

Online Appendix

An Equilibrium Analysis of the Effects of Neighborhood-based Interventions on Children

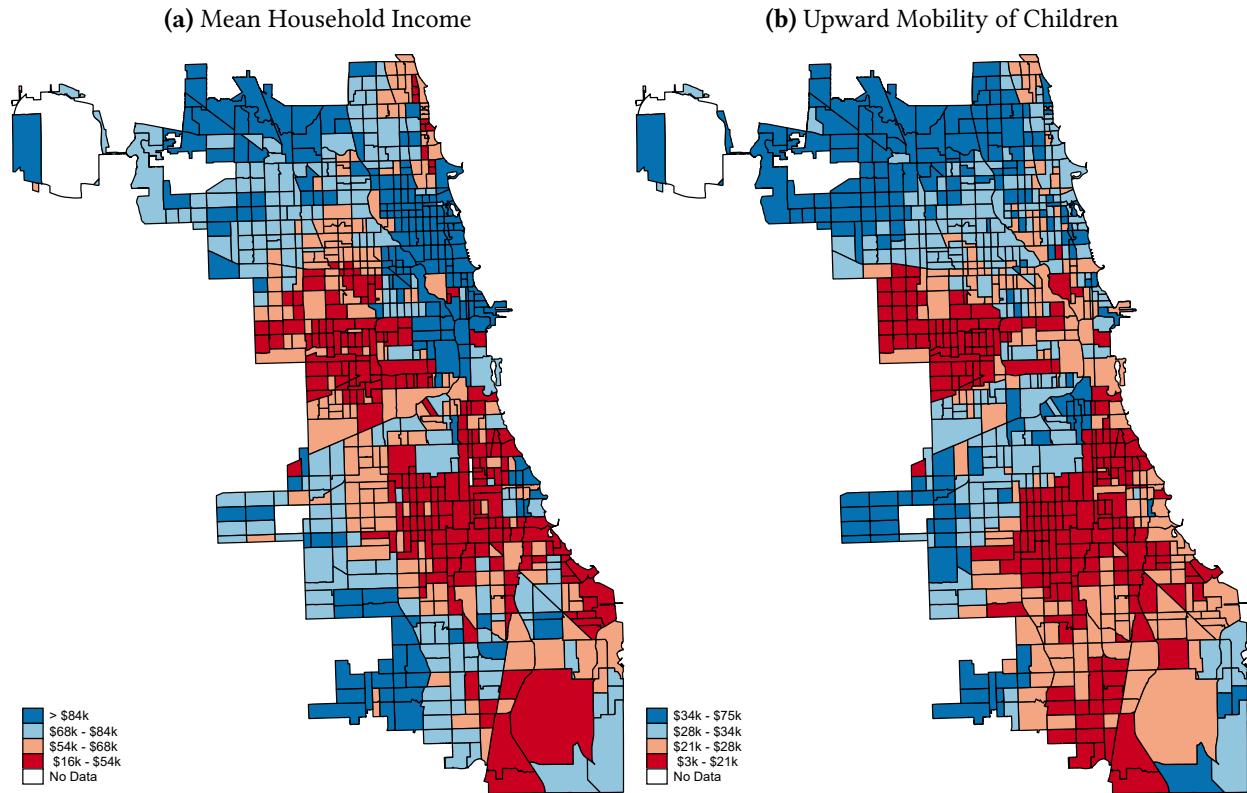
Eric Chyn and Diego Daruich

February 8, 2025

Online Appendix

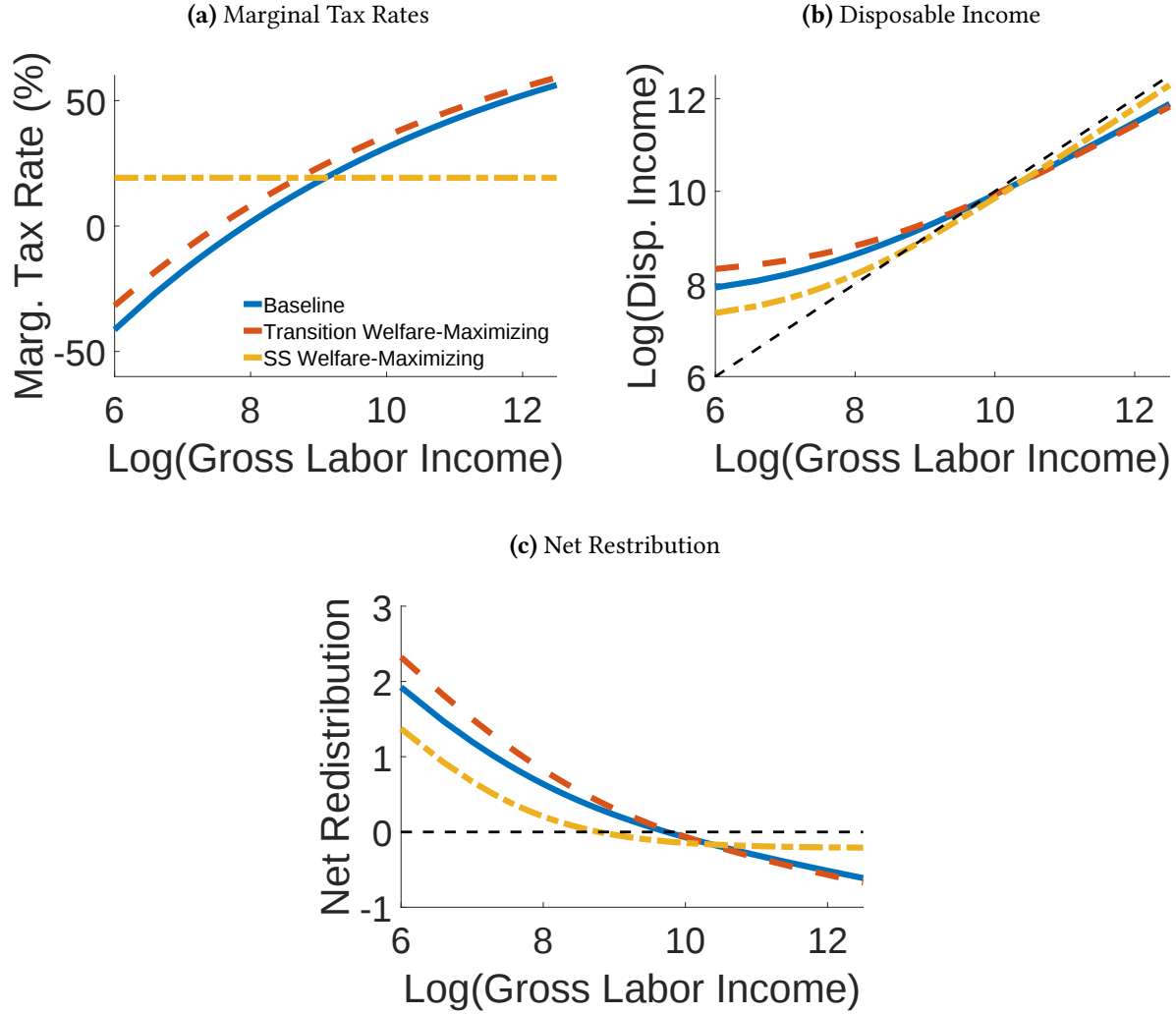
A Appendix Figures

Figure A1: Economic Outcomes Across Neighborhoods in Chicago



Notes: Panel (a) plots mean household income from the 2000 U.S. Decennial Census. Panel (b) plots estimates of mean household income ranks for children who grew up in the tract and had parents with household income at the 25th percentile of the national income distribution. This measure of “upward mobility” for children comes from the Opportunity Atlas (Chetty et al., 2018). The measure is specific to children who were born in the 1978-83 cohorts.

Figure A2: Taxes, Net Income, and Transfers Across the Household Income Distribution



Notes: Panels (a), (b), and (c) show how marginal tax rates (MTRs), disposable income, and net redistribution (the difference between the log of disposable income and log of gross income) vary with gross labor income. The results are based on alternative parameter values for the tax system. The solid, thick-dashed, and dashed-dot lines produce results from the baseline, steady-state (SS) maximizing, and transition-maximizing versions of our model, respectively.

A Appendix Tables

Table A1: Estimates of Wage Parameters

	(1)	(2)	(3)
Age	0.0356*** (0.003)		
Age ²	-0.000*** (0.000)		
Inv. Mills Ratio	-1.611*** (0.039)		
Υ		0.999*** (0.021)	
ρ			0.959*** (0.000)
σ_z			0.037*** (0.000)
σ_{η_0}			0.042*** (0.000)
R^2	0.116	0.146	–
# of households	3,052	2,509	2,509
Observations (N)	21,204	19,603	19,603

Notes: This table reports estimates of the parameters of the wage process in our model. Column 1 reports results for the age profile parameters. This is obtained using a sample constructed from the PSID (1968–2016) and regressing wages on age, age-squared, and controls for selection into work based on the Inverse Mills Ratio obtained from a Heckman-selection correction approach. The selection estimator is based on estimating an employment participation equation using the number of children and year-region fixed effects. Column 2 reports estimates of the return to skills. This is obtained using a sample from the NLSY and regressing of the idiosyncratic component of labor productivity ψ_j (measured as a residual based on the age profile estimates from Column 1) on the log of cognitive skills as measured by the AFQT score. Column 3 reports estimates of the parameters that govern the AR(1) process that we assume determines the shock η_j which is the idiosyncratic component of labor productivity. These estimates are obtained from the Minimum Distance Estimator developed by [Rothenberg \(1971\)](#). Standard errors are reported in parentheses. Statistical significance is denoted by: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A2: Estimates of the Elasticity of Time with Respect to Family Income

	(1)	(2)	(3)	(4)
