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White Paper
The Effect of the 2021 American Rescue Plan's Child Tax Credit on Labor Supply

Background

Under the Biden-Harris Administration, the American Rescue Plan Act of 2021 (ARP) significantly expanded the Child Tax Credit (CTC) compared to its previous revisions (H.R.1319 - 117th Congress, 2021). Exclusively for tax year 2021, the CTC was expanded to a maximum of $3,600 for each child under 6 and $3,000 for children between the ages of 6 and 16. The credit was also made fully refundable, meaning it could be claimed even if a taxpayer had no earned income or didn't owe any taxes. Additionally, for the first time in the credit's history, eligible families could receive half of their 2021 credit through monthly advance payments from July to December of 2021, rather than waiting to claim the full amount during tax filing season in early 2022. In comparison, the version of the CTC under the 2017 Tax Cuts and Jobs Act (TCJA) offered a maximum credit of $2,000 per child under 17, was only partially refundable (with a maximum refund of $1,400 per child), and required at least $2,500 in earned income to qualify.

Since the expiration of the expansion in 2022, debate has raged on the appropriateness of how generous to make the credit. Yet, there exists major skepticism and doubt about the true effect on labor supply surrounding a more generous provision of the CTC. For example, in a 2024 American Enterprise Institute analysis, it is suggested that nearly 702,000 consistently employed parents might decide to stop working every other year if the annual income requirement for the CTC is removed, with 69% of these parents being single mothers. Conversely, the analysis finds that around 395,000 parents who previously weren't working could enter the workforce every other year due to this policy change (Corinth, et al., 2024). The policy implication, specifically the effect on labor supply by a more generous CTC, is becoming more and more increasingly relevant, especially in an election year. In the most recent Presidential election, the Democratic nominee, Vice President Kamala Harris, announced a proposal to expand the CTC, which would provide families with newborns a $6,000 credit (Peck, 2024), while also advocating for the permanent extension of the ARP expansion. Meanwhile, the then-Republican vice-presidential nominee and Ohio Senator JD Vance suggested a general increase, supporting a $5,000 CTC for families (Picchi, 2024). The purpose of this paper will be to conduct an inference analysis, in which I will explore whether the CTC provisions of the ARP had any significant negative effects on labor supply.

Data

To better understand how the generous provisions of the ARP CTC affected labor supply, I'll require a dataset that provides demographic and employment-related information to determine whether individuals are employed and how many hours they reported working week to week. For this analysis, I plan to use cross-sectional data from the Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC) for the year 2022, reflecting data from 2021 (IPUMS CPS, n.d.). This dataset is a goldmine of high-quality microdata that includes U.S. households' demographic, employment, and income data. After cleaning and filtering the dataset, I am left with exactly 73,713 observations. The target variable of this analysis will be weekly hours worked, which is a continuous numerical variable representing the total number of hours an individual worked in a given week. This will serve as a proxy for labor supply. The primary feature variable of this analysis will be the Additional Child Tax Credit (ACTC) amount, that is, the refundable amount of the CTC. I also include several other features for context. Age is significant due to how it may influence both employment status and the number of hours worked, as younger individuals and retirees tend to work fewer hours. The Earned Income Tax Credit (EITC) amount is also relevant for the fact that it targets low-income workers, and its interaction with the ACTC may help explain changes in labor supply. Additionally, I include self-reported health status and physical limitations as they can affect individuals' ability to work, providing a fuller picture of how these factors might interact with the effects of the ACTC on labor supply. However, it's important to acknowledge some limitations of this dataset. First, the CPS does not clarify whether the ACTC amount refers to (1) the entire refundable amount for tax year 2021, or (2) only half of the remaining amount after the six-month disbursement period from July to December 2021. This is because the CPS, even in its basic monthly survey, does not include a variable indicating receipt of the Child Tax Credit during these months.

