. Child support rate is on a zero to one scale, and is computed as the ratio of the child support amount paid to the income of the father. Instruments used are the post-emancipation variable from Table 1 interacted with dataset indicators. Individual & year FEs are individual fixed effects and dataset-year fixed effects. Other controls are age-education-dataset fixed effects, and the log of the hourly wage interacted with dataset indicators. Average levels shows the non-logged mean dependent variable values. Dollar values are in thousands of 2016 US dollars; currency conversions are based on 2016 exchange rates.

Appendix Table A6: Sensitivity of the Frisch elasticity to including child and mother consumption in father's utility

Intensity of like for child consumption ($\kappa^*_{\mathfrak{c}}$)	Intensity of like for mother consumption ($\kappa^*_{\mathfrak{m}}$)										
	-0.5	-0.4	-0.3	-0.2	-0.1	0	0.1	0.2	0.3	0.4	0.5
0	0.48***	0.53***	0.58***	0.63***	0.68***	0.74***	0.80***	0.87***	0.96***	1.1***	1.2***
	(0.13)	(0.15)	(0.16)	(0.18)	(0.20)	(0.21)	(0.24)	(0.26)	(0.29)	(0.32)	(0.35)
0.1	0.50***	0.56***	0.60***	0.65***	0.71***	0.77***	0.83***	0.91***	0.1.***	1.1***	1.2***
	(0.14)	(0.16)	(0.17)	(0.19)	(0.20)	(0.22)	(0.24)	(0.27)	(0.30)	(0.33)	(0.37)
0.2	0.53***	0.58***	0.62***	0.67***	0.73***	0.79***	0.86***	0.95***	1.0***	1.2***	1.3***
	(0.15)	(0.16)	(0.18)	(0.19)	(0.21)	(0.23)	(0.25)	(0.28)	(0.31)	(0.35)	(0.39)
0.3	0.55***	0.60***	0.64***	0.70***	0.76***	0.82***	0.90***	0.98***	1.1***	1.2***	1.4***
	(0.15)	(0.17)	(0.18)	(0.20)	(0.22)	(0.24)	(0.27)	(0.29)	(0.33)	(0.37)	(0.42)
0.4	0.57***	0.62***	0.67***	0.72***	0.78***	0.85***	0.93***	1.0***	1.1***	1.3***	1.4***
	(0.16)	(0.18)	(0.19)	(0.21)	(0.23)	(0.25)	(0.28)	(0.31)	(0.34)	(0.39)	(0.44)
0.5	0.59***	0.64***	0.69***	0.75***	0.81***	0.89***	0.97***	1.1***	1.2***	1.3***	1.5***
	(0.17)	(0.18)	(0.20)	(0.22)	(0.24)	(0.26)	(0.29)	(0.32)	(0.36)	(0.41)	(0.47)

Notes: Standard errors in parentheses are for the last iteration of the procedure, and are clustered by individual. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. $\kappa^*_{\mathfrak{m}}$ and $\kappa^*_{\mathfrak{c}}$ capture the intensity of like for mother or child consumption out of child support, respectively. Highlighted cells are the values that are consistent with the bounding on $\kappa^*_{\mathfrak{m}}$ and $\kappa^*_{\mathfrak{c}}$ provided by the statutory child support rate.

B The weighting scheme of the meta-analysis estimator

B.1 The weighting scheme

The labor supply elasticity estimated in this paper is a weighted average of the labor supply elasticities estimated separately in each dataset. In this section, I derive the weighting scheme based on least squares geometry.[26] Intuitively, in OLS, the weights should increase with dataset size—larger datasets contribute more to the sum of squared residuals in the pooled dataset—and variation in the regressor's distribution—regressors further from the mean are more influential in OLS. The weighting scheme for 2SLS is similar, except that the strength of the first stage relationship plays a role as well. Because the estimator is more general than the context of this paper, this section uses more conventional regression notation, different from other sections of the paper.

The setting I consider is a 2SLS specification with covariates. We are interested in the partial effect $\boldsymbol{\beta}$ (a K-vector of coefficients) of a K-vector of endogenous variables $\boldsymbol{x}_{di}$ on a scalar outcome y_{di}, estimated using 2SLS with the L_d-vector of (excluded) instruments $\boldsymbol{z}_{di}$, where d indexes the dataset and i indexes an observation. We have an M_d-vector of covariates $\boldsymbol{w}_{di}$ (included instruments); we are not interested in the partial effect of these covariates, $\boldsymbol{\alpha}_d$, which differs by dataset. The number and identities of instruments and covariates can vary across datasets; for example, we might control for age in one dataset and not in another. Thus, we have the 2SLS specification

$$y_{di} = \boldsymbol{x}_{di}'\boldsymbol{\beta} + \boldsymbol{w}_{di}'\boldsymbol{\alpha}_d + \varepsilon_{di}, \tag{9}$$

$$\boldsymbol{x}_{di} = \boldsymbol{\theta}_d \boldsymbol{z}_{di} + \boldsymbol{\kappa}_d \boldsymbol{w}_{di} + \boldsymbol{\nu}_{di},$$

where, in addition to the objects defined above, ε_{di} and $\boldsymbol{\nu}_{di}$ are error terms, and $\boldsymbol{\theta}_d$ and $\boldsymbol{\kappa}_d$ are $K \times L_d$ and $K \times M_d$ matrices of first stage coefficients that differ based on dataset d.

We have D datasets, with each dataset d having n_d observations, for a total of n observations. We can obtain D estimates of $\boldsymbol{\beta}$ by sequentially restricting the sample to dataset d and estimating (9) by 2SLS; denote each restricted-dataset estimate by $\hat{\boldsymbol{\beta}}_d$. We can also obtain a meta-analysis estimate of $\boldsymbol{\beta}$ by estimating (9) on the full sample; denote this estimate by $\hat{\boldsymbol{\beta}}$. We want to understand the relationship between $\hat{\boldsymbol{\beta}}$ and the $\hat{\boldsymbol{\beta}}_d$'s.

For each dataset d, let $\boldsymbol{y}_d \equiv \begin{bmatrix} y_{d1} & \ldots & y_{dn_d} \end{bmatrix}'$, $\boldsymbol{X}_d \equiv \begin{bmatrix} \boldsymbol{x}_{d1} & \ldots & \boldsymbol{x}_{dn_d} \end{bmatrix}'$, $\boldsymbol{Z}_d \equiv \begin{bmatrix} \boldsymbol{z}_{d1} & \ldots & \boldsymbol{z}_{dn_d} \end{bmatrix}'$, and $\boldsymbol{W}_d \equiv \begin{bmatrix} \boldsymbol{w}_{d1} & \ldots & \boldsymbol{w}_{dn_d} \end{bmatrix}'$ be the $n_d \times 1$, $n_d \times K$, $n_d \times L_d$, and $n_d \times M_d$ data matrices (or vector) from the dataset. Application of the Frisch-Waugh-Lovell (FWL) theorem yields[27]

$$\hat{\boldsymbol{\beta}}_d = \left(\tilde{\boldsymbol{X}}_d' \boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d} \tilde{\boldsymbol{X}}_d\right)^{-1} \tilde{\boldsymbol{X}}_d' \boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d} \tilde{\boldsymbol{y}}_d, \tag{10}$$

where $\tilde{\boldsymbol{y}}_d \equiv \boldsymbol{M}_{\boldsymbol{W}_d}\boldsymbol{y}_d$, $\tilde{\boldsymbol{X}}_d \equiv \boldsymbol{M}_{\boldsymbol{W}_d}\boldsymbol{X}_d$, and $\tilde{\boldsymbol{Z}}_d \equiv \boldsymbol{M}_{\boldsymbol{W}_d}\boldsymbol{Z}_d$, and where for any arbitrary matrix $\boldsymbol{C}$, $\boldsymbol{P}_{\boldsymbol{C}} \equiv \boldsymbol{C}\left(\boldsymbol{C}'\boldsymbol{C}\right)^{-1}\boldsymbol{C}$ is the projection matrix and $\boldsymbol{M}_{\boldsymbol{C}} \equiv \boldsymbol{I} - \boldsymbol{P}_{\boldsymbol{C}}$ is the annihilator

[26] One implication of this is that this relationship is exact in the finite sample.

