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APPENDIX

SUPPLEMENTAL METHODS

Difference-in-difference-in-differences Analysis

The equation for the difference-in-difference-in-differences (DDD) model is:

$$
\begin{aligned}
Y_i = \alpha + \beta_1 Post_i x\ Children_i x\ Lowincome_i + \beta_2 Children_i x\ Lowincome_i \\
+ \beta_3 Children_i x\ Post_i + \beta_4 Lowincome_i x\ Post_i \\
+ \beta_5 Children_i + \beta_6 Post_i + \beta_7 Lowincome_i + \beta_8 Covars_i + \beta_9 Week_i + \varepsilon_i
\end{aligned}
$$

Y represents a mental health outcome of interest for each individual i. The variable $Children$ indicates whether households include children under 18. The variable $Post$ indicates whether the observation was recorded after Child Tax Credit (CTC) payments began in July 2021.

$Lowincome$ indicates whether the total household income is less than \$150,000 for married respondents and less than \$100,000 for non-married respondents. While the actual eligibility cutoff for non-married respondents (i.e., head of household filing status) was \$112,500, the income categories available in HPS do not allow us to create more fine-grained categories. We included all two-way and three-way interactions between these three variables. $Covars$ represents individual-level covariates described in the main text, and $Week$ represents fixed effects for week of survey completion. The coefficient of interest is β_1, on the triple-interaction term, which represents the effect of the policy on low-income families with children. As is standard in difference-in-differences (DID) analyses, we used linear models for both continuous and binary outcomes, since interaction terms have different interpretations in non-linear models.(1) For binary outcomes, analyses therefore represent linear probability models, and the coefficient can be interpreted as the percentage point change in risk.

Our analysis did not include survey weights, since the appropriateness of weights is diminished when adjusting for variables related to the sampling strategy and when the goal of modeling is causal inference rather than descriptive population characteristics (2).

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Model Assumptions

DID models rely on several assumptions. The first is that, in the absence of treatment, no differences in the trends in outcomes would exist between the treated and control groups. For example, one possible violation of this assumption may stem from the fact that the reference period for the GAD-2 and PHQ-2 questions shifted from the "last 7 days" in phase 3.1 of the survey (weeks prior to July 5, 2021) to the "last 2 weeks" in phase 3.2 (weeks after July 21, 2021). This may lead to a change in the percent of people who answer affirmatively to these questions from the pre- to the post-period, although such changes may also be due to other outside societal factors, e.g., related to pandemic-related stressors. As long as this change is non-differential between the treatment and control groups (a key assumption of DID analyses), this should not lead to bias in our estimates, since a DID design is ideally suited to subtracting out secular trends in the outcomes using the control group as a reference. Also, the order of the questions also changed during phase 3.2, which might lead to different non-response patterns. Reassuringly, we found that average rates of missingness for all of the model covariates differed by <1% between phases 3.1 and 3.2, and they differed by < 0.1% for the outcomes in particular. Nevertheless, the findings should be interpreted with caution.

Also, while this counterfactual scenario fundamentally cannot be tested, we can examine whether the control group is an adequate comparator by examining whether trends in the outcomes during the pre-expansion period were similar (i.e., the "parallel trends" assumption). To do so, we first qualitatively assessed trends by plotting the trends for adults with versus without children during the pre-expansion period. For both primary and secondary outcomes, the graphs illustrated parallel trends during these months for most outcomes. Mental health prescription medication was the only exception; regression results related to this outcome should therefore be interpreted cautiously. We also performed a quantitative evaluation of the validity of the parallel trends assumption by restricting the data to the pre-period and regressing each outcome on an interaction term between adults with versus without children and a continuous variable for time. In these tests, all coefficients were very small (Appendix Exhibit A2). While the estimates for several secondary outcomes were statistically significantly different from zero, indicating possible violations of this assumption, this may be because of the large sample size, and the small coefficient sizes provide somewhat reassuring evidence that this assumption is met.