Table 1: Definitions of variables

Variables	**Definitions**
Target	
Hours Worked *(UHRSWORKLY)*	This variable indicates the average number of hours per week that individuals worked in the previous year, including both full-time and part-time work, as well as temporary or seasonal jobs. Respondents who reported any form of employment during the past year were asked to provide this information
Features	
Additional Child Tax Credit Amount *(ACTCCRD)*	This variable represents the amount of the Additional Child Tax Credit that a respondent received. The Additional Child Tax Credit is available to individuals whose Child Tax Credit exceeds their tax liability
Receipt of ACTC *(CTCCRD_dummy)*	A binary variable indicating whether the respondent received the Additional Child Tax Credit, with "1" denoting receipt and "0" denoting non-receipt

EITC Amount *(EITCRED)*	This variable shows the amount of the Earned Income Tax Credit received by an individual or couple. The Earned Income Tax Credit is a refundable tax credit aimed at reducing tax obligations for low- and moderate-income workers, often serving as a wage subsidy. If the credit exceeds the owed tax, the excess amount is given as a cash refund
Health Status *(HEALTH)*	This variable captures how individuals rate their health, categorized into five options: excellent, very good, good, fair, or poor
Disability-Related Work Limitation *(DIFFANY)*	This binary variable identifies individuals who report having a health issue or disability that either prevents them from working or limits the type and amount of work they can do.

Methodology

To explore the relationship between the ACTC amount and weekly hours worked, I will utilize both parametric and non-parametric techniques. The parametric technique chosen is linear regression. Linear regression is appropriate here for the reason that it provides a straightforward method to estimate the average effect of ACTC amount on weekly hours worked as a numerical outcome. The intuition behind linear regression is that it estimates the change in the target, weekly hours worked, as a result of a change in the predictor variable, the ACTC amount, assuming that the effect is constant across the sample. For the non-parametric approach, I will use a decision tree classifier. Decision trees are effective because they split the data into smaller, more homogeneous groups based on key features, making them an intuitive and visually clear method for identifying patterns. However, a limitation of decision trees is that they can overfit the training data, meaning they might perform well on the data they were trained on but poorly on new, unseen data. Additionally, if one group is much larger than others, the tree can become biased toward that group. To address these issues, I've binned the weekly hours worked variable into three categories: 0-40, 41-80, and 81-100 hours worked. This converts the continuous variable into categorical data, which helps improve the decision tree model's performance. Additionally, I've set a maximum depth of 5 for the tree to prevent it from becoming too complex and overfitting. After training the model, I will evaluate its performance on both the training and test datasets

Both models align with the research question and the target variable. As mentioned previously, the target variable, weekly hours worked, is continuous and numerical; thus, linear regression is the most appropriate method for estimating the average effect of the ACTC amount on weekly hours worked. However, decision trees will be used to capture a potentially more complex, non-linear relationship between the ACTC amount and hours worked. This non-parametric method does not assume a specific relationship between variables, which allows it to identify patterns that linear regression might miss. While decision trees offer greater flexibility, they also carry the risk of overfitting the data, but they can provide deeper insights into how various factors interact with each other.

a. Literature review of each technique

Linear regression is a widely used approach for indicating the value of a dependent variable based on one or more independent variables. This model fits a linear equation that minimizes the discrepancies between predicted and actual values, providing a straightforward way to estimate relationships and generate predictions (IBM, n.d.). Linear regression is particularly valuable for its interpretability across multiple fields, from business and insurance to social and natural sciences. A prime example of a decision tree model is provided by Gathergood et al. (2019), who explore how individuals allocate debt repayments across multiple credit cards. In their research, decision trees are leveraged to model repayment behavior, providing insight into how factors like card balances and limits predict repayment allocation. Although a decision tree may capture complex patterns, the authors note that these models can sometimes overfit data, highlighting the importance of careful tuning. This study demonstrates the utility of decision trees for examining financial decision-making patterns, particularly when the aim is to identify behavioral tendencies within heterogeneous populations.

