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DISCUSSION PAPER SERIES

IZA DP No. 15670

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ABSTRACT

Households in Transit: COVID-19 and the Changing Measurement of Welfare*

The COVID-19 pandemic placed new constraints and prices on commuting to work around the world. However, traditional methods of measuring household welfare (and, accordingly, poverty and inequality) based on expenditures have not considered these changes. First, we present theory showing significant mismeasurement of welfare for households who can shift into remote work during the pandemic. We then propose methods to impute transportation cost equivalents for household expenditure aggregates. We use Georgia as a case study to compare these methods and assess impacts on poverty and inequality. The proportion of remote work is low, only about 9%, meaning that the impact on overall inequality is negligible. However, considering transportation costs can result in up to a 40% reduction in the measured poverty rate among remote-working households.

JEL Classification: I32, D30, R20, J32

Keywords: poverty measurement, inequality measurement, consumption aggregate, expenditures, imputation, living costs, COVID-19, welfare

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1 Introduction

The World Bank estimates that the COVID-19 pandemic has pushed nearly an additional 100 million people into poverty globally through 2021 (Mahler et al. 2021). Poverty is measured by using household consumption or expenditure in all low-income countries and the majority of middle-income countries (Mancini and Vecchi 2022). Consumption-based measures of poverty have theoretically better welfare properties, as they allow for household consumption smoothing over seasons and shocks, and are easier to compute in contexts where measuring income is difficult and self-employment or informal labor is common (Deaton and Zaidi 2002). Consumption is often largely approximated by expenditures. When interpreted in terms of a money metric unit, expenditures give a measure of how much money is needed for a household to reach a given level of living standards (Mancini and Vecchi 2022; Deaton and Zaidi 2002).

However, the COVID-19 pandemic has introduced new challenges for this method of measuring welfare and poverty. National lockdowns and increased health risks have constrained consumer choice, causing households to reallocate their expenditures. To the extent that households face different constraints on their decision making and different (unmeasured) prices, expenditures during the pandemic do not necessarily map one-for-one to welfare. And to the extent that these constraints are unequally distributed, this may have significant implications for the measurement of poverty and inequality.

In this paper, we will focus on the case of transportation costs.[4] During the pandemic, many workers gained the opportunity to work remotely. This implies a significant price reduction for commuting to work for households who are unconstrained by being required to work in-person. However, when there is a price reduction and expenditure measures are not adjusted, welfare increases but expenditures may decline. Further, access to remote work is not equally distributed among households and occupations, meaning that consumption-based measures may mask significant inequality. If the highest income households are more likely to face the commuting cost reduction allowed by remote work, then inequality may increase significantly while consumption-based measures of it decrease.

This paper offers several key contributions to the literature. Importantly, we are the first to evaluate the size of the potential problem that commuting costs pose for poverty and inequality measurement by documenting and studying pre- and during-pandemic inequalities in the cost of transportation and commuting, as well as the inequality in opportunities to work from home. As shown by Garrote Sanchez et al. (2020), the ability to work remotely is concentrated among high-income households in all countries. For example, in upper middle-income countries like Georgia, nearly none of the poorest decile can work from home, while the majority of the richest decile can. They estimate that inequalities in remote work will drive significant income inequality during the pandemic, but do not take into account the difference in commuting cost. We also provide additional evidence on the profiles of remote workers.

[4] A full treatment of all the costs of working in-person, such as uniforms, or remotely, such as electricity, is beyond the scope of this paper. Our previous analysis of expenditures worldwide suggests that the reductions in expenditures at the height of the pandemic were likely largely transport-related (Caron and Tiongson 2021).

Having documented the magnitude of the problem, we are the first to propose methods for consumption-based poverty and inequality measurement during and after the pandemic. Others have attempted to address the huge changes in welfare due to the pandemic by offering multidimensional poverty indexes which take into account unmeasured welfare changes like the risk of infection, but none have attempted to reconcile welfare changes with existing expenditure-based poverty measurement (Tavares and Betti 2021). We also build on previous work on imputing values of unobserved expenses or incomes, such as the literature on rent imputation for owner-occupied housing (Balcázar et al. 2017). We build on previous work showing theoretical problems with the consumption aggregate, including showing that partial consumption aggregates which do not collect information on all goods only satisfy desirable theoretical properties if the associated Engel curves are all linear (Christiaensen, Ligon, and Sohnesen 2021). We offer a general method that can be applied to other contexts, settings, and datasets.

In addition, we add to the literature on household decision-making during the pandemic by systematically discussing the changes in household welfare and the household utility maximization problem due to the possibility of remote work. To our knowledge, this issue has not been addressed theoretically to date, though we had previously discussed the welfare implications of remote work in an informal blog post (Caron and Tiongson 2021).

Furthermore, the issues discussed in this paper potentially relate to an older literature that has found it challenging to disentangle consumption and production expenses of the self-employed (see, e.g., de Mel, McKenzie, and Woodruff 2009 on the difficulty of measuring enterprise profits).[5] Similar imputations may be performed for self-employed and other workers who do not regularly commute to their workplaces, but these imputations have somewhat different motivations, as they do not involve changes in prices and constraints when comparing self-employed and wage-employed workers.[6]

Finally, we contribute also to the study of the poverty and inequality impacts of the pandemic. Many have suggested huge poverty impacts of the pandemic, with some estimating that by June 2020 the pandemic had already caused an additional 68 million person-years spent in poverty (Decerf et al. 2021). The pandemic has also been thought to increase inequality by driving wage losses among low-wage workers (Aspachs et al. 2021). We expand on this literature by offering new estimates of the pandemic's poverty and inequality impacts, while also illuminating an important driver of them in addition to the unequal distribution of job losses and infection rates.

2 Theory

We first lay out the theory of household welfare maximization. Households h in time t maximize utility u over consumption c_{ht}, savings s_{ht} with an interest rate r_{ht}, in-person labor l_{ht}^{ip} with wage w_{ht}^{ip}, and remote

[5] We thank Cesar Cancho for suggesting this point.