[27] To my knowledge, no formal derivation of the theorem exists for the overidentified 2SLS case exists, although the result has been used in econometric software. I provide this derivation in Section B.2.

matrix.

Next, stack the outcome and endogenous variables from the D datasets to obtain the n-vector $\boldsymbol{y}_d \equiv \begin{bmatrix} y_{d1} & \dots & y_{dn_d} \end{bmatrix}'$ and the $n \times K$ matrix $\boldsymbol{X} \equiv \begin{bmatrix} \boldsymbol{X}'_1 & \dots & \boldsymbol{X}'_D \end{bmatrix}'$. Since we fully interact the instruments and covariates with dataset indicators, the corresponding data matrix of instruments is the $n \times \sum_{d=1}^{D} L_d$ block diagonal matrix

$$\boldsymbol{Z} \equiv \begin{bmatrix} \boldsymbol{Z}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{Z}_D \end{bmatrix}$$

and the $n \times \sum_{d=1}^{D} M_d$ block diagonal matrix

$$\boldsymbol{W} = \begin{bmatrix} \boldsymbol{W}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{W}_D \end{bmatrix}.$$

The FWL theorem again yields

$$\hat{\boldsymbol{\beta}} = \left(\tilde{\boldsymbol{X}}'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}}\tilde{\boldsymbol{X}}\right)^{-1}\tilde{\boldsymbol{X}}'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}}\tilde{\boldsymbol{y}},$$

where $\tilde{\boldsymbol{y}} \equiv \boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{y}$, $\tilde{\boldsymbol{X}} \equiv \boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{X}$, and $\tilde{\boldsymbol{Z}} \equiv \boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}$.

To proceed, note that straightforward block diagonal matrix algebraic manipulation gives[28]

$$\boldsymbol{M}_{\boldsymbol{W}} = \begin{bmatrix} \boldsymbol{M}_{\boldsymbol{W}_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{M}_{\boldsymbol{W}_D} \end{bmatrix},$$

which implies that $\tilde{\boldsymbol{Z}}$ (a product of two block diagonal matrices with dimensions that match up) is itself block diagonal, with each block given by $\boldsymbol{M}_{\boldsymbol{W}_d}\boldsymbol{Z}_d = \tilde{\boldsymbol{Z}}_d$. This in turn implies that

$$\boldsymbol{P}_{\tilde{\boldsymbol{Z}}} = \begin{bmatrix} \boldsymbol{P}_{\tilde{\boldsymbol{Z}}_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{P}_{\tilde{\boldsymbol{Z}}_D} \end{bmatrix}.$$

[28] See, for example, Petersen and Pedersen (2012, p. 46).

Hence, we have

$$
\begin{aligned}
\hat{\boldsymbol{\beta}} &= \left(\tilde{\boldsymbol{X}}'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}}\tilde{\boldsymbol{X}}\right)^{-1}\tilde{\boldsymbol{X}}'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}}\tilde{\boldsymbol{y}} \\
&= \left(\sum_{d=1}^{D}\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{X}}_d\right)^{-1}\sum_{d=1}^{D}\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{y}}_d \\
&= \left(\sum_{d=1}^{D}\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{X}}_d\right)^{-1}\sum_{d=1}^{D}\left(\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{X}}_d\right)\left(\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{X}}_d\right)^{-1}\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{y}}_d \\
&= \left(\sum_{d=1}^{D}\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{X}}_d\right)^{-1}\sum_{d=1}^{D}\left(\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{X}}_d\right)\hat{\boldsymbol{\beta}}_d,
\end{aligned}
$$

where the second equality exploits the block diagonal nature of $\boldsymbol{P}_{\tilde{\boldsymbol{Z}}}$ and the ordering of the d datasets in $\tilde{\boldsymbol{X}}$ and $\tilde{\boldsymbol{y}}$ (so that dimensions match up), and the fourth equality follows from (10). Hence, $\hat{\boldsymbol{\beta}}$ is a weighted average of the $\hat{\boldsymbol{\beta}}_d$'s, with weights given by the $K \times K$ matrices $\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{X}}_d$.

We can decompose the weights into component parts:

$$
\begin{aligned}
\tilde{\boldsymbol{X}}_d'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}_d}\tilde{\boldsymbol{X}}_d &= \tilde{\boldsymbol{X}}_d'\tilde{\boldsymbol{Z}}_d\left(\tilde{\boldsymbol{Z}}_d'\tilde{\boldsymbol{Z}}_d\right)^{-1}\tilde{\boldsymbol{Z}}_d'\tilde{\boldsymbol{X}}_d \\
&= \tilde{\boldsymbol{X}}_d'\tilde{\boldsymbol{Z}}_d\left(\tilde{\boldsymbol{Z}}_d'\tilde{\boldsymbol{Z}}_d\right)^{-1}\tilde{\boldsymbol{Z}}_d'\tilde{\boldsymbol{Z}}_d\left(\tilde{\boldsymbol{Z}}_d'\tilde{\boldsymbol{Z}}_d\right)^{-1}\tilde{\boldsymbol{Z}}_d'\tilde{\boldsymbol{X}}_d \\
&= n_d\hat{\boldsymbol{\theta}}_d\left(\frac{1}{n_d}\tilde{\boldsymbol{Z}}_d'\tilde{\boldsymbol{Z}}_d\right)\hat{\boldsymbol{\theta}}_d',
\end{aligned} \tag{11}
$$

where in the last equality, $\hat{\boldsymbol{\theta}}_d$ is the OLS estimator of $\boldsymbol{\theta}_d$ in the first stage of (9). Thus, the weights are a function of the size of the dataset, the size of the first stage estimates (which captures the strength of the first stage relationships), and the sample covariance matrix of the partialled instruments (assuming that a constant is included in $\boldsymbol{w}_{di}$). Note that the last two factors are influenced by the institutional setting, the dataset sampling rules, and the choice of instruments and covariates; to the extent that these three factors are similar across datasets, the weights are essentially a function of the sample size.

I conclude this section with two remarks. First, if OLS were used instead of 2SLS, $\hat{\boldsymbol{\theta}}_d$ becomes the identity matrix and (11) collapses to weighting by dataset size and the sample covariance matrix of the regressors of interest. Second, we might want to relax the requirement that all the first stage coefficients ($\boldsymbol{\theta}_d$) and the partial effect of covariates ($\boldsymbol{\alpha}_d$ and $\boldsymbol{\kappa}_d$) differ across datasets in the meta-analysis estimate. This might be justified by the econometrician bringing in additional information to discipline the model; we might know that the life cycle profile of work hours is the same in several datasets after adjusting for a level effect, or that emancipation leads to the same drop in the child support rate in several datasets. Suppose we imposed that the last element of $\boldsymbol{\alpha}_1$ is equal to the last element of $\boldsymbol{\alpha}_2$, and similar for $\boldsymbol{\kappa}_1$ and $\boldsymbol{\kappa}_2$. This is equivalent to pooling datasets 1 and 2, applying an additional FWL partialling step at the start, and then proceeding as before. Hence, $\hat{\boldsymbol{\beta}}$ is still interpretable as a weighted average of the $\hat{\boldsymbol{\beta}}_d$'s, but with $\hat{\boldsymbol{\beta}}_1$ and $\hat{\boldsymbol{\beta}}_2$ estimated based on transformed data. Next, suppose that we imposed that the first stage effect of the last instruments in $\boldsymbol{z}_{1i}$ and $\boldsymbol{z}_{2i}$ are the same. In this case, there is no general weighting scheme that relates $\hat{\boldsymbol{\beta}}$ to the $\hat{\boldsymbol{\beta}}_d$'s because information based off dataset 1 restricts the first stage of dataset 2, and vice versa. Instead, $\hat{\boldsymbol{\beta}}$ is a weighted average of of $\hat{\boldsymbol{\beta}}_d, d = 3, 4, \dots D$, and $\hat{\boldsymbol{\beta}}_{1^*}$, where $\hat{\boldsymbol{\beta}}_{1^*}$ is the coefficient from pooling datasets 1 and 2 together and interacting dataset indicators with all covariates and all instruments other than the last. In either case (restriction of $\boldsymbol{\theta}_d$ or $\boldsymbol{\alpha}_d$ and $\boldsymbol{\kappa}_d$), bringing in some cross-dataset information changes the interpretation of the meta-analysis estimate slightly.