Results

The linear regression model, which estimates the average effect of the ACTC amount on hours worked, returned a set of coefficients that are quite insightful. The coefficient for the ACTC amount is 0.000026, indicating an incredibly small, if not negligible, relationship with hours worked. Interestingly, the coefficient for the ACTC receipt indicator is 2.408579, suggesting a positive association between just receiving an ACTC and the number of weekly hours worked. Specifically, those who received an ACTC worked, on average, about 2.41 more hours per week than those who did not. For the EITC amount received, the coefficient is -0.001694, indicating a very slight negative relationship with weekly hours worked. While this effect is small, it suggests that individuals receiving the EITC might work slightly fewer hours. Other coefficients highlight the influence of demographic factors on labor supply. The coefficient for age is 0.036138, showing a positive relationship between age and hours worked, with older individuals tending to work slightly more hours per week. As for health, the coefficient is -0.270331, indicating that individuals who report worse health tend to work fewer hours. Similarly, the coefficient for physical limitations is -2.687206, revealing that, to no surprise, individuals with physical limitations work significantly fewer hours on average, about 2.69 fewer hours per week compared to those without such limitations. However, for the linear regression model, the performance on both the training and test datasets was evaluated using the R^2 score, which indicates how well the model explains the variance in the outcome variable. The training data R^2 score was 0.026, and the test data R^2 score was 0.025. These low R^2 values suggest that the model is only explaining a particularly small portion of the variance in weekly hours worked. This implies that while the model identifies a relationship between the ACTC amount and weekly hours worked, other unaccounted factors may be influencing labor supply, and the model is not capturing these influences effectively. For the decision tree classifier, which I used to capture more complex, non-linear relationships, the model performed reasonably well. After training, the decision tree classifier showed a training accuracy of 78.28% and a test accuracy of 78.05%. These results demonstrate that the model is generalizing well, with minimal overfitting. While decision trees offer flexibility in capturing non-linear patterns, the relatively high performance suggests that the decision tree was able to identify key segments of the data where the ACTC amount has a stronger effect on labor supply.

The results from the linear regression model show a very weak, almost negligible, association between the ACTC amount and weekly hours worked. As illustrated in **Graph 1**, the coefficient for the ACTC amount is very small, suggesting that the relationship, if any, is minimal if not negligible. This indicates that the expansion of the broader CTC may not have had a significant direct impact on labor supply in 2021. Moving on to the decision tree classifier shown in **Graph 2**, which is built with a maximum depth of 5, the model categorizes individuals into different hour-worked groups based on features such as ACTC amount, age, EITC amount, and health status. The most important feature in the tree is the EITC amount, which forms the primary split. Age and ACTC amount follow as secondary splits, refining the classifications further. Health status plays a minor role in the tree, suggesting that health does not significantly influence labor supply in this dataset. However, the feature importance plot, illustrated in **Graph 2(b),** highlights that age is actually the most influential factor, followed by EITC and ACTC amounts. Other features, such as the binary indicator for receiving the ACTC, health status, and disability-related limitations, have relatively low importance, indicating a smaller effect on the model's predictions. The validation curve for the decision tree classifier, shown in **Graph 2(c)**, indicates that the model's performance declines as the maximum depth increases. This suggests that deeper trees are overfitting to the data. A depth range of 5-10 would likely be optimal, striking a balance between underfitting and overfitting. Finally, the learning curve for the decision tree classifier, illustrated in **Graph 2(d)** shows that the training score remains high as the training size increases, while the cross-validation score plateaus. This pattern again points to overfitting, meaning the model is learning noise from the training data rather than the underlying trends in the data.

Interpretation

In this analysis, I examined the effects of the expanded 2021 CTC on labor supply, specifically on weekly hours worked. Through the application of both linear regression and decision tree models, I explored how the ACTC amount, along with other demographic and employment-related factors, interacted to influence labor supply. The results from the linear regression model showed a minimal and statistically inconsequential relationship between the ACTC amount and weekly hours worked, suggesting that the expanded CTC may not have had a substantial direct effect on labor supply. On the other hand, the decision tree model highlighted a more complex pattern, showing that while ACTC amount had some effect on labor supply, factors such as age, and the EITC amount played a more prominent role in predicting hours worked. Overall, while the data indicates some positive effects on labor supply for those receiving the ACTC, it also suggests that other variables, like age, health status, and the EITC, are more influential in shaping individuals' work behavior. However, given the limitations of the data and the modeling techniques used, further research is required to better understand how policies like the ARP CTC expansion impact employment dynamics.

