Political Effects of the Expanded Child Tax Credit

Fighting Chance *for* Families *Action*

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Introduction

Since its launch in July, **Fighting Chance for Families Action**, a project of Data for Progress and Groundwork Collaborative, has tracked the political feedback effects of the monthly expanded Child Tax Credit (CTC). Our initial analysis found that CTC recipients were slightly more likely to approve of President Biden. This initial analysis provided preliminary evidence that the CTC confers some political advantage to the implementing party, in this case, the Democrats.

In this memo, we attempt to expand on this initial research. Our goal is to take a deeper look to identify what kind of political impact the CTC had if any.

To examine this, we built upon our previous analysis by using a two-stage estimation procedure. The basic idea is that we fit a model for Biden support using data only from polls taken shortly before the first CTC checks were sent. This establishes a baseline approval level based on demographic and partisan characteristics. In the second stage, we fit a model on polls taken after the introduction of the first checks, which uses the model score from the first stage as a feature along with the other effects we are interested in estimating.

Some Key Takeaways

- We find an initial CTC effect on Biden approval of roughly four percent among monthly CTC recipients. Over the duration of the expanded CTC program, Biden's overall approval dropped substantially, and the size of the CTC effect slipped somewhat as well, though to a much smaller extent.
- Most recipients credit Biden and Democrats for the check, though not all do. We also find that after receiving a check, recipients report higher subjective economic well-being and more optimism about the future.
- This could be connected to voters accurately recognizing Biden as a benefactor and supporting him for that reason, or voters feeling generally more at ease and more content with the current members of government and their future prospects, relative to similarly situated voters who did not receive a check. It's likely the case that a mix of both of these is at work.
- We also found that voters trust Democrats over Republicans to support parents with children. However, learning that Democrats allowed the expanded CTC to expire substantially reduces respondents' trust in Democrats on this issue. Conversely, telling respondents that Democrats would work to continue the program increases trust.

We also tested a second model, which included effects for the number of weeks that had passed since the last round of checks went out (an adjustment meant to help uncover if there are any repeating patterns that may exist within each check cycle). The second model suggests that, while on a month-to-month basis the movement in the CTC effect is fairly smooth, in the week following the issue of a check, the effect appears to tick up slightly. This is followed by a period of fast slippage before the effect ticks up again after the next round of checks go out.

While not massive, these effects are clear at the margins – which is extremely important in politics. This is particularly true of the expanded CTC, which is a case where the policy design features that have led to unambiguously successful policy outcomes such as reductions in child poverty appear to also be the key factor in maximizing the potential for positive political feedback.

Monthly checks give families financial stability because they're reliable. There's no need to wait for tax time to receive the money, and families can use the cash right away if they need to. This flexibility can be especially important if families experience changes in income due to loss of employment, illness, or whatever else life may throw at them, and it gives the program an extra poverty-fighting benefit.

At the same time, the checks give recipients a monthly dose of persuasive political messaging, which is not easy to replicate in the context of something like a campaign ad. Even better, if Republicans want to generate opposition to the CTC, they need to actively consume limited airtime and resources to do so. Republicans could certainly get their base of voters as well as some swing voters worked up with the usual tropes of "undeserving" people benefitting from the CTC, but there are other, more fruitful topics they could turn their outrage machine toward. On the other hand, the checks themselves and their persuasive effects remain on autopilot — provided that Congress can reinstate the program.