[6] Alternatively, commuting self-employed workers can be compared with remote-working self-employed workers to help identify production expenses and distinguish them from consumption expenditures.

labor l_{ht}^{r}, with wage w_{ht}^{r}. Assume that the utility function is monotonically increasing in c_{ht} and decreasing in l_{ht}^{r} *and* l_{ht}^{ip} (disutility of working). Take t = 0 to represent the pre-pandemic period and t = 1 to represent during or after pandemic. If households work in-person, they must pay a transportation cost tr_{ht} and receive disutility from commuting d_{ht} for all t.[7] Thus, the household maximization problem is

$$\max_{c_{ht},s_{ht},l_{ht}^{r},l_{ht}^{ip}} u\left(c_{ht}, l_{ht}^{ip}, l_{ht}^{r}\right)$$
$$\text{s.t.} \quad c_{ht} + s_{ht} \le rs_{ht-1} + w^{r}l_{ht}^{r} + \left(w^{ip} - tr_{ht}\right)l_{ht}^{ip}$$

2.1 Short-term: COVID-19 pandemic lockdowns prevent in-person work

In the general problem above, households can choose whether to work entirely in-person, entirely remotely, or a combination of both, depending on the disutilities associated with each of them. We assume that, before the pandemic, remote work was not available to households. Further, during pandemic-related lockdowns, policy determined households' choice in this respect. We also assume that, in the short-term, wages are sticky, so that in-person and remote work wages are both equal to *w*.[8]

For simplicity, assume that, in the short term, households are of two types: in-person only and remote work only. The former faces a constraint in both periods: if $l_{ht}^{ip} > 0$, they must pay a transportation cost tr_{it} and receive disutility from commuting d_{it} for all t. Thus, the in-person only household i faces the problem in each t:

$$\max_{c_{it},s_{it},l_{it}} u\left(c_{it}, l_{it}^{ip}\right) - d_{it}l_{it}^{\mathrm{ip}}$$
$$\text{s.t.} \quad c_{it} + \mathrm{s}_{\mathrm{it}} \le rs_{it-1} + (w - tr_{it})l_{it}^{ip}$$

Effectively, working in person means that the net wage rate is lowered.

The remote shifter household j faces the above problem for t = 0. However, for t = 1, the remote shifter household faces tr_{j1} = 0 and instead solves

$$\max_{c_{jt},s_{jt},l_{jt}} u\left(c_{jt}, l_{jt}^{r}\right)$$
$$\text{s.t.} \quad c_{jt} + s_{jt} \le rs_{jt-1} + wl_{jt}^{r}$$

There are two differences from the above: the household faces a higher net wage rate (or a price reduction in the cost working). In addition, they are not penalized by the disutility of commuting. In this setting, as long as r > 0, a price reduction will unambiguously increase welfare. The removal of the disutility of commuting also unambiguously increases welfare.

[7] This theoretical transportation cost also includes the cost of foregone leisure, labor, or household production due to the time cost of commuting.

[8] As explained above, we do not address explicitly the costs associated with working from home, for example, increased electricity expenses. These can be thought of as a decrease in the net wage associated with remote work. Then, this assumption amounts to the assumption that the in-person wage net of commuting costs is lower than the remote wage net of remote work costs.

However, expenditures for any household h are given by $e_{ht} = c_{ht} + tr_{ht} l_{ht}^{ip}$. For any fixed t (that is, under a fixed tr_{ht} and fixed prices), welfare should increase monotonically with e_{ht}. If the household chooses a larger level of c_{ht} or l_{ht}^{ip}, it must be because these are the utility-maximizing values. However, between $t = 0$ and $t = 1$, welfare does not vary monotonically with e_{ht}. The key distinction is that tr_{ht} is a cost that does not enter directly (or positively) into the utility function, unlike c_{ht} and l_{ht}^{ip}. There are several sources of this divergence:

<u>Proposition 1:</u> The change due to the pandemic means that remote households are unambiguously better off, even though their e_{jt} has decreased.

<u>Proof</u>. As long as $\frac{\partial u}{\partial c_{it}} > 0$, the marginal utility of consumption is positive. This implies that the budget constraint is binding. As such, a decline in the transportation cost leads to increased consumption. At the same time, the elimination of the transportation cost amounts to an increase in the net wage associated with labor, which makes the consumer better off. Finally, the elimination of the disutility of commuting necessarily increases utility.

<u>Proposition 2:</u> If $tr_{i0} < tr_{i1}$, that is, if transportation costs increased during the pandemic (e.g., because public transportation was closed), we have $e_{i0} > e_{i1}$ while welfare has declined.

<u>Proof.</u> For in-person households, the Envelope Theorem implies that $\frac{\partial u}{\partial tr} = -\lambda_{it} l_{it}^{ip*}$, where λ_{it} gives the shadow price of consumption and l_{it}^{ip*} gives the optimal in-person labor supply. As long as $\frac{\partial u}{\partial c_{it}} > 0$, the first order conditions (Karush-Kuhn-Tucker conditions) imply that $\lambda_{it} > 0$. Thus, $\frac{\partial u}{\partial tr} < 0$ as long as $l_{it}^{ip*} > 0$, that is, as long as the household is employed. If the household loses employment, then the positive shadow price of consumption also implies a reduction in utility as a result.[9] In either case, the tightening of the budget constraint implies a decrease in consumption. The net wage rate decreases, leaving households worse off.

<u>Proposition 3:</u> If $d_{i0} < d_{i1}$, that is, if the disutility of commuting increases (e.g., because of higher risk of infection), in-person households may become weakly worse off with no change in expenditures.

<u>Proof.</u> The Envelope Theorem implies that $\frac{\partial u}{\partial d} = \frac{\partial u\left(c_{it}^{*}, l_{it}^{ip*}, l_{it}^{r*}\right)}{\partial l_{it}^{*ip}} - l_{it}^{ip*} - \lambda_{it} tr_{it} l_{it}^{ip*}$. As described in the proof of Proposition 2, the last term is weakly negative. As long as the total disutility of working is equal to or greater than that contributed by commuting, the first term is necessarily negative. Thus, $\frac{\partial u}{\partial d} \leq 0$.

[9] Note that both Propositions 2 and 3 hold weakly even if the in-person household becomes unemployed due to the pandemic. On the other hand, Proposition 1 predicting the unambiguous increase in the welfare of remote-shifter households during the pandemic does not hold if the household becomes unemployed, as this implies a decline in welfare.

