

Online Appendix

The Online Appendix is organized as follows. Appendix A lays out the theoretical model described in Section 2.2 in detail. Appendix B discusses political economy considerations of social protection systems. Appendix C describes the conditionalities of various CCT programs and types of pension programs in detail.

A Model

In this appendix we formally analyze the model set up in Section 2.2.

The welfare recipient's problem. Consider first the recipient's problem. Individual utility is given by

$$y + T + t(y^* - \alpha\tilde{y} - (1 - \alpha)(y + \epsilon)) - \frac{a}{2}E_\epsilon(y + \epsilon - \tilde{y})^2 \quad (1)$$

Assuming interior optima, the optimal choice of \tilde{y} is given by

$$-\alpha t + a(y - \tilde{y}) = 0$$

which tells us that

$$\tilde{y} = y - \alpha t/a \quad (2)$$

The government's problem in the homogeneous case. We start with the case where all welfare recipients have the same cost of misreporting income, i.e., there is a single value of a for everyone (we will relax this below). Under this assumption, and noting that self-reported income is $\tilde{y} = y - \frac{\alpha t}{a}$, the social maximand can be written as

$$\int^{\hat{y}} g(y) h(y) E_\epsilon u \left(y + T + t \left(y^* - y + \frac{\alpha^2 t}{a} - (1 - \alpha) \epsilon \right) \right) dy \quad (3)$$

The government's budget constraint is given by

$$\int^{\hat{y}} h(y) E_\epsilon \left[T + t \left(y^* - y + \frac{\alpha^2 t}{a} - (1 - \alpha) \epsilon \right) \right] = B$$

which reduces to

$$T = B - t(y^* - \bar{y}) - \frac{\alpha^2 t^2}{a}$$

where \bar{y} is the mean income, i.e., $\bar{y} = \int^{\hat{y}} h(y) y$. Combining terms, we can write the social maximand $W(t)$ as

$$W(t) = \int^{\hat{y}} g(y) h(y) E_\epsilon u \left(y + t(-y) + B - t(1 - \alpha) \epsilon \right) dy. \quad (4)$$

Several key observations follow from this expression.

Implications. To find the optimal level of transfers, we consider $W'(t)$. Differentiating equation (4) with respect to t yields

$$W'(t) = \int^{\hat{y}} g(y) h(y) E_\epsilon \left[((-y) - (1 - \alpha) \epsilon) u'(y + t(-y) + B - t(1 - \alpha) \epsilon) \right] dy \quad (5)$$

which can be rewritten as

$$\begin{aligned} W'(t) = & \int^{\hat{y}} g(y) h(y) (-y) E_\epsilon \left[u'(y + t(-y) + B - t(1 - \alpha) \epsilon) \right] dy \\ & - \int^{\hat{y}} g(y) h(y) (1 - \alpha) E_\epsilon \left[\epsilon u'(y + t(-y) + B - t(1 - \alpha) \epsilon) \right] dy. \end{aligned} \quad (6)$$

The first term in $W'(t)$ represents the welfare gains from more effective targeting of the benefits towards the poor when t is higher. This first term is always positive.⁴⁵ Offsetting this, however, the second term in $W'(t)$ captures the welfare losses from the fact that greater targeting of benefits to the poor creates more random variation in the transfers, as a result of the noise ϵ in the government's audit function. This noise reduces social welfare so long as there is some weight on audits (i.e., $\alpha < 1$) and the government cares about horizontal equity ($u'' < 0$), and if so, then the second term is negative.⁴⁶

A.1 Results with homogeneous costs of misreporting

Several observations follow from the structure of equations (4) and (6).

First, equation (6) implies that a positive slope to the benefits function is always optimal, i.e., $t > 0$. To see this, note that when $t = 0$, the second term vanishes, so $W'(0) > 0$.⁴⁷ Intuitively, this is because the second term captures the social losses from noise in the targeting function, and if there were no income-dependent transfers, the noise would not matter. The fact that $W'(0) > 0$ then implies that $t > 0$; that is, the social optimum in this model cannot be strictly a universal transfer; some income-dependent component of the transfer scheme is always optimal.

Second, if the government puts no weight on horizontal equity, the social optimum does not feature any lump sum component. To see this, note that when the social welfare function $u(y)$ is linear so that $u'(y)$ is a constant, the second term in the expression for $W'(t)$ drops

⁴⁵To see this, compare the value of the integrand when $y = +\Delta$ with when $y = -\Delta$, $\Delta > 0$. Clearly, as long as $g(y)$ is strictly decreasing, $g(+\Delta)$ is smaller than $g(-\Delta)$. Alternately, if $u(y)$ is strictly concave, u' is higher when $y = -\Delta$ than when $y = +\Delta$. In other words, either of these conditions is enough to ensure that the value of the integrand is higher when $-y > 0$ than when it is positive. As a result, the positive terms, i.e., the people for whom $(-y) > 0$, dominate and the full expression is positive.

⁴⁶To see this mathematically, note that $u'' < 0$ implies that u' is greater when ϵ is positive than when it is negative. Thus, the terms where ϵ is positive dominate, which implies that $E_\epsilon [\epsilon u'(y + t(-y) + B - t(1 - \alpha) \epsilon)] > 0$ and the entire second term will be negative.

⁴⁷It vanishes because, when $t = 0$, $E_\epsilon [\epsilon u'(y + t(-y) + B - t(1 - \alpha) \epsilon)]$ can be rewritten as $E_\epsilon [\epsilon u'(y + B)] = u'(y + B) E_\epsilon \epsilon$. Since $E_\epsilon \epsilon = 0$, this implies that when $t = 0$ the entire second term is 0.

out. Intuitively, this is because when $u(y)$ is linear, the noise from the targeting formula does not create any social losses—one person’s loss is another person’s gain. Thus, when $u(y)$ is linear, as long as poorer people get social welfare weight ($g'(y) < 0$), $W'(t) > 0$ for all values of t . In this case, it is optimal to raise t as far as possible and set $T = 0$, i.e., no universal transfer.

Third, from the expression for $W(t)$ in equation (4), it is clear that more noise in the audit process (a mean-preserving spread of ϵ) reduces $W(t)$ as long as u is strictly convex and the government is using the audit data, i.e., when $u'' < 0$ and $\alpha < 1$. This is because it increases horizontal inequity in the targeting process.

Fourth, when α , the weight the government places on self-reported data, increases, the noise in the audit data matters less, and social welfare is higher, so $\frac{\partial W}{\partial \alpha} > 0$.⁴⁸ This implies that the optimum is to set $\alpha = 1$, that is, the optimal scheme relies entirely on self-reports, and does not use the audit data at all. Moreover, when $\alpha = 1$, the second term in equation (6) vanishes, so $W'(t) > 0$ for all values of t whenever $\alpha = 1$. Thus, if the government can choose both α and T , it will choose $\alpha = 1$ and $T = 0$; that is, the optimal scheme is based entirely on self-reports, has no universal component, and features the maximum possible income-dependence on transfers.

Finally, note that the expression for $W(t)$ is independent of a . In other words, it is possible to achieve the same targeting as in the case where people are fully truthful. This is despite the fact that the self-reported data is always distorted, and the distortion is greater when the tax rate is higher. The reason is that, effectively, the government understands exactly by how much people are distorting their self-reported income, and can work around it. (This may not be fully realistic, for reasons we will discuss below.) Thus, with $\alpha = 1$, the government not only makes no inclusion or exclusion errors, but it achieves the first-best level of targeting.

