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# Consumer Immobility Predicts both Macroeconomic Contractions and Household Poverty during COVID-19

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## INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

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#### Notices

**Abstract**

Amid extreme uncertainty during the COVID-19 pandemic, economic policymakers have struggled to respond to rapidly changing circumstances with appropriate speed and scale. One policy obstacle is the dearth of real-time indicators of the pandemic's economic impacts, especially in low and middle income countries (LMICs). Here we show that an 'immobility' indicator from Google™ – measuring the extent to which consumers are staying at home more – is a powerful predictor of changes in household poverty in Myanmar, as well as aggregate national consumption and gross domestic product (GDP) in cross-country data. Combined, this evidence suggests that real-time mobility indicators have the potential to inform a wide range of policy deliberations, including forecasting models, fine-tuning the timing of both economic stimulus and social protection interventions, and tracking economic recovery from this unprecedented crisis.

**Keywords:** COVID-19; mobility indicators; poverty; consumption; economic growth

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## Introduction

COVID-19 has resulted in an economic crisis without precedent in modern times, involving economic contraction in almost all countries (1), rising unemployment (2), dramatic economic shut-downs (3), and perhaps as many as 140 million people falling into extreme poverty in low and middle income countries (LMICs) (4).

The sheer speed of COVID-19 shocks has resulted in many governments struggling to accurately assess the economic damage, resulting in sluggish economic stimulus and social protection interventions (2). One significant obstacle to more timely responses has been the dearth of real-time indicators of economic impacts, especially in the absence of in-person surveys.

In this study we use regression analysis to show that an immobility index from Google (5) – measuring how much more consumers stay at home compared to a pre-COVID baseline – is a powerful predictor of poverty dynamics in a household panel from Myanmar, as well as of changes in household consumption, expenditure, and GDP in cross-country data. This index is publicly updated every 2-3 days, thereby offering policymakers a real-time indicator for informing rapid economic assessments and the design of appropriate policy responses. Given the continued economic disruptions caused by COVID-19, as well as the risk of future pandemics, these kinds of mobility indices offer a valuable tool for improving economic policy responses to pandemics.

## Results

### *Mobility shocks predict poverty dynamics in Myanmar in 2020*

Mobility indices offer information on the economic impacts that COVID-19 case data or policy measures do not, as the example of Myanmar indicates (Figure 1). Myanmar imposed strict COVID-19 prevention measures in late March and April (See the Stringency Index in Figure 1), which coincided with phone-owners staying home around 30% more than the pre-COVID baseline of this index. However, although prevention measures in Myanmar remained stringent throughout 2020, the stay-at-home index (SAHI) fell to around 10% above baseline over May to August as COVID-19 cases stabilized. A far more serious outbreak in late August led to a sharp increase in phone-owners staying at home, which persisted for much longer as COVID cases continued to grow. Hence, the relationship between stringency, COVID-19 cases and SAHI is relatively weak because consumers respond to both policies and contagion risks, and can choose to violate COVID-19 policies.

Next we assessed whether these variations in mobility predict poverty dynamics in Myanmar using a large phone-based panel survey conducted from June-November 2020 in urban Yangon and villages in the rural dry zone region (see Figure 1 for survey timings). The survey asked respondents to estimate total household income in the past month as well as in January 2020, and these income data were used to estimate income-based poverty at the $1.90/day World Bank extreme poverty line.

Figure 2 reports both the survey-based estimates of poverty as well poverty trends predicted from a least squares regression of household poverty status against SAHI in the urban (Panel A) and rural (Panel B) sub-samples. In both samples a 10% increase in staying at home increases the risk of poverty by around 15-16%, although the model has greater predictive power in the urban sample, explaining 22% of the total variation in household poverty across rounds compared to 15% in the rural sample. This difference likely stems from the fact that farm incomes in rural areas are highly seasonal and less affected by COVID-19 disruptions (3). However, the fact that mobility still predicts rural poverty quite strongly likely stems from non-farm activities accounting for two-thirds of rural income in this part of Myanmar (7).

Additional results are reported in the Appendix. Our main results are robust across livelihoods, with the expected exception of there being much lower explanatory power for poverty dynamics among salaried households (Appendix Table A1). We also compared the predictive power of

SAHI to the lagged monthly averages of the policy stringency index and growth in COVID-19 cases, but these indicators explained much less variation in poverty than SAHI, especially in the urban sample.