A more appropriate expenditure-based proxy of welfare might take tr_h to be the pre-pandemic transportation cost. Then, we can evaluate $e_{ht} = c_{ht} + tr_h l_{ht}$ where $l_{ht} = l_{ht}^{ip} + l_{ht}^{r}$. We will focus only on transportation expenses, so assume that all other prices are constant. Under certain conditions, welfare increases monotonically with e_{ht}. This is clear for the c_{ht} term because consumption enters directly and monotonically in the utility function. Welfare will increase monotonically with l_{ht} as long as the net wage is positive and labor supply does not decrease for remote households in $t = 1$. That is, we assume that any income effect reducing labor supply is not large enough to offset the substitution effect plus the effect of the removed disutility of commuting term.

The mechanism of this model is shown graphically in Figure 1. In this figure, we consider an example. Imagine the case where the remote work shifter household is relatively more wealthy than the in-person household. Pre-pandemic, using an expenditure-based poverty line, the in-person household is poor while the remote work shifter is not. There is large inequality in their expenditures. They both face a disutility of commuting and spend on commuting costs which do not otherwise increase welfare, which means that their true welfare is lower than what is measured by their expenditures by a constant amount.

During the pandemic, the remote work shifter moves to remote work, no longer incurring the disutility from commuting. Their expenditures have also fallen because they no longer pay the commuting cost. Their expenditures may fall so much that they become poor, even though welfare has increased dramatically. On the other hand, the in-person household faces the same costs and disutility as before (or, we can imagine them being even greater). When we compare poverty based on expenditures only, poverty has increased because of the pandemic, but welfare has also weakly increased for both households. It also appears that inequality has decreased during the pandemic, when true inequality as measured by welfare has increased dramatically. Our measure moves much more closely with true welfare, remaining the same for the in-person household and increasing for the remote work shifter. However, it is important to note that our measure does not completely reflect welfare because we still do not observe the disutility of commuting. Thus, our measure captures much of the increase in inequality during the pandemic, but still underestimates it somewhat.

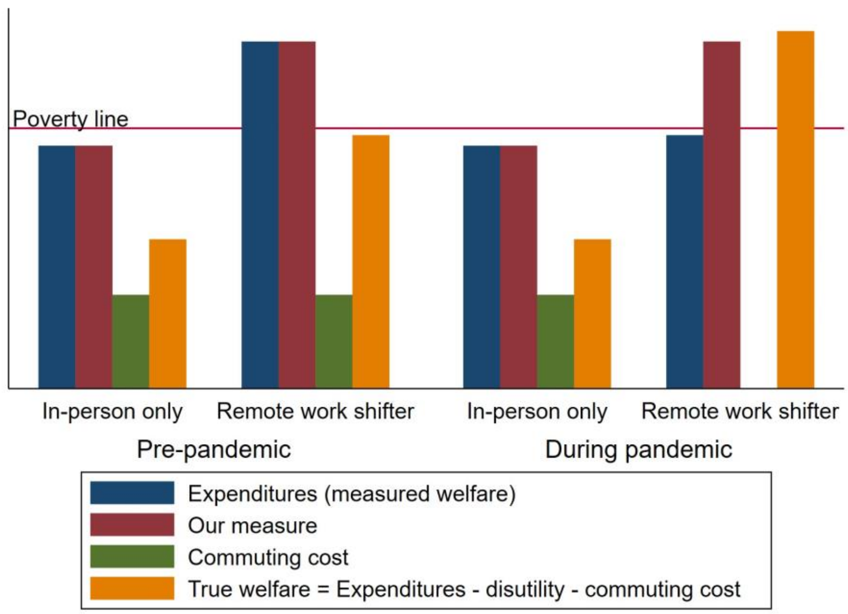

Figure 1: Welfare and expenditures pre- and during pandemic.

2.2 Long-term: restrictions lifted

As pandemic restrictions are lifted, households are able to choose whether to work in-person or remotely, particularly in the medium- and long-term as they are able to change occupations. Further, in the long term, wages can adjust for differences in productivity between remote and in-person work. This case is not analyzed in depth in this paper, but similar expenditure measurement issues arise.

3 Background on COVID-19 and Transportation in Georgia

On March 12, 2020, the government of Georgia announced a national measure requiring workers to work remotely if they had traveled or been exposed to COVID-19 and encouraging employers to place employees in work mode, particularly public sector workers (Government of Georgia 2020). On March 21, 2020, the government declared a national emergency with measures that included a curfew, suspension of all public transportation except taxis, prohibiting public gatherings, and limiting carpooling.[10] These measures were reduced but restored in full force at the end of November 2020 as cases rose again (*Reuters* 2020).

[10] https://covidnews.eurocities.eu/wp-content/uploads/2020/05/Tbilisi_Covid-19.pdf

Previous descriptive studies show that as many as 22% of firms allowed some employees to work from home through September 2020, but this was concentrated among large firms, where the rate was nearly 61% (PWC 2020). Although, among workers, rates of remote work may have been less than 10%, the rate was significantly higher among skilled workers (Julakidze and Kardava 2021).

The government of Georgia implements several transportation programs which are of interest for studying transportation expenses. First is the Georgia Subsidy for Public Transportation, which allows certain groups (pensioners, teachers, IDPs, disabled people, and gov employees, retired and socially vulnerable) in Tbilisi to pay a reduced fare for public transportation in the city (Cancho and Bondarenko 2017). This means that transportation expenses, at least in the capital area, are likely to be concentrated among higher-income households who do not qualify for the subsidy. The HIES data we have available does include some measure of the value of transportation received free or charge, but it is likely that reduced-fare transactions were not recorded in this section.

According to some reports, the lockdown and closure of public transportation allowed the government to quicken improvements to bus routes in the capital city (CDIA 2020).

4 Empirical Approach and Estimation

In our econometric framework, we frame the problem of measuring poverty and inequality as the problem of imputing tr_h based on the household head's characteristics. It should be noted that household survey data generally only includes information on the monetary costs of commuting, not the time spent commuting, and, as such, this section discusses estimation of the monetary costs only. This will be an underestimate of the true transportation cost. There are several potential approaches to estimating the monetary transportation cost in the short- and long-term, under different assumptions. In all cases, it is first necessary to identify which households are of the remote work shifter type and which are not. As new data become available, this information may be collected about households or individuals in income and expenditure surveys. However, to date, few household surveys contain information both on remote work and on transportation expenditures, so it may be necessary instead to estimate the propensity to work remotely using another data source.