Another assumption is that there are no differential compositional changes in the treatment and control groups. For example, despite its random sampling procedure, HPS may have inadvertently selected respondents with different characteristics in different survey waves. Alternately, by shifting the order of the GAD-2 and PHQ-2 questions in the redesign of the phase 3.2 questionnaire, this may have affected the characteristics of the sample receiving these questions due to increasing drop-out from the survey as the questionnaire progresses. To evaluate this assumption, we conducted a balance test, which is a similar analysis as the primary analysis above, but in which each sociodemographic characteristic was the dependent variable on the left-hand side of the model. A null result for these regressions would suggest that there were no differential pre-post changes in composition among the adults with versus without children. There were statistically significant differences in a handful of sociodemographic characteristics (e.g., gender, marital status) (Appendix Exhibit A3). This may mean that HPS unintentionally interviewed participants of different sociodemographic backgrounds across different waves, although again, these coefficients were very small and may be statistically significant due to the large sample size. We controlled for all these variables in our analyses to account for potential confounding, but cannot rule out differences in unmeasured confounders, a limitation of any DID analysis.

Missingness

In our sample restricted to those with responses on the mental health outcomes of interest, missingness for each variable was less than 1%, with the exception of income, which was missing 10.9% of values. We therefore conducted a sensitivity analysis employing multiple imputation using chained equations (MICE) using the *mi* package in Stata to impute missing covariates. The MICE method does not require that variables be normally distributed, allowing us to include a variety of different variable types (e.g., categorical, binary). We assumed that data were missing at random rather that missing completely at random (3). All variables from the main models (including the outcomes) were included in the imputation models, in order to improve the prediction of income. We did not use imputed values of the outcome variables in our analyses, however, as this is likely to add noise to subsequent estimates (4). We produced 30 imputed data sets, which is a sufficient number to reduce sampling variability from the imputation process (5).

Sample Definition

Notably, HPS asks participants whether there are individuals under 18 in their households, but not whether these are their own children or dependents. Regardless, these children's caregivers or parents are likely to also be members of the household, such that the respondent may have benefited from increased household income, even if the children were not theirs. Since we cannot confirm that respondents are themselves parents, throughout this manuscript we therefore refer to them as "adults with children."

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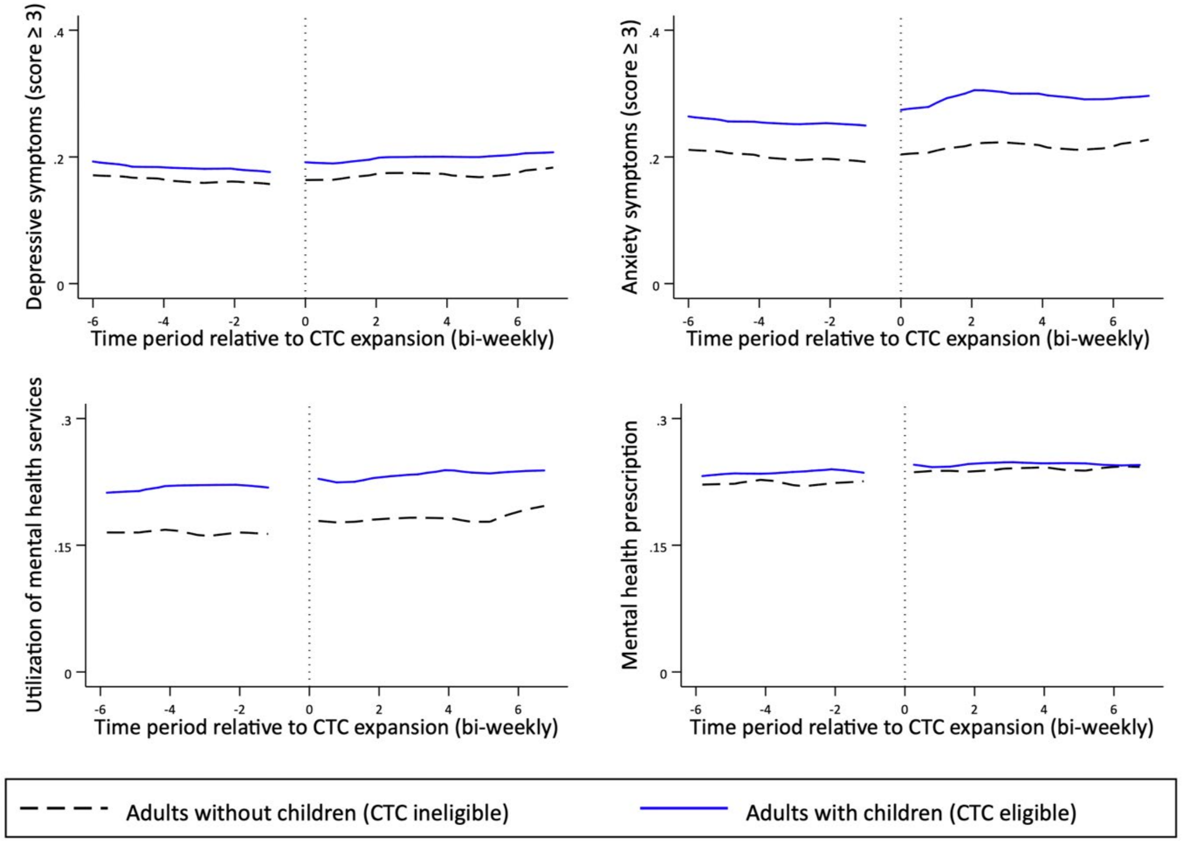
Appendix Exhibit A1
Caption: Qualitative evaluation of parallel trends assumption



