The Role of Teleworkability in the Educational Inequalities Observed at the Onset of COVID-19

Luke Motley

The Unverisity of Illinois at Urbana-Champaign

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Abstract

At the onset of COVID, the widening of educational achievement gaps along income was observed both using Google search data for online schooling resources and in student engagement on the online learning platform Zearn. This paper identifies teleworkability as a potential mechanism. It uses median household income and the percentage of teleworkable jobs in an area as independent variables. At the county-level, it regresses both income-alone and income and teleworkability on the Trends and Zearn outcome measures. The effect of a standard deviation ($14,000 per year in 2018) increase in income on the outcome measures post-COVID diminishes by roughly 40% when teleworkability controls are added. The effect of a standard deviation increase in the percentage of teleworkable jobs (5.6%) is comparable to the equivalent income effect. Both increase the Zearn outcomes and searches for parent-centered resources by 5-10% post-COVID, and increase searches for school-centered resources by more than 10%. I intend to make some slight adjustments and add additional controls to the model to better estimate the causal role of teleworkability. Given that teleworkability likely plays a role in these inequalities and will continue in some capacity indefinitely, long-term solutions may be required to close the gaps.

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1 Introduction

In early March 2020, states began preparing for temporary closure in response to the worsening COVID-19 pandemic. From March 16-March 24, every state ordered or recommended temporary closure. For every state except Montana and Wyoming, the guideline was extended to the end of the year.[1] Concurrently, workers across the country began working from home. During the first week of April, over one-third of workers reported having shifted to remote work in response to the crisis (Bynjolfsson et al., 2020). The level of the shift varied significantly across industry and predominantly occurred among better-educated, higher-paid workers (Bartik et al., 2020). Early studies of the transition to online learning suggest that low-income students may be disproportionately affected (Horowitz, 2020; von Hippel, 2020).

At the onset of COVID, high-income areas exhibited significantly larger increases in the seeking of online resources as measured by Google searches Bacher-Hicks et al. (2020). They also showed substantially smaller decreases in achievement on the online math platform Zearn (Chetty et al., 2020). This paper demonstrates that the ability to work from home (teleworkability) could play a role in both of the observed gaps. It replicates the regression analyses of Bacher-Hicks et al. (2020), incorporating the Zearn outcome measures. The income effects diminish by roughly 40% when teleworkability controls are added. In the models with both income and teleworkability, a standard deviation increase in the percentage of teleworkable jobs has a comparable effect on the outcome measures as a standard deviation increase in median household income. I intend to add additional controls to better isolate the causal role of teleworkability, as it likely correlates with demographic, regional, and other SES measures.

2 Background

Bacher-Hicks et al. (2020) demonstrate that the COVID-19 pandemic will likely widen edu-

[1] School closure information from Education Week.

cational gaps along socioeconomic dimensions. Using Google Trends search intensity data, they identify two distinct types of searches for online-learning resources: school-centered searches (for specific programs, e.g., Google Classroom) and parent-centered searches (for a general resource, e.g., online school). The nomenclature indicates which group is assumed to more often perform and benefit from the search. School-centered resources exhibit significantly higher search intensity, and the difference is due to a small number of most-searched terms.[2] There was a sharp increase in search intensity for both types of searches at the onset of the COVID, and the average increase in search intensity in areas with above-median socioeconomic status (SES) was double the average increase in areas with below-median SES. Google Trends can predict present economic activity, suggesting that this pattern indicates real differences between SES groups in school and parent adjustment to online learning. (Choi & Varian, Predicting the Present with Google Trends).

The change in student engagement with online material in reaction to COVID also differed between income groups. The search intensity data positively correlates with math progress as measured by differences in badges earned in the online math program Zearn (Bacher-Hicks et al., 2020). The distributions of key demographics of students (income, education, and race) are similar in the Zearn dataset and the U.S. as a whole, which suggests that the data is representative. The change in Zearn math lessons completed falls starkly at the onset of COVID, and, when broken into income quartiles, the magnitude of the drop-off decreases monotonically as income increases. The difference between the top-quartile and the middle-quartiles is more than double the difference between the middle-quartiles and bottom-quartile, so the advantage of being in the top group is particularly pronounced (Chetty et al., 2020).

Evidence from the Trends data and the Zearn data reveals an indisputable relationship

[2]Pre-COVID, the top term, "Google Classroom," was searched with three times the intensity of the second term, "Kahoot," which is searched with double the intensity of the third time "Khan Academy" Bacher-Hicks et al. (2020). After this point, the search intensities between school-centered and parent-centered terms are comparable. Post-COVID the difference in search intensity between the two categories widens even more.

between SES and changes in educational patterns due to the pandemic. However, details of the causal relationships between student behavior, the searching for resources, and exogenous characteristics impacting both (such as SES) are not obvious. This paper investigates the relationship between measures of actual student behavior and the seeking of resources by schools and parents in more detail. It also introduces and tests a candidate for an underlying mechanism, differences in the capability to work from home.

Dingel & Neiman (2020) classify the feasibility of working at home (teleworkability) for a comprehensive class of occupations using surveys and occupation descriptors obtained from the O*NET database, a U.S. Department of Labor sponsored project. They find that teleworkable jobs pay more than jobs that are not teleworkable. Similarly, GDP positively correlates with teleworkability. Similar work demonstrates the power of the Dingel and Neiman teleworkability measure. Their measure estimates that 37 percent of U.S. jobs could be done from home; 35 percent of U.S. workers worked entirely from home in May 2020 (Bick et al., 2020)There was a high correlation between the industries high in the Dingel and Neiman teleworkability measure and the actual industries that shifted to remote work due to COVID. Using survey data, Bartik et al. (2020) confirmed the measure's accuracy in predicting the industries that moved to remote work. Further, the responses they received suggest that work will never return to its pre-COVID state in some sectors. Roughly forty percent of firms anticipate that at least forty percent of their workers will continue engaging in remote work after the crisis.