Log(Family Income)	0.105*** (0.006)	0.095*** (0.006)	0.103*** (0.007)	0.097*** (0.007)
R^2	0.154	0.156	0.184	0.190
Observations (N)	26,408	26,408	26,408	26,408
Controls?				
Number and age of children	✓	✗	✗	✗
Household type	✓	✓	✗	✗
Respondent occupation	✓	✓	✓	✗
Commuting zone	✓	✓	✓	✓

Notes: This table reports estimates of the elasticity of quality time spent with children and family income. Columns report estimates that vary based on the set of controls included in the specification. The sample used for the analysis is based on the ATUS, as described in Section III. Note that family income is defined as the combined income of all family members during the last 12 months (including money from jobs, net business income, farm or rent, pensions, dividends, interest, Social Security payments, and any other money received by family members who are 15 years of age or older). Standard errors are reported in parentheses. Statistical significance is denoted by: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A3: Alternative Neighborhood Quality Results: “Bad Apples” and “Shining Light” Versions of Externalities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Rent Subsidy			Wage Subsidy		Interpretation	
ϕ	Subsidy Rate	Wage Below Decile	Welfare	Subsidy Rate	Welfare	$\frac{y_h(y_l=0.5\bar{y})}{\bar{y}}$	$\frac{y_h(y_l=0.1\bar{y})}{\bar{y}}$
0.25	100%	40%	4.68%	0%	0.00%	1.81	4.27
0.50	100%	80%	4.67%	0%	0.00%	1.67	2.84
0.75	100%	80%	4.81%	0%	0.00%	1.57	2.23
Baseline	100%	80%	4.94%	0%	0.00%	1.50	1.90
1.25	100%	80%	5.08%	0%	0.00%	1.44	1.70
1.50	100%	90%	5.22%	0%	0.00%	1.39	1.57
1.75	100%	90%	5.37%	0%	0.00%	1.36	1.48
5.00	100%	90%	6.88%	27%	0.55%	1.15	1.15

Notes: This table reports policy features and the associated welfare impacts of rent vouchers and wage subsidy programs. Columns 1-5 report results from models that vary in how family income is aggregated to define neighborhood quality. Specifically, we assume $s_n = (\sum_i y_i^\phi / N_n) \wedge (1/\phi)$ as the definition of neighborhood quality. The case of $\phi = 1$ reduces to our baseline model. The cases when $\phi < 1$ correspond to “bad apples” models in which disadvantaged families. In contrast, the cases when $\phi > 1$ correspond to “shining light” models in which advantaged families have more influence over neighborhood quality. To aid the interpretation of our results, Columns 6 and 7 report the hypothetical value of family income y_h that would be needed to fully offset the impact of adding one low-income family that has 50 and 10 percent, respectively, of the local income to a neighborhood. For example, consider our baseline model in which $\phi = 1$. In a hypothetical neighborhood with mean income $\bar{y}$, the addition of a low-income family with income $y_l = 0.10\bar{y}$ can only be offset by adding an advantaged family with income $y_h = 1.5\bar{y}$ to preserve the overall mean. As ϕ decreases, the value of y_h increases as the influence of disadvantaged neighbors on externalities grows.