Source: Author's analysis of data from U.S. Census Household Pulse Survey, bi-weekly waves from April 14, 2021 – January 10, 2022.
Notes: The vertical dotted line represents the first payment of the expanded Child Tax Credit (July 15, 2021).

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Appendix Exhibit A2
Caption: Quantitative evaluation of parallel trends assumption for primary outcomes

	Mental health and healthcare utilization outcomes			
	Depressive symptoms	**Anxiety symptoms**	**Utilization of mental health services**	**Mental health prescription**
Coefficient	0.001	-0.000	-0.001	-0.000
[95% CI]	[-0.001, 0.003]	[-0.002, 0.001]	[-0.003, 0.000]	[-0.002, 0.001]
(p-value)	(0.54)	(0.70)	(0.09)	(0.62)
Observations	309,010	309,124	308,810	309,199

Source: Authors' analysis of data from U.S. Census Household Pulse Survey
Note: **p < 0.01, *p<0.05. For the purposes of this analysis, the data set was restricted to the pre-expansion period. Coefficients are derived from models in which the primary exposure is an interaction term between a binary variable representing adults with (versus without) children and a continuous variable for time.

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Appendix Exhibit A3
Caption: Evaluation of differential compositional changes in treatment and control groups

	Coefficient [95% CI] (p-value)
Age	0.285** [0.157, 0.412] (<0.001)
Male	-0.009** [-0.013, -0.005] (<0.001)
Marital Status	
Married	0.005* [0.001, 0.009] (0.02)
Separated	0.003 [-0.001, 0.007] [0.105]
Never married	-0.008** [-0.012, -0.005] (<0.001)
Less than high school or high school	-0.001 [-0.004, 0.002] (0.42)
Race/Ethnicity	
Non-Hispanic White	0.000 [-0.004, 0.004] (0.92)
Non-Hispanic Black	0.002 [-0.000, 0.005] (0.05)
Hispanic	-0.002 [-0.004, 0.001] (0.15)
Asian	-0.003** [-0.005, -0.001] (0.003)
Other	0.002 [-0.000, 0.003] (0.08)
Income	
Less than $25,000	-0.004** [-0.008, -0.001] (0.005)
$25,000 - $34,999	-0.006** [-0.008, -0.003] (<0.001)
$35,000 - $49,999	-0.004* [-0.007, -0.001] (0.01)

\$50,000 - \$74,999	-0.001 [-0.004, 0.003] (0.76)
\$75,000 - \$99,999	0.001 [-0.003, 0.004] (0.63)
\$100,000 - \$149,999	0.006** [0.002, 0.009] (0.005)
\$150,000 - \$199,999	0.008** [0.005, 0.011] (<0.001)
\$200,000 and above	0.000 [-0.003, 0.003] (0.87)

Source: Authors' analysis of data from U.S. Census Household Pulse Survey
Note: **p < 0.01, *p<0.05. Coefficients are derived from models in which the primary exposure is an interaction term between a binary variable for adults with (versus without) children and an indicator for whether the interview occurred after (versus before) the CTC expansion. The models examine whether differential compositional differences exist in the demographic characteristics of adults with and without children. A null result would indicate that there are no differential compositional changes in the treatment and control groups over time for a given covariate.