### ***Mobility shocks predict consumption and GDP growth in cross-country data***

Do mobility shocks explain other economic outcomes in 2020 across a broader array of countries? To assess this, we combined annual averages of SAHI with the IMF's GDP growth estimates for 2020 (1) for 107 countries, and quarterly SAHI averages with private household consumption expenditure (hereafter 'consumption') for the first three quarters of 2020 for 25 OECD countries.

Figure 3 shows scatterplots of these associations, both of which are negative, although the bivariate association is stronger for consumption growth (Panel B) than it is for GDP growth (Panel A). However, since mobility shocks should indeed primarily affect the consumption component of GDP, it is important to net out the effects of international shocks on the trade and investment components of GDP. Hence, in Table 1 the GDP growth regressions control for measures of structural exposure to international shocks and pre-COVID economic growth, while the OECD consumption panel absorbs a wide range of structural characteristics with country fixed effects.

In the full sample of 107 countries a 1.0% increase in SAHI predicts a -0.30% decline in GDP growth in 2020, although the estimated elasticities are somewhat larger when the sample is split into LMIC (-0.39) and high income subsamples (-0.43). In the OECD quarterly panel on consumption growth we obtain an even larger elasticity for SAHI (-0.48) and a very high within R-squared, suggesting that mobility shocks explained 85% of the variation in consumption growth in OECD countries in the first three quarters of 2020.

Appendix Table A3 shows that SAHI outperforms the policy stringency index and cumulative COVID-19 caseload estimates in predicting GDP growth, but Appendix Table A4 suggests that the policy stringency index performs equally well in explaining consumption growth in the OECD panel, perhaps because of the very strong association between policy measures and mobility in this sample.

## **Discussion**

In the current economic crisis mobility indices may be highly predictive of poverty dynamics and economywide shocks more broadly. Previous research has demonstrated the predictive value of mobility indicators for industrial output (8) and point-of-sale consumption in Latin America (9), although the present study is the first to link immobility to poverty, and to important national accounts aggregates in a much broader swathe of countries.

The predictive power of mobility indices, their real-time availability for a wide range of countries, and their high potential for spatial granularity, imply that they have tremendous potential to inform policy deliberations during the unique uncertainties of the COVID-19 pandemic. Mobility indices are likely to be especially useful in LMICs where there is a paucity of high-frequency data, and could be used more extensively for forecasting models (4), to assess the economic impacts of pandemic-related economic shocks, and to design appropriate economic stimulus and social protection interventions, such as scaling up household cash transfers during lockdowns (10). Real-time mobility data could also speed up policy responses. In Myanmar, macroeconomic forecasts were misleadingly optimistic in 2020, and only months after the onset of the crisis did household surveys ultimately show that household incomes had declined precipitously (11, 12). Mobility data would likely have been a much better short-term guide to the economic health of a population during this pandemic than macroeconomic forecasts, and they may yet be a better guide to economic recovery.

## Methods and materials

To assess the predictive power of mobility indices we downloaded Google™ mobility data (5) – which is derived from location tracking on mobile phones – for 107 countries in 2020 and used their residential mobility index, which we re-named the Stay-at-Home Index (SAHI). SAHI measures the extent to which phone users make fewer and shorter trips outside the home relative to a corresponding baseline day measured as the median value from the 5-week period January 3rd to February 6th, 2020.

For Myanmar we first compared trends in SAHI to a COVID-19 Policy Stringency Index as well as cumulative COVID-19 cases (6). We then estimated how well SAHI predicted income-based poverty dynamics using an unbalanced panel derived from six rounds of monthly phone surveys implemented from June through November 2020, covering 2,201 households in urban Yangon and rural areas of the dry zone (13). Respondents estimated total household income in the past month and in January 2020 (pre-COVID), which was used to measure income-based poverty at the $1.90 per day poverty line in 2011 PPP dollars. We then estimated household fixed effects regressions to estimate how poverty risks varied with SAHI shocks in the past month, plotted the predicted poverty rate against the survey-based poverty rate, and used the within R-squared to assess predictive power. We repeated this exercise for the lagged stringency index and COVID-19 caseload growth.