These methods will generally have the most predictive power when there are many covariates and they are good predictors of propensity to work remotely. One option is to use another survey, such as a labor force survey, with information on remote work and a variety of individual or household characteristics. Models will only be useful if they only use covariates that appear in both surveys. For example, occupation or industry of work may be strong predictors of remote work but are often not collected in household budget surveys. Instead, proxies like education or wage income may be used. Alternatively, in the absence of high-quality household survey data, the researcher may turn to firm-side data. There may be data on firms that report information on employee characteristics and whether they work remotely.

Another possibility is to use data from mobile phones or social networks, which may still contain some covariates which would allow extrapolation to a household budget survey (see, for example, Lee and Finerman 2021; Lokesh and Marsden 2021; Fajgelbaum et al. 2021). Data on public transit ridership, road congestion, tolling revenue, or other data on the use of transportation infrastructure can provide insights regarding the potential magnitude of remote work, as well as regional variation. Similarly, Google Mobility Reports may give a sense of the percent reduction in commuting by region (for some countries), which can then be distributed to households in survey data. However, these methods might fail to capture certain inequalities, such as the concentration of remote work ability in high-income households or certain occupations.

The most basic linear probability model for this purpose is:

$$H_h = AX_{h,1} + u_{h,1}$$

for household h in time period 1 (that is, during the pandemic) with characteristics $X_{h,1}$. Once the coefficients A are estimated, they can be applied to the households in the expenditure survey, providing estimates of the propensity to work remotely for each. A downside of the linear probability model is that it may give estimated propensities outside of the range from 0 to 1, so a logit or probit model may be used instead.

However, with any of these models, there is a risk of overfitting, the case where in-sample prediction performs well but out-of-sample prediction suffers. An alternative is to use LASSO to penalize non-zero coefficients and select the most relevant covariates. An advantage of using LASSO is that interactions or flexible polynomials in various covariates can be included. Previous work in the propensity score estimation literature has indicated that LASSO generally performs well for this purpose, better than a probit in small samples, although the difference matters less in large samples (Goller et al. 2020). Other machine learning methods like random forest have been applied in this literature, but may not perform well when the share of households working remotely is small (Goller et al. 2020). However, it should be noted that this application is more general than propensity score estimation, since we are not using the estimated remote work status for matching or causal estimation.

Alternatively, nonparametric methods, such as coarsened exact matching, may be used. These methods involve creating bins of each covariate and creating groups of households which fall into the same bins on every covariate. Then, probabilities of remote work can be imputed for households in the expenditure survey by using the probability of remote work among households in the same bin in the labor force survey.

4.1 Predicting pre-pandemic commuting cost equivalents

Once we have identified remote work shifter households, we must estimate their counterfactual commuting costs, in the absence of a remote work option. One method is to consider the counterfactual to be pre-pandemic commuting costs and predict these from data from the pre-pandemic period. Again, this relies on having a dataset with a rich set of covariates from which to predict transportation expenses.

The prediction can be done parametrically or semi-parametrically. The most basic parametric version would amount to estimating the equation

$$tr_{h,-1} = \beta X_{h,-1} + \gamma X_{h,-1} \times H_h + \varepsilon_{h,-1}$$

for household h in the pre-period, time -1, with characteristics $X_{h,-1}$.

Since we suspect that remote-shifter households and in-person households may be systematically different in how they determine transportation expense even before the pandemic, we add an interaction with predict household type H_h. We can compute these households' type even though we don't observe their choice.

One covariate that may be desirable to include is expenditures on other goods, since these may correlate with transportation expenditures. However, the relationship may be highly nonlinear, especially as high-expenditure households may not pay the same per-unit cost of transportation as low-expenditure households. Because of this, as above, it may be desirable to include interactions and flexible polynomials in other expenses in the regression and consider a method like LASSO to avoid overfitting. Alternatively, we may use a semiparametric method, such as a partially linear model, to estimate the transportation expenses. However, it should be noted that semiparametric methods cannot offer predictions for covariate values beyond the observed range.

Once we have estimated the coefficients using one of these methods, we predict $\widehat{tr}_{h,1}$ using the during-pandemic data. There are two interpretations of this estimate. First, if we assume that remote-shifter households eliminated all of their transportation activities from the pre-pandemic period, we should add this estimate directly to the expenditure aggregate. Under this assumption, any transportation expenses that exist in 2020 for remote-shifter households are interpreted as additional, pandemic-related expenses that would not have occurred in 2019. Thus, we must leave them in the aggregate in order to be able to compare to expenditure aggregates from 2019. On the other extreme, we might suspect that all of the transportation cost for remote-shifters during the pandemic was for the same non-commuting activities as in 2019. In that case, we should replace this cost with the new estimate. That is, we should remove the observed transportation cost from the aggregate and add back the estimated one. The most realistic case is likely between these two, and they may constitute the upper and lower bounds for the size of counterfactual transportation expenses.

4.2 Predicting commuting cost equivalents during the pandemic

On the other hand, another possibility is to predict commuting cost by comparing remote-shifter households and in-person only households during the pandemic. The basic model takes the form:

$$tr_{i,1} = \alpha X_{i,1} + v_{i,1}$$

for in-person only household i in the pandemic, at time 1, with characteristics $X_{i,1}$. We then use the estimated coefficients to predict transportation expense for likely remote-shifter households. The same estimation considerations from above apply to this case.

However, it is important to note that this model masks heterogeneity within the group of in-person only households. Some households may be in-person only because their job does not allow them to work remotely, that is, they are constrained by the opportunities available in their workplace or the nature of their work. Others may choose not to work remotely even though they are not constrained. When comparing households, these remote work non-compliers will be naturally very different than remote work compliers.

Thus, it would be more optimal to estimate the above model only for the constrained in-person households but identifying them may not be possible given data constraints.

Once we have estimated the transportation cost for remote work shifters, we use it to replace the observed transportation cost in the expenditure aggregate. This is akin to assuming that the counterfactual transportation cost for remote-shifters is the same as that for in-person only households.