About the updated analysis

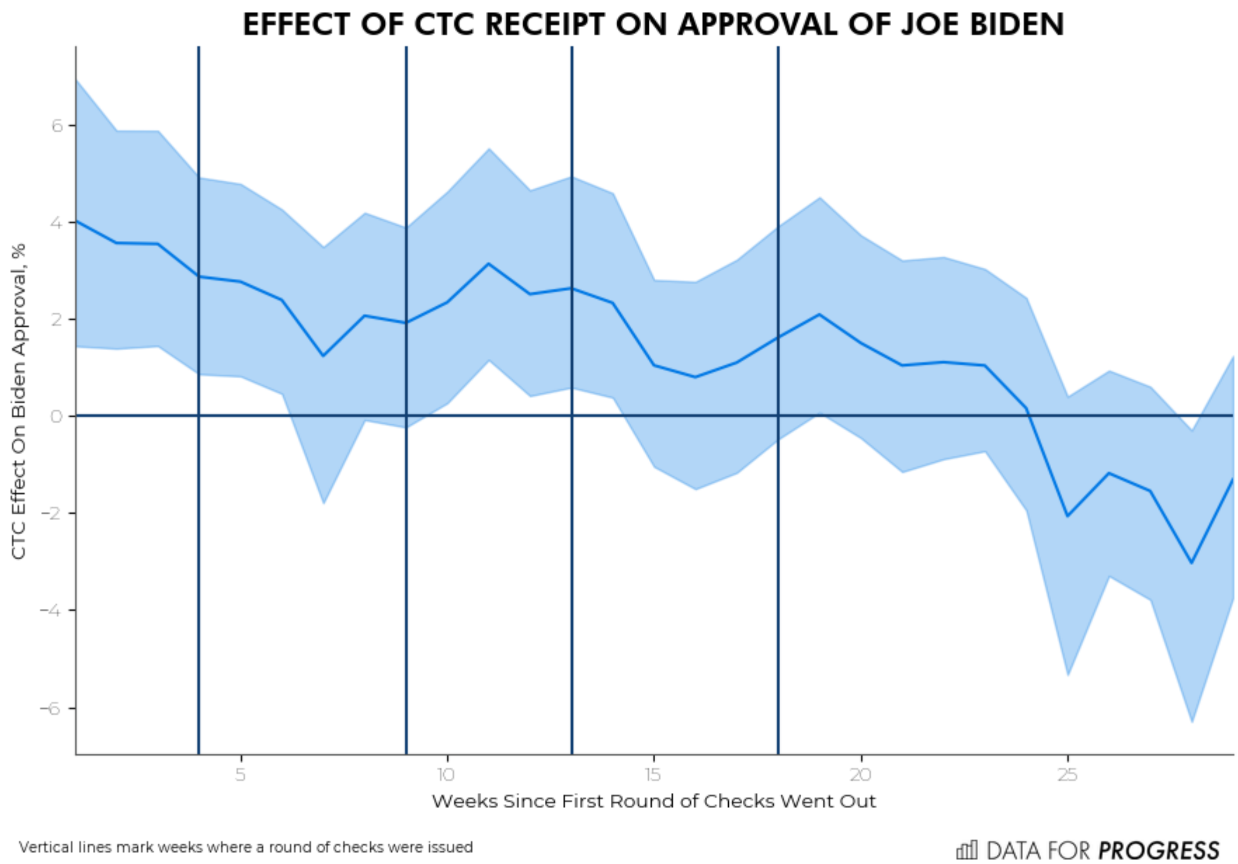
Since President Biden's inauguration, the concept of "feedback loops" and public policy have been invoked at regular intervals. This concept drawn from political science asserts that policy choices can shape public opinion. New attitudes among the public can either buttress or undermine shifts in policy.

In both quantitative and qualitative terms, our original analysis and the two-stage analysis are consistent with one another. However, the two-stage analysis makes it easier for us to improve the original analysis in two key ways. The first is that, since the first-stage score condenses a large number of control variables into a single number, we have a better chance at trying to unpack trends in effects over time, which otherwise would thin out the data too much for us to say much of anything. The second is that this helps us better discern between the effect of receiving a check from the effect of simply being a parent. These can be hard to separate since the overwhelming majority of parents are also recipients, which can introduce instabilities into the estimation procedure we used in our original analysis.