Appendix

Table 2: Descriptive Statistics - Feature Variables

Variables	*Mean*	*Std. Dev.*	*Min*	*Max*	*Skew*	*Kurt*
UHRSWORKLY *(Reported Hours Worked Weekly)*	*39.14*	*10.99*	*1*	*99*	*-0.13*	*3.53*

*Notes. The variable **UHRSWORKLY** represents the usual hours worked per week in the last year. A value of 99 indicates individuals who reported working **99 hours or more**. This coding is consistent with the **IPUMS Current Population Survey (CPS)** dataset documentation.*

Table 2(b): Descriptive Statistics - Feature Variables

Variables	*Mean*	*Std. Dev.*	*Min*	*Max*	*Skew*	*Kurt*
ACTCCRD *(Additional Child Tax Credit Amount)*	*1,201*	*2674*	*1*	*37,800*	*2.74*	*9.37*
EITCRED *(Earned Income Tax Credit Amount)*	*271.127*	*912.70*	*0*	*6728*	*4.41*	*21.10*
HEALTH	*2.14*	*0.93*	*1*	*5*	*0.46*	*-0.30*
AGE	*43.10*	*14.32*	*18*	*85*	*0.25*	*-0.70*

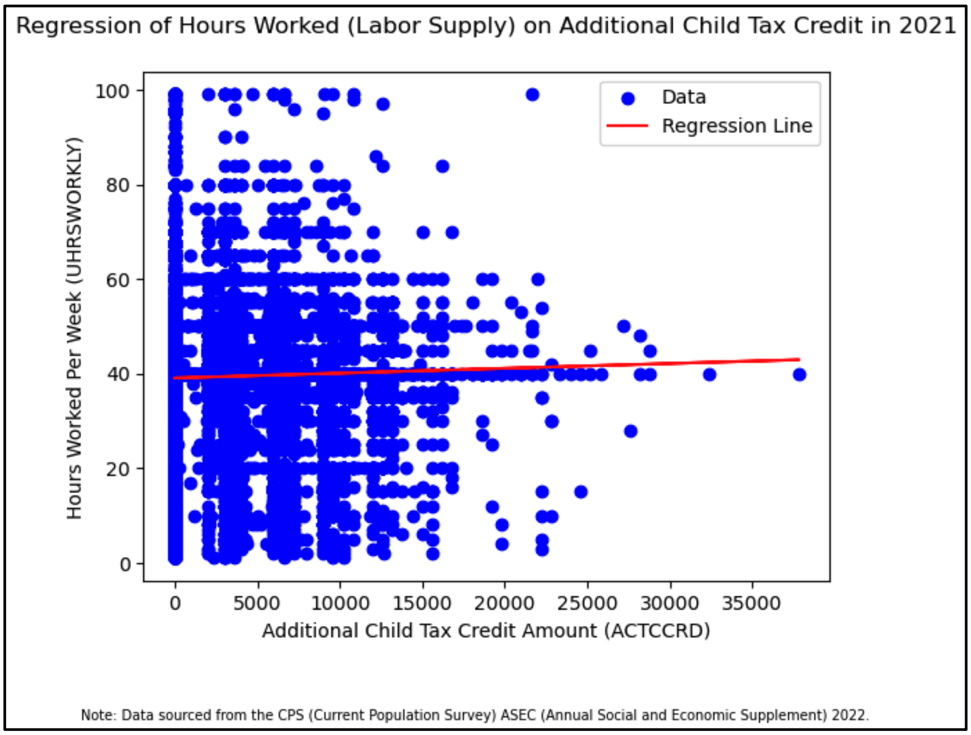
Table 2(c): Descriptive Statistics - Feature Binary Variable: Receipt of Additional Child Tax Credit

Variable ***ACTCCRD*** *(Receipt and use of Additional Child Tax Credit)*	***Frequency*** ***(n)***	***Percentage*** ***(%)***
Yes	*16,492*	*22.23*
No	*57,691*	*77.77*