For the cross-country analysis, the annual average of SAHI was merged with GDP growth estimates for 2020 (1) and year-on-year growth in quarterly private household consumption expenditure for 25 OECD countries for the first three quarters of 2020 (14). We used scatterplots and least squares regression fits to visually inspect the relationships of these indicators with SAHI. For the cross-section of GDP growth estimates we then estimated least squares regression fits that controlled for oil and mineral exports (%GDP), total trade (%GDP) and tourism receipts as a share of total exports (15) to capture exposure to COVID-related trade shocks, as well as average GDP growth over 2010-2019 from the IMF (1) to capture pre-COVID economic momentum. For the OECD consumption panel we estimated regressions with country fixed effects and time period effects to control for common global shocks. The coefficients on SAHI in these regressions represent elasticities with respect to growth/consumption, while the within R-squared was also used to assess the overall predictive power of the mobility index in the OECD consumption panel. We also repeated these analyses for the average value of the COVID-19 policy stringency index and cumulative COVID-19 caseloads.

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## Figures

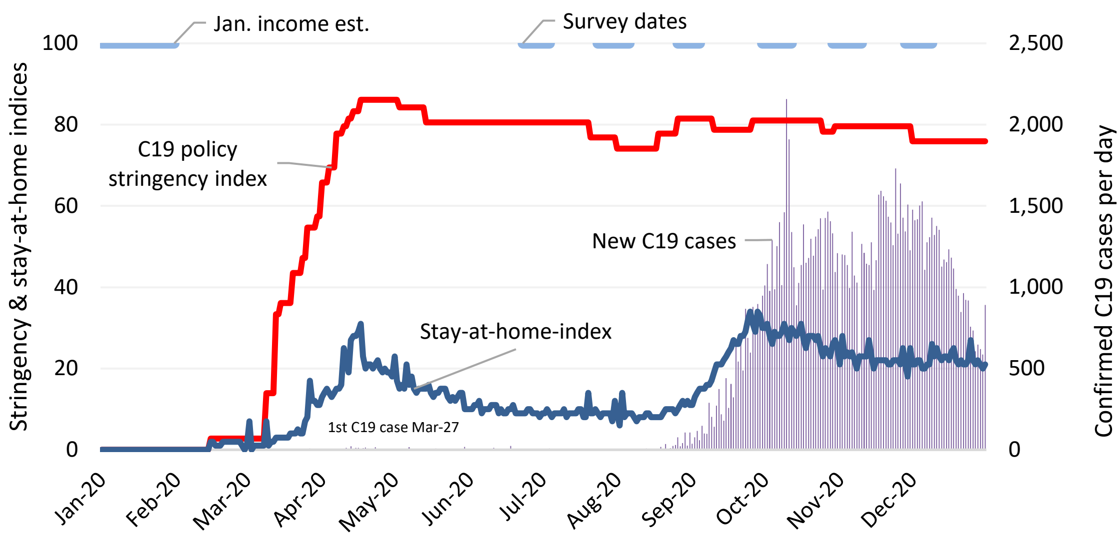
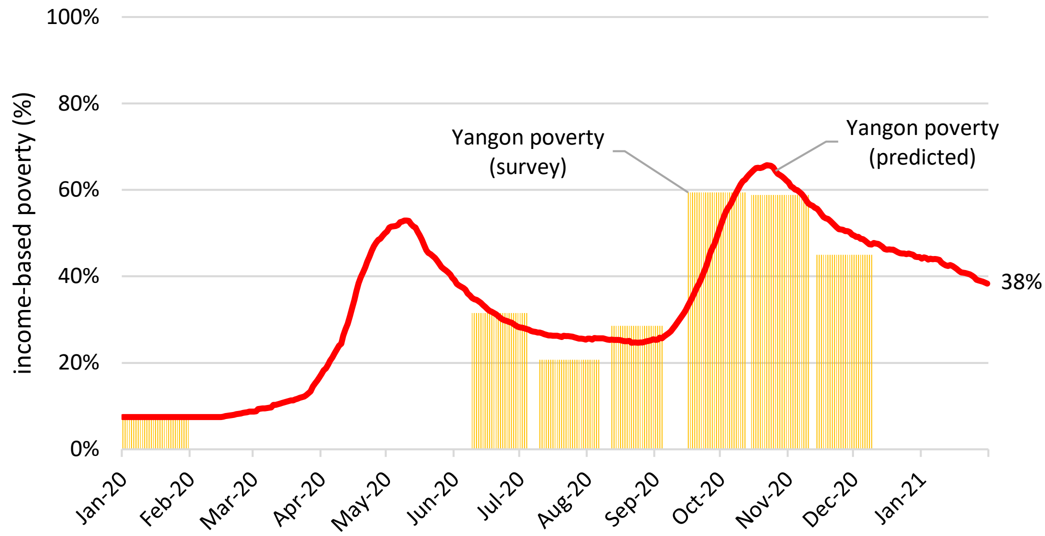
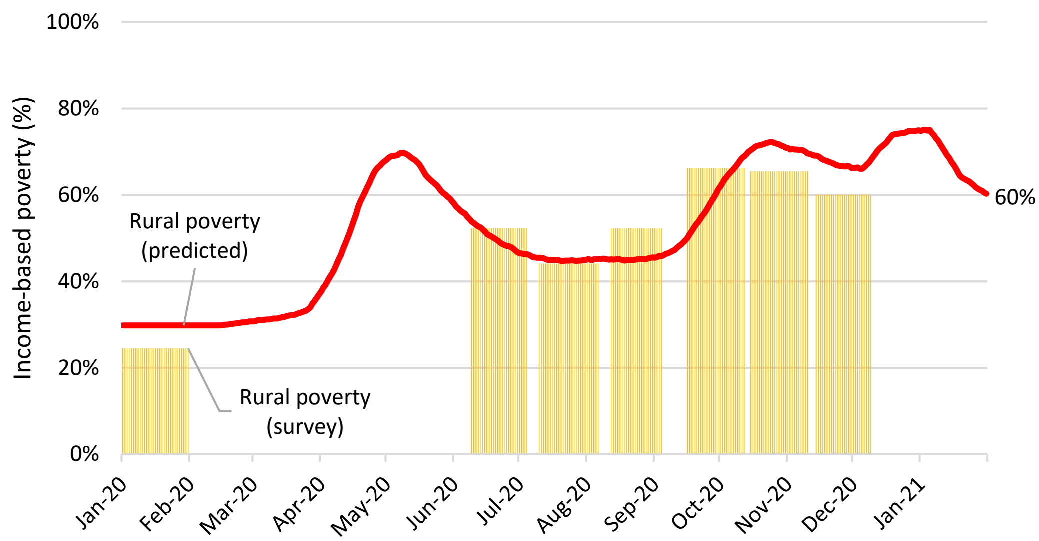