We have a few different options for looking at time trends in the CTC effect. The first option is to ignore time trends entirely and pool all of the post-CTC data together to estimate an effect. This is what we did in our initial analysis, and while it is sufficient to show a positive effect, we lose a lot of nuances when pooling the data together in this way. At the other extreme, we could run one independent model per each week's worth of data, or even for each individual poll. While this technically lets us keep information about time trends, it also thins out the data so much that it becomes hard to separate noisy poll-to-poll variation from real trends over time. This is especially difficult when we are dealing with small effect sizes, as is the case for the CTC.

As a compromise, we use a multilevel model to account for trends over time. In this way, the model does not discard information by ignoring time and pooling all the data together. The model can also make more efficient use of all the information available to help deal with the fact that we do not have enough data to reliably estimate effects from individual polls taken alone. In particular, we use a "random walk" specification, which helps smooth over time but does not impose excessively restrictive assumptions.

We find an initial CTC effect on Biden approval of roughly 4 percent (which again translates to less than a point overall since recipients make up a small part of the total voter population). Over the duration of the expanded CTC program, Biden's overall approval dropped substantially, and the size of the CTC effect slipped somewhat as well, though to a much smaller extent.



Comparing the two new models

Using standard model checking procedures, we can't say much about which model is better from an empirical perspective given the data available, and the bounce in the CTC effect after each check is likely to be small at best. Since it is less complex, we prefer the first model, but if you're interested in more information and discussion about these models, we've added more details in the addendum of this post.

Regardless of whether individual check effects exist, it seems likely that any CTC effect would have disappeared almost immediately had it not been designed with the monthly check structure of the current program. In fact, this is exactly what we see happen upon the expiration of the program earlier this year, where now-former CTC recipients approve of Biden at the same (or perhaps even lower) rate as similarly situated non-recipients.

From a previous analysis of state-level rollouts of the Earned Income Tax Credit, we can clearly see that designing policy to maximize the potential for durable political feedbacks is critical. Compared to the EITC, the CTC has a few advantages in this regard. CTC checks are easier to claim and reach more of the types of people that campaigns struggle to engage. They also reach people at all times of the year as opposed to just during tax or election season, which our analysis suggests is useful for increasing the salience of the program among recipients.

Over the long term, our best estimate is that potential feedbacks from the CTC will be marginal, but positive, which in light of the overwhelming success of the program from a policy perspective, should be more than enough for all Democrats to rally around reinstating the program.

Perhaps more importantly, allowing the program to expire is not politically cost-free for Democrats. A striking finding from the EITC study is that Republicans benefitted more than Democrats from implementing a state-level EITC program. The authors suggest that one explanation may be that voters generally do not see Republicans as being the party that helps low-income people, and so the implementation of an income support program prompts voters to update this view and start to see Republicans more favorably. If Democrats can not maintain credibility as the party that helps ordinary people, then they lose their most powerful advantage over Republicans. But maintaining this credibility can not come from rhetoric alone, but must come from governing effectively and actually delivering from the members of their coalition.

Reinstating the expanded CTC would restore a much-needed lifeline that would help millions of families live the life they deserve — and help Democrats hold their place as the party that looks out for parents with young children.

Methodological Note

To estimate the impact of receipt of expanded Child Tax Credit checks on Biden favorability, we use a two-stage estimation procedure. In the first stage, we train a model for Biden favorability on data collected shortly before July 15, 2021, when the first CTC checks were issued. This is an L1 regularized linear model which accounts for factors such as self-reported partisanship scale, which includes leaners, education, income, race, age, parental status, and gender. In both stages, we code respondents who said they are somewhat or strongly favorable of Biden as a 1, and code respondents who are somewhat unfavorable, strongly unfavorable, or don't know as 0.