We summarize all these results as follows:

Result 1 *In the baseline model with homogeneous preferences over the penalty for misreporting, the optimal redistributive scheme always has the maximum feasible slope with respect to earnings and has no universal component ($T = 0$). The optimal scheme relies entirely on self-reports ($\alpha = 1$). Moreover, this scheme delivers the first-best level of targeting.*

This stark result has a simple intuition. As long as all potential beneficiaries have the same cost of misreporting incomes, the amount by which they distort is predictable, and the optimal targeting mechanism can take that fully into account and avoid using the noisy audit data.

This result also implies that *heterogeneity* in the cost of misreporting, i.e., heterogeneity in a , is key to understanding why governments may want to use audit data, why there are inclusion and exclusion errors in the targeting process, and why there may be reasons to limit the extent to which transfers are income dependent, because heterogeneity in a means that

⁴⁸Differentiating (4) with respect to α yields $\frac{\partial W}{\partial \alpha} = \int^{\hat{y}} g(y) h(y) E_{\epsilon}(t\epsilon) u'(y + t(-y) + B - t(1 - \alpha)\epsilon) dy$. This is positive by the same argument given in footnote 45.

the government can no longer perfectly back out true incomes from distorted self-reports. We explore this next.

A.2 Introducing heterogeneity in the cost of misreporting

Suppose now that a takes two values, a_1 and a_2 , with $a_1 < a_2$. Let μ denote the fraction of the population that are a_1 types. The cost of misreporting a is unobserved by the government.

We begin with the case where both types have the same income distribution $h(y)$. Given these assumptions, we can rewrite equation (3) as

$$W(t) = \int^{\hat{y}} g(y) h(y) \left[\mu E_\varepsilon u \left(y + T + t(y^* - y + \frac{\alpha^2 t}{a_1} - (1 - \alpha)\epsilon) \right) + (1 - \mu) E_\varepsilon u \left(y + T + t(y^* - y + \frac{\alpha^2 t}{a_2} - (1 - \alpha)\epsilon) \right) \right] dy. \quad (7)$$

The government's budget constraint is given by

$$\mu \int^{\hat{y}} h(y) E_\varepsilon \left[T + t(y^* - y + \frac{\alpha^2 t}{a_1} - (1 - \alpha)\epsilon) \right] + (1 - \mu) \int^{\hat{y}} h(y) E_\varepsilon \left[T + t(y^* - y + \frac{\alpha^2 t}{a_2} - (1 - \alpha)\epsilon) \right] = B$$

which reduces to

$$T = B - t(y^* - \bar{y}) - \mu \frac{\alpha^2 t^2}{a_1} - (1 - \mu) \frac{\alpha^2 t^2}{a_2}.$$

where \bar{y} is the mean income, as above.

Substituting, the social maximand from equation 4 can now be rewritten as

$$W(t) = \int^{\hat{y}} g(y) h(y) \left[\mu E_\varepsilon u \left(y + t(-y) + B + (1 - \mu) \alpha^2 t^2 A - t(1 - \alpha)\epsilon \right) + (1 - \mu) E_\varepsilon u \left(y + t(-y) + B - \mu \alpha^2 t^2 A - t(1 - \alpha)\epsilon \right) \right] dy \quad (8)$$

where $A = \frac{1}{a_1} - \frac{1}{a_2} > 0$.

When $A > 0$, there is now an additional effect: transfer schemes that rely on self-reports, in effect, redistribute from those with high values of a (those who do not misreport incomes very much) to those with low values of a (those who do). That is, the government can no longer fully unravel misreports, which helps those who are willing to misreport more.

To see this algebraically, note that for any value of y , the type a_1 's (i.e., the lower a_1 , who misreport more) are getting a positive shock of $(1 - \mu) \alpha^2 t^2 A$, while type a_2 's are getting a negative shock of $\mu \alpha^2 t^2 A$. Note that the expected value of the two shocks together is zero since there are μ fraction of type a_1 and $1 - \mu$ fraction of type a_2 . This effect—redistributing

towards those who misstate their income more—occurs to some degree whenever there is heterogeneity in a , whenever there is a redistributive element to the scheme ($t > 0$), and whenever the scheme relies even a bit on self-reports ($\alpha > 0$). This effect is strongest in precisely the scheme that was optimal in the previous model (maximal t and complete reliance on self-reports, i.e., $\alpha = 1$).

This model therefore features a tradeoff. On the one hand, as the government relies more and more on the unbiased but noisy audit data and less on self-reports (i.e., as we lower α), the redistribution from a_2 types to a_1 types falls. On the other hand, as before, the more the government relies on audits, the greater the social welfare loss induced by the ϵ 's in the audit process. The net effect of lowering α depends on the relative sizes of these effects. In the limit, holding other parameters fixed, as the audit process becomes better and better ($Var(\epsilon) \rightarrow 0$), the government will rely entirely on the audit process (i.e., $\alpha = 0$); conversely, as the two types become more similar (i.e., $A \rightarrow 0$), the government will rely entirely on self-reports (i.e., $\alpha = 1$).

When both forces are present—i.e., when $Var(\epsilon) > 0$ and $A > 0$ —it can be optimal for the government to use the audit data, i.e., it can be the case that $\alpha < 1$, unlike before. However, it will always be optimal to rely at least a bit on self-reports, so $0 < \alpha < 1$. To see this, note that since the welfare loss from redistribution from a_2 types to a_1 types depends on α^2 , for α small enough, raising α has a second order negative effect on $W(t)$ but first order positive effect by reducing the cost of targeting noise ϵ . Hence in this model one will not completely ignore self-reports, though it can clearly now be optimal to combine self-reports with audit data.⁴⁹

Turning next to t , as before, a higher t still means more transfers go to the poor. But, unlike in the previous model, now there are two forces pushing in the opposite direction. First, the social losses from redistributing from a_2 to a_1 types are greater as t is higher. Second, since we no longer have $\alpha = 1$, there are also losses due to targeting noise ϵ , and these are also stronger when t is higher. Hence relative to the case where $A = 0$, as in Section 2.2.1, the optimal value of t may be lower.⁵⁰ That is, there is less redistribution when there is more heterogeneity in the ability to misreport income.

Summing up, we have the following result:

Result 2 *If there is heterogeneity in the cost of misrepresenting incomes, it can be optimal for the government to use audit data as part of the targeting process. The weights placed on audit data relative to self-reports is increasing in heterogeneity in misreporting costs (A) and decreasing in noise in the audit process ($Var(\epsilon)$). Moreover, it can now be optimal for the benefits to have a universal component, and not be entirely income-based.*

A numerical example showing how the optimal choices of α and t change as we change A and $Var(\epsilon)$ can be found in Appendix Section A.4 below.

⁴⁹In practice, if there is a fixed cost of collecting the self-report data, and if the optimal α is very small absent these fixed costs, the government may not bother paying the fixed costs and may choose to ignore self-reports altogether.

⁵⁰Of course, we may still be at the maximum value of t , but it is now possible that the optimal solution will feature some lump-sum component T and less than the maximum level of t .

A.3 When heterogeneity in misreporting is correlated with incomes

In the previous example, the fact that u is strictly concave was key to the results. With linear u , the government no longer cares about horizontal equity, so the mean preserving spread in consumption due to an increase in A does not matter to the government. However, this is because in the previous section, we assumed that the two types have the exact same income distribution, that is, that the heterogeneity in misreporting costs was uncorrelated with incomes.