These findings show that remote work originating with the pandemic is widespread, will persist in some capacity indefinitely, and is inequitable between the same demographics as the changes in online education behavior due to the pandemic, most notably favoring high SES, urban areas. There are several plausible explanations for the connection: one, the demographic variables cause variable explaining both inequities; two, areas with high teleworkability cause the change in behavior related to online education and correlate with the demographics; three, both demographic variables and teleworkability cause the change in behavior to some extent. The second explanation is intuitively plausible. If there is a high-density of teleworkable jobs in an area, parents and teachers could be more likely to assist their children with homework and spend time searching for online learning resources. Conversely, it is not conceivable that behavior related to online schooling has a causal effect on the capability to work from home.

Besides being a thought-provoking question, identifying the correct explanation is necessary when crafting responsive education policy due to the persistence of teleworkability after COVID. Suppose teleworkability is the driving mechanism for the disparities observed. In that case, we expect one-time relief efforts to be ineffective, given that the results were due to an abrupt, permanent change in lifestyle that will likely remain. Concretely, it would imply that parents and schools can pay more attention to their children and students' education when working from home. Since differences in teleworkability did not exist before COVID and will remain afterward, the educational gaps could last even when schools return to traditional instruction. If factors such as income are the driving force, a single effort to correct the inequality makes sense. There is less reason to expect that the behavior changes observed in parents, students, and schools to be perpetual, so there is no need for a long-term solution.

It is crucial to continue to investigate the issue in real-time. The causal tree during COVID-19 could prove to be a poor representation of the post-COVID world. Recognizing this fact complicates the discrete explanations presented above. For example, teleworkability could have been the essential variable in determining the initial educational response to the shock of the pandemic since there was not enough time for purchasable solutions to arise. Then, as people adapt and innovative educational products and services emerge, income becomes more significant. Bacher-Hicks & Goodman (2020) express their concerns about the potential for mistakes such as this vividly. Specifically, they outline the challenge in estimating the impact of any particular educational policy response to COVID. They preemptively cast doubt on any be all, end all research that describes and solves the pandemic's education-related problems and raise the bar for work that seeks to contribute the solution.

The challenge in identifying the problem and solutions gives power to platform data, search data, new measures, and the analysis and methodologies of the works referenced above.[3] They allow us to return to studies of the educational response at the start of the COVID with new variables and incorporate real-time data into ongoing current analysis frameworks. This research does the former. It uses existing methodology to relate three different data sources that are crucial to explaining the events at the onset of COVID: the Dingel and Neiman teleworkability measure, Zearn Data, and Google Trends Data.

3 Data

3.1 Data

Weekly Google Trends "search interest" data by Designated Market Area (DMA), the finest comprehensive level available for the U.S., serves as an outcome measure of demand for online resources in an area. The search interest measure represents the rate at which a specific keyword or group of keywords is searched relative to total searches in an area. In our dataset, it is specifically the proportion of searches in an area for the specified keyword(s), normalized across time and region so that the DMA-week observation with the highest proportion is assigned a search interest of 100. The other search interest observations are relative to the maximum search interest. Our analyses use the logarithm of search intensity to interpret coefficient estimates as percent changes. Overall Google search volume did not significantly change at the onset of the pandemic, so an increase in relative search intensity across time can be interpreted as an increase in raw searches Bacher-Hicks et al. (2020).

The search intensity observations in the dataset come from the set created by Bacher-Hicks et al. (2020).[4] To create the set, they grouped a list of 45 potential keywords into

[3]Specifically, I am referring to Bacher-Hicks et al. (2020), Chetty et al. (2020), and Dingel & Neiman (2020).

[4]It was kindly provided by Dr. Andrew Bacher-Hicks.

two categories: school-centered and parent-centered resources. School-centered keywords are for branded learning resources (e.g., "Google Classroom", "Khan Academy", "Kahoot"). Most often, schools facilitate the use of these platforms. Parent-centered keywords are for general learning resources (e.g., "online school", "math game", "home school") and do not directly involve the school. We cannot distinguish between parents and guardians, teachers, administrators, or students performing the searches. Rather, the categorization indicates whether a given search is likely to be motivated by the school. Search interest for school-centered resources is substantially higher than search interest for parent-centered resources.

The dependent variable in my regressions is often the combined search interest for the ten most-searched terms in one of the two categories. In both groups, the top-ten keywords dominate total searches in the category, so the measure captures the majority of activity in the group. By selecting the top-ten, Bacher-Hicks et al. avoided several issues associated with gathering Google Trends data while still capturing a measure of demand for online learning resources.

Zearn data provides an outcome measure of student engagement and achievement online. Zearn is a non-profit that provides online math lessons to supplement in-person instruction. Roughly 925,000 U.S. students used Zearn in Spring 2020, and comparison with the American Community Survey reveals the group to be representative of K-12 students in the U.S. as a whole along income, education, and race and ethnicity (Chetty et al., 2020). "Engagement" measures participation as the number of students using Zearn whereas "badges" measures achievement as the number of lessons completed by students. The observations are weekly, aggregated to the county level, and normalized relative to the base period of January 6-February 7. The raw data is obtained from the publicly available Opportunity Insights Economic Tracker.

An estimate for the percentage of teleworkable jobs (teleworkability) in a Metropolitan Statistical Area (MSA) interacts with week indicators to form the independent variables in the regressions. The teleworkability percentage is attained using the Dingel and Neiman measure of suitability for work from home. To create the measure, they use descriptions from the O*NET database on a comprehensive set of 1,000 occupations to answer pre-existing surveys about work conditions. From the answers, they classify whether a job can be performed at home. Using employment number for each population by MSA, I recreated the Dingel and Neiman dataset to close agreement by weighting employment per occupation in an MSA by the occupation's teleworkability percentage and dividing by the total employment in the MSA. Their data and replication code are publicly available and allow for adjustments in assumptions.[5] Their measure has been shown to have strong predictive power with respect to U.S. jobs that switched to remote in response to the COVID-19 pandemic (Bick et al., 2020; Bartik et al., 2020). Analyses containing the teleworkability measure only include counties that belong to an MSA. Roughly 86% of the US population lives within an MSA.[6] The results may not generalize to the remaining portion of the country due to inherent differences between urban and rural areas.