4.3 Exploiting exogenous changes in commuting costs

The two methods described above have the weaknesses that there may be systematic differences in households that are in-person only and remote work shifters. Using the first method, we can take into account pre-period differences, but we cannot take into account the difference in pandemic impacts and have to make either an upper or lower bound assumption. In the second, we only take into account differences in transportation costs during the pandemic, and not true counterfactual costs. To address these, we may wish to use a difference-in-differences method, which will allow us to estimate the difference in pandemic impacts on transportation costs for in-person only and remote-shifter households.

To implement this, we usually must construct pseudo panels since expenditure surveys rarely have a panel structure. We must exploit some change in commuting restrictions to compare the groups before and after this change. This may be pandemic-related lockdowns; however, this method naturally extends to other commuting restrictions, such as poor weather or natural disasters, violence, or other crises. Where firm-side data is available, it may be possible to exploit changes in the remote work policies of large firms for this kind of analysis.

5 Data: Case Study on Georgia

To demonstrate these methods, we will perform a case study using real-world data from the country of Georgia. We will use data from two sources: the Georgia Household Income and Expenditure Survey (HIES) from 2019 through 2020 and the Georgia Labor Force Survey (LFS) from 2020.

First, using the LFS, we will compare the methods described above to estimate propensity to work remotely. We will focus on remote workers during the second wave of lockdowns in November and December of 2020, as these likely represent “true" remote workers after labor market adjustments and layoffs that occurred in the first lockdowns in March 2020.

Next, we can use our findings on the impact of the pandemic on transportation expenses to impute a transportation expenditure equivalent for the remote working households by the methods above. By construction, our measure will reduce the estimated impacts of the pandemic on poverty, since we add transportation expenses, and our measure of imputed expenditures will always be larger than the regular expenditure measure. However, the extent to which it affects the estimated poverty impacts is enlightening. We can compare which households would be mis-categorized into or out of poverty using the regular expenditure measure.

More interestingly, we also compute measures of inequality, such as the Gini coefficient, using both expenditure measures. The impacts of the pandemic on inequality may be exaggerated or underplayed by the lack of accounting for transportation expenses in the regular expenditure measure. To the extent that higher-income households are the ones able to work remotely, the pandemic's impacts on inequality in welfare may be severely underestimated by the regular expenditure measure.

Finally, we perform simulations under different future remote work scenarios to understand the broader implications of this method.

6 Preliminary Results

6.1 Propensity to work remotely

First, we show that the size of this problem by outlining the substantial size of commuting costs for households: pre-pandemic, households in the poorest quintile allocated 4% of their monthly expenditures to transportation, while households in the richest quintile allocated 10% (Figure 2). During 2020, households across the distribution reduced transportation expenditures as a share of total income, with households at the top of the distribution experiencing the greatest reductions. These reductions are concentrated in the months immediately after the initial lockdowns in March 2020, as well as near the end of 2020 when a second wave of lockdowns limited in-person activities again (Figure 3). In fact, these measures mask some of the inequality, since they consider transportation expenses as a share of all expenditures: other expenditures may have also declined during the pandemic, and a 1 percentage point decrease in the transportation share for the wealthiest households is much larger in absolute terms than a 1 percentage point decrease for the poorest households.

Remote work is relatively rare in this context: only about 9% of employed workers report working remotely some or all of the time in November and December 2020. This figure is low relative to many other countries, especially high-income countries, where rates of remote work often remained above 10% throughout 2020 and may have reached as high as 45% in November and December (OECD 2021b; Ker, Montagnier, and Spiezia 2021).

Further, pairing these two datasets presents a challenge, since the HIES does not include any information about household members' employment status, type of work, occupation, or industry. However, both datasets include information on education, nationality, age, sex, urban/rural, marital status, and wage earnings. We estimate three types of models: a linear probability model using selected covariates, a logit using the same covariates, and a LASSO selecting among the full set of covariates with interactions and polynomials.

The results from the three models are quite similar. In all cases, estimating the propensity to work remotely with the given set of covariates is a challenge. Table 1 reports R^2 and mean squared error from the three models. The LPM and logit use a limited set of covariates: the quintile of earnings; indicators for primary school, secondary or vocational school, and tertiary education; gender, and urban/rural. The LASSO begins with a 3rd degree polynomial in age and earnings, as well as a full set of interactions between urban/rural, gender, employment, education level, nationality, and marital status. However, after cross-validation to select the penalty parameter that optimizes out-of-sample fit, only 14 covariates are selected to have nonzero coefficients. The LASSO improves the R^2 of the LPM from 0.11 to 0.13. Further, the Pearson correlation and the Spearman rank correlation between the predicted probabilities from each model are quite high (higher than 0.83) (Table 1). The choice of estimation method is not as important as having high-quality data to work with. Future work may consider combining the survey datasets we have with other datasets described above to obtain more detailed information.

The full models appear in Appendix Table A1. The sign of the coefficients is in line with expectations: across all models and measures, higher earners are more likely to work from home, as are those with tertiary education (Gottlieb et al. 2021; Garrote Sanchez et al. 2020). Women are more likely to work remotely (Gottlieb et al. 2021).

One challenge to using these types of regression to predict remote work in this setting is that the small incidence of remote work means that the models rarely, if ever, assign a probability of working remotely greater than 0.5. Instead, to assign remote-shifter household status, we take the 9% of households with the largest propensities to work remotely. This percentage can be tuned to simulate results in a similar setting with higher incidence of remote work.

However, comparing log transportation costs throughout 2020 for the predicted remote-shifter households and predicted in-person only households, we see that our measure appears to capture these households fairly well (Figure 4). That is, we see that the decline in transportation expenses at the end of 2020 is concentrated among the predicted remote-shifter households and is small for the predicted in-person only households. As expected, the remote-shifter households are also those with the largest expenditures and are concentrated in the top quintile of expenditures overall, as previous work has shown that high-income workers were disproportionately likely to work from home during the pandemic, while low-income workers may have had to stop working altogether (OECD 2021a).

6.2 Imputed transportation costs

Since the choice of model seems to make little difference, for ease of interpretation, we will continue using the LPM described above. We can next impute counterfactual transportation expenditures using the methods above. For example, using the pre-pandemic households to predict transport costs for 2020, we find again that our results describe patterns that seem reasonable: the largest average imputed transportation costs are among the top quintile (Figure 5). It is important to note that these averages also take into account zeros for in-person only households, so the inequality is driven both by inequality in propensity to work remotely between quintiles and the difference in transport expenditures between the groups. This implies that consumption inequality using the new transportation expenditures is likely larger than inequality using the previous measures, especially if we use the upper bound interpretation above.