B.2 Derivation of FWL for overidentified 2SLS

Section B.1 uses the FWL theorem applied in an overidentified 2SLS setting. To my knowledge, no formal derivation exists, although Stata's user-created package *ivreg2* uses the result in its *partial* option, and a proof exists for the exactly-identified 2SLS case (Baum et al., 2007; Giles, 1984). Here, I extend the method in Giles to show the result for the overidentified setting.

Suppose we estimated the 2SLS specification

$$y_i = \boldsymbol{x}_i'\boldsymbol{\beta} + \boldsymbol{w}_i'\boldsymbol{\alpha} + \varepsilon_i, \tag{12}$$

$$\boldsymbol{x}_i = \boldsymbol{\theta}\boldsymbol{z}_i + \boldsymbol{\kappa}\boldsymbol{w}_i + \boldsymbol{\nu}_i,$$

where y_i is a scalar outcome variable, $\boldsymbol{x}_i$ is a K-vector of endogenous variables, $\boldsymbol{z}_i$ is an L-vector of (excluded) instruments, $\boldsymbol{w}_i$ is an M-vector of covariates (included instruments), ε_i and $\boldsymbol{\nu}_i$ are error terms, and $\boldsymbol{\beta}$, $\boldsymbol{\alpha}$, $\boldsymbol{\theta}$, and $\boldsymbol{\kappa}$ are coefficients. The 2SLS estimator of $\begin{bmatrix} \boldsymbol{\beta}' & \boldsymbol{\alpha}' \end{bmatrix}$ based on a dataset of size n is

$$\begin{bmatrix} \hat{\boldsymbol{\beta}} \\ \hat{\boldsymbol{\alpha}} \end{bmatrix} = \left(\begin{bmatrix} \boldsymbol{X}' \\ \boldsymbol{W}' \end{bmatrix} \boldsymbol{P}_{\begin{bmatrix} \boldsymbol{Z} & \boldsymbol{W} \end{bmatrix}} \begin{bmatrix} \boldsymbol{X} & \boldsymbol{W} \end{bmatrix} \right)^{-1} \begin{bmatrix} \boldsymbol{X}' \\ \boldsymbol{W}' \end{bmatrix} \boldsymbol{P}_{\begin{bmatrix} \boldsymbol{Z} & \boldsymbol{W} \end{bmatrix}} \boldsymbol{y}, \tag{13}$$

where $\boldsymbol{y} \equiv \begin{bmatrix} y_1 & \dots & y_n \end{bmatrix}'$, $\boldsymbol{X} \equiv \begin{bmatrix} \boldsymbol{x}_1 & \dots & \boldsymbol{x}_n \end{bmatrix}'$, $\boldsymbol{Z} \equiv \begin{bmatrix} \boldsymbol{z}_1 & \dots & \boldsymbol{z}_n \end{bmatrix}'$, and $\boldsymbol{W} \equiv \begin{bmatrix} \boldsymbol{w}_1 & \dots & \boldsymbol{w}_n \end{bmatrix}'$, and $\boldsymbol{P}_{\cdot}$ is the projection matrix operator defined in Section B.1 (i.e. $\boldsymbol{P}_{\boldsymbol{C}} \equiv \boldsymbol{C}\left(\boldsymbol{C}'\boldsymbol{C}\right)^{-1}\boldsymbol{C}$). We want to show that

$$\hat{\boldsymbol{\beta}} = \left(\tilde{\boldsymbol{X}}' \boldsymbol{P}_{\tilde{\boldsymbol{Z}}} \tilde{\boldsymbol{X}} \right)^{-1} \tilde{\boldsymbol{X}}' \boldsymbol{P}_{\tilde{\boldsymbol{Z}}} \tilde{\boldsymbol{y}},$$

where $\tilde{\boldsymbol{y}} \equiv \boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{y}$, $\tilde{\boldsymbol{X}} \equiv \boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{X}$, and $\tilde{\boldsymbol{Z}} \equiv \boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}$, and $\boldsymbol{M}_{\cdot}$ is the annihilator matrix operator defined in Section B.1 (i.e. $\boldsymbol{M}_{\boldsymbol{C}} \equiv \boldsymbol{I} - \boldsymbol{P}_{\boldsymbol{C}}$).

First, block matrix algebraic manipulation gives

$$\left(\begin{bmatrix} \boldsymbol{Z}' \\ \boldsymbol{W}' \end{bmatrix} \begin{bmatrix} \boldsymbol{Z} & \boldsymbol{W} \end{bmatrix} \right)^{-1} = \begin{bmatrix} \boldsymbol{C}_1 & \boldsymbol{C}_2 \\ \boldsymbol{C}_2' & \boldsymbol{C}_4 \end{bmatrix},$$

where

$$\boldsymbol{C}_1 \equiv \left(\boldsymbol{Z}'\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}\right)^{-1},$$

$$\boldsymbol{C}_2 \equiv -\boldsymbol{C}_1 \boldsymbol{Z}'\boldsymbol{W}\left(\boldsymbol{W}'\boldsymbol{W}\right)^{-1},$$

and

$$\boldsymbol{C}_4 \equiv \left(\boldsymbol{W}'\boldsymbol{W}\right)^{-1} + \left(\boldsymbol{W}'\boldsymbol{W}\right)^{-1}\boldsymbol{W}'\boldsymbol{Z}\boldsymbol{C}_1\boldsymbol{Z}'\boldsymbol{W}\left(\boldsymbol{W}'\boldsymbol{W}\right)^{-1}.$$

Expanding the definition of $\boldsymbol{P}_{\left[\begin{array}{cc}\boldsymbol{Z} & \boldsymbol{W}\end{array}\right]}$, and after some agebraic manipulation, we get

$$\boldsymbol{P}_{\left[\begin{array}{cc}\boldsymbol{Z} & \boldsymbol{W}\end{array}\right]} = \boldsymbol{P}_{\boldsymbol{W}} + \boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}}.$$

Hence,

$$\left[\begin{array}{c}\boldsymbol{X}' \\ \boldsymbol{W}'\end{array}\right]\boldsymbol{P}_{\left[\begin{array}{cc}\boldsymbol{Z} & \boldsymbol{W}\end{array}\right]} = \left[\begin{array}{c}\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{W}} + \boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}} \\ \boldsymbol{W}'\end{array}\right], \tag{14}$$

where I have used the fact that $\boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}}\boldsymbol{W} = 0$ and $\boldsymbol{W}\boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}} = 0$ due to the annihilating property of $\boldsymbol{M}_{\boldsymbol{W}}$.