To see what can happen when the income distributions are correlated with misreporting costs, consider the following (somewhat extreme) example. Assume as before that there are two types a_1 and a_2 in proportions μ and $1 - \mu$, but now assume that incomes of the two types are $y_1 < y^*$ (for a_1) and $y_2 < y_1$ (for a_2), and consider the case when u is linear. Given these assumptions

$$W(t) = \mu g(y_1) y_1 + (1 - \mu) g(y_2) y_2 + T + \mu g(y_1) \left[(y^* - y_1) t + \frac{\alpha^2 t^2}{a_1} \right] + (1 - \mu) g(y_2) \left[(y^* - y_2) t + \frac{\alpha^2 t^2}{a_2} \right] \quad (9)$$

and the budget constraint is

$$B = T + \mu \left[(y^* - y_1) t + \frac{\alpha^2 t^2}{a_1} \right] + (1 - \mu) \left[(y^* - y_2) t + \frac{\alpha^2 t^2}{a_2} \right].$$

Substituting for T using the budget constraint and using the fact that $\mu(g(y_1) - 1) = -(1 - \mu)(g(y_2) - 1)$, we get

$$W(t) = \mu g(y_1) y_1 + (1 - \mu) g(y_2) y_2 + (1 - \mu) (g(y_2) - 1) \left[(y_1 - y_2) t + \frac{\alpha^2 t^2}{a_2} - \frac{\alpha^2 t^2}{a_1} \right] \quad (10)$$

Finally, note that:

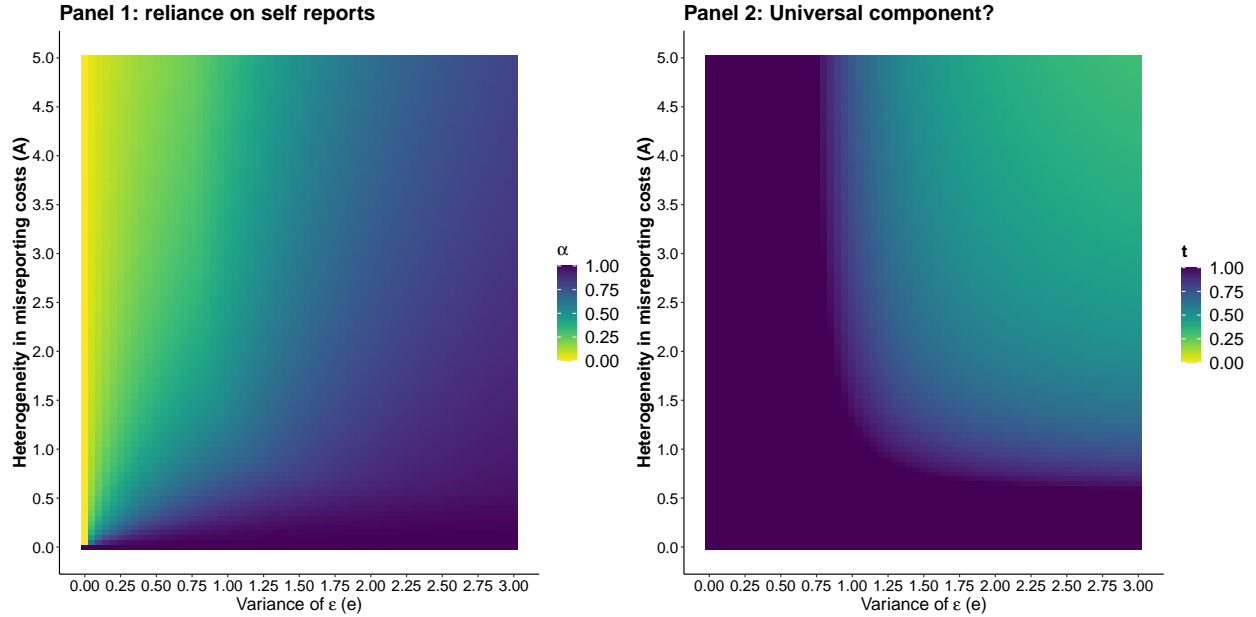
$$W'(t) = (1 - \mu) (g(y_2) - 1) \left[(y_1 - y_2) + \frac{2\alpha^2 t}{a_2} - \frac{2\alpha^2 t}{a_1} \right] \quad (11)$$

Two observations follow from this revised expression for $W'(t)$. First, as long as $a_2 < a_1$ this expression will be always positive, so it makes sense to maximize t and set $T = 0$, just as in the homogeneous case with linear social welfare function.

Second, if $a_2 > a_1$, then there is a clear benefit from setting $\alpha = 0$, since from equation 10 $W(t)$ is decreasing in α whenever $a_2 > a_1$. Setting $\alpha = 0$, it is also clear that one should set t as large as possible and set $T = 0$. We summarize this as follows:

Result 3 *If preferences are linear, it may even be optimal to ignore self-reports entirely and to use just audit data. This will occur if those with higher incomes have a lower misreporting cost.*

Figure A.1: Noise vs. heterogeneity



Note: This figure presents simulation results for Equation 8 in Section A.2, over different values of A and $Var(\epsilon)$, and assuming a linear, CRRA utility function. To compute the values of α and t , we numerically optimise for alpha and t over each set of parameters. Optimal values of α and t are depicted by colours ranging from yellow (0) to dark blue (1).

A.4 Model Simulations

A.4.1 Simulating the model in Section A.2

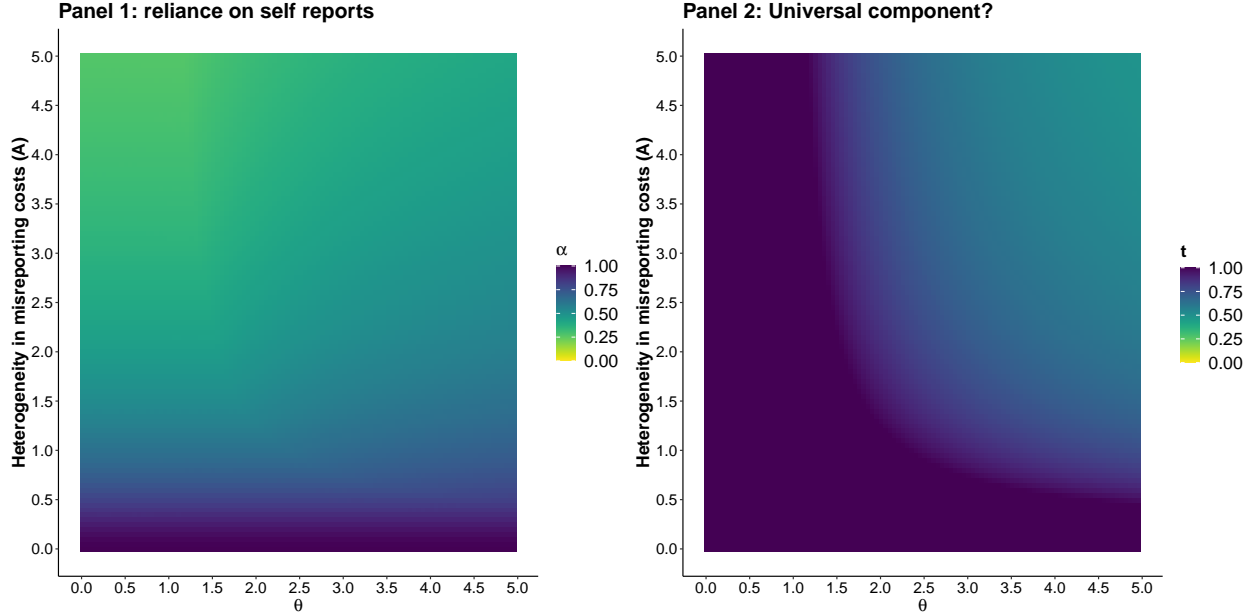
The figures below present simulation results for Equation 8, in Section A.2, numerically optimising for α and t over different values of A , θ and $Var(\epsilon)$, and assuming that households have Constant Relative Risk-Aversion (CRRA) utility functions.