I crosswalk the Google Trends data to the county level using DMA to county information from Nielsen.[7] Similarly, I move the teleworkability scores to the county level using the NBER.[8] These operations assume the respective measures to be uniform across counties within the larger area. In principle, the assumption is false. To allow results to be interpreted at the level of the individual, the analyses weight by population. This method also recovers the results of (Bacher-Hicks et al., 2020).

3.2 Methodology

I use county-level linear regressions of the four outcome measures (school-centered search interest, parent-centered search interest, Zearn engagement, Zearn badges) on both standardized median household income alone and on standardized median household income

[5] https://github.com/jdingel/DingelNeiman-workathome

[6] Using 2019 Census Bureau population data.

[7] Sood, Gaurav, 2016, "Geographic Information on Designated Media Markets", https://doi.org/10.7910/DVN/IVXEHT, Harvard Dataverse, V9.

[8] https://www.nber.org/research/data/census-core-based-statistical-area-cbsa-federal-information-processing-series-fips-county-crosswalk.

and standardized teleworkability percentage. In every regression, I interact the variables with a time dummy variable that either indicates whether the observation was after March 1, 2020 or indicates the specific week the observation took place relative to March 1, 2020. The regressions include fixed effects by week of year and year. Each is weighted by population so the results can be interpreted at the level of the individual. Following the specification of (Bacher-Hicks et al., 2020), we can write the models as follows:

$$\begin{aligned} log(Outcome_t) =& \sum_{t=-7}^{-1} \alpha_t Before_t + \sum_{t=1}^{15} \alpha_t After_t + \sum_{t=-7}^{-1} \beta_t Before_t \times \; Std.Inc \\ &+ \sum_{t=1}^{15} \beta_t After_t \times \; Std.Inc + \mu_{w(t)} + \lambda_{y(t)} + \epsilon_t \end{aligned} \quad \textbf{(1)}$$

$$log(Outcome_t) = \alpha PostCOVID_t + \beta_{inc} PostCOVID_t \times \; Std.Inc + \mu_{w(t)} + \lambda_{y(t)} + \epsilon_t \quad \textbf{(2)}$$

$$\begin{aligned} log(Outcome_t) =& \sum_{t=-7}^{-1} \alpha_t Before_t + \sum_{t=1}^{15} \alpha_t After_t + \sum_{t=-7}^{-1} \beta_t Before_t \times \; Std.Inc \\ &+ \sum_{t=1}^{15} \beta_t After_t \times \; Std.Inc + \sum_{t=-7}^{-1} \beta_t Before_t \times \; Std.Tele \\ &+ \sum_{t=1}^{15} \beta_t After_t \times \; Std.Tele + \mu_{w(t)} + \lambda_{y(t)} + \epsilon_t \end{aligned} \quad \textbf{(3)}$$

$$\begin{aligned} log(Outcome_t) =& \alpha PostCOVID_t + \beta_{inc} PostCOVID_t \times \; Std.Inc + \\ & \beta_{tele} PostCOVID_t \times \; Std.Tele + \lambda_{y(t)} + \mu_{w(t)} + \epsilon_t \end{aligned} \quad \textbf{(4)}$$

$Outcome_t$ is either Google search interest or a normalized Zearn measure. Since the Zearn data measures include negative values, I transform each with the operation $X = X + 1 + -1 * \min X$. We interpret the β coefficients as the percentage increase in the outcome measure associated with a one standard deviation increase in the interaction term in the specified time period. For example, the coefficient of the $\beta_5 Before_5 \times Std.Inc$ term in model 3 is the expected percentage change in the outcome measure when median household income increases by one standard deviation.

These models show us how the impact that income has on our outcome measures changed after COVID. By compare the income coefficient from model 2 with the income coefficient in model 4, we see how the effect modulates from the addition of teleworkability controls. The percentage decrease in the coefficient, $\frac{\beta_{inc(2)}-\beta_{inc(4)}}{\beta_{inc(2)}}$, serves as an estimate of the percent of the income gap that is explained by teleworkability.

4 Results

Using model 2 with the Google Trends outcomes and all available data replicates the results of Bacher-Hicks et al. (2020). The results are shown in Table 2, and demonstrate close, but not perfect agreement with the values reported in their paper.[9] The discrepancies are caused by slight differences in method. They exclude certain weeks from their regressions and include fixed effects by school rather than calendar year. I see the merit of both adjustments and am in the process of incorporating them.

Restricting our dataset to counties within MSAs to ensure that systematically missing teleworkability data does not bias estimates, I perform the four specified regressions on each of the four outcomes. Table 3 displays the results of regressions 2 and 4, including the estimate for the fraction of the effect of income on the change in the outcome due to COVID, β_{inc}, that can be explained by teleworkability. For each measure except Zearn engagement, roughly 40% of the income effect is explained by differences in the capability to work from home across regions. Roughly two-thirds of the effect of income on Zearn Engagement is explained by differences in the capability to work from home.

Comparing the four, full models, we see that a standard deviation increase in either income or teleworkability after COVID has a larger effect on search interest than on student engagement or achievement. Most starkly, we see a roughly 11% increase in search interest for school centered resources from a one standard deviation increase in teleworkability percentage, which is nearly twice as large as any other coefficient. However, note that the

[9]See Table 2 of Bacher-Hicks et al. (2020)

effect also carries higher error than in other models—the p-value is 0.064, whereas the other teleworkability coefficients are significant at the 0.1% level. The results of these regressions confirm that education gaps widened at the onset of the COVID-19 pandemic, suggest that part of the effect was due to differences in the ability to work from home across regions, and demonstrate that both teleworkability and income both were contributing factors to the phenomenon. These statements hold for both differences in search patterns for online resources and in changes in student use of online learning platforms.

The coefficients of interest from the full regressions, models 1 and 3, on our four outcomes are displayed in Figure 5 and Figure 6. They provide a clear picture of the time trends of the described effects. It is not until April that teleworkability and income become clear predictors of an increase in search intensity and Zearn usage. For parent-centered resources and the Zearn outcomes, the income and teleworkability effects are roughly constant and move in parallel. For school-centered resources, there is much more variation, and, for several weeks after the closure of schools, the income effect shrinks and the teleworkability emerges as a dominant predictor. We see a sharp decline in both of the effects on parent-centered resources at the onset of summer, and a corresponding steady decline in the income effect for all of the other outcomes. The teleworkability and income effects are possibly diverging at the onset of summer, with teleworkability remaining a key factor while the income coefficients diminish. If this finding were confirmed, it would reveal interesting differences between the two different types of outcomes that we use. I intend to investigate this further.