**Figure 1. Trends in daily COVID-19 cases, the Oxford prevention stringency index and the Google™ stay-at-home index in Myanmar**

Source: See Methods and Materials for details.



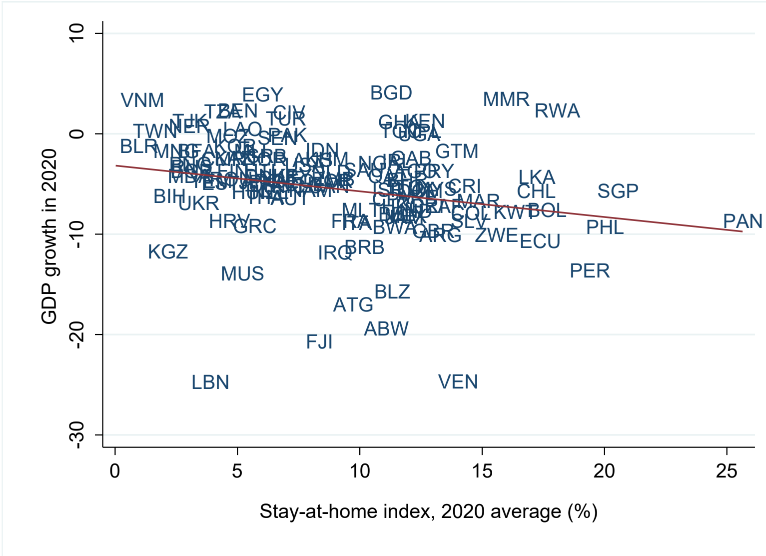

**Panel A: Urban Yangon**



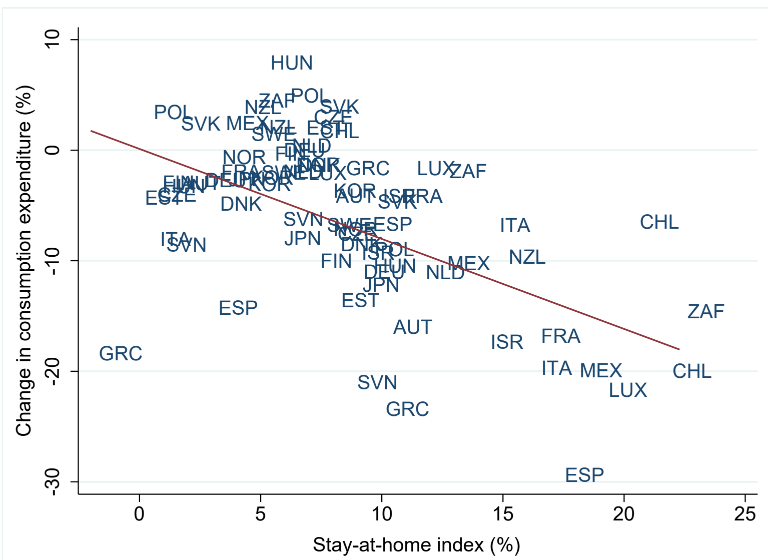

**Panel B: Rural dry zone**

**Figure 2. Comparing survey estimates of income-based poverty to poverty trends predicted by the Google$^{TM}$ Stay-at-home index**

Notes: Income-based poverty refers to income per adult equivalent at the $1.90/day poverty line in 2011 international dollars. The orange bars refer to poverty estimated over the various survey reference periods, while the red line refers to poverty trends predicted by a linear probability model regression of poverty against the stay-at-home index. See Materials and Methods for more details.




**Panel A: GDP growth and the Stay-at-home index in 2020 across 107 countries**




**Panel B: Quarterly consumption growth and the Stay-at-home index in 25 OECD countries**

**Figure 3. Scatterplots of changes in GDP and private consumption expenditure against the Google™ Stay-at-home index in 2020**

Source: See Materials and Methods for more details. ISO3 country codes are reported in the scatterplots while the red lines report least squares regression fits.

**Tables**

**Table 1. Estimated elasticities between annual GDP growth and quarterly consumption growth and Stay-at-home index shocks in 2020**

| | (1) | (2) | (3) | (3) |
|---|---|---|---|---|
| Dependent variable | Annual GDP growth | Annual GDP growth | Annual GDP growth | Quarterly consumption growth |
| Estimator | Least squares | Least squares | Least squares | Fixed effects OLS |
| Sample | 108 countries | 69 LMICs | 38 High income countries | 25 OECD countries |
| Stay-at-home index | -0.30*** | -0.39*** | -0.43*** | -0.48*** |
| | (0.07) | (0.09) | (0.10) | (0.15) |
| Other controls? | Yes | Yes | Yes | |
| Country fixed effects? | | | | Yes |
| Time period effects? | | | | Yes |
| Observations | 108 | 70 | 37 | 75 |
| R-squared | 0.53 | 0.44 | 0.82 | 0.85 |

Notes: See Materials and Methods for more details on control variables. Standard errors in parentheses with significance levels as follows: *** p<0.01, ** p<0.05, * p<0.1. Regression (3) reports standard errors clustered at the country level.

## Appendix

**Table A1. Fixed effects linear probability model estimates of the change in poverty risks associated with a 10% increase in the stay-at-home index (SAHI) in various samples**

| | (1) | (2) | (3) |
|---|---|---|---|
| **Sample of households** | **Total** | **Urban** | **Rural** |
| Number of observations | 13,690 | 6,859 | 6,831 |
| Number of households | 2,201 | 1,163 | 1,038 |
| Poverty risk of 10% increase in staying at home | 0.157*** | 0.154*** | 0.162*** |
| | (0.004) | (0.004) | (0.006) |
| *R-squared (within)* | *0.176* | *0.224* | *0.129* |
| | **(4)** | **(5)** | **(6)** |
| **Sample of households (livelihood)** | **Farming** | **Unskilled labor** | **Skilled labor** |
| Number of observations | 2,006 | 4,912 | 2,268 |
| Number of households | 312 | 798 | 371 |
| Poverty risk of 10% increase in staying at home | 0.168*** | 0.161*** | 0.171*** |
| | (0.011) | (0.006) | (0.009) |
| *R-squared (within)* | *0.140* | *0.178* | *0.211* |
| | **(7)** | **(8)** | **(9)** |
| **Sample of households (livelihood)** | **Trade** | **Salary** | **Other** |
| Number of observations | 1,028 | 2,306 | 1,170 |
| Number of households | 170 | 368 | 182 |
| Poverty risk of 10% increase in staying at home | 0.159*** | 0.090*** | 0.242*** |
| | (0.012) | (0.007) | (0.010) |
| *R-squared (within)* | *0.174* | *0.102* | *0.352* |