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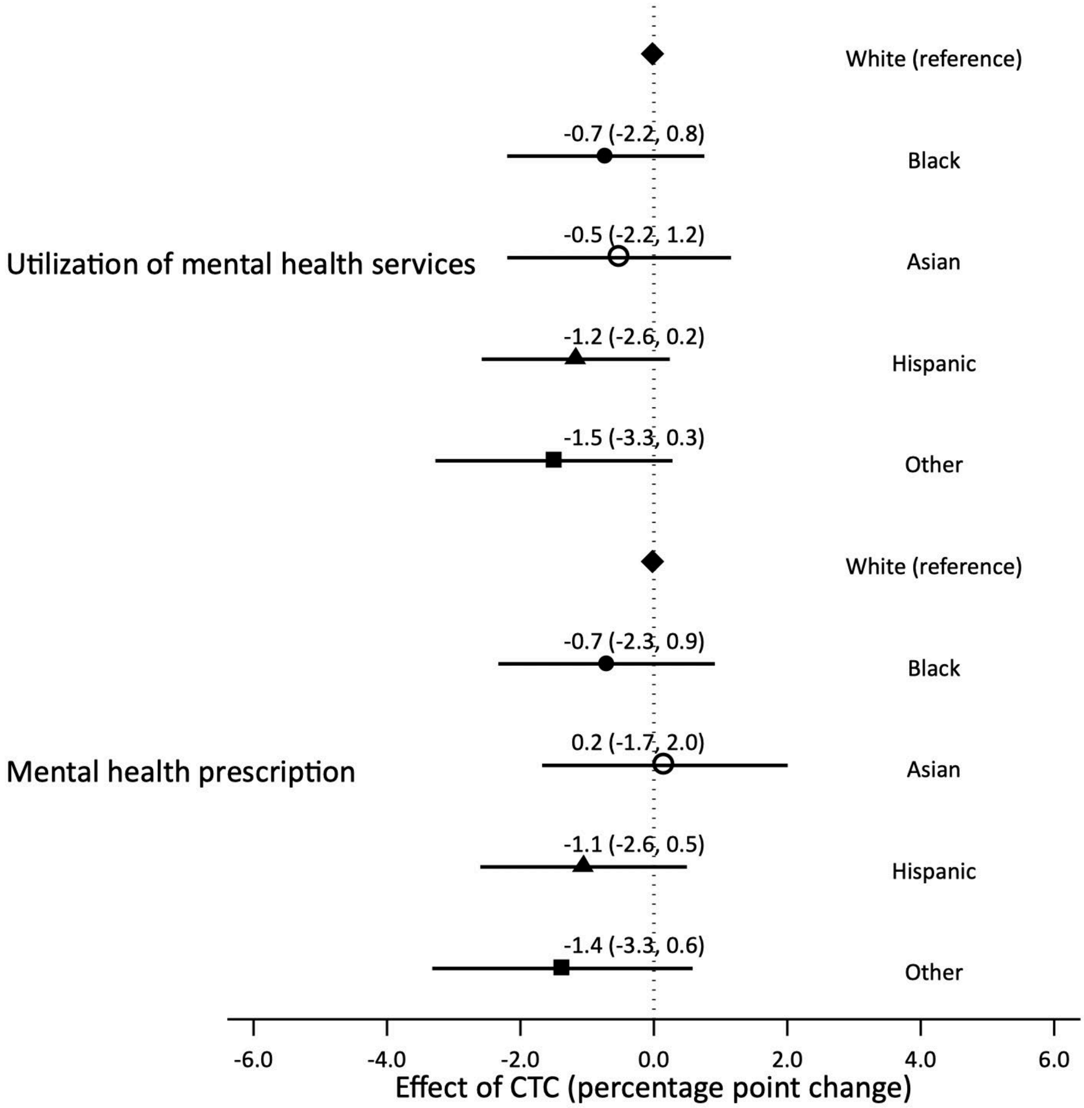
Appendix Exhibit A4.
Caption: Racial differences in the effects of the 2021 Child Tax Credit expansion on mental healthcare utilization