5 Discussion and Further Plans

The findings demonstrate that teleworkability could be an important explanatory factor as we research and respond to inequalities caused by COVID and suggest that up to 40% of the educational gaps along income that we observed is due to teleworkability. In metropolitan areas where adults are more likely to be able to work from home, we see larger increase in searches for online learning resources and more engagement with online resources at the onset of COVID. The effect is especially stark after April, when we know most schools had started remote learning and a significant portion of people had switched to remote work.

However, the current models do not firmly establish the causal role of teleworkability. Since the models only control for income, it is plausible that teleworkability correlates with other important socioeconomic factors, biasing our coefficients. Moreover, we know that teleworkability negatively correlates with unemployment, which could certainly contribute to the observed effects. As a result, I intend to introduce the other SES factors used by Bacher-Hicks et al. (2020), add unemployment as an independent variable, apply regional and demographic controls, and perform further tests of robustness.

Regardless of the drawbacks, the framework and results should be considered when crafting policy to address the emerging inequalities. There are two possible stories for what happened at the arrival of COVID. One, there was an immediate shock, high-income people responded better to it, but the slopes of educational progress over time for high-income groups and low-income groups did not permanently change relative to each other. Two, COVID induced a permanent change in the educational environment that caused the slope of educational progress over time for high-income groups to increase relative to the slope of low-income groups educational progress over time. The former warrants short-term monetary relief to close a temporary gap. The latter requires a lasting solution.

Given that teleworkability could be an important causal piece and is expected to continue even after the pandemic, the second story may be the one that occurred, and we may need to consider a long-term approach to the problem. This prescription is true even if it is effectively standing in for other socioeconomic factors. Since the problem is not purely monetary, money alone may not solve it. Getting a clearer picture of the socioeconomic factors causing the gaps and their relative importance is an important starting point. This part can be done with regional-level data as used in this paper. The next is to determine how the educational environments changed unequally along the important factors. For example, is teleworkability important simply because they struggle with online learning technology and need adult assistance, or is it important because adults take a generally more active role in their children's lives when they work from home? These scenarios warrant different responses, and, in reality, it is likely a complicated combination of many such pictures. We will need research at the level of the household to address the problem at this level of detail.

6 Conclusion

This work demonstrates the need to consider the impact of remote work when interpreting the inequalities in education that emerged at the onset of the COVID-19 pandemic. Using data from Google Trends and the Zearn online learning platform, it estimates that roughly 40% of the relative increase in search interest and student achievement attributed to a standard deviation increase in median household income can be explained by teleworkability. In the full model, a standard deviation increase in the percentage of teleworkable jobs has a comparable effect to a standard deviation increase in income for all outcomes. For engagement and achievement on Zearn, as well as search interest for parent-oriented online learning terms, this corresponds to a 5-10% increase in the outcome measures for a standardized increase in income or teleworkability post-COVID. For search interest for school-oriented search terms, the magnitude could be as large as 15-20%. Note that a standard deviation of median household income is roughly $14,000 per year in 2018 dollars. A standard deviation of percentage of teleworkable jobs in an area is approximately 5.6%.The time trends exhibit interesting patterns, including a noticeable spike in the importance of teleworkability relative to income in early April.

Moving forward, I am going to make several adjustments and additions. I will change the model to cover the entire school year. I will add additional controls associated with SES, demographic, and region to better isolate the causal role of teleworkability. I also want to dig deeper into the time trends in the model, incorporate Zearn summer and fall data, and consider how areas with already high-search intensity responded in comparison to areas with already low-search intensity. Currently, the findings suggest that teleworkability was potentially a key mechanism in the widening of the observed educational opportunity gaps. These additions will further test the claim.

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Tables

Table 1: Summary Statistics by County

	(1)			
	Teleworkable	Income	School-Centered	Parent-Centered
Mean	0.3481425	52556.28	3.763262	2.049761
SD	0.0561238	14062.57	.3166221	0.2738377
Minimum	0.207805	21161	2.897789	1.64813
10th percentile	0.2804962	37420	3.363272	1.764343
25th percentile	0.3060193	43426.88	3.569736	1.874144
Median	0.347564	50690	3.750175	1.973431
75th Percentile	0.3878205	58916	3.970906	2.165515
90th Percentile	0.417998	69936	4.201214	2.427695
Maximum	0.520927	136268	5.065485	3.404333
Counties	833	1849	1842	1797

Note: Percentage of jobs teleworkable; median household income; search interest for school-centered resources; search interest for parent-centered resources.

Table 2: Replications

	(1)	(2)	(3)	(4)
	School-Centered	Parent-Centered	Google Classroom	Khan Academy
Post-COVID	0.533***	0.375***	0.802***	0.426***
	(0.0603)	(0.0439)	(0.0650)	(0.0637)
Post-COVID	0.289***	0.206***	0.573***	0.247***
	(0.0716)	(0.0471)	(0.0775)	(0.0740)
& High-Income	0.309***	0.213***	0.290***	0.225***
	(0.0785)	(0.0274)	(0.0833)	(0.0389)

Clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Approximate replications of regressions from Table 2 in Bacher-Hicks et al. (2020). Weighted by county population, included fixed-effects by year and week of year. Clustered by week and DMA to determine standard errors. Differed from Bacher-Hicks et al. methodology because it: *(i)* did not drop March or school holiday data, *(ii)* controlled for year, not school year, and *(iii)* considered income rather than a combined measure of SES. Continued work on the project may incorporate their methods.