B Estimation Details

B1 Child Skill Production Function

We rely on estimates from [Cunha, Heckman and Schennach \(2010\)](#) for the calibrated model. Specifically, they estimate the following multistage production function for children's cognitive (c) and non-cognitive skills (nc):

$$\theta'_{q,k} = \left[\alpha_{1,q,j} \theta_{c,k}^{\rho_{q,j}} + \alpha_{2,q,j} \theta_{nc,k}^{\rho_{q,j}} + \alpha_{3,q,j} \theta_c^{\rho_{q,j}} + \alpha_{4,q,j} \theta_{nc}^{\rho_{q,j}} + \alpha_{5,q,j} I^{\rho_{q,j}} \right]^{1/\rho_{q,j}} e^{v_q}, \quad v_q \sim N(0, \sigma_{q,j,v})$$

for $q \in \{c, nc\}$. Using a nonlinear factor model with endogenous inputs, their main estimates, which are based on two-year periods, are reported in Table B4 below. We interpret their first stage estimates as referring to the period in which the child is born in our model when the parent's age-period is $j = 8$ and the child's age-period is $j' = 1$ (i.e., 0–3 years old). The second stage is assumed to refer to the last period of skill development when the parent's age-period is $j = 11$ and the child's age-period is $j' = 4$ (i.e., 12–15 years old). We use linear interpolation to obtain the estimates for $j = 9$ and $j = 10$.

Table B4: Child Skill Production Function Estimates from [Cunha, Heckman and Schennach \(2010\)](#)

	Cognitive Skills		Non-Cognitive Skills	
	1st Stage ($j = 8$)	2nd Stage ($j = 11$)	1st Stage ($j = 8$)	2nd Stage ($j = 11$)
Current Cognitive Skills ($\hat{\alpha}_{1,q,j}$)	0.479 (0.026)	0.831 (0.011)	0.000 (0.026)	0.000 (0.010)
Current Non-Cognitive Skills ($\hat{\alpha}_{2,q,j}$)	0.070 (0.024)	0.001 (0.005)	0.585 (0.032)	0.816 (0.013)
Parent's Cognitive Skills ($\hat{\alpha}_{3,q,j}$)	0.031 (0.013)	0.073 (0.008)	0.017 (0.013)	0.000 (0.008)
Parent's Non-Cognitive Skills ($\hat{\alpha}_{4,q,j}$)	0.258 (0.029)	0.051 (0.014)	0.333 (0.034)	0.133 (0.017)
Investments ($\hat{\alpha}_{5,q,j}$)	0.161 (0.015)	0.044 (0.006)	0.065 (0.021)	0.051 (0.006)
Complementarity parameter ($\hat{\rho}_{q,j}$)	0.313 (0.134)	-1.243 (0.125)	-0.610 (0.215)	-0.551 (0.169)
Variance of Shocks ($\hat{\sigma}_{q,j,v}$)	0.176 (0.007)	0.087 (0.003)	0.222 (0.013)	0.101 (0.004)

Notes: Standard errors in parentheses. The first stage refers to the period in which the child is born when the parent's age-period is $j = 8$ and the child's age-period is $j' = 1$ (i.e., 0–3 years old). The second stage refers to the period after the child is born when the parent's age-period is $j = 11$ and the child's age-period is $j' = 4$ (i.e., 12–15 years old).

To go from two-year periods to four-year periods (as in our model), we follow the steps in [Darulich \(2020\)](#). Using $\hat{\alpha}$ to notate the estimates in [Cunha, Heckman and Schennach \(2010\)](#) and α for the values in our model, the two main steps/assumptions for the transformation are: (i) we iterate in the production function under the assumption that the shock ν only takes place in the last iteration, i.e., replace $\theta_{q,k}$ by $\left[\alpha_{1,q,j} \theta_{c,k}^{\rho_{q,j}} + \alpha_{2,q,j} \theta_{nc,k}^{\rho_{q,j}} + \alpha_{3,q,j} \theta_c^{\rho_{q,j}} + \alpha_{4,q,j} \theta_{nc}^{\rho_{q,j}} + \alpha_{5,q,j} I^{\rho_{q,j}} \right]^{1/\rho_{q,j}}$; ¹ and (ii) we assume that the cross-effect of skills (i.e., of cognitive on non-cognitive and of non-cognitive on cognitive) is only updated every two periods. ² Under these assumptions, the persistence parameter needs to be squared (i.e., $\alpha_{1,c,j} = \hat{\alpha}_{1,c,j}^2$ and $\alpha_{2,nc,j} = \hat{\alpha}_{2,nc,j}^2$), while other parameters inside the CES function need to be multiplied by 1 plus the persistence parameter (e.g., $\alpha_{2,c,j} = (1 + \hat{\alpha}_{1,c,j}) \hat{\alpha}_{2,c,j}$).

B2 Replacement benefits: US Social Security System

The pension replacement rate is obtained from the Old Age Insurance of the US Social Security System. We use the skill level to estimate a proxy for average lifetime income, on which the replacement benefit is based. Average income at age j is estimated as $\hat{y}_j(\theta_c) = wE_j(\theta_c, \bar{\eta}) \times \bar{h}$ where $\bar{\eta}$ is the average shock (i.e., zero) and $\bar{h}$ are the average hours worked (in the economy). Averaging over j allows average lifetime income $\bar{y}(\theta_c)$ to be calculated and used in (B1) to obtain the replacement benefits.