Figure A.1 highlights the tradeoff between noise in audit process and heterogeneity in misreporting costs. Panel 1 shows how the optimal level of reliance on self-reports changes with these parameters, and Panel 2 shows how these parameters impact whether it is optimal to have a universal component to transfers.

With no noise in the government's audit function, and some heterogeneity in misreporting costs, α is always 0 and the government should rely entirely on the audit process. When incomes are homogeneous $A = 0$, α and t always equal 1 and there should be complete reliance on self-targeting. There should be no universal transfer component ($t = 1$) when heterogeneity in misreporting costs is low (< 0.55) (regardless of $Var(\epsilon)$), and when $Var(\epsilon)$ is low (< 0.70).

Figure A.2 highlights the tradeoff between curvature of the utility function and heterogeneity in misreporting costs. As in Figure A.1, Panel 1 shows how the optimal level of reliance on self-reports changes with these parameters, and Panel 2 shows how these parameters impact whether it is optimal to have a universal component to transfers. The gradient regions

Figure A.2: When should there be a universal component to transfers?



Note: This figure presents simulation results for Equation 8 in Section A.2, for different values of A and $Var(\epsilon)$, or when $a = 1$ (assuming positive, non-zero noise in the government’s audit function). To compute the values of α and t , we numerically optimise for alpha and t over each set of parameters. Optimal values of α and t are depicted by colours ranging from yellow (0) to dark blue (1).

in both panels indicate when there should be a mixture of reliance on self-reporting and audit data, and a universal component to transfers. This case assumes a constant, positive (non-zero) $Var(\epsilon)$.

As Panel 1 shows, in this case, it is never optimal to set $\alpha = 0$, and have complete reliance on the audit data. When incomes are homogeneous ($A = 0$), α and t always equal 1 and there should be complete reliance on self-reports. There should be no universal transfer component ($t = 1$) when heterogeneity in misreporting costs is low (< 0.45) (regardless of θ), or when θ is low (< 1.16) (regardless of A).

A.5 An alternative framing of misreporting costs

Suppose in the beneficiary’s maximand we replace $F = \frac{a}{2}(y^a - \tilde{y})^2$ by $C = \frac{a}{2}(y - \tilde{y})^2$, i.e just replace y^a by y , the household’s actual income. C can be thought of as the cost to the household of claiming to have income \tilde{y} when it’s true income is y . The cost can come from reduced consumption of visible assets, or it could be an action (standing in line, filling out forms, etc.) that is costlier the richer you actually are relative to what you are claiming to be (for example, it could be that the more egregious the gap between your actual and claimed income, the more lines the household would need to stand in to make the case that it is deserving, or the more social stigma the household would face when it goes to apply).

Notice that the household’s decision problem has exactly the same solution as before: $\tilde{y} =$

$y - \frac{\alpha t}{a}$, and as a result, so does the government’s maximization problem. Hence Results 1, 2, and 3 from the above apply in this case as well.

However, in the case where the beneficiary has to make some costly choice to be able to apply for benefits, the social welfare function may put some weight on the cost to the beneficiary. To see the implications of this, we focus on the case where $\alpha = 1$, i.e the government relies entirely on self-reports. In this case, the social maximand from equation (4) is now reduced by $C = \frac{a}{2}(y - \tilde{y})^2$ for each household. This simplifies to

$$W(t) = \int^{\hat{y}} g(y)h(y)u(y + t(\bar{y} - y) + B - \frac{t^2}{2a})dy \quad (12)$$

Compared to the case analyzed above, this case is different because the cost of using self-reports, $C = \frac{a}{2}(y - \tilde{y})^2$, does not net out here. Relative to the previous model, this also introduces a new cost of raising t and moving away from a universal benefit, which comes from the fact that t forces households to take costly actions. Interestingly the cost is lower when a is large, essentially because the household then does not try to distort its income very much.

B The Politics of Social Protection Systems

To run a social protection system or program, one cannot abstract away from the politics. The politics affects different aspects of how programs run, as voters make decisions about the level of redistribution they want and the form of it. Differences in who has political power and access may further determine how programs are designed and who ultimately benefits from them. And, as with any government program, there are interesting dynamics on how politicians think about these programs—do they design platforms on social protection around addressing voter views and needs? Or, do incumbents manipulate the programs by, for example, changing programs to shore up support with certain groups prior to elections?

While we cannot comprehensively review the entire politics literature on this topic here, we highlight a few of the issues below. We refer the interested reader to the review by [Golden and Min \(2013\)](#) for a discussion of related issues from the political science perspective.

B.1 Voters

The existence or receipt of social protection programs may affect voter behavior—either positively or negatively. For example, some voters may reward parties or politicians that introduce or improve these programs due to a stated preference towards greater redistribution—regardless of whether they receive benefits or not. Moreover, voters who receive these programs may reward the parties that implement them either because they are happy with the services and help that they are receiving from the government, or because they are dependent on the help and would want the programs to continue. But others may vote against those that implement these programs, either due to an inherent preference against

redistribution, because they are not benefiting directly from these programs, or because they believe that the quality of the programs is poor.

A number of studies have looked at whether the introduction or expansions of social protection can induce political participation and/or change voting patterns. This is empirically hard to disentangle, as voting may induce the introduction of social protection as well. A number of different empirical strategies have been used to understand these issues.

Several studies use regression discontinuity designs that compare those who are just above the poverty eligibility cutoff with those just below to understand the impact of receiving a transfer versus missing out. These papers have typically concluded that directly receiving benefits leads to increased political engagement and political support for those who designed or implemented the program. One such study is [Manacorda, Miguel and Vigorito \(2011\)](#), which studies PANES, a large targeted temporary cash program in Uruguay. Using survey data on voting outcomes, the authors find that beneficiaries were more likely to favor the government that implemented the program. This was true even after the program itself ended, suggesting that it was less about people voting based on their current receipt of benefits but perhaps due to a change in belief about the party's beliefs on redistribution.

A second study employing these methods was [Pop-Eleches and Pop-Eleches \(2012\)](#) that studied a \$200 coupon to poor families for the purchase of a computer. They also found that beneficiaries were more likely to support the incumbent government coalition, driven by both high mobilization and party-switching. But, interestingly, the higher trust was only to the local government officials who administered the program, but not the central government that designed and funded the program. A final example is from Colombia's CCT program, Familias en Acción. [Conover et al. \(2020\)](#) explored discontinuities in program eligibility and variation in program enrollment across voting booths and found that the program increased the beneficiaries' probability to register to vote, especially for women, who were the direct recipients of the program.

A series of other papers have taken advantage of experimental variation in the roll-out of transfers programs to look at the effect of the roll-out on political outcomes of everyone in an area, regardless of whether they received the program. The results are mixed. [Labonne \(2013\)](#) shows that a CCT program in the Philippines also led to increased vote share for the incumbent, but this effect was only evident in municipalities where there were high levels of political competition. [Blattman, Emeriau and Fiala \(2018\)](#), however, examine a randomized allocation of grants to youth to fund entrepreneurship activities in Uganda, and find no effects on support for the ruling party. Likewise, [Imai, King and Velasco Rivera \(2020\)](#) find no electoral impact of a large-scale randomized trial in Mexico which randomized health insurance to selected areas (discussed above).