Table 3: Regressions on Standardized Income and Teleworkability

	(1) School-Centered	(2) Parent-Centered Resources	(3) Zearn Engagement	(4) Zearn Badges
Post-COVID	0.415***	0.301***	-0.0669***	-0.0704***
	(0.0559)	(0.0464)	(0.00774)	(0.0104)
Standardized Income	-0.0195	-0.0399***	-0.00154	-0.00705***
	(0.0198)	(0.0101)	(0.00142)	(0.00182)
Post-COVID×Std. Income	0.132***	0.0816***	0.0337***	0.0557***
	(0.0341)	(0.0106)	(0.00320)	(0.00431)
Post-COVID	0.420***	0.303***	-0.0668***	-0.0703***
	(0.0547)	(0.0452)	(0.00775)	(0.0104)
Standardized Income	0.00791	-0.0177*	0.00879***	0.00705**
	(0.0193)	(0.00804)	(0.00190)	(0.00243)
Post-COVID×Std. Income	0.0783**	0.0522***	0.0110**	0.0320***
	(0.0240)	(0.0118)	(0.00418)	(0.00553)
Standardized Teleworkability	-0.0569*	-0.0462***	-0.0223***	-0.0305***
	(0.0242)	(0.0104)	(0.00236)	(0.00306)
Post-COVID×Std. Teleworkability	0.113	0.0612***	0.0489***	0.0511***
	(0.0605)	(0.0136)	(0.00504)	(0.00633)
Fraction of β_{inc} Explained by Teleworkability	0.407	0.360	0.674	0.425
R^2	0.722	0.348	0.609	0.555
Observations	285616	272330	72902	72913

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table displays the results of eight different county level regressions on the following dependent variables: (1) the natural log of Google Trends search interest for school-centered resources; (2) the natural log of Google Trends search interest parent-centered resources; (3) Zearn engagement normalized relative to a base period from January 6-February 7, 2020; and (4) Zearn badges normalized relative to a base period from January 6-February 7, 2020. The first panel corresponds to a regression on median household income alone, and the second corresponds to a regression on median household income and the percentage of teleworkable jobs. Each includes fixed effects for year and week of year. The standard errors are clustered by DMA and date for the Trends regressions and are robust for the Zearn regressions. One standard deviation in income is approximately $14,000 per year. One standard deviation in teleworkability percentage is approximately 5.6%

Figures

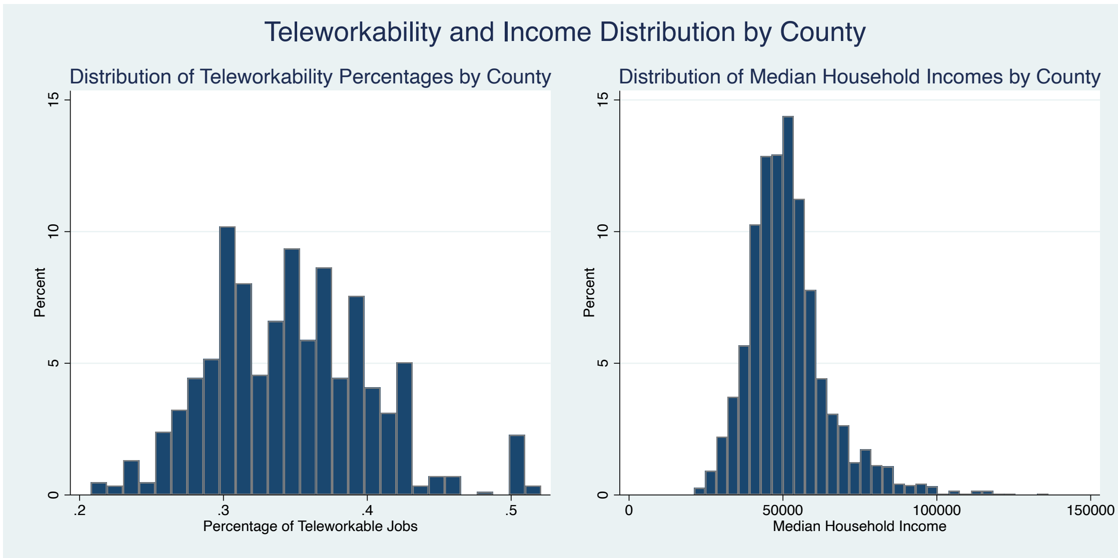

Figure 1: Histograms of Teleworkability Percentages and Median Household Income by County

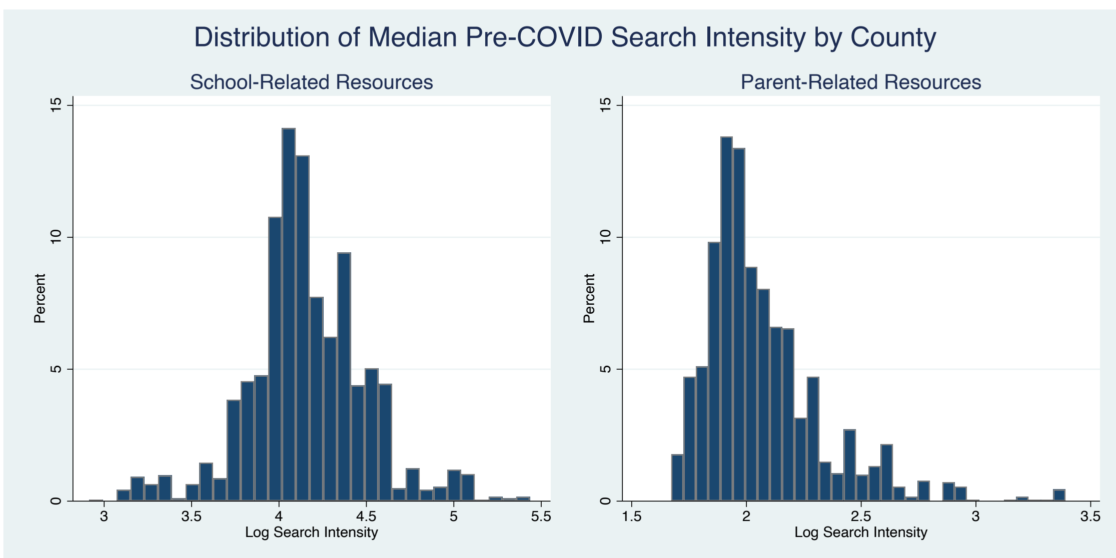

Figure 2: Histogram of Median Pre-COVID Search Intensities by County from June 2015-Dec 2019