The pension formula is given by

$$\pi(\theta_c) = \begin{cases} 0.9\bar{y}(\theta_c) & \text{if } \bar{y}(\theta_c, e) \leq 0.3\bar{y} \\ 0.9(0.3\bar{y}) + 0.32(\bar{y}(\theta_c) - 0.3\bar{y}) & \text{if } 0.3\bar{y} \leq \bar{y}(\theta_c) \leq 2\bar{y} \\ 0.9(0.3\bar{y}) + 0.32(2 - 0.3)\bar{y} + 0.15(\bar{y}(\theta_c) - 2\bar{y}) & \text{if } 2\bar{y} \leq \bar{y}(\theta_c) \leq 4.1\bar{y} \\ 0.9(0.3\bar{y}) + 0.32(2 - 0.3)\bar{y} + 0.15(4.1 - 2)\bar{y} & \text{if } 4.1\bar{y} \leq \bar{y}(\theta_c) \end{cases} \quad (\text{B1})$$

where $\bar{y}$ is approximately \$288,000 (\$72,000 annually).

B3 Simulated Method of Moments: More Details and Discussion of Moment Selection

We internally estimate $P = 15$ parameters to match $P = 15$ moments following two main steps. The first step is to estimate the model globally. Given a hypercube of the parameter space, we draw approximately 100,000 candidate parameter vectors from uniform Sobol (quasi-random) points,

¹We assume that the variance of the shock in the 4-year model is twice the one in the 2-year model (i.e., $\sigma_{q,j}, v^2 = \hat{\sigma}_{q,j}, v^2$).

²Removing this assumption does not change results significantly since the weights corresponding to these elements are very small or even zero in the estimation (in Table B4, see row 2 under columns 1 and 2, as well as row 1 under columns 3 and 4), but it eliminates the CES functional form if $\rho_{c,j} \neq \rho_{nc,j}$.

solve and simulate the model, and compute the implied moments in steady state. The second step is to implement a local search algorithm. In particular, we use the best 400 parameter sets as initial points and a Nelder-Mead algorithm. The resulting estimation is shown in Table 2.

In addition, we use the method developed in [Daruich \(2020\)](#) to show which parameters are closely related to each moment, which helps justify our selection of moments. By having an exactly identified approach (i.e., equal number of moments and parameters), we are able to show this mapping between parameters and moments one-by-one, for each parameter.

Although the model is highly nonlinear, so that (almost) all parameters affect all outcomes, the identification of some parameters relies on some key moments in the data. Figure [B3](#) shows the result of the following identification exercise. For each parameter, we associate a relevant target moment and divide the vector of this particular parameter into 50 quantiles and compute the 25th, 50th, and 75th percentiles of the associated moment in each quantile. It is important to notice that for each quantile, the remaining $P - 1$ parameters are randomly drawn, and, thus, potentially far away from their estimated values. Finally, we show these percentiles of the moment along with the value of that moment in the real-world data.

We claim that a moment is important for a parameter's identification if, as we move across quantiles, the percentiles of the associated moment change and cross the horizontal dashed line (i.e., the value of that moment in the real-world data). The slope of each curve shows how important that parameter is for the associated moment (a steeper curve implies the moment is more informative). The difference between the 25th and 75th percentiles is informative about the relative importance of the remaining parameters. Other parameters are more important when the moment's 25th and 75th percentiles are further apart, since that implies that there is at least one other parameter that has a relevant impact on this moment. Instead, if these two lines are very close to each other, it means that only the parameter selected is quantitatively relevant for the selected moment.

The success of this exercise relies on finding a relevant moment for each parameter. For example, the data on transfers to children helps identify the altruism parameter. As shown by panel (a) of Figure [B3](#), there is a positive relationship between the level of altruism ($\tilde{\beta}$) and transfers to children. As parents value their children more (i.e., have higher $\tilde{\beta}$), they increase the transfers to them. Moreover, the gap between the 25th and 75th percentiles is relatively small, suggesting that this moment is not particularly affected by other parameters. Similarly, panel (b) shows that there is a negative association between the disutility of work (μ) and average hours worked. The rest of the figures can be interpreted in similar ways.

There are two sets of moments that seem to be particularly affected by more than the param-

eter selected. The first set is related to skill development, i.e., panels (g), (i), (k) and (l). This is due to the fact that, for example, when ξ approaches zero all parents invest the same amount of time (i.e., the maximum), or alternatively, when the neighborhood importance share $\alpha_{I,j=1}$ approaches 1, time with children is reduced to almost zero by all parents. The second set is related to the size and income characteristics of each neighborhood, i.e., panels (c) and (d). The reason is that the two associated parameters (i.e., the preference shock and neighborhood fixed amenities) affect both moments. For example, when the variance of the preference shock increases, preference shocks become relatively more important and, thus, neighborhood sizes and income characteristics become more similar (since shocks are i.i.d.). Similarly, when (dis)amenity of neighborhood 1 (v_1) increases, more people choose to live in neighborhood $n = 2$ and only the poorest (who cannot afford it) are left behind in $n = 1$.