[Brollo, Kaufmann and La Ferrara \(2020\)](#) show that beneficiaries may react to specific program features, not only the program as a whole. Using random variation in the timing of when beneficiaries learned about penalties for noncompliance with Bolsa Família's conditions around the 2008 municipal elections, they find a lower vote share for candidates aligned with the president in areas where more beneficiaries received penalties shortly before (as opposed to shortly after) the elections.

B.2 Politicians

A key question is how politicians develop social protection programs and policies based on political incentives. The best case, but overly simplistic, scenario is that voters have preferences over redistribution and the design of such policies and programs, they make their voices heard through activism and voting, and politicians respond by providing the types of programs that citizens need. However, there are many challenges here—as citizen voices are not always aggregated perfectly through the voting booth, with those who may be most vulnerable often excluded from the systems. To gain support with particular voters or groups, politicians may also change spending patterns or manipulate rules or programs to confer benefits to particular groups.

A number of papers aim to understand whether politicians strategically time their spending around elections, which could have implications for general macroeconomic conditions (e.g., too much spending in good times, and thus limitations in available budget to increase spending in recessions), following on the work of Nordhaus (1975). For example, Khemani (2004) found that, in India, public investment increased more before scheduled elections, but then contracted in other times to keep the net balance unchanged. Composition of spending changed too, as Khemani (2004) found that resources shifted to narrow interest groups (e.g., tax breaks provided to small groups of producers) rather than broad-based consumption spending. Drazen and Eslava (2010) also found, for Colombia, that the composition of spending changed before elections, particularly around targeted expenditures.

In addition to changing spending patterns, politicians can also adjust the rules or implementation of existing programs to target particular groups and voters. For example, Camacho and Conover (2011), discussed above, finds evidence of manipulation of the targeting rules before elections, while Brollo, Kaufmann and La Ferrara (2020), also discussed above, finds that enforcement of CCT rules become more lax before elections in municipalities where the incumbent associated with the program could run for election.

Given the political context, can improving representation and voice improve incentives for politicians? Can it shift policies and programs towards the previously unrepresented groups? A number of papers implies that it can. For example, Pande (2003) and Chattopadhyay and Duflo (2004) find that improving representation of minorities and women in India through political reservations led to spending allocations that better mirrored citizens' preferences. Similarly, Fujiwara (2015) found that increasing the enfranchisement of less educated citizens through electronic voting led to increased spending towards health care, which benefits low-income populations.

Note, however, that spending decisions—even they align well with voters—may come at a cost in terms of other human capital investments. For example, Burszty (2016) found that governments invested less in public education because lower-income decisive voters preferred them to allocate resources mostly toward redistributive programs, such as cash transfers. This could potentially be welfare enhancing if, for example, public systems are poor and households decide how to invest in their child's education through private systems that improve education. But, it could also come at a cost if parents do not fully take into account the full benefits of education for their children and underinvest in schooling, or if

other challenges—pressure from other family members for funds, other immediate spending needs—also lead to an underinvestment in education. It also suggests that social protection spending needs to be examined through the overall budget lens, and not just through individual components in making decisions on overall human capital investment needs.

C Tables

Table 1: Comparing conditionalities of large-scale CCT programs around the world

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions					
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others
<i>Large programs (cover at least 1% of population)</i>										
Asignación Universal por Hijo para la Protección Social	Argentina	2009 -	4,400,000 children (2021)	9.61%	✓	✓	✓			
Familias por la inclusión social	Argentina	2005-2010	2,012,066 children (2009)	4.97%	✓	✓	✓			
Jefas y Jefes de Hogar Desocupados	Argentina	2002-2005	1,500,000 families (2005)	3.86%	✓	✓	✓		✓	
Stipend for primary students	Bangladesh	2002-	13,000,000 students (2021)	1.63%	✓					• School performance
Secondary Education Quality and Access Enhancement Project Stipend	Bangladesh	2008-	2,300,000 beneficiaries (2013)	1.51%	✓					• School performance • Children to remain unmarried
Female School Stipend Program (FSSP)	Bangladesh	1982-	2,270,343 students (2005)	7.82%	✓					• School performance • Children to remain

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions						
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others	
Bono Pinto	Juancito	Bolivia	2006-	2,200,000 children (2018)	21.98%	✓					unmarried
Bono Juana Azurduy		Bolivia	2009-	2,600,500 women since inception of program (2021)	19.38%		✓				
Bolsa Escola		Brazil	2001-2003 (integrated into Bolsa Familia)	15,200,000 beneficiaries (2003)	8.36%	✓					
Bolsa Familia		Brazil	2003-	46,900,000 beneficiaries (2018)	22.39%	✓	✓	✓			
Programa de Erradicação do Trabalho Infantil (PETI)		Brazil	1996-2006 (integrated into Bolsa Familia)	3,300,000 beneficiaries (2002)	1.84%	✓					<ul style="list-style-type: none"> • Attend work • Ensure children not participating in child labour • Exhibit positive behavioural change/participate in social education

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions					
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others
Subsidio unico familiar (SUF)	Chile	1981-	2,015,393 beneficiaries (2015)	3.06%	✓	✓	✓			• Additional eligibility criteria: households with at least one elderly or disabled member
Ingreso Ético Familiar	Chile	2011-	549,000 beneficiaries (2015)	11.22%	✓	✓				
Más Familias en Acción	Colombia	2001-	13,672,125 beneficiaries (2015)	28.77%	✓	✓	✓		✓	• School performance
LISUNGI Safety Nets System Project	Congo, Rep.	2014-	119,314 beneficiaries (2021)	2.11%	✓	✓	✓			
Avancemos	Costa Rica	2006-	167,029 students (2015)	3.45%	✓	✓				• School performance
Creceemos	Costa Rica	2019-	200,000 students (2020)	3.93%	✓					
Progressing with Solidarity	Dominican Republic	2012-	2,542,384 beneficiaries (2015)	7.70%	✓	✓			✓	

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions					
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others
Programa Solidaridad (Solidarity program)	Dominican Republic	2005-2012	755,683 households (2011)	24.73%		✓			✓	• Additional eligibility criteria: households with at least one elderly member
Desnutricion cero	Ecuador	2011-	1,481,009 beneficiaries (2015)	9.14%		✓				• Birth attended by professional/ at a government or accredited private facility
Takāful and Karama	Egypt	2015-	3,100,000 households (2020)	3.03%	✓	✓		✓	✓	
Comunidades Solidarias Rurales	El Salvador	2005-	75,000 households (2014)	1.19%	✓	✓	✓			• Attend work
Support for Education, Empowerment & Development (SEED)	Grenada	2011-	7,368 beneficiaries (2015)	6.72%	✓	✓			✓	
Mi Bono Seguro – Bono Seguro Escolar	Guatemala	2012-	1,021,959 households (2013)	6.79%	✓				✓	

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions						
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others	
Bono Mejor/Bono 10,000	Vida	Honduras	2010-	259,879 individuals (2015)	2.85%	✓	✓		✓		
Program Keluarga Harapan (PKH)	Indonesia	2007-	10,000,000 families (2018)	3.74%	✓	✓					• Additional eligibility criteria: households with at least one elderly or disabled member
Programme of Advancement Through Health and Education	Jamaica	2001-	350,000 beneficiaries (2021)	11.77%	✓	✓	✓				
National Aid Fund Cash Transfer	Jordan	1986-	331,453 beneficiaries (2018)	3.33%	✓		✓				• Household members cannot beg or commit domestic violence
Tekavoul – conditional cash transfers	Mauritania	2016-	54,249 households (2022)	1.14%						✓	
Prospera	Mexico	2014-2019	6,168,900 households (2015)	5.01%	✓	✓		✓	✓		