Source: Authors' analysis of data from U.S. Census Household Pulse Survey
Note: **p < 0.01, *p<0.05. Coefficients are plotted as point estimates (boxes) with 95% confidence intervals (whiskers). Coefficients are derived from models in which the primary exposure is a triple interaction term between an indicator for whether the interview occurred after (versus before) the CTC expansion, a binary variable representing adults with (versus without) children, and a binary variable for whether the interviewee belonged to a given racial/ethnic group (reference category: White). All regressions adjust for gender, race/ethnicity, income, marital status, number of children, and level of education as well as fixed effects for bi-weekly waves.

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Appendix Exhibit A5
Caption: Panel Event Study - point estimates of weekly effects of the 2021 Child Tax Credit expansion on primary outcomes, for low income (less than $35000)

Waves related to CTC expansion	Mental health and healthcare utilization outcomes			
[95% CI] (p-value)	Depressive symptoms	Anxiety symptoms	Utilization of mental health services	Mental health prescription
6 waves before	-0.022 [-0.048, 0.005] (0.11)	-0.003 [-0.032, 0.026] (0.85)	0.001 [-0.026, 0.029] (0.92)	0.012 [-0.018, 0.042] (0.44)
5 waves before	0.006 [-0.019, 0.032] (0.62)	0.003 [-0.025, 0.031] (0.82)	0.017 [-0.009, 0.043] (0.20)	0.011 [-0.018, 0.040] (0.44)
4 waves before	-0.009 [-0.035, 0.016] (0.48)	-0.022 [-0.050, 0.006] (0.13)	0.004 [-0.023, 0.030] (0.79)	-0.010 [-0.039, 0.019] (0.49)
3 waves before	-0.012 [-0.038, 0.014] (0.36)	0.002 [-0.026, 0.031] (0.86)	-0.001 [-0.028, 0.025] (0.92)	0.007 [-0.023, 0.036] (0.66)
2 waves before	-0.012 [-0.038, 0.014] (0.35)	-0.012 [-0.041, 0.017] (0.42)	0.006 [-0.021, 0.033] (0.65)	0.012 [-0.018, 0.041] (0.44)
1 wave1 before (reference)				
CTC expansion	-0.014 [-0.040, 0.012] (0.28)	-0.024 [-0.052, 0.005] (0.10)	0.006 [-0.021, 0.033] (0.65)	-0.005 [-0.035, 0.025] (0.74)
1 wave after	-0.018 [-0.043, 0.008] (0.17)	-0.023 [-0.052, 0.005] (0.10)	0.024 [-0.002, 0.051] (0.07)	0.006 [-0.023, 0.035] (0.68)
2 waves after	-0.017 [-0.043, 0.008] (0.18)	-0.054** [-0.082, -0.026] (<0.001)	0.003 [-0.024, 0.029] (0.84)	0.015 [-0.015, 0.044] (0.33)
3 waves after	-0.012 [-0.038, 0.014] (0.36)	-0.045** [-0.074, -0.016] (0.002)	0.029* [0.002, 0.056] (0.04)	0.022 [-0.008, 0.052] (0.15)
4 waves after	-0.025 [-0.052, 0.001] (0.06)	-0.040** [-0.069, -0.011] (0.01)	0.007 [-0.021, 0.034] (0.63)	0.017 [-0.013, 0.047] (0.27)
5 waves after	-0.012 [-0.039, 0.015] (0.38)	-0.023 [-0.053, 0.006] (0.12)	0.013 [-0.015, 0.041] (0.36)	0.011 [-0.020, 0.041] (0.49)
6 waves after	-0.035** [-0.061, -0.010] (0.01)	-0.041** [-0.069, -0.013] (0.004)	-0.026 [-0.053, 0.001] (0.06)	0.012 [-0.017, 0.042] (0.41)
7 waves after	-0.049** [-0.073, -0.025] (<0.001)	-0.057** [-0.083, -0.030] (<0.001)	-0.007 [-0.032, 0.018] (0.57)	-0.007 [-0.035, 0.020] (0.59)

Source: Authors' analysis of data from U.S. Census Household Pulse Survey
Note: **p < 0.01, *p<0.05. Coefficients are derived from models in which the primary exposure is an interaction term between a binary variable for adults with (versus without) children and an indicator for whether the adult belonged to lower income (or high-income) group and if interview occurred in which wave after (versus before) the CTC expansion.