Next, the above and block matrix inversion gives

$$\left(\left[\begin{array}{c}\boldsymbol{X}' \\ \boldsymbol{W}'\end{array}\right]\boldsymbol{P}_{\left[\begin{array}{cc}\boldsymbol{Z} & \boldsymbol{W}\end{array}\right]}\left[\begin{array}{cc}\boldsymbol{X} & \boldsymbol{W}\end{array}\right]\right)^{-1} = \left[\begin{array}{cc}\boldsymbol{C}_5 & \boldsymbol{C}_6 \\ \boldsymbol{C}_6' & \boldsymbol{C}_8\end{array}\right], \tag{15}$$

where

$$\boldsymbol{C}_5 \equiv \left(\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}}\boldsymbol{X}\right)^{-1}, \tag{16}$$

$$\boldsymbol{C}_6 \equiv -\boldsymbol{C}_5\boldsymbol{X}'\boldsymbol{W}\left(\boldsymbol{W}'\boldsymbol{W}\right)^{-1}, \tag{17}$$

and

$$\boldsymbol{C}_8 \equiv \left(\boldsymbol{W}'\boldsymbol{W}\right)^{-1} + \left(\boldsymbol{W}'\boldsymbol{W}\right)^{-1}\boldsymbol{W}'\boldsymbol{X}\boldsymbol{C}_5\boldsymbol{X}'\boldsymbol{W}\left(\boldsymbol{W}'\boldsymbol{W}\right)^{-1}.$$

Substituting (14) and (15) into (13), we get

$$\left[\begin{array}{c}\hat{\boldsymbol{\beta}} \\ \hat{\boldsymbol{\alpha}}\end{array}\right] = \left[\begin{array}{c}\boldsymbol{C}_5\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{W}}\boldsymbol{y} + \boldsymbol{C}_5\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}}\boldsymbol{y} + \boldsymbol{C}_6\boldsymbol{W}'\boldsymbol{y} \\ \boldsymbol{C}_6'\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{W}}\boldsymbol{y} + \boldsymbol{C}_6'\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}}\boldsymbol{y} + \boldsymbol{C}_8\boldsymbol{W}'\boldsymbol{y}\end{array}\right],$$

and simplifying the upper block gives

$$\begin{aligned}\hat{\boldsymbol{\beta}} &= \boldsymbol{C}_5\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{W}}\boldsymbol{y} + \boldsymbol{C}_5\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}}\boldsymbol{y} - \boldsymbol{C}_5\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{W}}\boldsymbol{y} \\ &= \left(\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}}\boldsymbol{X}\right)^{-1}\boldsymbol{X}'\boldsymbol{P}_{\boldsymbol{M}_{\boldsymbol{W}}\boldsymbol{Z}}\boldsymbol{y} \\ &= \left(\tilde{\boldsymbol{X}}'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}}\tilde{\boldsymbol{X}}\right)^{-1}\tilde{\boldsymbol{X}}'\boldsymbol{P}_{\tilde{\boldsymbol{Z}}}\tilde{\boldsymbol{y}},\end{aligned}$$

where the first and second equalities follow from (16) and (17) respectively, and the third equality uses the idempotency of $\boldsymbol{M}_{\boldsymbol{W}}$.

C Labor supply response of mothers

The strategy in the paper can be used to estimate the labor supply response of mothers in response to receiving child support. In this section, I describe the issues involved, estimates, and the interpretation.

C.1 Data

I use the US Census Bureau's 1990 to 2008 SIPP panels to estimate the effect of receiving child support on mothers' labor supply.[29] Each panel's interviews are conducted every four months for between two to five years, with questions on income and public transfers for each of the past four months. Each panel also includes a set of topical modules that are asked only in specific interviews; in particular, the second wave of all panels include a marital history module and a fertility history module. The 1992 and 1993 panels also include a follow-up Survey of Program Dynamics panel on the same individuals between 1998 to 2002; I include these observations in the sample as well to be exhaustive in treatment.

Compared to the fathers panel, the SIPP fertility history modules do not include questions on middle children. Hence, identification of child support eligible children uses only the birth information for the first- and last-born children and the timing of the last marriage of each mother. Additionally, the short panel nature of the SIPP precludes using earlier-age residency history when identifying child support eligibility. Except for the above, all other key variables are treated in the same way as in the fathers panel.

I use all female observations between ages 26 and 59. Of the restrictions imposed on the fathers panel, I include only the first and the last. Respectively, these restrictions mean that I exclude mothers who never had an eligible child, and I exclude observations when the youngest eligible child is younger than 5. The other restrictions are not relevant for the SIPP due to limited fertility information and the short panel nature.

C.2 Interpretation and estimation strategy

Because child support received by mothers is not dependent on their own earnings, the estimated effect is an income effect. In an intertemporal setting, this is also a weak test of rationality. Suppose that surprise increases in wealth lead to a decrease in labor supply, and that mothers do not expect the drop in child support as the youngest eligible children are emancipated. In this case, they should work more upon emancipation of the child. A lack of response on emancipation is indicative that the income effect is zero, or that rational expectations hold for mothers.

Estimation of the labor supply response of mothers is complicated by the fact that the child lives with the mother, and is expected to leave home after emancipation. Because of this, the estimation strategy for fathers cannot be used wholesale for mothers. Instead, I

[29] To my knowledge, the SIPP is the largest panel data source with marriage and fertility information for mothers. Estimates based on the annual panels used for fathers are similar to those in the SIPP, but less precise. I do not use the Current Population Survey since few individuals appear in both the March Annual Social and Economic Supplement (required for child support income receipt) and the June Fertility and Marriage Supplement (required for eligibility status).

use a local-linear RD specification to yield a causal estimate of the labor supply response to receiving child support. Specifically, I restrict the sample to observations within 24 months of emancipation on both sides, and estimate the specification

$$\begin{aligned} \log y_{it} &= \psi_i + \zeta_{d(i)t} + \boldsymbol{Z}'_{it}\boldsymbol{\alpha}_{d(i)} + \gamma s_{it} + \rho^{pre}_{d(i)} r_{it} + \rho^{post}_{d(i)} r_{it} IV_{it} + \varepsilon_{it} \\ s_{it} &= \tilde{\psi}_i + \tilde{\zeta}_{d(i)t} + \boldsymbol{Z}'_{it}\tilde{\boldsymbol{\alpha}}_{d(i)} + \tilde{\gamma} IV_{it} + \tilde{\rho}^{pre}_{d(i)} r_{it} + \tilde{\rho}^{post}_{d(i)} r_{it} IV_{it} + \nu_{it}. \end{aligned} \tag{18}$$

Equation (18) is almost the same as Equation (1), and except for IV_{it}, all repeated variables have the same definition. The RD running variable r_{it} is the age of the youngest eligible child relative to the emancipation age of the jurisdiction, and IV_{it} takes a value of one if r_{it} is greater than zero, and zero if smaller. I exclude the observation when r_{it} is exactly zero. The linear slopes for the RD are allowed to be different before and after emancipation, and across SIPP panels—I treat each panel as a different dataset. Different from Equation (1), I do not allow the effect of the instrument to be heterogeneous across SIPP panels in the first stage. I do this to improve power in the first stage, and because the SIPP's questionnaire wording and the US's child support system are relatively stable over the period of analysis. Similar to before, I cluster standard errors at the individual level. The main coefficient of interest is again γ; receiving child support deters work if γ is negative.

C.3 Results

Appendix Figure D1 graphically shows the first stage of the RD design (solid purple line). On achieving the emancipation age, the amount of child support received drops, falling from 1,800 dollars per year in the month before emancipation age to 900 dollars per year twelve months after emancipation age. The figure also plots three potentially confounding variables that are likely to change with relative age—whether the child has left home, which potentially confounds because of changes in consumption needs (dash-dotted line), the earnings of the child (short-dashed line), and the amount of government transfers that depend on the presence of children (long-dashed line). Visually, all three variables have different levels before and after emancipation, but do not exhibit a discontinuity achieving the on emancipation age. Appendix Table D1 formally shows that the first stage is statistically significant, and that the potential confounders do not change sharply on emancipation.[30]