Notes: Coefficients are derived from linear probability models with household fixed effects, with standard errors clustered at the household level.

**Table A2. Comparing the predictive power of one-month lags of Stay-at-home index, the COVID-19 policy stringency index and COVID-19 case growth in predicting income-based poverty dynamics in urban and rural areas of Myanmar**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Sample of households** | **Urban** | **Urban** | **Urban** | **Rural** | **Rural** | **Rural** |
| Observations | 6,859 | 6,859 | 6,859 | 6,831 | 6,831 | 6,831 |
| Number of households | 1,163 | 1,163 | 1,163 | 1,038 | 1,038 | 1,038 |
| Stay-at-home index (10-point change) | 0.154*** | | | 0.162*** | | |
| | (0.004) | | | (0.006) | | |
| C19 Stringency Index (10-point change) | | 0.043*** | | | 0.041*** | |
| | | (0.001) | | | (0.002) | |
| Growth C19 cases (100-unit change) | | | 0.026*** | | | 0.020*** |
| | | | (0.001) | | | (0.001) |
| *Within R-squared* | *0.224* | *0.105* | *0.136* | *0.129* | *0.090* | *0.081* |

Notes: Coefficients are derived from linear probability models with household fixed effects, with standard errors clustered at the household level.

**Table A3. Comparing elasticities and explanatory power of Stay-at-home index, the C19 stringency index and cumulative COVID-19 cases in explaining GDP growth in 2020 across a cross-section of 107 countries**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Observations (countries) | 107 | 107 | 107 | 107 |
| Stay-at-home index (%) | -0.300*** | | | -0.270*** |
| | (0.070) | | | (0.089) |
| C19 Stringency Index (%) | | -0.081*** | | -0.019 |
| | | (0.028) | | (0.035) |
| C19 cases per 1000 | | | -0.017 | -0.001 |
| | | | (0.022) | (0.022) |
| Tourism (%exports) | -0.101*** | -0.107*** | -0.110*** | -0.101*** |
| | (0.028) | (0.029) | (0.030) | (0.028) |
| Oil/mining (%GDP) | -0.082* | -0.075* | -0.104** | -0.078* |
| | (0.042) | (0.045) | (0.045) | (0.043) |
| Trade (%GDP) | -0.015** | -0.019*** | -0.014* | -0.016** |
| | (0.006) | (0.006) | (0.007) | (0.007) |
| GDP growth 2010-2019 (%) | 1.229*** | 1.153*** | 1.139*** | 1.214*** |
| | (0.145) | (0.152) | (0.166) | (0.156) |
| *R-squared* | *0.526* | *0.484* | *0.444* | *0.528* |

See Materials and Methods for more details. Robust standard errors are in parentheses with significance levels as follows: *** p<0.01, ** p<0.05, * p<0.1.

**Table A4. Comparing elasticities and explanatory power of Stay-at-home index, C19 stringency index and cumulative COVID-19 cases in explaining private consumption expenditure growth in fixed effects regressions for a panel of 25 OECD countries**

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| Observations | 75 | 75 | 75 |
| Number of countries | 25 | 25 | 25 |
| Stay-at-home index (%) | -0.484*** | | |
| | (0.153) | | |
| C19 Stringency Index (%) | | -0.146*** | |
| | | (0.035) | |
| C19 cases per 1000 | | | 0.566** |
| | | | (0.274) |
| Country fixed effects? | Yes | Yes | Yes |
| Time effects? | Yes | Yes | Yes |
| *R-squared* | *0.846* | *0.844* | *0.803* |

See Materials and Methods for more details. Standard errors are in parentheses and clustered at the country level, with significance levels as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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