Figure B3: Identification Exercise: Global Results

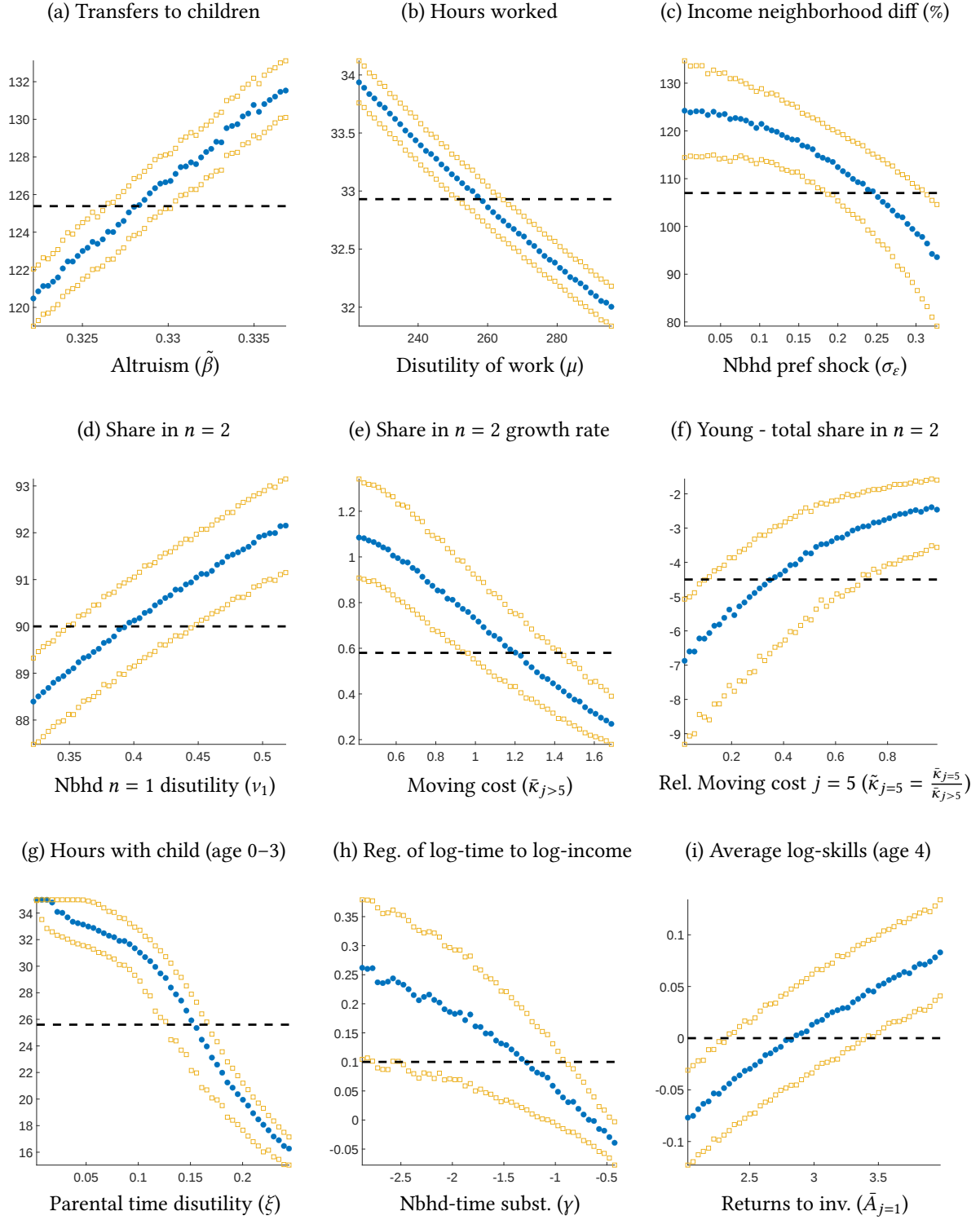
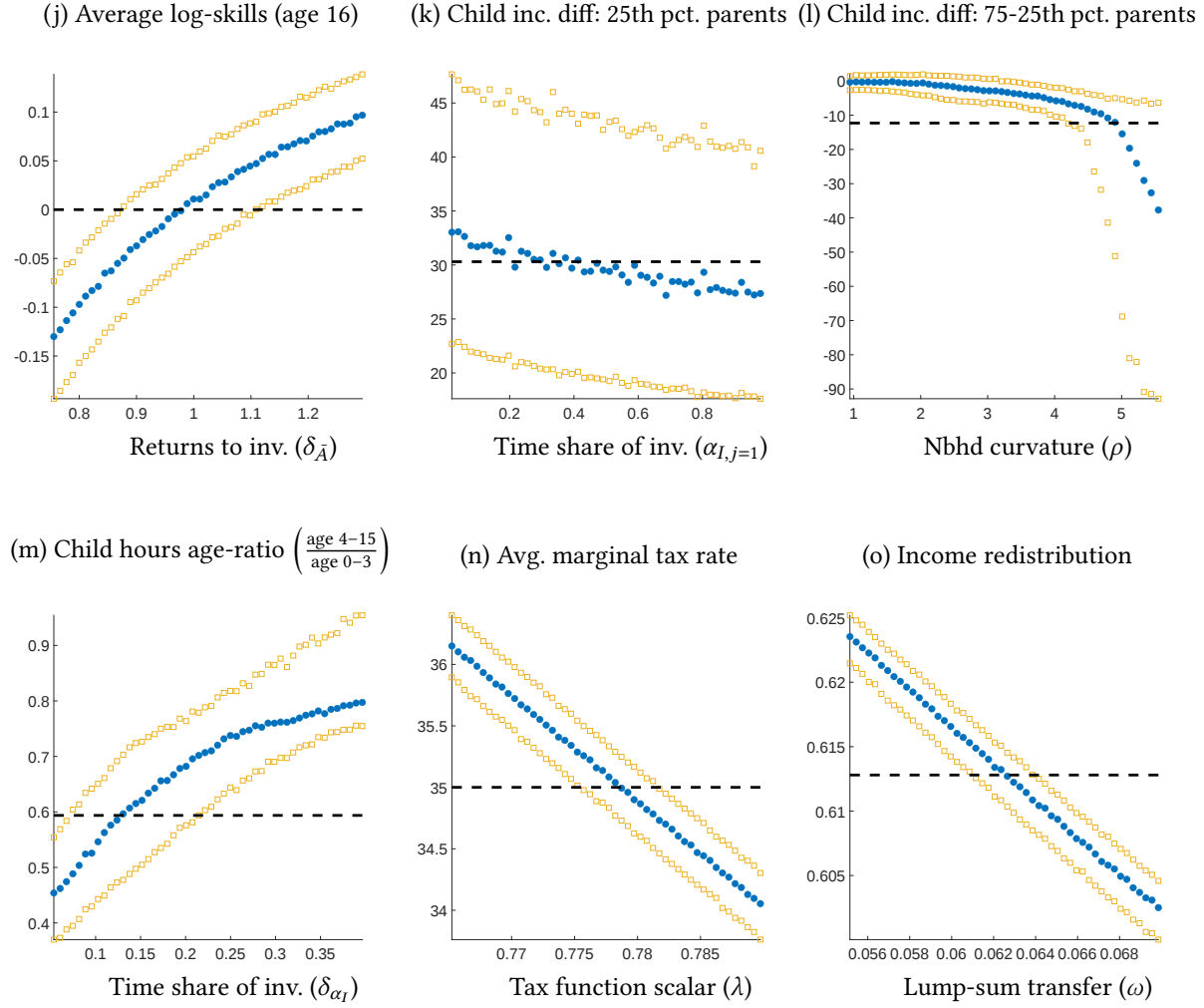


Figure B3: Identification Exercise: Global Results (continued)



Notes: This figure provides results from identification exercises for the parameters used in the model specified in Section II. The vertical axis of each panel is a moment in the simulated data (and denoted in the panel label) while the horizontal axis is a focal parameter (which is labeled under the x-axis). For each parameter's quantile, the blue dots shows the median of the assigned moment. Similarly, the yellow squares show the 25th and 75th percentiles, while red dots show the 10th and 90th percentiles. The black dashed line shows the value of the moment in the data. Transfers to children are estimated as a share of income. Income redistribution refers to the ratio of the variances of log-income after taxes and before taxes. See Appendix B3 for further details on the methodology.