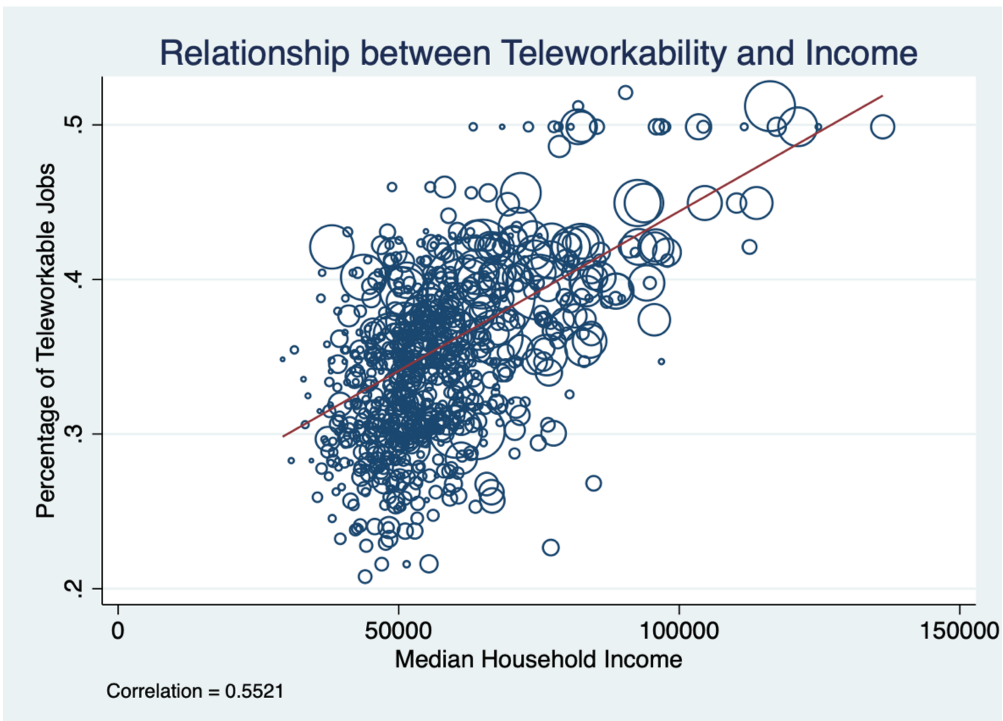

Figure 3: Histogram of Median Pre-COVID Search Intensities by County from June 2015-Dec 2019

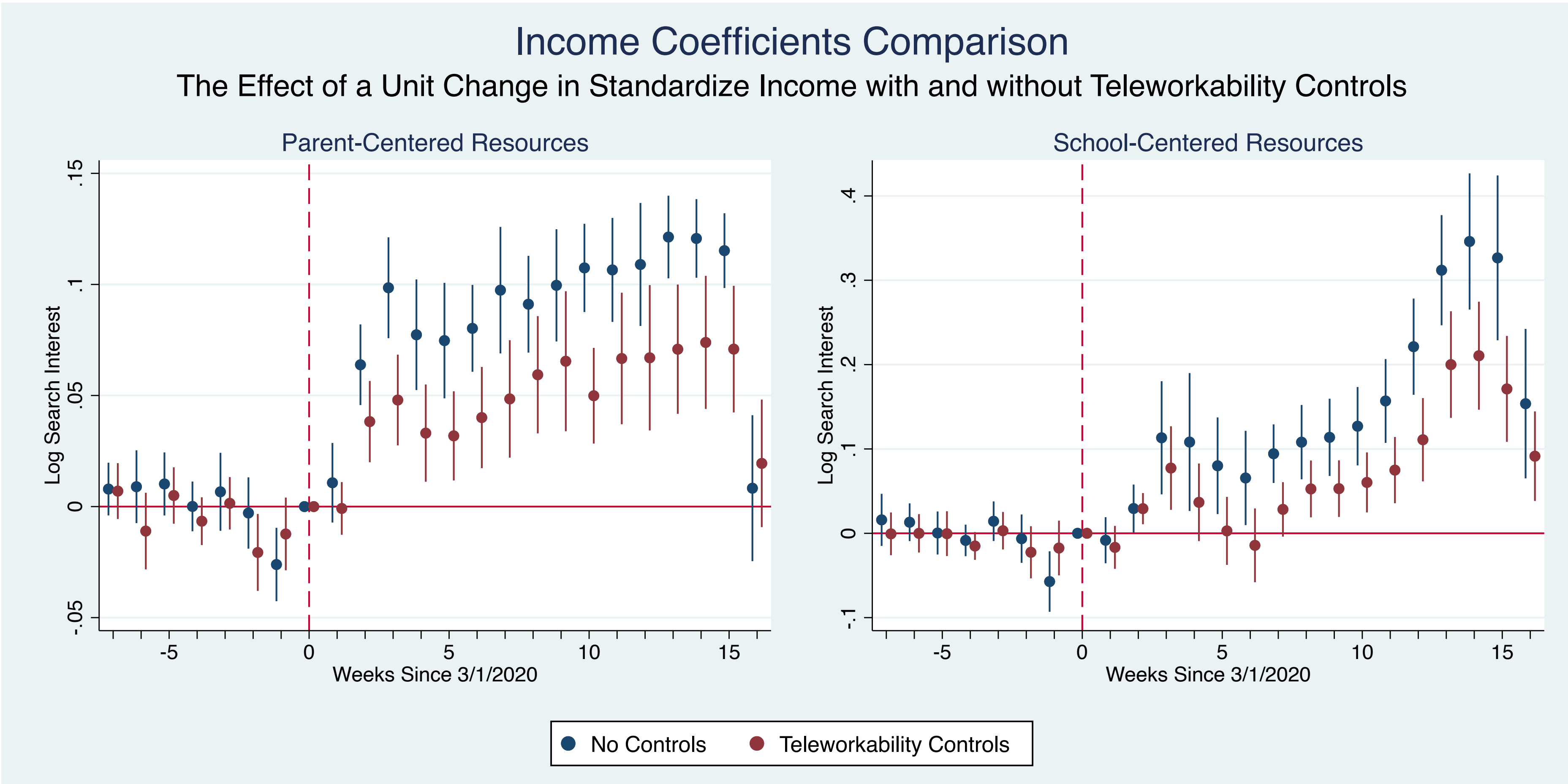

Figure 4: Change in Income Coefficients when Teleworkability Controls are Added (a)