6.3 Revised poverty and inequality estimates

In line with our theoretical discussion, omitting the imputation leads to misclassification of remote-shifter households into absolute poverty. Using the global upper bound poverty line ($5.50 USD 2011 PPP per person per day, or 5.7 GEL per person per day[11]), before the imputation, the poverty headcount among remote-shifter households is 3.8%, compared with 14.6% among the in-person only households. This falls to only 3.1% for remote-shifter households after the transportation expenses are added. This is a 19% decline in the measured poverty rate among this group.

Further, Georgia also uses a relative measure of poverty, the share of the population under 60% of the median consumption. Figure 7 shows the same analysis using this poverty line (in our data, this amounts to about 3.8 GEL per person per day). The misclassification of poverty is even larger here, indicating that many of the remote-shifter households are just below the relative poverty line. The rate of relative poverty is nearly 21% for in-person only households, and only 7.5% for remote-shifters before the imputation. As a result of the imputation, this falls to 4.6%, a 39% decline in the poverty rate measured among this group. This is quite large considering that transportation expenditures are a relatively small share of the household budget, as discussed above. Figure 8 shows how the imputation affects the distribution of expenditures among remote-shifter households.

However, aggregate effects in the population are difficult to detect since only 9% of households are of the remote-shifter type and predicted transportation expenses are only, on average, about 5% of their total expenditures. Thus, despite the inequality of imputed transport expenditures, the net effect on measures of overall income inequality like the Gini are slight. If we use the expenditure measure as reported in the survey, the population Gini coefficient is 0.333. However, once we impute transportation expenditures, the Gini rises to 0.334. This difference could become much larger in a setting where remote work is more common or where transportation expenses are larger.

Conclusions & Implications

In this paper, we have outlined and discussed the implications of remote work for the measurement of household welfare. During the COVID-19 pandemic, households who became able to work remotely faced a change in their consumption decisions due to not needing to pay transportation costs or face a disutility of commuting. Because of this change, approximations of welfare using household expenditures do not follow welfare monotonically. This poses important challenges to measuring the poverty and inequality impacts of the pandemic.

We propose a method for imputing counterfactual transportation costs for remote working households in cross-sectional survey data. Consumption or budget survey data often does not include information on

[11] https://databank.worldbank.org/data/download/poverty/987B9C90-CB9F-4D93-AE8C-750588BF00QA/AM2020/Global_POVEQ_GEO.pdf

households' mode of work, requiring methods for imputation of remote working status based on other data sources. We next discuss various methods for imputing transportation costs for these households.

We show the importance of this kind of imputation using a case study from Georgia, where about 9% of households worked remotely. Among remote working households, the imputation of transportation costs results in a 19% decline in the measured absolute poverty rate among this group and a 39% decline in the relative poverty rate among them. Overall average impacts may be larger in settings where remote work is even more common.

Future work should consider several extensions. We work only with expenditure-based poverty measures, but a similar imputation may be appropriate for multidimensional poverty measures as well. In addition, future work should consider expanding the model to include other changes and constraints imposed on the household consumption decision due to the pandemic, such as changes in childcare, meals out of the home, and payments for clothing needed for in-person working.

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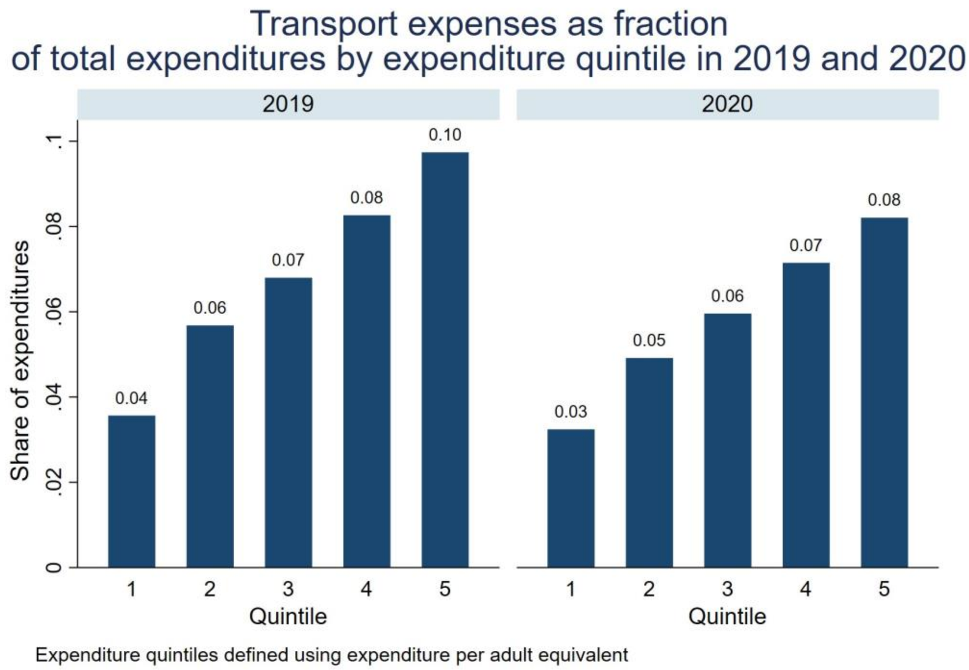

Figure 2: Transportation share of expenditures by quintile, 2019 and 2020. Source: Georgia HIES