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions					
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others
Oportunidades/ Progres	Mexico	1997-2014	5,800,000 households (2011)	5.06%	✓	✓		✓	✓	
Tayssir	Morocco	2008-	2,611,000 beneficiaries (2022)	6.99%	✓					
Aama Programme (Safe Motherhood Programme)	Nepal	2005-	401,839 beneficiaries (2017)	1.45%		✓				• Birth attended by professional/ at a government or accredited private facility
120 a los 65	Panama	2009-	120,652 individuals (2021)	2.75%		✓			✓	• Must not use cash for gambling, alcohol, drugs and narcotics
Red de Oportunidades	Panama	2006-	67,385 households (2015)	1.70%	✓	✓	✓		✓	

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions					
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others
Universal Educational Assistance Programme (PASE-U)	Panama	2020-	617,000 students (2021)	14.08%	✓		✓	✓		<ul style="list-style-type: none"> • Exhibit positive behavioural change/participate in social education • Parent/guardian attend school meetings
Tekoporã	Paraguay	2005-	722,377 households (2015)	10.80%	✓	✓			✓	
Juntos	Peru	2005-	769,158 families (2015)	2.52%	✓	✓	✓	✓		
Pantawid Pamilyang Pilipino Program (PPPP)	Philippines	2007-	4,400,000 households (2015)	4.31%	✓	✓	✓	✓	✓	
Abono de Família para Crianças e Jovens	Portugal	2003-	820,330 beneficiaries (2020)	7.96%						<ul style="list-style-type: none"> • Children must not be working during school year • Children aged 16 and over to comply with educational

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions						
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others	
National transfer programme	cash pro-	Senegal	2013-	300,000 households (2016)	2.00%	✓		✓			requirements
Social Safety Nets Program		Sierra Leone	2014-	136,768 beneficiaries (2016)	1.87%					✓	
Productive Social Safety Net (PSSN)		Tanzania	2012-	1,098,856 households (2016)	2.07%	✓	✓				• Additional eligibility criteria: households with at least one disabled member
Bolsa da Mae		Timor-Leste	2012-	47,539 beneficiaries (2021)	3.54%	✓		✓			• School performance
Targeted Conditional Cash Transfer Program (TCCTP)		Trinidad and Tobago	2005-	24,327 households (2017)	6.49%					✓	• Enroll at employment agency
Social Risk Mitigation Project		Turkey	2004-2007	2,600,000 children (2007)	3.74%						• Increased use of health and education services

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions					
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others
Asignaciones Familiares	Uruguay	2008-	372,231 individuals (2018)	10.79%	✓	✓				
Plan de Atención Nacional a la Emergencia Social	Uruguay	2005-2007	130,000 beneficiaries (2007)	3.87%	✓	✓				
<i>Small programs (cover less than 1% of population)</i>										
Programa de Ciudadanía Porteña	Argentina	2005-	100,855 families (2020)	0.22%	✓					• Additional eligibility criteria: households with at least one disabled or pregnant member
Building Opportunities for Our Social Transformation, BOOST	Belize	2011-	3,116 households (2019)	0.80%	✓	✓	✓			
Bolsa Alimentação	Brazil	2001-2003 (integrated into Bolsa Família)	1,500,000 beneficiaries (2003)	0.83%		✓	✓			

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions					
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others
Subsidios Condicionados a la Asistencia Escolar	Colombia	2005-2012	46,003 students (2010)	0.10%	✓					• School performance
Ghana's Livelihood Empowerment against Poverty (LEAP) programme	Ghana	2008-	146,074 beneficiaries (2015)	0.52%	✓	✓	✓			• Ensure children not participating in child labour
Bono Social	Guatemala	2012-	128,253 households (2020)	0.76%	✓	✓				
Ti Manman Cheri	Haiti	2012-	86,234 beneficiaries (2014)	0.82%	✓					
For the Road	Hungary	Birth grant: 1998- Kindergarten allowance: 2009-2015 Schooling allowance: 2010-	26,000 beneficiaries (2008)	0.26%	✓	✓				• School performance

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions					
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others
Janani Suraksha Yojana (JSY)	India	2005-	4,546,933 beneficiaries (2015)	0.35%						• Birth attended by professional/ at a government or accredited private facility
Pradhan Mantri Matru Vandana Yojana	India	2017-	6,500,000 women (2020)	0.47%		✓	✓			
Program Kesejahteraan Sosial Anak, PKSA	Indonesia	2009-	173,611 beneficiaries (2013)	0.07%						• Exhibit positive behavioural change/ participate in social education
Filets Sociaux de Sécurité TMDH	Madagascar	2015-	200,000 households (2020)	0.72%	✓				✓	
Stipends Program (Ministry of Education)	Myanmar	2009-	192,000 students (2018)	0.36%	✓					• School performance
Red de Protección Social	Nicaragua	2000-2006	28,129 households (2006)	0.51%	✓	✓	✓		✓	

Name of Program	Country	Years in place	Number of beneficiaries	Population covered (%)	Conditions					
					School enrollment & attendance	Health check-ups	Complete vaccination schedule	Health control compliance	Training sessions/workshops	Others
Benazir Income Support Program (BISP), CCT Component (Waseela-e-Taleem)	Pakistan	2012-	1,300,000 beneficiaries (2016)	0.64%	✓					
Punjab Female School Stipend Program (FSSP)	Pakistan	2003-	393,000 children (2014)	0.20%	✓					
Temporary Assistance for Needy Families (TANF)	United States	1996-	783,252 households (2022)	0.24%	✓	✓	✓		✓	<ul style="list-style-type: none"> • Beneficiaries required by most states to work a pre-specified number of hours per week • Precise conditions vary by state
Basic Education Support for Girls CCT	Yemen	2004-	39,791 beneficiaries (2014)	0.15%	✓					<ul style="list-style-type: none"> • School performance
Cash for nutrition	Yemen	2015-	40,000 beneficiaries (2019)	0.14%				✓	✓	

Note: This table compares the conditionalities of sixty-seven large-scale, government-implemented CCTs in forty-five countries around the world, including programs that are no longer operational. We only considered CCTs with at least some health or education-related component. The most common conditions are school enrollment and attendance (52 CCTs), health check-ups (38 CCTs), completing vaccination schedules (22 CCTs), attendance of training sessions or workshops (20 CCTs) and health control compliance (e.g. child growth monitoring) (8 CCTs). Sources cited in references section below. Population data from [World Bank \(2021\)](#)

Table 2: Types of pension systems enacted, by country

Country	Pension type	
	Contributory	Non-contributory
Albania	●	●
Algeria	●	○
Andorra	●	●
Angola	●	○
Antigua and Barbuda	●	●
Argentina	●	●
Armenia	●	●
Aruba	●	○
Australia	●	●
Austria	●	●
Azerbaijan	●	●
Bahamas, The	●	●
Bahrain	●	○
Bangladesh	○	●
Barbados	●	●
Belarus	●	●
Belgium	●	●
Belize	●	●
Benin	●	○
Bermuda	●	●
Bhutan	●	●
Bolivia	●	●
Botswana	○	●
Brazil	●	●
British Virgin Islands	●	○
Brunei Darussalam	●	●
Bulgaria	●	●
Burkina Faso	●	○
Burundi	●	○
Cabo Verde	●	●
Cambodia	○	○
Cameroon	●	●
Canada	●	●
Central African Republic	●	○
Chad	●	○
Chile	●	●
China	●	●
Colombia	●	●
Congo, Dem. Rep.	●	○
Congo, Rep.	●	○
Costa Rica	●	●
Cote d'Ivoire	●	○
Croatia	●	○
Cuba	●	●
Cyprus	●	●
Czech Republic	●	○
Denmark	●	●