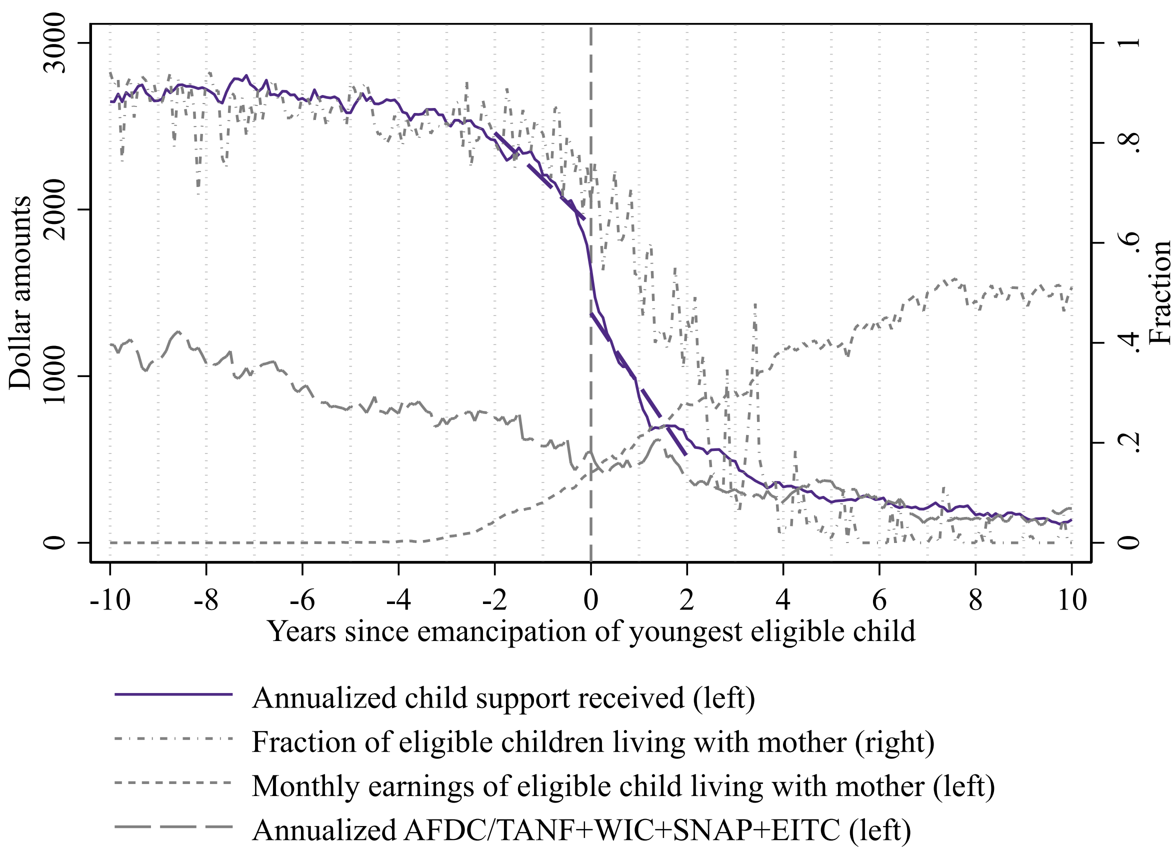
Appendix Table D2 shows estimates of the labor supply response to receiving child support, the main estimates of interest in this section. In order, the table shows estimates based on log work hours, log earnings, any positive work hours, and any positive earnings. In my preferred specification, all estimates are not significantly different from zero. At the 5 percent level, I can reject estimates of -0.4 for the intensive margin (columns 2 and 4) and -0.2 for the extensive margin (columns 6 and 8). However, the F statistic associated with instrument relevance in the first stage is weaker than for the dataset on fathers, and in particular below conventional levels for the extensive margin. In Appendix Table D3, I show that the results are robust to changes in the bandwidth and polynomial order, excluding observations around

[30]In principle, fixed effects and covariates should be uncorrelated with IV_{it} conditional on the other RD variables (r_{it} and $r_{it}IV_{it}$) in an RD specification. Hence, I show results from a specification that includes only panel fixed effects alongside my preferred specfication.

emancipation or just after emancipation, and allowing heterogeneity across SIPP panels in the effect of emancipation on the support rate in the first stage.

Finally, analogous to the falsification test done for fathers, Appendix Table D4 shows results from a falsification test estimated on a sample of mothers whose oldest children are born after their last marriages, and thus should not be receiving child support for any of their children. For these mothers, emancipation of the youngest child does not lead to changes in labor supply, as expected.

Appendix Figure D1: First stage of RD for mothers



Notes: The sample comprises all mother-year-months with non-missing child support rates. Each point on the figure is the average value (among non-missing observations) for all mothers at the specified month relative to emancipation of the child. Vertical dashed line marks the month of emancipation.

Appendix Table D1: RD first stage and reduced form estimates of potential confounders

	Dependent variable:						
	Child support rate		Child lives with mother	IHS of AFDC/TANF+ WIC+SNAP+ EITC		IHS of earnings of child in family	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post-emancipation	-0.017***	-0.016***	-0.015	-0.15	-0.043	-0.22	-0.22
	(0.0034)	(0.0031)	(0.030)	(0.13)	(0.082)	(0.16)	(0.15)
Observations	152,683	152,485	3,918	31,955	31,910	42,469	42,419
No. of mothers	7,445	7,253	3,918	2,468	2,435	2,119	2,076
Fraction/earnings	0.073	0.073	0.66	562.4	562.6	4762.6	4764.3
With controls		x			x		x

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises all mother-year-months. Child support rate is on a zero to one scale, and is computed as the ratio of the child support amount received to the income of the mother. Child lives with mother is an indicator variable that takes a value of one if the child is living with the mother, and zero otherwise. The source of this variable is the fertility history module of the SIPP, which occurs once per individual. AFDC/TANF+WIC+SNAP+EITC is the annualized amount of transfers in 2016 dollars from the following government programs: Aid to Families with Dependent Children or Temporary Assistance for Needy Families (depending on panel), Special Supplemental Nutrition Program for Women, Infants, and Children, Supplemental Nutrition Assistance Program, and Earned Income Tax Credit (EITC). EITC amounts are only available in the taxation topical modules (not available in all waves), and the annual amount is added to the annualized amounts of the other transfers. Earnings of child in family is the annualized gross income from work of the youngest eligible child if he is living with the mother, if the child is identifiable based on the birth month. IHS is the inverse hyperbolic sine transformation. Post-emancipation is an indicator variable that takes a value of 1 if the youngest eligible child is older than emancipation age, and zero if younger. The specification used is a uniform-kernel local-linear sharp RD design with the month relative to the emancipation month as the running variable. The bandwidth used is two years (inclusive) on each side of the emancipation month; the emancipation month itself is excluded. The linear specification is allowed to differ pre- and post-emancipation, and across panels. All columns include a panel fixed effect. All controls are individual fixed effects, panel-year-month fixed effects, age-education-panel fixed effects, and the log of the hourly wage interacted with panel indicators. Sample sizes and numbers of clusters reported are effective numbers used in the RD.

Appendix Table D2: Estimates of the labor supply response of mothers to receiving child support

	Dependent variable:							
	Log of work hours		Log of earnings		Has positive work hours		Has positive earnings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Child support rate	0.20	0.15	-0.27	0.64	-0.27	0.023	-0.29	-0.17
	(0.51)	(0.44)	(0.91)	(0.54)	(0.41)	(0.15)	(0.39)	(0.19)
Observations	114,457	114,249	117,797	117,560	145,874	145,685	152,683	152,485
No. of mothers	6,429	6,229	6,515	6,286	7,355	7,171	7,445	7,253
Mean hours/earnings/fraction	1932.1	1932.5	37265.1	37279.8	0.78	0.78	0.77	0.77
First stage F-stat.	38	43	53	55	21	23	24	25
All controls		x		x		x		x

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises all mother-year-months. Work hours are the annualized work hours of the mother. Earnings are the annualized gross income from work of the mother, in 2016 US dollars. Child support rate is on a zero to one scale, and is computed as the ratio of the child support amount received to the income of the mother. The specification used is a uniform-kernel local-linear fuzzy RD design with the month relative to the emancipation month as the running variable. The bandwidth used is two years (inclusive) on each side of the emancipation month; the emancipation month itself is excluded. The linear specification is allowed to differ pre- and post-emancipation, and across panels. All columns include a panel fixed effect. All controls are individual fixed effects, panel-year-month fixed effects, age-education-panel fixed effects, and the log of the hourly wage interacted with panel indicators. Sample sizes and numbers of clusters reported are effective numbers used in the RD.