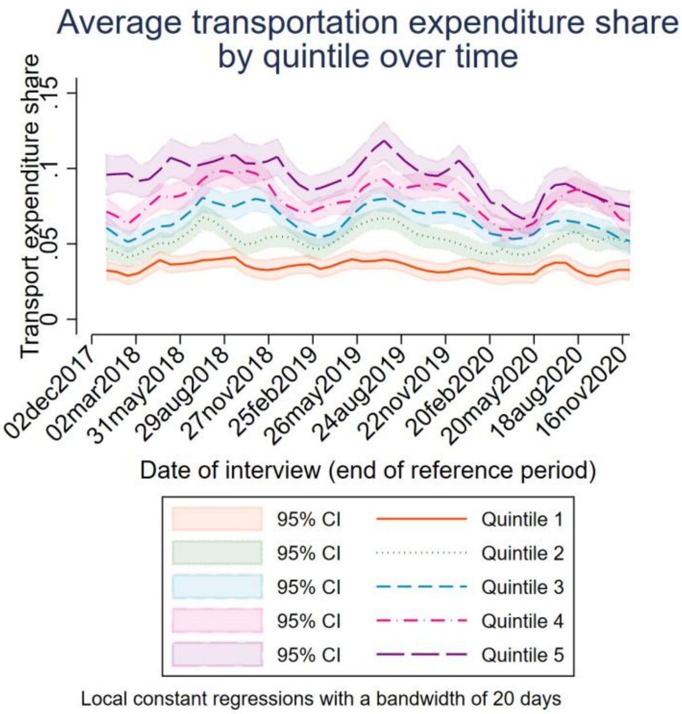

Figure 3: Transportation share of expenditures by quintile over time. Source: Georgia HIES

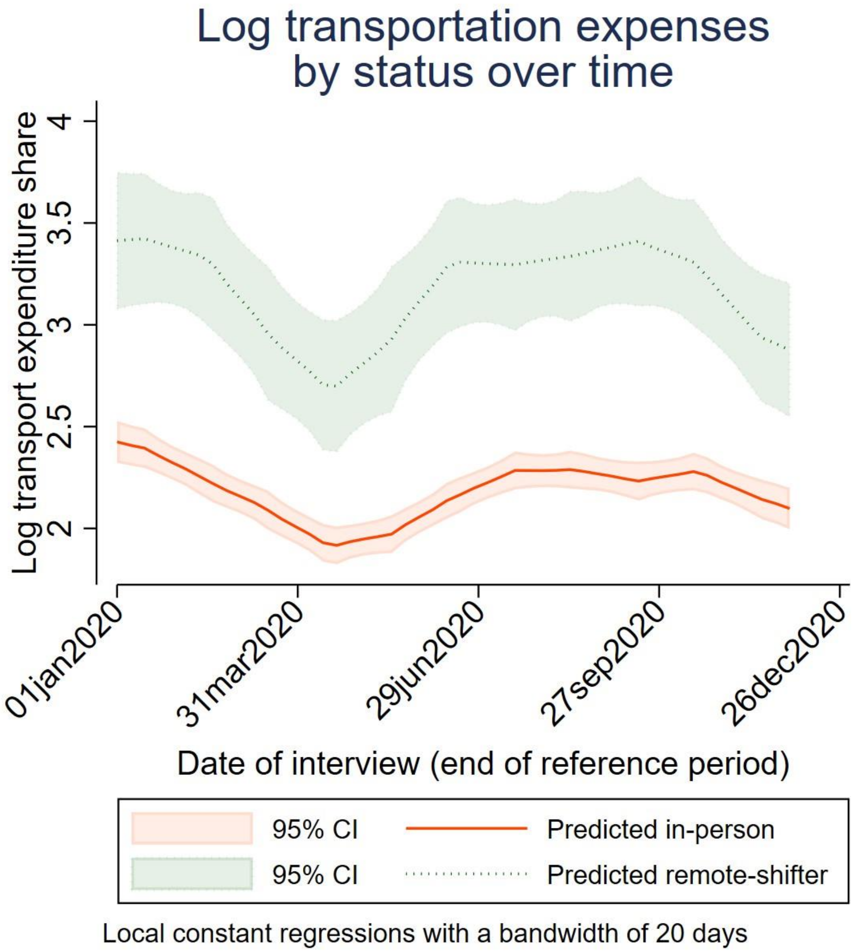

Figure 4: Log of transportation expenditures for remote-shifter and in-person only households. Source: Georgia HIES

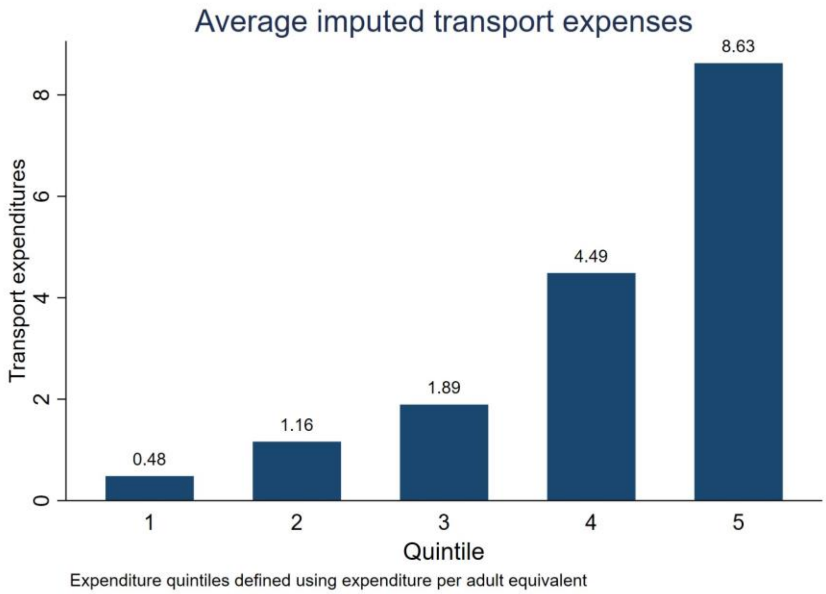

Figure 5: Predicted transportation expenditures by quintile. Source: Georgia HIES

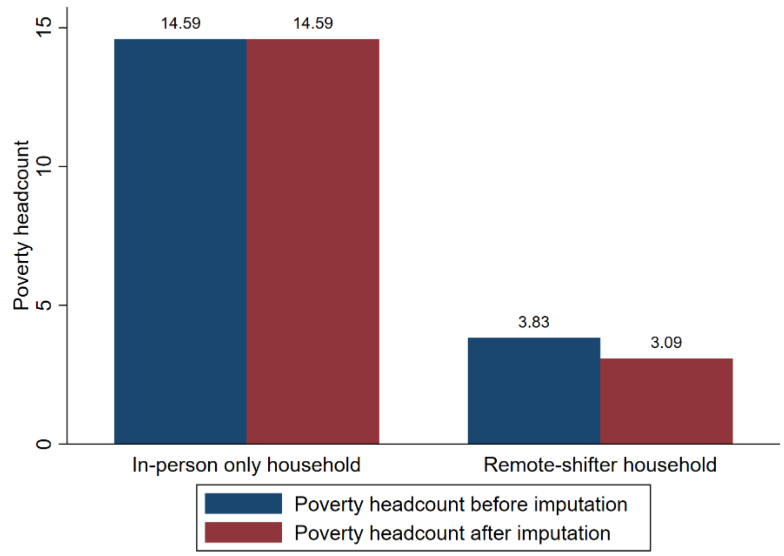

Figure 6: Absolute poverty headcount before and after imputation (upper bound poverty line)