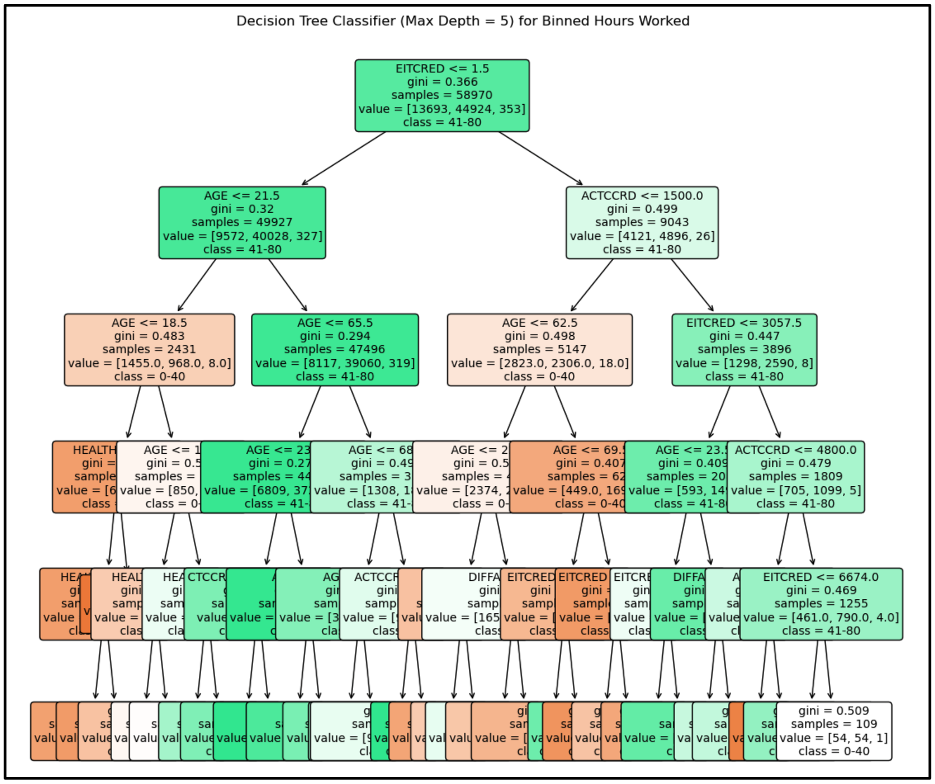
Table 2(d): Descriptive Statistics - Feature Binary Variable: Disability-Related Work Limitation

Variable ***DIFFANY*** *(Disability-Related Work Limitation)*	***Frequency*** ***(n)***	***Percentage*** ***(%)***
Yes	*3,625*	*4.92*
No	*70,088*	*95.08*

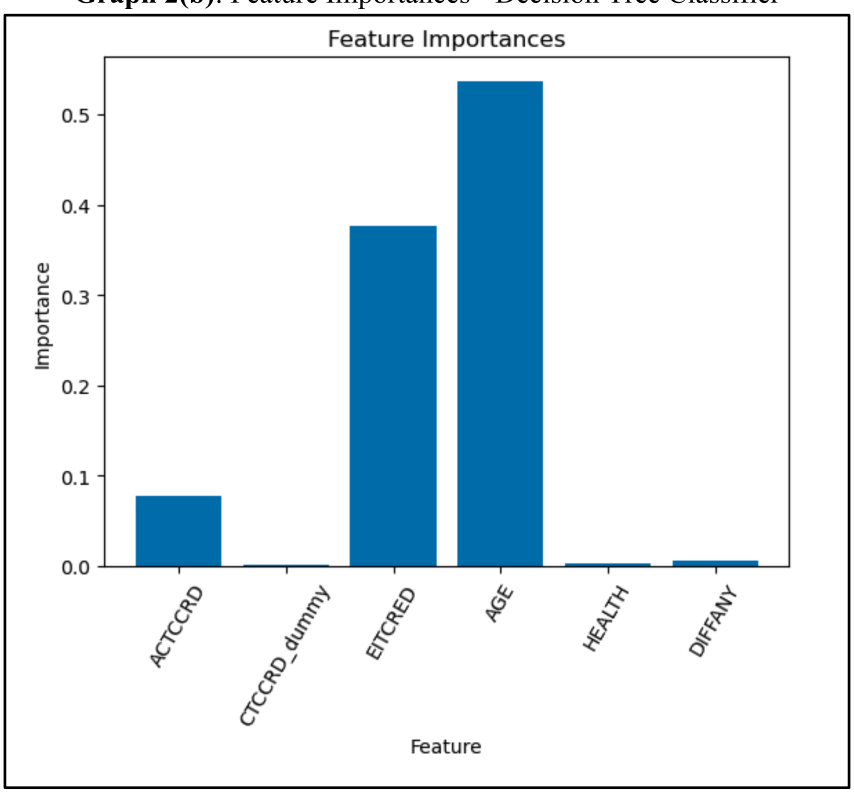
Graph 1: Regression of Hours Worked on Additional Child Tax Credit Amount