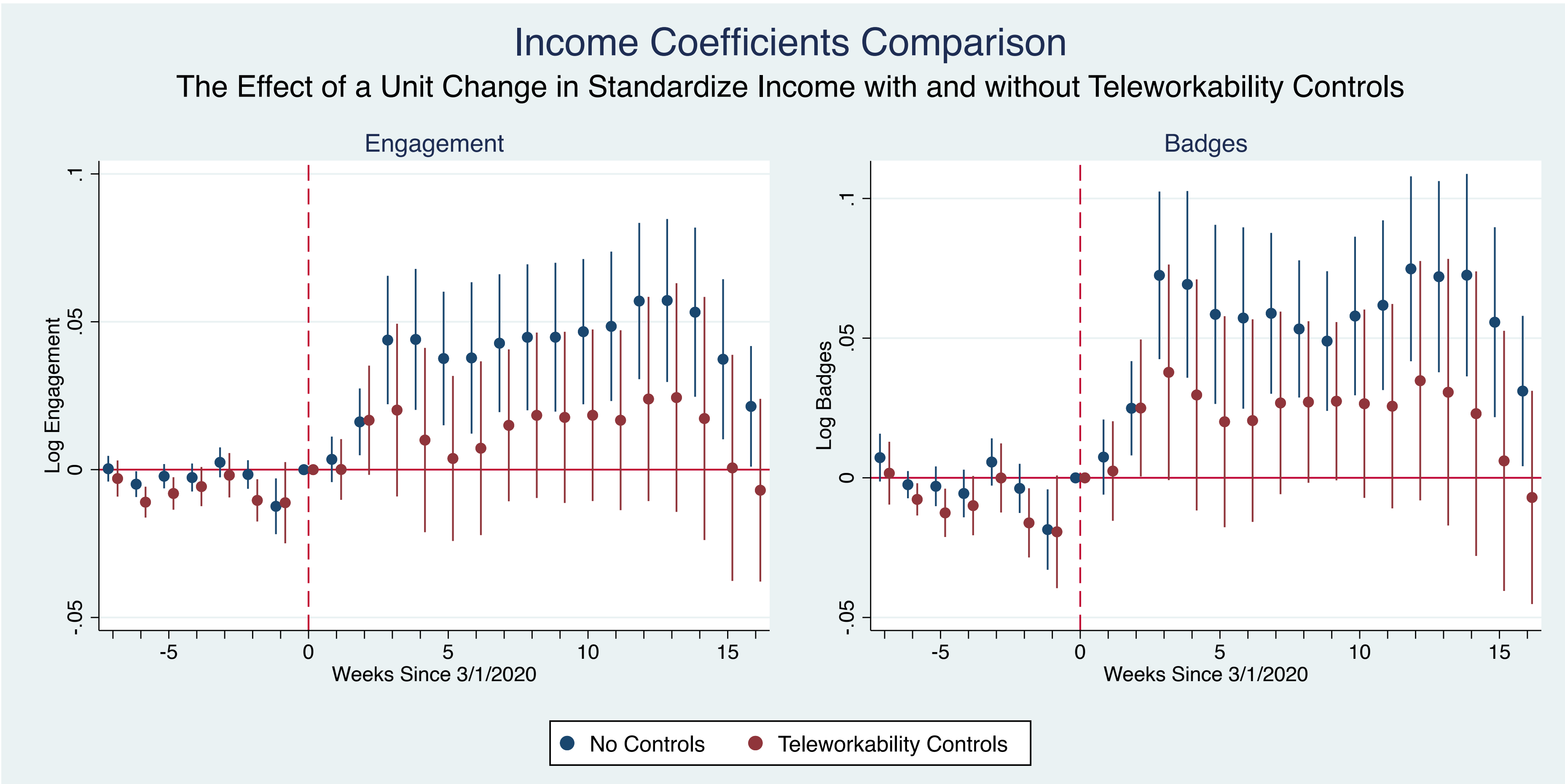

Figure 5: Change in Income Coefficients when Teleworkability Controls are Added (b)