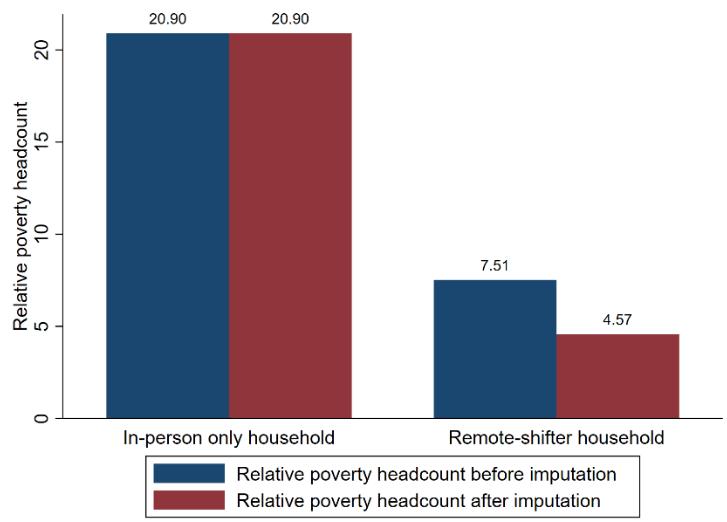

Figure 7: Relative poverty headcount before and after imputation (under 60% of median consumption)

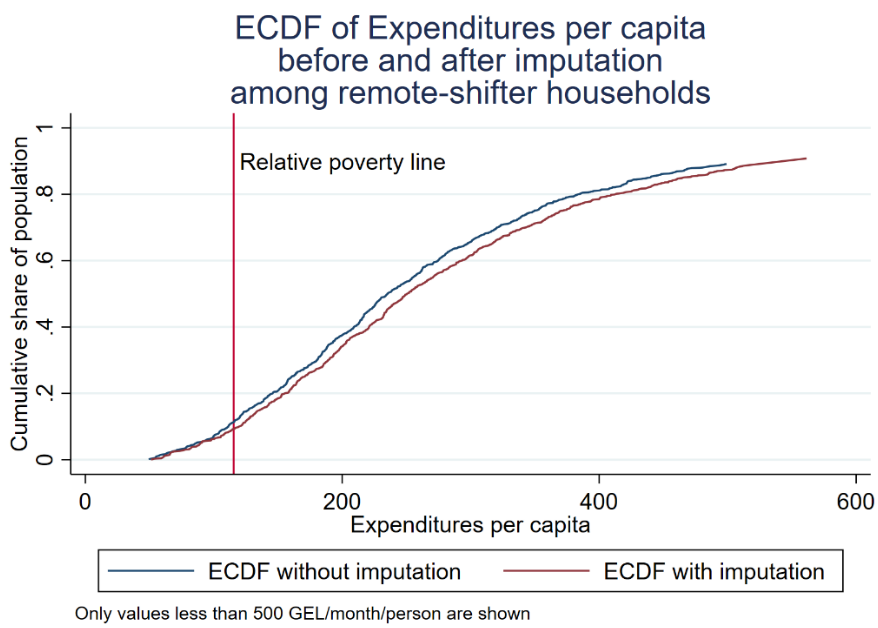

Figure 8: Empirical CDFs of expenditures before and after imputation

Table 1: Comparison of goodness-of-fit between models predicting WFH propensity

	LPM	Logit	LASSO
R2/Pseudo R2	0.11	0.16	0.13
MSE	0.0896	-	0.0868
Pearson correlation with LASSO predictions	0.77	0.81	1
Pearson correlation with logit predictions	0.94	1	0.81
Spearman correlation with LASSO predictions	0.83	0.83	1
Spearman correlation with logit predictions	0.99	1	0.83

Appendix

Table A1: Models predicting propensity to WFH

	(1) LPM	(2) Logit	(3) LASSO
Q2 of earnings	0.0301	0.388	
	(0.0160)	(0.251)	
Q3 of earnings	0.0845***	0.909***	
	(0.0219)	(0.252)	
Q4 of earnings	0.130***	1.254***	
	(0.0268)	(0.257)	
Q5 of earnings	0.104***	1.138***	
	(0.0234)	(0.261)	
Primary education only	-0.0247	-	
	(0.00932)	-	
Secondary or vocational education	-0.141***	-1.646***	
	(0.0144)	(0.193)	
woman	0.101***	1.066***	
	(0.0152)	(0.177)	
urban	-0.0264	-0.253	
	(0.0138)	(0.154)	
woman=1 # Master or equivalent			0.150
employee=1 # Master or equivalent			0.0350
urban=0 # employee=1 # Master or equivalent			0.00463
urban=1 # woman=1 # Master or equivalent # Armenian			0.0894
employee=1 # Bachelor or equivalent # Azeri			0.0846
employee=1 # Doctor or equivalent # Georgian			0.131
urban=0 # employee=1 # Master or equivalent # Azeri			0.155
woman=0 # employee=1 # Doctor or equivalent # Georgian			0.0338
Bachelor or equivalent # Married			0.0508

woman=1 # Bachelor or equivalent # Married			0.0134
woman=1 # employee=1 # Master or equivalent # Married			0.0399
urban=0 # woman=1 # employee=1 # Bachelor or equivalent # Married			0.0284
urban=0 # employee=1 # Master or equivalent # Azeri # Married			0.255
Interval of earnings			0.00876
Constant	0.102***	-2.607***	0.0190
	(0.0203)	(0.270)	
Observations	2052	1980	2052

Heteroskedasticity-robust standard errors in parentheses. Note that the sample size differs for logit because primary education predicts failure perfectly, and thus that group is omitted. No standard errors are estimated for LASSO.
* p<0.05, ** p <0.01, *** p<0.001