Country	Pension type	
	Contributory	Non-contributory
Djibouti	●	○
Dominica	●	●
Dominican Republic	●	○
Ecuador	●	●
Egypt, Arab Rep.	●	●
El Salvador	●	●
Equatorial Guinea	●	○
Estonia	●	●
Eswatini	●	●
Ethiopia	●	●
Fiji	●	●
Finland	●	●
France	●	●
Gabon	●	○
Gambia, The	●	○
Georgia	●	●
Germany	●	●
Ghana	●	○
Gibraltar	○	○
Greece	●	●
Grenada	●	○
Guatemala	●	●
Guinea	●	○
Guinea-Bissau	●	○
Guyana	●	●
Haiti	●	●
Honduras	●	○
Hong Kong SAR, China	●	●
Hungary	●	○
Iceland	●	●
India	●	●
Indonesia	●	○
Iran, Islamic Rep.	●	○
Ireland	●	●
Isle of Man	●	●
Israel	●	●
Italy	●	●
Jamaica	●	●
Japan	●	○
Jordan	●	○
Kazakhstan	●	●
Kenya	●	●
Kiribati	●	●
Korea, Rep.	●	●
Kosovo	●	●
Kuwait	●	○
Kyrgyz Republic	●	●
Lao PDR	●	○
Latvia	●	●

Country	Pension type	
	Contributory	Non-contributory
Lebanon	●	○
Lesotho	○	●
Liberia	●	○
Libya	●	○
Liechtenstein	●	○
Lithuania	●	●
Luxembourg	●	○
Madagascar	●	○
Malawi	●	○
Malaysia	●	●
Maldives	●	●
Mali	●	○
Malta	●	●
Marshall Islands	●	○
Mauritania	●	○
Mauritius	●	●
Mexico	●	●
Micronesia, Fed. Sts.	●	○
Moldova	●	○
Monaco	●	○
Mongolia	●	●
Morocco	●	○
Mozambique	●	●
Myanmar	●	○
Namibia	●	●
Nepal	●	●
Netherlands	●	○
New Zealand	○	●
Nicaragua	●	○
Niger	●	○
Nigeria	●	○
North Macedonia	●	○
Norway	●	●
Oman	●	○
Pakistan	●	○
Palau	●	○
Panama	●	●
Papua New Guinea	●	○
Paraguay	●	●
Peru	●	●
Philippines	●	●
Poland	●	○
Portugal	●	●
Qatar	○	●
Romania	●	○
Russian Federation	●	●
Rwanda	●	○
Samoa	●	●
San Marino	●	○

Country	Pension type	
	Contributory	Non-contributory
Sao Tome and Principe	●	○
Saudi Arabia	●	○
Senegal	●	○
Serbia	●	○
Seychelles	●	●
Sierra Leone	●	○
Singapore	●	●
Slovak Republic	●	○
Slovenia	●	○
Solomon Islands	●	○
South Africa	○	●
Spain	●	●
Sri Lanka	●	○
St. Kitts and Nevis	●	●
St. Lucia	●	○
St. Vincent and the Grenadines	●	●
Sudan	●	○
Suriname	●	●
Sweden	●	●
Switzerland	●	○
Syrian Arab Republic	●	○
Taiwan, China	●	●
Tajikistan	●	●
Tanzania	●	○
Thailand	●	●
Timor-Leste	●	●
Togo	●	○
Tonga	●	○
Trinidad and Tobago	●	●
Tunisia	●	○
Turkey	●	●
Turkmenistan	●	●
Uganda	●	○
Ukraine	●	●
United Kingdom	●	●
United States	●	●
Uruguay	●	●
Uzbekistan	●	●
Vanuatu	●	○
Venezuela, RB	●	●
Vietnam	●	●
Yemen, Rep.	●	○
Zambia	●	○
Zimbabwe	●	○

Note: This table indicates the type(s) of pension systems each country has in place, if any. A black dot indicates that this country has the specific type of pension in place, and a white dot indicates that there is no such system in place. Sources: [International Social Security Association](#) (n.d.), [Social Security Administration](#) (n.d.) and [International Labour Organization, Social Protection Department](#) (2014).

References

- Administration for Children & Families.** 2022. “Temporary Assistance for Needy Families (TANF): Caseload Data - Fiscal Year (FY) 2022.” Type: dataset.
- Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A. Olken, Ririn Purnamasari, and Matthew Wai-Poi.** 2016. “Self-targeting: Evidence from a field experiment in Indonesia.” *Journal of Political Economy*, 124(2): 371–427. University of Chicago Press.
- Bailey, Sarah, and Francesca Ciardi.** 2020. “Shock-Responsive Social Protection in the Caribbean Belize Case Study.”
- Bastagli, Francesca, Jessica Hagen-Zanker, Luke Harman, Valentina Barca, Georgina Sturge, Tanja Schmidt, and Luca Pellerano.** 2016. “Cash transfers: what does the evidence say?” *Working Paper*, 1(7).
- Blattman, Christopher, Mathilde Emeriau, and Nathan Fiala.** 2018. “Do Anti-Poverty Programs Sway Voters? Experimental Evidence from Uganda.” *The Review of Economics and Statistics*, 100(5): 891–905.
- Brollo, Fernanda, Katja Kaufmann, and Eliana La Ferrara.** 2020. “The Political Economy of Program Enforcement: Evidence from Brazil.” *Journal of the European Economic Association*, 18(2): 750–791. Publisher: Oxford Academic.
- Buenos Aires Ciudad.** 2021. “Promedio mensual de personas beneficiarias del Programa Ciudadanía Porteña Con Todo Derecho por grupo de edad y por sexo. Ciudad de Buenos Aires. Años 2014/2021.”
- Bursztyn, Leonardo.** 2016. “Poverty and the Political Economy of Public Education Spending: Evidence from Brazil.” *Journal of the European Economic Association*, 14(5): 1101–1128.
- Camacho, Adriana, and Emily Conover.** 2011. “Manipulation of Social Program Eligibility.” *American Economic Journal: Economic Policy*, 3(2): 41–65.
- Center for Global Development.** n.d.. “Punjab’s Female School Stipend Program.”
- Chattopadhyay, Raghavendra, and Esther Duflo.** 2004. “Women as policy makers: Evidence from a randomized policy experiment in India.” *Econometrica*, 72(5): 1409–1443.
- Conover, Emily, Román A. Zárate, Adriana Camacho, and Javier E. Baez.** 2020. “Cash and Ballots: Conditional Transfers, Political Participation, and Voting Behavior.” *Economic Development and Cultural Change*, 68(2): 541–566. Publisher: The University of Chicago Press.
- De La O, Ana L.** 2013. “Do conditional cash transfers affect electoral behavior? Evidence from a randomized experiment in Mexico.” *American Journal of Political Science*, 57(1): 1–14. Publisher: Wiley Online Library.
- Drazen, Allan, and Marcela Eslava.** 2010. “Electoral manipulation via voter-friendly spending: Theory and evidence.” *Journal of development economics*, 92(1): 39–52.
- Fonds d’Intervention pour le Développement Madagascar.** 2020. “Filets Sociaux de Sécurité - 2019-2022.”
- Fujiwara, Thomas.** 2015. “Voting Technology, Political Responsiveness, and Infant Health: Evidence From Brazil.” *Econometrica*, 83(2): 423–464.
- Golden, Miriam, and Brian Min.** 2013. “Distributive Politics Around the World.” *Annual Review of Political Science*, 16(1): 73–99.
- Government of Pakistan.** n.d.. “Benazir Income Support Programme: Evaluation of the Waseela-e-Taleem Conditional Cash Transfer Programme 2016.”