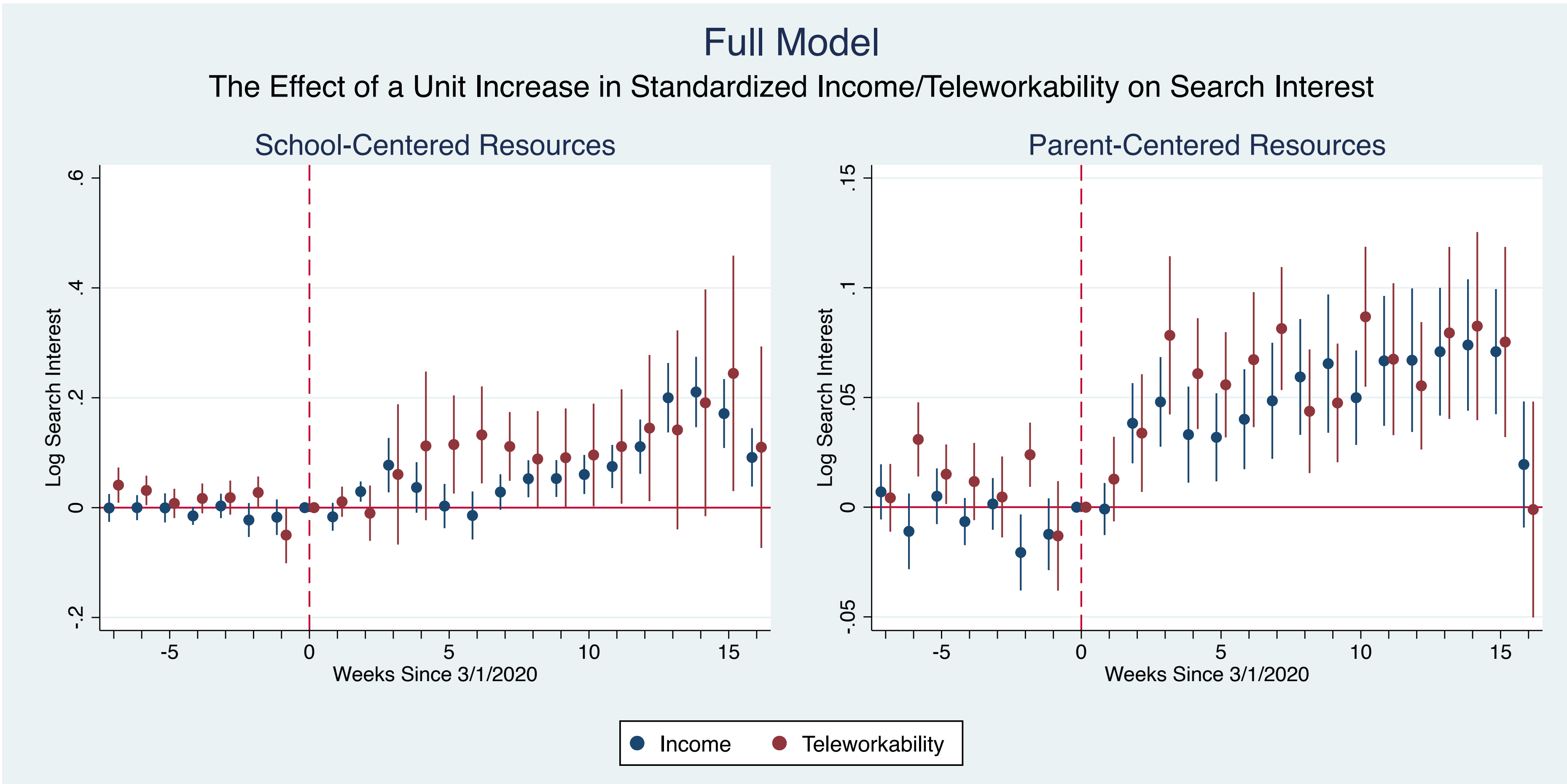

Figure 6: Full Regression Income and Teleworkability Coefficients (a)

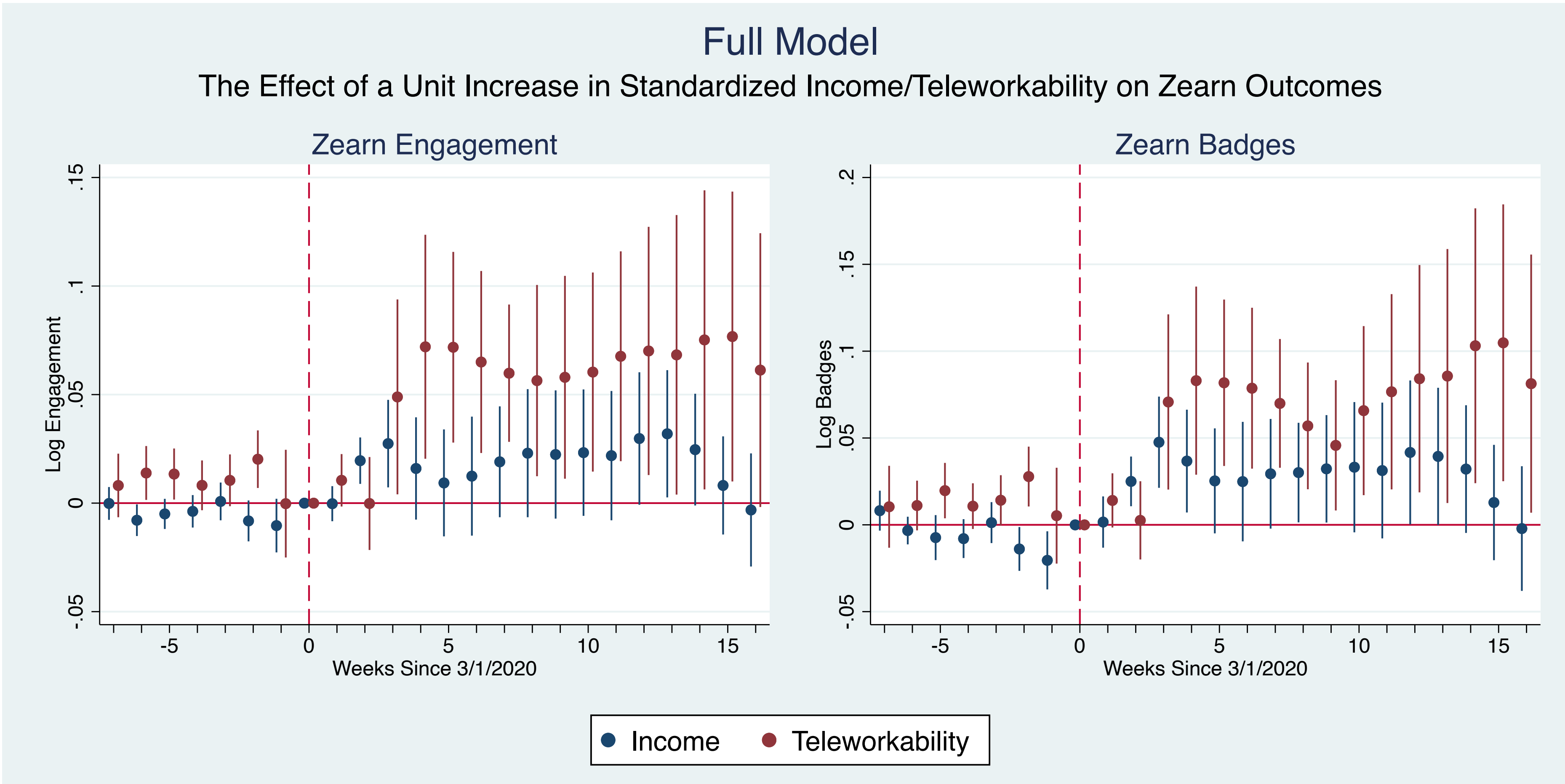

Figure 7: Full Regression Income and Teleworkability Coefficients (b)