Appendix Table D3: Estimates of the labor supply response of mothers based on robustness specifications

		Dependent variable:			
		Log of work hours	Log of earnings	Has positive work hours	Has positive earnings
		(1)	(2)	(3)	(4)
0	Main estimates	0.15	0.64	0.023	-0.17
		(0.44)	(0.54)	(0.15)	(0.19)
1	Double bandwidth	0.035	0.56	0.070	-0.011
		(0.31)	(0.40)	(0.086)	(0.12)
2	Halve bandwidth	1.21	2.03*	0.088	0.16
		(0.94)	(1.07)	(0.27)	(0.23)
3	Local-quadratic RD	2.23	3.90	-0.50	-0.46
		(1.67)	(2.61)	(1.27)	(0.98)
4	Exclude 6 months on both sides of emancipation	-0.0081	0.25	0.077	-0.13
		(0.45)	(0.51)	(0.12)	(0.14)
5	Exclude 12 months after emancipation	0.21	0.34	0.083	0.062
		(0.43)	(0.45)	(0.11)	(0.13)
6	IV fully interacted with SIPP panel	-0.16	0.21	0.0074	-0.12
		(0.40)	(0.44)	(0.13)	(0.10)

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises all mother-year-months. Work hours are the annualized work hours of the mother. Earnings are the annualized gross income from work of the mother, in 2016 US dollars. Each cell is the result of a fuzzy RD design analogous to that in Table D2, with the specified change in specification. Row 0: Estimates are the same as in Table D2. Row 1: The bandwidth used is four years (inclusive) on each side of the emancipation month; the emancipation month itself is excluded. Row 2: The bandwidth used is one year (inclusive) on each side of the emancipation month; the emancipation month itself is excluded. Row 3: The specification is a local-quadratic fuzzy RD design. The quadratic specification is allowed to differ pre- and post-emancipation, and across panels. Row 4: The bandwidth used is 2.5 years (inclusive) on each side of the emancipation month; the sample excludes the six months (inclusive) on each side of the emancipation month. Row 5: The bandwidth used is 2 years before and three years after the emancipation month; the sample excludes observations between 0 and 1 year (inclusive) of the emancipation month. Row 6: The instrument is interacted with panel fixed effects in the first stage. All cells include all controls in Table D2, and definitions not specified are the same as in that table.

Appendix Table D4: Falsification regressions for mothers

	Dependent variable:			
	Log of work hours	Log of earnings	Has positive work hours	Has positive earnings
	(1)	(2)	(3)	(4)
After ineligible child emancipated	0.0056	-0.0010	0.0025	-0.0021
	(0.0060)	(0.0073)	(0.0023)	(0.0023)
Observations	115,592	115,703	151,471	156,384
No. of mothers	5,933	5,903	7,210	7,263
Mean hours/earnings/fraction	1825.5	39691.3	0.76	0.74

Notes: Standard errors clustered by individual in parentheses. Asterisks denote significance: * $p < .10$, ** $p < .05$, *** $p < .01$. The sample comprises all mother-year-months for mothers whose oldest children are born after the mother's last marriage, and whose last marriages are intact at the last interview. Work hours are the annualized work hours of the mother. Earnings are the annualized gross income from work of the mother, in 2016 US dollars. After ineligible child emancipated is an indicator variable that takes a value of 1 if the youngest child is older than emancipation age, and zero if younger. The specification used is a uniform-kernel local-linear sharp RD design with the month relative to the emancipation month as the running variable. The bandwidth used is two years (inclusive) on each side of the emancipation month; the emancipation month itself is excluded. The linear specification is allowed to differ pre- and post-emancipation, and across panels. All columns include all controls from Table D2. Sample sizes and numbers of clusters reported are effective numbers used in the RD.

D Solutions to models

D.1 Main model for Frisch elasticity derivation

The recursive version of the problem is

$$V_t\left(a_{it,}\Phi_{it},S_{it}\right)=\max_{c_{it},a_{i,t+1},h_{it}}\left\{u\left(c_{it}\right)-\frac{e^{\boldsymbol{Z}'_{it}\boldsymbol{\alpha}+U_{it}}}{1+\frac{1}{\gamma}}h_{it}^{1+\frac{1}{\gamma}}\right.$$
$$\left.+\beta\hat{E}\left[V_{t+1}\left(a_{i,t+1},\Phi_{i,t+1},S_{i,t+1}\right)|\Phi_{it}\right]\right\} \tag{19}$$

$$\text{s.t. } c_{it}+\frac{1}{1+r}a_{i,t+1}=a_{it}+w_{it}h_{it}-S_{it},$$
$$S_{i,t+1}=s_{it}w_{it}h_{it}.$$

The first order condition (FOC) for $a_{i,t+1}$ is

$$\beta\left(1+r\right)\hat{E}\left[\frac{\partial}{\partial a_{i,t+1}}V_{t+1}\left(a_{i,t+1},\Phi_{i,t+1},S_{i,t+1}\right)|\Phi_{it}\right]=\lambda_{it}, \tag{20}$$

where λ_{it} is the marginal utility of wealth (and the Lagrangian multiplier for the budget constraint), and the FOC for h_{it} is

$$e^{\boldsymbol{Z}'_{it}\boldsymbol{\alpha}+U_{it}}h_{it}^{\frac{1}{\gamma}}=\lambda_{it}w_{it}+\beta\hat{E}\left[\frac{\partial}{\partial h_{it}}V_{t+1}\left(a_{i,t+1},\Phi_{i,t+1},S_{i,t+1}\right)|\Phi_{it}\right].$$

Since $a_{i,t+1}$ is a function of state variables and parameters (and not other choice variables), and $\Phi_{i,t+1}$ does not depend on h_{it}, this simplifies slightly to

$$e^{\boldsymbol{Z}'_{it}\boldsymbol{\alpha}+U_{it}}h_{it}^{\frac{1}{\gamma}}=\lambda_{it}w_{it}+\beta s_{it}w_{it}\hat{E}\left[\frac{\partial}{\partial S_{i,t+1}}V_{t+1}\left(a_{i,t+1},\Phi_{i,t+1},S_{i,t+1}\right)|\Phi_{it}\right]. \tag{21}$$

The envelope theorem gives

$$\frac{\partial}{\partial a_{it}}V_t\left(a_{it},\Phi_{it},S_{it}\right)=\lambda_{it}, \tag{22}$$

and

$$\frac{\partial}{\partial S_{it}}V_t\left(a_{it},\Phi_{it},S_{it}\right)=-\lambda_{it}. \tag{23}$$

Substituting (22) and (23) in (20) and (21), we have

$$\beta\left(1+r\right)\hat{E}\left[\lambda_{i,t+1}|\Phi_{it}\right]=\lambda_{it}, \tag{24}$$

and

$$e^{\boldsymbol{Z}'_{it}\boldsymbol{\alpha}+U_{it}}h_{it}^{\frac{1}{\gamma}}=\lambda_{it}w_{it}-\beta s_{it}w_{it}\hat{E}\left[\lambda_{i,t+1}|\Phi_{it}\right]. \tag{25}$$

Substituting (24) in (25), and defining $\dot{s}_{it} \equiv \frac{s_{it}}{(1+r)}$, we have

$$e^{\boldsymbol{Z}'_{it}\boldsymbol{\alpha}+U_{it}} h_{it}^{\frac{1}{\gamma}} = (1-\dot{s}_{it})\, \lambda_{it} w_{it}, \tag{26}$$

or in logs,

$$\log h_{it} = \gamma \log (1-\dot{s}_{it}) + \gamma \log \lambda_{it} + \gamma \log w_{it} - \gamma \boldsymbol{Z}'_{it}\boldsymbol{\alpha} - \gamma U_{it}. \tag{27}$$

The Frisch elasticity is defined as $\frac{\partial \log h_{it}}{\partial \log w_{it}}\big|_{\lambda_{it}}$; examining equation (27) shows this is γ in this model.