In the second stage, we use data collected in the weeks after July 15 to estimate the effect of receipt of the expanded credit. We use a linear model of probability as an estimating equation and consider four different specifications for handling effects in time, but each one roughly follows this format

$$\textbf{Biden\_favorability} \sim \alpha_{intercept} + \alpha_{score}\,score + \alpha_{check}\,gotCheck$$

Score is the model score from the first stage, which accounts for the patterns in Biden favorability which existed before checks were sent; gotCheck is a binary flag for if the respondent reported getting a check.

The details of the different specifications for handling time are given below.

FULLY POOLED MODEL

In this model we pool all the post-check data together and do not consider any heterogeneity in time. We have

$$\boldsymbol{\mu} \sim \alpha_{intercept} + \alpha_{score}\,score + \alpha_{check}\,gotCheck$$

$$\textbf{Biden\_favorability} \sim \mathrm{Normal}(\mu,\sigma)$$

Where each coefficient is drawn from independent Normal(0,2) distributions

UNPOOLED MODEL

Here we consider independent regressions for each time period t.

$$\boldsymbol{\mu}_t \sim \alpha_{intercept.\,t} + \alpha_{score,\,t}\,score + \alpha_{check,\,t}\,gotCheck$$

$$\textbf{Biden\_favorability} \sim \mathrm{Normal}(\mu_t,\sigma)$$

Where again each coefficient is drawn from independent Normal(0,2) distributions

PARTIALLY POOLED MODEL WITH RANDOM WALK

Our final specification uses a random walk instead of a linear trend to account for changes over time. We have

$$\boldsymbol{\mu}_t \sim \alpha_{intercept.\,t} + \alpha_{score,\,t}\,score + \alpha_{check,\,t}\,gotCheck$$

$$\textbf{Biden\_favorability} \sim \mathrm{Normal}(\mu_t,\sigma)$$

Where the coefficients are now drawn from

$$\alpha_{i,t} \sim \mathrm{Normal}(\mu_{i,t-1},\sigma_i)$$

$$\sigma_{i,t} \sim \mathrm{HalfNormal}(0,1)$$

PARTIALLY POOLED MODEL WITH LINEAR TIME TREND AND EFFECTS FOR WEEKS SINCE LAST CHECK

This model adds an additional component to the time trend, which accounts for the number of weeks which have passed since the last check went out, in addition to the random walk. The effect of weeks since the last check does not appear to be well captured by a linear term, which makes sense since there is a bit of a lag between the checks hitting and approval ticking up. For this reason, we use discrete random effects to account for weeks since the last check.

$$\boldsymbol{\mu}_t \sim \alpha_{intercept.\,t} + \alpha_{score,\,t}\,score + \alpha_{check,\,t}\,gotCheck$$

$$\textbf{Biden\_favorability} \sim \text{Normal}(\mu_t, \sigma)$$

Where the coefficients are now drawn from

$$\alpha_{i,t} \sim \text{Normal}(\alpha_{i,t-1} + \gamma_{i,weeksSince}, \sigma_i)$$

$$\sigma_i \sim \text{HalfNormal}(0,1)$$

$$\gamma_{i,weeksSince} \sim \text{Normal}(0, \sigma_{weeksSince})$$

$$\sigma_{weeksSince} \sim \text{HalfNormal}(0,1)$$

Model Comparison

Below we show a model comparison, which uses an information criterion to estimate the expected out-of-sample performance of each model. It combines how well the model fits the data with a penalty term for model complexity. By this method, the two random walk models are the best but are not distinguishable from one another in an empirically meaningful sense. The fully unpooled model has the highest in-sample predictive accuracy, but faces a large penalty due to model complexity, implying that it may be overfitting the data. The fully pooled model is essentially the reverse of this, where it has low in-sample accuracy but only a small complexity penalty since it is the simplest model possible.

	Rank	LOO Score	LOO Penalty
Random Walk w/ Weeks Since Last Check Effects	1	-18719	36
Random Walk	2	-18723	33
Fully Unpooled	3	-18746	93
Fully Pooled	4	-18842	5