- Hossain, Naomi.** 2020. “The Politics of Distributing Social Protection in Bangladesh: Insights From the Primary Education Stipends Project (Phase 3).” *ESID Working Paper*.
- IEG Review Team.** 2019. “Grenada - GD Safety Net Advancement.” World Bank Text/HTML ICRR0021747.
- Imai, Kosuke, Gary King, and Carlos Velasco Rivera.** 2020. “Do Nonpartisan Programmatic Policies Have Partisan Electoral Effects? Evidence from Two Large-Scale Experiments.” *The Journal of Politics*, 82(2): 714–730. Publisher: The University of Chicago Press.
- Instituto Mixto de Ayuda Social.** 2020. “En su primer año, Crecemos llega a más de 200 mil estudiantes de preescolar y primaria.”
- International Labour Organization, Social Protection Department.** 2014. “Social protection for older persons: Key policy trends and statistics.” ISSN: 1020-959X ISBN: 9789221292029.
- International Social Security Association.** n.d.. “Country profiles.”
- Kementerian Sosial Republik Indonesia.** 2019. “Program Keluarga Harapan (PKH).”
- Khemani, Stuti.** 2004. “Political cycles in a developing economy: effect of elections in the Indian states.” *Journal of development Economics*, 73(1): 125–154. Publisher: Elsevier.
- Kurdi, Sikandra, Yashodhan Ghorpade, and Hosam Ibrahim.** 2019. “The Cash for Nutrition Intervention in Yemen.” International Food Policy Research Institute Working Paper 19.
- Labonne, Julien.** 2013. “The local electoral impacts of conditional cash transfers: Evidence from a field experiment.” *Journal of Development Economics*, 104: 73–88.
- Lindert, Kathy, Anja Linder, Jason Hobbs, and Benedicte de la Briere.** 2005. “The nuts and bolts of Brazil’s bolsa familia program : implementing conditional cash transfers in a decentralized context.” World Bank Text/HTML.
- Manacorda, Marco, Edward Miguel, and Andrea Vigorito.** 2011. “Government Transfers and Political Support.” *American Economic Journal: Applied Economics*, 3(3): 1–28.
- Martínez, María Eugenia.** 2008. “Panes impactó en la subjetividad de los beneficiados.”
- Martins, Filomeno.** 2021. “Timor-Leste-Australia will sign an agreement on financial support for communities’ resilience efforts.”
- Mesa-Lago, Carmelo, and Mario De Franco.** 2009. “Estudio sobre la protección social en Centroamérica: Volumen I Informae General (El Salvador, Guatemala, Honduras y Nicaragua).”
- Ministère de l’Economie et des Finances et de la Réforme de l’Administration, and Ministère de l’Education nationale, du Préscolaire et des Sports.** 2022. “Evaluation des impacts social (EIS) du programme Tayssir.”
- Ministerio de Desarrollo Social.** 2009. “Programa Familias por la Inclusión Social.”
- Ministerio de Desarrollo Social.** 2019. “Cantidad de beneficiarios de Asignaciones Familiares, Plan de Equidad.” Type: dataset.
- Ministerio de Desarrollo Social.** 2021. “Bono Social benefició a más de 128 mil familias en 2020.”
- Ministerio de Economía y Finanzas Publicas.** 2018. “El Ministro de Economía entrega el Bono Juancito Pinto a 728 estudiantes del colegio María Ayma.”
- Ministerio de Educacion.** 2020. “Que crea el Programa de Asistencia Social Educativa Universal.”
- Ministerio de Salud y Deportes de Bolivia.** 2021. “Ministerio de Salud y Deportes inicia el pago del bono "Juana Azurduy" gestión 2021.”
- Ministry of Gender, Children and Social Protection.** n.d.. “Livelihood Empowerment Against Poverty (LEAP).”
- Ministry of Health and Family Welfare.** 2015. “Beneficiaries under Janani Suraksha Yojana.”
- Ministry of Labour and Social Security.** n.d.. “PATH.”
- Nordhaus, William D.** 1975. “The Political Business Cycle.” *The Review of Economic Studies*, 42(2): 169–190.
- Pande, Rohini.** 2003. “Can mandated political representation increase policy influence for disadvantaged minorities? Theory and evidence from India.” *American Economic Review*, 93(4): 1132–1151.
- Pop-Eleches, Cristian, and Grigore Pop-Eleches.** 2012. “Targeted government spending and political preferences.” *Quarterly Journal of Political Science*, 7(3): 285–320.
- Rodríguez, Lorena.** 2021. “ANSES: cuánto cobrarán los beneficiarios de AUH y AUE en septiembre con los nuevos aumentos.”

- Schubert, Bernd, Binahayati Rusyidi, Ajeng Purnama Pratiwi, and M. Akbar Halim.** 2015. “Rapid Assessment of the Child Social Welfare Program (PKSA).” UNICEF.
- Schurmann, Anna T.** 2009. “Review of the Bangladesh Female Secondary School Stipend Project Using a Social Exclusion Framework.” *Journal of Health, Population, and Nutrition*, 27(4): 505–517.
- socialprotection.org.** 2022*a*. “Aama Programme (Safe Motherhood Programme).”
- socialprotection.org.** 2022*b*. “Targeted Conditional Cash Transfer Program (TCCTP) (2005-) - Conditional Cash Transfer Programmes.”
- Social Security Administration.** n.d.. “Social Security Programs Throughout the World.”
- Tcherneva, Pavlina R.** 2012. “Beyond Full Employment: The Employer of Last Resort as an Institution for Change.”
- The Hindu.** 2021. “PMMVY beneficiaries cross 1.75 crore.” *The Hindu*.
- UNICEF Jordan.** 2019. “National Aid Fund Cash Transfer Pilot: Post Distribution Review.”
- United Nations Development Programme.** n.d.. “Progresa/Oportunidades: A conditional cash transfer programme.”
- United Nations Economic Commission for Latin America and the Caribbean.** n.d.*a*. “120 to 65: Special programme of economic assistance for the elderly (2009-).”
- United Nations Economic Commission for Latin America and the Caribbean.** n.d.*b*. “Conditional Subsidies for School Attendance (2005-2012).”
- United Nations Economic Commission for Latin America and the Caribbean.** n.d.*c*. “Desnutrición Cero (2011-).”
- United Nations Economic Commission for Latin America and the Caribbean.** n.d.*d*. “Programa Solidaridad (2005-2012).”
- Vargas, Luis Hernán, Pedro Cueva, and Nadin Medellín.** 2017. “¿Cómo funciona Ingreso Ético Familiar?: Mejores prácticas en la implementación de programas de transferencias monetarias condicionadas en América Latina y el Caribe.” BID.
- World Bank.** 2014. “Bangladesh: Incentivizing Secondary Education.”
- World Bank.** 2018*a*. “Myanmar - Decentralizing Funding to Schools Project : Additional Financing and Restructuring.”
- World Bank.** 2018*b*. *The State of Social Safety Nets 2018*. World Bank.
- World Bank.** 2020*a*. “Strengthening Conditional Cash Transfers and the Single Registry in Brazil: A Second-Generation Platform for Service Delivery for the Poor.”
- World Bank.** 2020*b*. “Takaful and Karama: A Social Safety Net project that Promotes Egyptian Women Empowerment and Human Capital.”
- World Bank.** 2021. “Population, total.”
- World Bank.** 2022*a*. “CG Rep. LISUNGI Safety Nets System Project - P145263.”
- World Bank.** 2022*b*. “Social Safety Net System Project II - P171125.”