Figure B4: Identification Exercise: Local Results

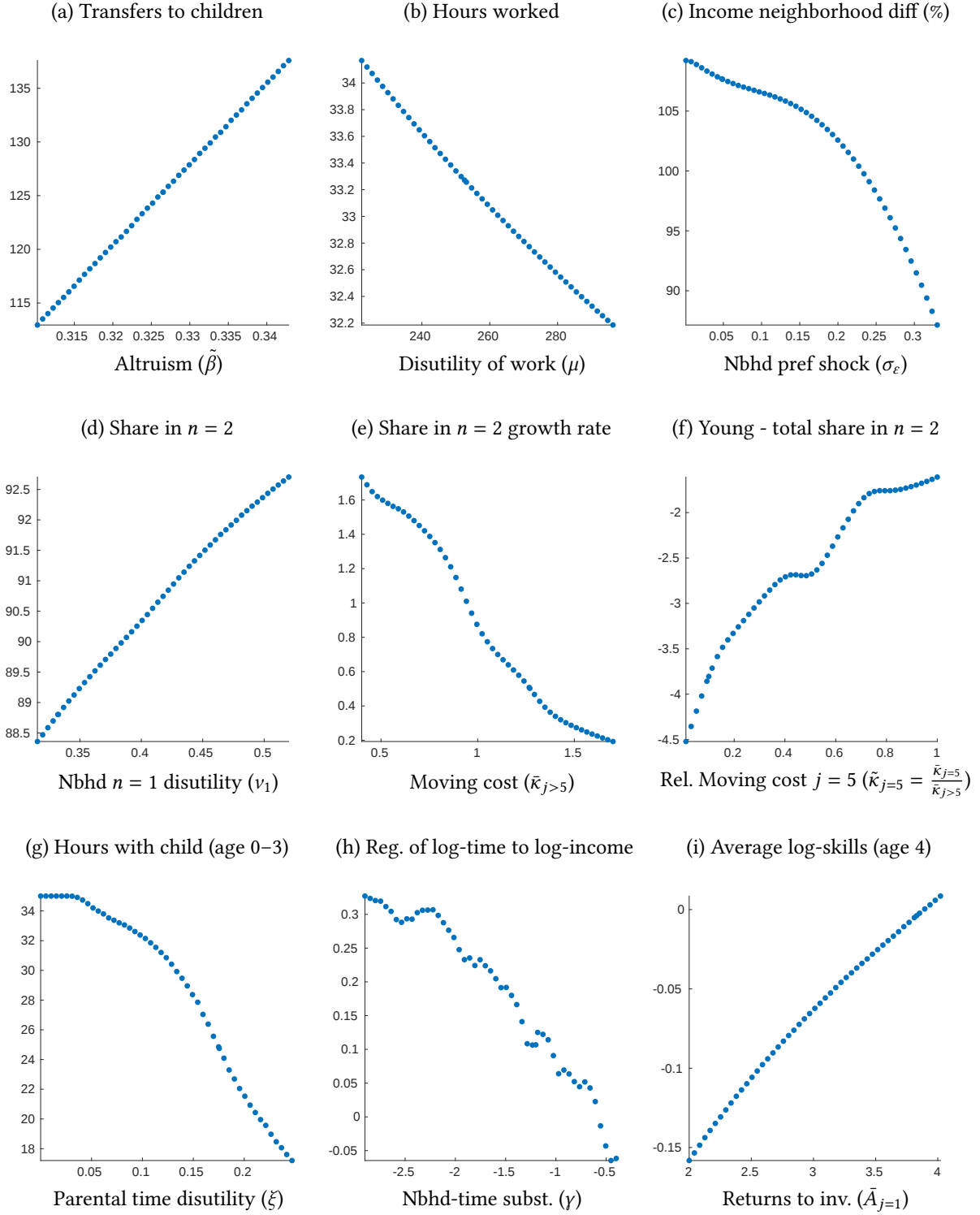
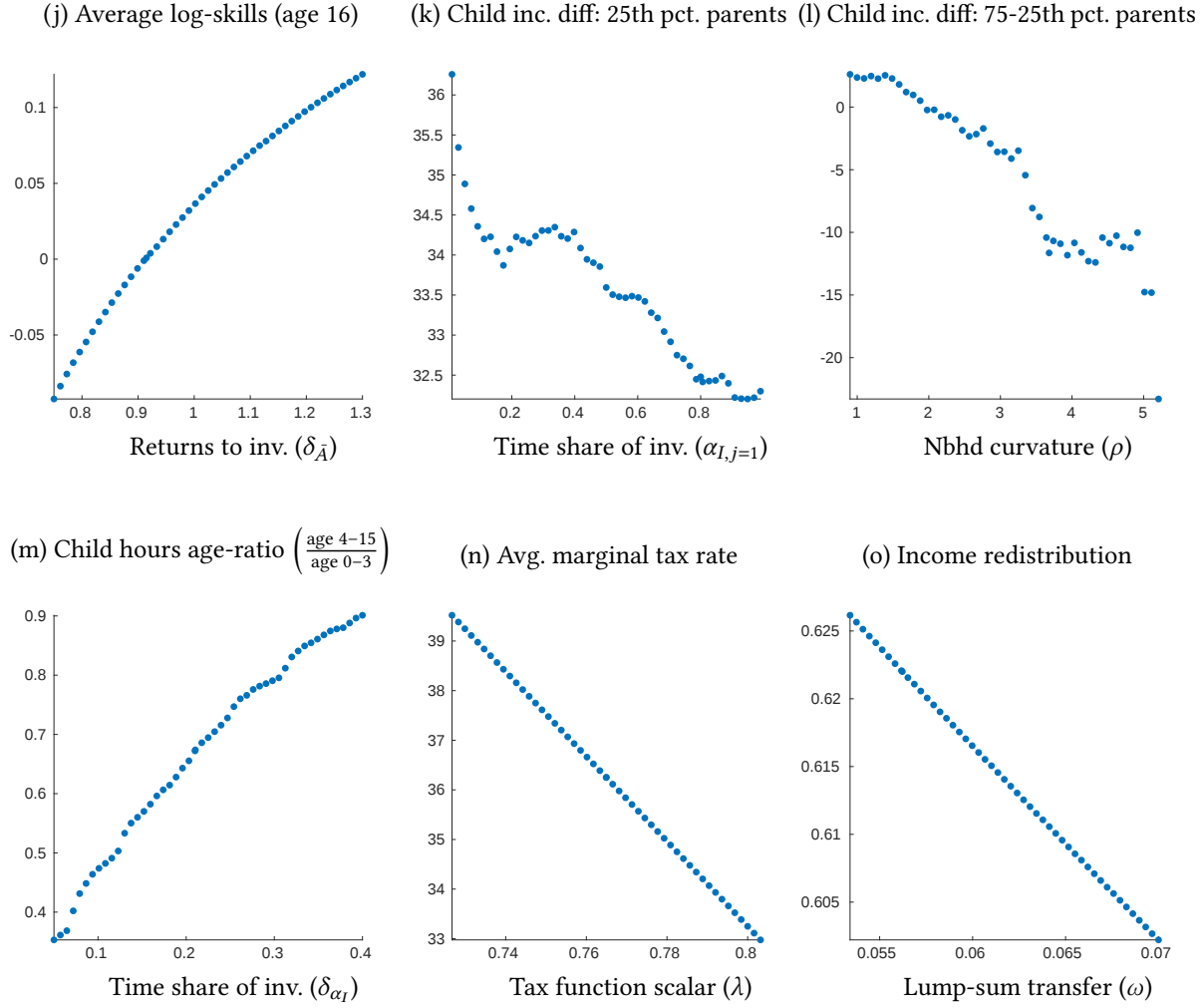