If we assumed that λ_{it} is independent of s_{it} or w_{it}, we could estimate Equation (27). However, this assumption is inconsistent with the model, since the Lagrangian multiplier is a function of all parameters. It is also a function of the state variables, including the information set at time t, and hence a function of any instrument we can use. To get around this problem, I implement the strategy of MaCurdy (1981) (among others).[31] Rewrite the marginal utility of wealth equation of motion (24) as

$$\beta (1+r) \frac{\lambda_{i,t+1}}{\lambda_{it}} = 1 + \epsilon_{i,t+1} \tag{28}$$

where $\epsilon_{i,t+1} \equiv \beta (1+r) \frac{\lambda_{i,t+1}}{\lambda_{it}} - \hat{E}\left[\beta (1+r) \frac{\lambda_{i,t+1}}{\lambda_{it}} | \Phi_{it}\right]$ is an expectation error that captures the unpredicted components of changes in future wages, child support rates, and preference shifters. Assuming that $\epsilon_{i,t+1} > -1$, we can take logs of (28) to get

$$\log \lambda_{i,t+1} = \log \lambda_{it} + \log \frac{1}{\beta (1+r)} + \log (1+\epsilon_{i,t+1}), \tag{29}$$

and repeat substitution of (29) gives

$$\log \lambda_{it} = \log \lambda_{i0} + t \log \frac{1}{\beta (1+r)} + \sum_{\tau=1}^{t} \log (1+\epsilon_{i\tau}), \quad \text{all } t \geq 1. \tag{30}$$

Substituting (30) into (27), we get

$$\begin{aligned} \log h_{it} = {} & \gamma t \log \frac{1}{\beta (1+r)} + \gamma \log (1-\dot{s}_{it}) + \gamma \log \lambda_{i0} \\ & + \gamma \log w_{it} - \gamma \boldsymbol{Z}'_{it}\boldsymbol{\alpha} - \gamma U_{it} + \gamma \sum_{\tau=1}^{t} \log (1+\epsilon_{i\tau}), \quad \text{all } t \geq 0. \end{aligned} \tag{31}$$

This equation says that an optimizing father plans his future labor supply in the following way. First, he takes into consideration his baseline marginal utility of wealth, $\log \lambda_{i0}$, which progresses deterministically over time ($\gamma t \log \frac{1}{\beta(1+r)}$). Next, there is a contribution from wages ($\log w_{it}$), child support ($\log (1-\dot{s}_{it})$), observable characteristics ($\boldsymbol{Z}_{it}$), and unobservable characteristics (U_{it}), all of which could be random variables from the perpective of time 0.

[31] In particular, the formulation of the expectation error follows that of Altuğ and Miller (1990), which has the advantage of not requiring a Taylor series expansion until we try to interpret the exogeneity condition.

Random shocks to the marginal utility of wealth cumulate over time (the $\log(1+\epsilon_{i\tau})$ terms), and explain the differences between what happens at t and what the person expects (at time 0) to happen at t. Note that while (31) reflects father i's planned labor supply choices at time 0, the planned choice is still the optimal one upon realization of $(w_{it}, s_{it}, \boldsymbol{Z}_{it}, U_{it}, \epsilon_{i1}, \ldots \epsilon_{it})$ at time t (since we solved by backward induction). Hence, the implicit assumption that fathers optimize ensures that the planned choice coincides with the actual choice observed in the data, which allows us to estimate (31) using data on $(w_{it}, s_{it}, \boldsymbol{Z}_{it})$ and h_{it}.

D.2 Model-based interpretation of instrument exogeneity

Suppose we have a relevant instrument IV_{it}. For notational simplicity, let $\boldsymbol{z}_{it}$ be the vector of included instruments and IV_{it} (i.e. all observable variables we would put in the first stage of an IV regression). Suppose that (i) the instruments are known in advance, i.e. $\boldsymbol{z}_{it}$ is in Φ_{i0}, (ii) fathers have rational expectations regarding future marginal utility of wealth changes, i.e. $\hat{E}\left[\frac{\lambda_{it}}{\lambda_{i,t-1}}|\Phi_{i0}\right] = E\left[\frac{\lambda_{it}}{\lambda_{i,t-1}}|\Phi_{i0}\right]$; (iii) $\boldsymbol{z}_{it}$ is uncorrelated with U_{it}; and (iv) $\boldsymbol{z}_{it}$ is uncorrelated with the second and further powers of ϵ_{it}. Also, assume that $\epsilon_{it} < 1$ (we assumed $\epsilon_{it} > -1$ earlier). Note that assumption (ii) aligns expectations so that we can use a well-known property of expectations errors:

$$\begin{aligned} E\left[\epsilon_{it}|\Phi_{i0}\right] &= \beta\left(1+r\right)E\left[\frac{\lambda_{it}}{\lambda_{i,t-1}} - \hat{E}\left[\frac{\lambda_{it}}{\lambda_{i,t-1}}|\Phi_{i,t-1}\right]|\Phi_{i0}\right] \\ &= \beta\left(1+r\right)E\left[\frac{\lambda_{it}}{\lambda_{i,t-1}} - E\left[\frac{\lambda_{it}}{\lambda_{i,t-1}}|\Phi_{i,t-1}\right]|\Phi_{i0}\right] \\ &= 0. \end{aligned} \tag{32}$$

Then,

$$\begin{aligned} E\left[\boldsymbol{z}_{it}\varepsilon_{it}\right] &= -\gamma E\left[\boldsymbol{z}_{it}U_{it}\right] + \gamma\sum_{\tau=1}^{t} E\left[\boldsymbol{z}_{it}\log\left(1+\epsilon_{i\tau}\right)\right] \\ &= \gamma\sum_{\tau=1}^{t} E\left[\boldsymbol{z}_{it}\sum_{k=1}^{\infty}\left(-1\right)^{k+1}\frac{\epsilon_{i\tau}^{k}}{k}\right] \\ &= \gamma\sum_{\tau=1}^{t} E\left[\boldsymbol{z}_{it}\epsilon_{i\tau}\right] \\ &= \gamma\sum_{\tau=1}^{t} E\left[\boldsymbol{z}_{it}E\left[\epsilon_{i\tau}|\Phi_{i0}\right]\right] \\ &= \boldsymbol{0}, \end{aligned}$$

where the second equality follows from assumption (iii) and a Taylor series expansion around $\epsilon_{i\tau} = 0$, the third equality follows from assumption (iv), the fourth equality follows from iterated expectations and assumption (i), and the last equality follows from (32).

D.3 Model incorporating mother's and child's consumption

The augmented model is

$$V_t\left(a_{it,} \Phi_{it}, S_{it}\right) = \max_{c_{it}, a_{i,t+1}, h_{it}} \Bigg\{ u_i\left(c_{it}\right) - \frac{e^{\boldsymbol{Z}'_{it}\boldsymbol{\alpha}+U_{it}}}{1+\frac{1}{\gamma}} h_{it}^{1+\frac{1}{\gamma}} + \mathfrak{M}\left(\mathfrak{m}_{it}\right) + \mathfrak{C}\left(\mathfrak{c}_{it}\right) + \beta \hat{E}\left[V_{t+1}\left(a_{i,t+1}, \Phi_{i,t+1}, S_{i,t+1}\right) | \Phi_{it}\right] \Bigg\} \tag{33}$$

$$\begin{aligned}
\text{s.t. } c_{it} + \frac{1}{1+r} a_{i,t+1} &= a_{it} + w_{it} h_{it} - S_{it}, \\
S_{i,t+1} &= s_{it} w_{it} h_{it}, \\
\mathfrak{m}_{it} &= (1-k)\, S_{it}, \\
\mathfrak{c}_{it} &= k S_{it},
\end{aligned}$$

where $\mathfrak{M}(\cdot)$ is a disutility function and $\mathfrak{C}(\cdot)$ is a utility function that capture the father's preferences for mother's ($\mathfrak{m}_{it}$) and child's ($\mathfrak{c}_{it}$) consumption out of child support respectively, and k is the child's share of consumption. The last two constraints model mother and child consumption as static shares of the support amount.