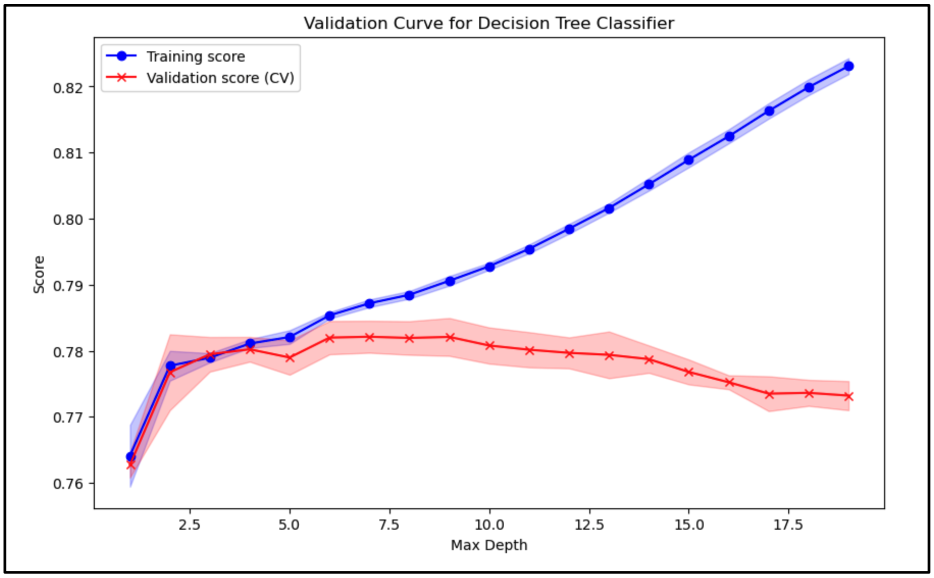
Graph 2: Decision Tree Classifier



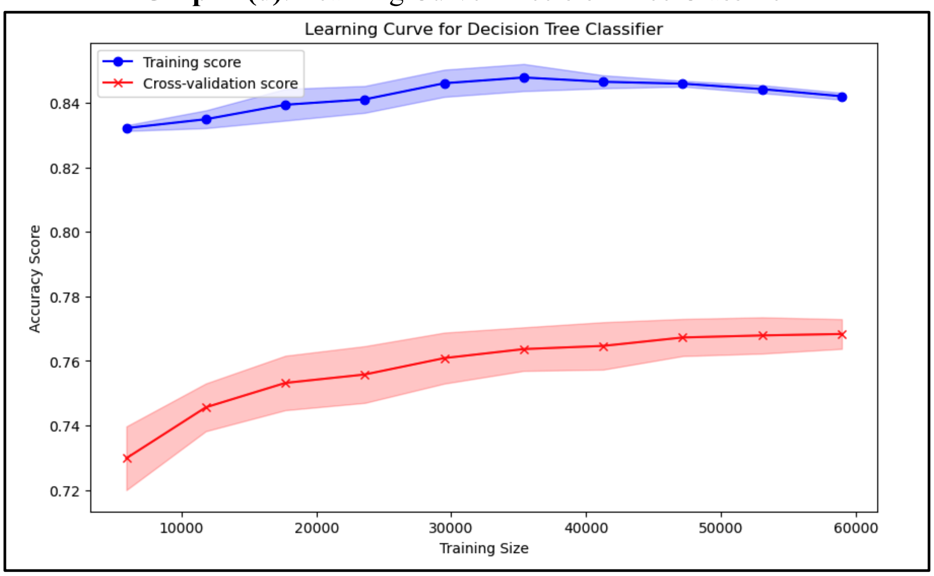
Graph 2(b): Feature Importances - Decision Tree Classifier



Graph 2(c): Validation Curve - Decision Tree Classifier



Graph 2(d): Learning Curve - Decision Tree Classifier



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