Figure B4: Identification Exercise: Local Results (continued)



Notes: This figure provides results from identification exercises for the parameters used in the model specified in Section II. The vertical axis of each panel is a moment in the simulated data (and denoted in the panel label) while the horizontal axis is a focal parameter (which is labeled under the x -axis). In each figure, all parameters are kept constant at the estimated values except for the parameter in the horizontal axis. The blue dots show the assigned moment when this parameter changes. Transfers to children are estimated as a share of income. Income redistribution refers to the ratio of the variances of log-income after taxes and before taxes. See Appendix B3 for further details on the methodology.

C Welfare Measure

Our analysis centers on evaluating aggregate welfare under scenarios that feature different policies. Welfare is defined by the consumption equivalence under the veil of ignorance in the baseline economy relative to the economy with the policy in place. Formally, let $P \in \{0, 1, 2, \dots\}$ denote the set of policies, with $P = 0$ being the initial economy (with no voucher or wage-subsidy program) in steady state. We refer to the consumption equivalence as the percentage change in consumption Δ in the initial economy that makes individuals indifferent between being born in the initial economy ($P = 0$) and the one in which the policy $P \neq 0$ is in place. Denote $V_{j=5}^P(a, \theta, n, \epsilon, \Delta)$ be the welfare of agents with initial state of the economy if their consumption (and that of their descendants) were multiplied by $(1 + \Delta)$:

$$\widetilde{V}_{j=5}^P(a, \theta, n, \epsilon, \Delta) = \mathbb{E}^P \sum_{j=5}^{j=J_d} \beta^{j-5} u(c_j^P(1 + \Delta), h_j^P, n_j) + \beta^{12-5} \delta \widetilde{V}_{j'=5}^P(\widehat{a}, \theta_k, n_{j=11}, \epsilon', \Delta),$$

where for the sake of clarity the expression above suppresses the utility terms for moving costs and disutility of time with children. Note that the policy functions are assumed to be unchanged when Δ is introduced. For example, consumption c_j^P is consumption chosen by individuals in economy P (in age j) and is not affected by Δ . For any measure Δ , the average welfare is:

$$\overline{V}^P = \int_{a, \theta, n, \epsilon} \widetilde{V}^P(a, \theta, n, \epsilon, \Delta) \mu_P(a, \theta, n, \epsilon),$$

where μ_P is the distribution of initial states $\{a, \theta, n, \epsilon\}$ in the economy P . We define Δ^P as the consumption equivalence that makes individuals indifferent between being born in the baseline economy or one in which policy P is in place:

$$\overline{V}^0(\Delta^P) = \overline{V}^P(0).$$

By definition, the welfare gains come from two sources. First, there are changes in the expected discount utilities at each state $\widetilde{V}_{j=5}^P(a, \theta, \epsilon, n, \Delta)$. Second, there are also shifts in the probabilities of each state $\mu_P(a, \theta, n, \epsilon)$.

D Baseline Model Robustness Exercises: Detailed Discussion and Results

In this section, we expand our analysis of how welfare impacts vary when moving away from the parameters of the baseline model presented in Section III. Specifically, we estimate changes in the welfare gains of voucher and place-based wage subsidies when we increase each of the baseline model parameters by one percent while holding other parameters constant.³ Appendix Table D5 reports estimates of welfare changes where the rows report results for the the highest steady-state rent voucher program and the version of the wage subsidy program that we evaluate in the validation exercise (i.e., a wage subsidy program of 20 percent). We focus on the wage subsidy program from the validation exercise given that all non-zero subsidies generate negative welfare impacts. We do not study robustness for a zero percent wage subsidy since small changes in a single parameter would not changed our welfare conclusions.