The FOCs and $\frac{\partial}{\partial a_{it}} V_t\left(a_{it}, \Phi_{it}, S_{it}\right)$ are unchanged, but now we have

$$\frac{\partial}{\partial S_{it}} V_t\left(a_{it}, \Phi_{it}, S_{it}\right) = (1-k)\, \mathfrak{M}'\left((1-k)\, S_{it}\right) + k \mathfrak{C}'\left(k S_{it}\right) - \lambda_{it}. \tag{34}$$

Substituting (22) and (34) in (20) and (21), and after some manipulation, we get

$$e^{\boldsymbol{Z}'_{it}\boldsymbol{\alpha}+U_{it}} h_{it}^{\frac{1}{\gamma}} = \lambda_{it} w_{it} - \dot{s}_{it} \lambda_{it} w_{it} + \dot{s}_{it} \xi_{it} \lambda_{it} w_{it} \tag{35}$$

in place of (26), where

$$\xi_{it} \equiv \beta\left(1+r\right) \frac{1}{\lambda_{it}} \hat{E}\left[(1-k)\, \mathfrak{M}'\left((1-k)\, S_{i,t+1}\right) + k \mathfrak{C}'\left(k S_{i,t+1}\right) | \Phi_{it}\right] \tag{36}$$

captures how much the father values mother and child consumption out of child support relative to his own. Finally, following the rest of the steps in the main solution, we obtain

$$\begin{aligned}
\log h_{it} = {} & \gamma t \log \frac{1}{\beta\left(1+r\right)} + \gamma \log\left(1 - \dot{s}_{it} + \dot{s}_{it} \xi_{it}\right) + \gamma \log \lambda_{i0} \\
& + \gamma \log w_{it} - \gamma \boldsymbol{Z}'_{it} \boldsymbol{\alpha} - \gamma U_{it} + \gamma \sum_{\tau=1}^{t} \log\left(1 + \epsilon_{i\tau}\right),
\end{aligned} \tag{37}$$

in place of (8). The only difference between (37) and (8) is that the $\log\left(1 - \dot{s}_{it} + \dot{s}_{it}\xi_{it}\right)$ term now includes an additional $\dot{s}_{it}\xi_{it}$ term.

I parameterize $\mathfrak{M}(\cdot)$ and $\mathfrak{C}(\cdot)$ using a linearization of the father's own family consumption utility:

$$\mathfrak{M}\left(\mathfrak{m}_{it}\right) = -\kappa_{\mathfrak{m}}^{*}\tilde{u}_i\left(\mathfrak{m}_{it}\right),$$
$$\mathfrak{C}\left(\mathfrak{c}_{it}\right) = -\kappa_{\mathfrak{c}}^{*}\tilde{u}_i\left(\mathfrak{c}_{it}\right),$$

where $\tilde{u}_i\left(c_{it}\right) \equiv u_i\left(\tilde{c}_i\right) + u_i'\left(\tilde{c}_i\right)\left(c_{it} - \tilde{c}_i\right)$ is the first order Taylor expansion of $u_i\left(c_{it}\right)$ around a $\tilde{c}_i$ specified below, and $\kappa_{\mathfrak{m}}^{*}$ and $\kappa_{\mathfrak{c}}^{*}$ are parameters that capture the intensity of like or dislike for mother or child consumption out of child support. While incorporating concavity in $\mathfrak{M}(\cdot)$ and $\mathfrak{C}(\cdot)$ might be a better reflection of preferences over mother and child consumption, linearization removes the need for consumption data, yields an easily interpretable form for ξ_{it}, and in any case is required for $\mathfrak{M}(\cdot)$ to represent either a concave utility or concave disutility term.[32] The linearization point $\tilde{c}_i$ is chosen such that $\tilde{u}_i'\left(\tilde{c}_i\right) = e^{\frac{1}{T}\sum_t \log \lambda_{it}}$—in other words, linearization is done at the point that yields the individual's geometric mean of his marginal utility of wealth. Then, the derivatives of $\mathfrak{M}(\cdot)$ and $\mathfrak{C}(\cdot)$ are constant for each father:

$$\mathfrak{M}'\left(\mathfrak{m}_{it}\right) = \kappa_{\mathfrak{m}}^{*}\tilde{u}_i'\left(\tilde{c}_i\right) = \kappa_{\mathfrak{m}}^{*}e^{\frac{1}{T}\sum_t \log \lambda_{it}},$$
$$\mathfrak{C}'\left(\mathfrak{c}_{it}\right) = \kappa_{\mathfrak{c}}^{*}\tilde{u}_i'\left(\tilde{c}_i\right) = \kappa_{\mathfrak{c}}^{*}e^{\frac{1}{T}\sum_t \log \lambda_{it}}.$$

Substituting into (36), we have

$$\xi_{it} = \beta\left(1+r\right)\left(\left(1-k\right)\kappa_{\mathfrak{m}}^{*} + k\kappa_{\mathfrak{c}}^{*}\right)\frac{e^{\frac{1}{T}\sum_t \log \lambda_{it}}}{\lambda_{it}}. \tag{38}$$

In other words, ξ_{it} is the average-to-contemporaneous ratio in the marginal valuation of the father's own consumption, scaled by the intensity terms. Finally, I set k to 0.3 and assume that $\beta\left(1+r\right) = 1$ to yield

$$\xi_{it} = \left(0.7\kappa_{\mathfrak{m}}^{*} + 0.3\kappa_{\mathfrak{c}}^{*}\right)\frac{e^{\frac{1}{T}\sum_t \log \lambda_{it}}}{\lambda_{it}}. \tag{39}$$

I obtain an estimate of the Frisch elasticity after accounting for mother and child consumption at various calibrated values of $\kappa_{\mathfrak{m}}^{*}$ and $\kappa_{\mathfrak{c}}^{*}$. Because the marginal utility of wealth λ_{it} is in the ξ_{it} term in Equation (39), the solution is iterative. Specifically, starting with a guess for the Frisch elasticity $\hat{\gamma}$, I compute the log of the marginal utility of wealth $\hat{\lambda}_{it}$ using

$$\frac{1}{\hat{\gamma}}\log h_{it} = \log\left(1 - \dot{s}_{it}\right) + \log\hat{\lambda}_{it} + \log w_{it},$$

which arises from the first order condition of h_{it} after I normalize $e^{\boldsymbol{Z}_{it}'\boldsymbol{\alpha} + U_{it}}$ to 1.[33,34] The estimated $\hat{\lambda}_{it}$ is then used to compute $\hat{\xi}_{it}$ using Equation (39), and new 2SLS estimates of $\hat{\gamma}$

[32]In particular, the negative of the commonly-used constant relative risk aversion function is convex and hence produces corner solutions.

[33]The normalization is done because I do not have causal estimates of $\boldsymbol{\alpha}$. It is almost without loss of generality since the marginal utility of wealth appears in both the numerator and denominator of Equation (39).

[34]The distribution of $\hat{\lambda}_{it}$ is highly skewed, which causes problems for convergence since it enters as a ratio in Equation (39). Because of this, I winsorize $\hat{\lambda}_{it}$ at the 5 and 95th percent before the next step.

are obtained using Equation (37). The above process is iterated until $\hat{\gamma}$ converges.

D.4 Bound on $\kappa_{\mathfrak{c}}^*$

The child support rate provides some information that can be used to bound the intensity of like for child consumption $\kappa_{\mathfrak{c}}^*$. Intuitively, ignoring household size effects, a father who values the consumption of his child as much as his own consumption should be consuming half of his income and sending the other half to the child, which is rejected by the data.

Suppose the father valued his family's and child's consumption directly.[35] If he liked the child consumption out of support $\kappa_{\mathfrak{c}}^*$ times as much as his own, correcting for household size, we have

$$\frac{\mathfrak{c}}{numofchildren} = \kappa_{\mathfrak{c}}^* \frac{c}{famsize},$$

where $\mathfrak{c}$ is the child consumption out of support (the notation follows the main text as far as possible), c is his own family's consumption, and $numofchildren$ and $famsize$ are equivalence scale-corrected number of children supported and own family size, respectively. In a static setting, the child support rate s is

$$s = \frac{\mathfrak{c}}{\mathfrak{c} + c}.$$

Solving the two, we have

$$\kappa_{\mathfrak{c}}^* = \frac{famsize}{numofchildren} \frac{s}{1-s}.$$

In the data, the average pre-emancipation own-family size is 2.6, and the average number of children supported is 1.5. Using a square root equivalence scale when correcting for family size, and the statutory rate per child of around 10 to 15% for s, I obtain the upper bound $\kappa_{\mathfrak{c}}^* = \sqrt{\frac{2.6}{1.5}} \frac{0.15}{0.85} = 0.24$.

[35]We could motivate this formally using a constant relative risk aversion utility function, which yields even tighter bounds.