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Appendix Exhibit A6
Caption: Effects of the 2021 Child Tax Credit expansion on mental health and healthcare utilization outcomes, for low income (less than $35000) using imputed data

	Mental health and healthcare utilization outcomes			
	Depressive symptoms	**Anxiety symptoms**	**Utilization of mental health services**	**Mental health prescription**
Coefficient	-0.011*	-0.031**	0.003	0.006
[95% CI]	[-0.021, -0.001]	[-0.042, -0.019]	[-0.007, 0.013]	[-0.006, 0.017]
(p-value)	0.026	(<0.001)	0.576	0.336
Observations	658,119	658,445	657,936	658,436

Source: Authors' analysis of data from U.S. Census Household Pulse Survey
Note: **p < 0.01, *p<0.05. Missing income values were imputed using multiple imputation using chained equations. In this analysis lower income was defined as below $35,000 in annual household income. Coefficients are derived from models in which the primary exposure is a triple interaction term between an indicator for whether the interview occurred after (versus before) the CTC expansion, a binary variable representing adults with (versus without) children, and a binary variable for whether the interviewee belonged to a lower (versus higher) income group. All regressions adjusted for gender, race/ethnicity, income, marital status, number of children, and level of education as well as fixed effects for bi-weekly waves. Depressive symptoms were captured using the Patient Health Questionnaire-2 scale, and anxiety symptoms were captured using the Generalized Anxiety Disorder-2 scale.

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Appendix Exhibit A7
Caption: Racial differences in the effects of Child Tax Credit expansion on mental health and healthcare utilization outcomes using imputed data

	Mental health and healthcare utilization outcomes			
Racial/ethnic subgroup (Reference: White) Coefficient [95% CI] (p-value)	**Depressive symptoms (binary)**	**Anxiety symptoms (binary)**	**Utilization of mental health services**	**Mental health prescription**
Black	-0.018*	-0.026**	-0.011	-0.010
	[-0.033, -0.003]	[-0.042, -0.011]	[-0.026, 0.003]	[-0.027, 0.006]
	(0.02)	(<0.001)	(0.14)	(0.23)
Hispanic	-0.009	-0.029**	-0.012	-0.007
	[-0.023, 0.005]	[-0.044, -0.014]	[-0.026, 0.003]	[-0.023, 0.008]
	0.22	(<0.001)	(0.11)	(0.39)
Asian	-0.001	-0.019*	-0.007	0.003
	[-0.018, 0.016]	[-0.037, -0.001]	[-0.024, 0.010]	[-0.016, 0.022]
	(0.90)	(0.04)	(0.45)	(0.77)
Other	-0.011	-0.032**	-0.014	-0.011
	[-0.029, 0.006]	[-0.051, -0.013]	[-0.032, 0.004]	[-0.031, 0.009]
	(0.21)	(<0.001)	(0.13)	(0.28)
Observations	682,558	682,884	682,375	682,875

Source: Authors' analysis of data from U.S. Census Household Pulse Survey
Note: * p < 0.01 & **p<0.05. 95% confidence interval in parentheses the second row. P-values in parentheses in the third row. Missing income values were imputed using multiple imputation using chained equations. Coefficients represent the triple interaction between an indicator for whether the interview occurred after (versus before) the CTC expansion, a binary variable representing parents with children (versus adults without children) and a binary variable for whether the interviewee belonged to a given racial/ethnic group (reference category: White). All regressions adjust for gender, race/ethnicity, income, marital status, number of children, and level of education as well as fixed effects for bi-weekly waves.

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