There are two main takeaways from our sensitivity analysis. First, the sensitivity analysis shows that a one percent change in each parameter often has small and same-signed impacts on the welfare gains associated with the two policies we study. Second, the pattern of generally small changes in results is reassuring, but it remains instructive to use this analysis to understand the effect of key parameters. An interesting case is altruism because the parameter $\tilde{\beta}$ most directly relates to the missing contract problem that stems from the fact children cannot fully compensate their parents for the cost of moving to the more advantaged neighborhood. As noted in Section II, the potential for welfare improvements from rental voucher policies stems at least partly from this incomplete contracts problem. As expected, when altruism is higher, the potential gains from the rent voucher are reduced. Moreover, gains from the wage subsidy increase (likely because parents are less likely to move into the disadvantaged area even when the wage subsidy is introduced). Given that changing this parameter generates opposite signed effects on the welfare effects of the two policies, a back-of-the-envelope calculation is informative as to whether large changes in this parameter are empirically reasonable. Specifically, $\tilde{\beta}$ would need to more than quadruple to cause the welfare gains of the rent voucher program to fall below the wage subsidy. While a formal analysis would require knowing the standard deviation of altruism, we can assess the plausibility of this change by evaluating how such an increase would affect non-welfare moments and compare the resulting (changed) moments to empirical benchmarks. For example, Appendix Figure B3, Panel (a), implies that increasing $\tilde{\beta}$ by one percent would increase the parental-transfer estimation moment (i.e., the average parental transfer as a share of average income) by 3.28 per-

³More precisely, we do this by calculating the difference in welfare gains when we increase each parameter by one percent and decrease each parameter by one percent. This difference is then divided by two to obtain a more precise (and direction independent) measure of the effect of changing parameters by one percent.

centage points (from 126 percent in our benchmark voucher program). Thus, quadrupling $\tilde{\beta}$ would require increasing this parent-transfer moment to over 900 percent—relatively far from the empirical benchmark of 125.4 percent. We reach similar conclusions from the sensitivity analysis based on other parameters. In sum, we interpret our sensitivity analysis in Appendix Table D5 as suggesting that welfare gains are not significantly altered by empirically-reasonable changes in the additional model parameters studied in this section.

Table D5: Welfare Changes and Parameter Sensitivity Analysis

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Change in Welfare Given 1 Pct. Increase in Parameter							
Panel A. Parameters:									
	Baseline Welfare Gain	μ	$\tilde{\beta}$	σ_{ε}	$\bar{v}_1$	$\bar{\kappa}_{j>5}$	$\bar{\kappa}_{j=5}$	ξ	γ
Rent Voucher	4.94	0.029	-0.005	0.002	-0.008	-0.007	-0.000	-0.005	0.004
Wage Subsidy	-0.40	0.019	0.006	0.002	-0.110	0.057	-0.002	0.003	-0.006
Panel B. Parameters:									
	Baseline Welfare Gain	$\bar{A}_{j=5}$	δ_A	$\alpha_{I,j=5}$	ρ	δ_{α_I}	λ	ω	θ_h
Rent Voucher	4.94	-0.011	-0.017	-0.008	0.051	-0.010	-0.014	0.001	0.004
Wage Subsidy	-0.40	0.007	0.011	-0.004	-0.002	-0.002	-0.032	0.002	-0.001

Notes: This table provides an analysis of the sensitivity of welfare gains to changes in the parameter values used in our calibrated model. Columns 1-8 report results from increasing a given parameter (e.g., the altruism parameter $\tilde{\beta}$) by one percent. We examine sensitivity to changes in 16 different parameters spread across two panels of the table. Rows indicate whether the results are specific to either of the policies studied in Sections IV. For comparison, the left of the table reports the baseline welfare gains of 4.3 and 0.5 for the rent voucher and wage subsidy programs, respectively. See text for further details on all calculations.

References

- Autor, David H., and David Dorn.** 2013. “Replication Data for: The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market.” Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2019-10-11.
- Bureau of Labor Statistics, U.S. Department of Labor.** 2003–2019. “American Time Use Survey: Microdata Files.” Retrieved from <https://www.bls.gov/tus/data.htm> (Accessed July 2020).
- Bureau, U.S. Census.** 2015. “American Community Survey 2015: Owner-Occupied Housing, Tables B25077 and B25103.” Retrieved from <https://data.census.gov/> (Accessed July 2020).
- Chetty, Raj, John N Friedman, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter.** 2018. “The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility.” National Bureau of Economic Research Working Paper 25147.
- Chetty, Raj, John N. Friedman, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter.** 2022. “The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility: Dataset.” Harvard Dataverse V2. <https://doi.org/10.7910/DVN/NKCQM1>.
- Chetty, Raj, Nathaniel Hendren.** 2022. “Replication Data for: The Impacts of Neighborhoods on Intergenerational Mobility: (I) Childhood Exposure Effects, and (II) County-Level Estimates.” Harvard Dataverse V1. <https://doi.org/10.7910/DVN/EI4WE2>.
- Chyn, Eric, and Diego Daruich.** 2025. “An Equilibrium Analysis of the Effects of Neighborhood-based Interventions on Children: Dataset.” *American Economic Review*.
- Cunha, Flavio, James J. Heckman, and Susanne M. Schennach.** 2010. “Estimating the Technology of Cognitive and Noncognitive Skill Formation.” *Econometrica*, 78(3): 883–931.
- Daruich, Diego.** 2020. “The Macroeconomic Consequences of Early Childhood Development Policies.”
- Manson, Steven, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Rugles.** 2022. “IPUMS National Historical Geographic Information System: Version 17.0 [dataset].” Minneapolis, MN: IPUMS. <http://doi.org/10.18128/D050.V17.0>.
- Portal, Chicago Data.** 2010. “U.S. Census Tract Boundaries.” Retrieved from <http://data.cityofchicago.org> (Accessed July 2021).
- Rothenberg, Thomas J.** 1971. “Identification in Parametric Models.” *Econometrica*, 39(3): 577–591. Publisher: [Wiley, The Econometric Society].
- Survey Research Center, Institute for Social Research, University of Michigan.** 2019. “Panel Study of Income Dynamics.” Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.
- U.S. Bureau of Labor Statistics, U.S. Department of Labor.** 2019. “National Longitudinal Survey of Youth 1979 Cohort, 1979-2016 (Rounds 1-27).” Produced and distributed by the Center for Human Resource Research.