Is mobility a good proxy for economic activity?

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Abstract

This paper documents the relationship between mobility and economic activity, employing a unique longitudinal dataset of transactions to proxy spending at both country and local level in the United Kingdom. I disaggregate online and in-store spending, and employ fixed effects and panel vector autoregression models. In doing so, I demonstrate that retail and recreational mobility is a reliable proxy for in-store spending. Moreover, no correlation is found between online shopping and mobility, suggesting that online shopping does not substitute for in-store spending, even when the latter is legislatively constrained.

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JEL: C21, C22, C55, L81, R12.

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1. Introduction

In order to evaluate the impact of government-imposed Covid-19 restrictions on human mobility, the scientific community has heavily relied on novel digital footprints such as mobility data (for a selective survey, see Weill et al., 2021). Furthermore, social scientists quickly began to use mobility data to measure economic activity for research purposes from the start of the pandemic (WEO, 2020, Deb et al., 2020, Boone and Ladreit, 2021, Buono and Conteduca, 2020). The utility of high-resolution mobility data becomes apparent when considering the localized nature and dynamic environment of epidemics like Covid-19 and their accompanying restrictions. Nevertheless, the extent to which mobility serves as a reliable proxy for economic activity remains uncertain.

Early studies, such as OECD (2020), observed that mobility indices can explain approximately 75% of the cross-country variation in private spending. Similarly, Sampi Bravo and Jooste (2020) found mobility to be a leading indicator for nowcasting industrial production in Latin American countries. The most comprehensive attempt to analyze the relationship between mobility and activity can be found in Gamtkitsulashvili and Plekhanov (2021), which suggests that mobility data perform well in out-of-sample forecasts when compared with alternative benchmarks. However, these studies investigate the relationship at country level and at low frequency, by looking at macroeconomic aggregates with no breakdown between spending categories.

This paper is the first to document the relationship between mobility and activity at sub-national level and for sub-components of spending. Leveraging a unique dataset provided by Fable Data Ltd, comprising granular transaction-level information at high frequency, I construct multiple spending indicators. In line with many studies that have employed transaction data to proxy activity, I consider these series as

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[1]For a review on the use of transaction data as an economic indicator, see Baker and Kueng (2022). A selection of works that

indicators of consumption.[1] Notably, I distinguish between online and in-store spending, and disaggregate the data by merchant type. The analysis draws on mobility data sourced from the Google Mobility Report, encompassing both time series data at the country level and panel data at the local authority district level in the United Kingdom. To estimate elasticities between various types of spending and mobility, I employ two-way fixed-effects models and panel VAR models.

The major finding is that mobility is a significant predictor of in-store spending, with a particularly strong correlation when we purchases from groceries and pharmacies are excluded (as these were excluded from lockdown rules in the United Kingdom during Covid-19). Moreover, I find that mobility is not correlated with online spending, regardless of the mobility index employed.

These findings suggest that mobility data can be a useful high-frequency granular indicator of retail spending, with important implications for applied work like micro-level natural experiments or quasi-experimental designs. The results also provide insights into the economic dynamics of the Covid-19 mobility restrictions in the United Kingdom. The main policy-relevant implication of the results is that negative shocks to mobility are expected to be associated with falls in retail spending but not with increases in online shopping. Thus, negative shocks to mobility should lead to falls in spending overall.

2. Data and methods

I use a rich dataset of transaction and mobility data for the UK at national and sub-national level. Mobility data are obtained from the Google Mobility Report, which aggregates anonymized information regarding trends in visits to categorized places from Google users that have opted in using their 'location history' setting.[2] These data are expressed as percentage deviations from a baseline, which is the median daily value over a five-week period spanning 3rd January to 6th February 2020. These data are aggregated into five categories: retail and recreational places (RRM), groceries and pharmacies (GPM), transit stations, working places and places of residence. I mainly focus on RRM, as other studies (e.g., Buono and Conteduca, 2020) have employed this type of mobility to proxy consumption. The two key advantages of mobility data are their high frequency (daily) and their granularity (local authority district).

The transaction-level data are provided by Fable Data Ltd, which collects and aggregates hundreds of millions of anonymized transactions for selected European countries (`https://www.fabledata.com/`). For each transaction there is information on the date, monetary value, country, currency, merchant code, type of transaction, and whether it occurred in-store or online. Moreover, there are metadata on users (i.e., the owner of the account connected to each transaction) such as the geographical location of their primary address, as well as metadata on the merchant, such as the postcode of the physical store.

I aggregate total transaction values to local authority level at weekly frequency, and distinguish between online and in-store purchases. When aggregated at national level, in-store spending and online spending amount to approximately 11% and 49% of total transactions, respectively. The remaining proportion cannot clearly be identified as offline or online. In-store spending is filtered by merchant code to obtain, for example, a series of transactions in groceries and pharmacies to match the classifications adopted in the Google Mobility Report. The result is five series: total spending, online spending, in-store spending, in-store groceries and pharmacies (ISG), and in-store excluding groceries and pharmacies (ISX). Depending on the model, the transaction data are examined in natural logs, as percentage deviations from the pre-pandemic median, or scaled by local population. After districts with missing data are excluded, the final database is composed of 187 districts with the sample spanning the 7th week of 2020 to the 5th week of 2021. Further information on the dataset is provided in the online appendix.

The results presented below are a combination of descriptive statistics, fixed effects regression estimates, and VAR estimates. To estimate the elasticities of

employ transaction data to study the impact of the pandemic include Chen et al. (2021), Andersen et al. (2020), Baker et al. (2020), Carvalho et al. (2021), Chronopoulos et al. (2020), Hacioglu Hoke et al. (2020), Casado et al. (2020), and particularly Gathergood et al. (2020) and Gathergood and Guttman-Kenney (2020) which use Fable transaction data. Note that mobility data are available for many more countries than transaction data, hence the importance of understanding whether the former can proxy for the latter.

[2]For a detailed explanation of the data aggregation process, see Aktay et al. (2020).

various types of spending to mobility, I employ a two-way fixed effects model as follows:

$$spending_{it} = \alpha_i + \delta_t + \beta \times mobility_{it} + \epsilon_{it}, \quad (1)$$

in which $spending_{it}$ and $mobility_{it}$ represent the spending and mobility series for local authority i in week t, while α_i and δ_t represent unit and time fixed effects.

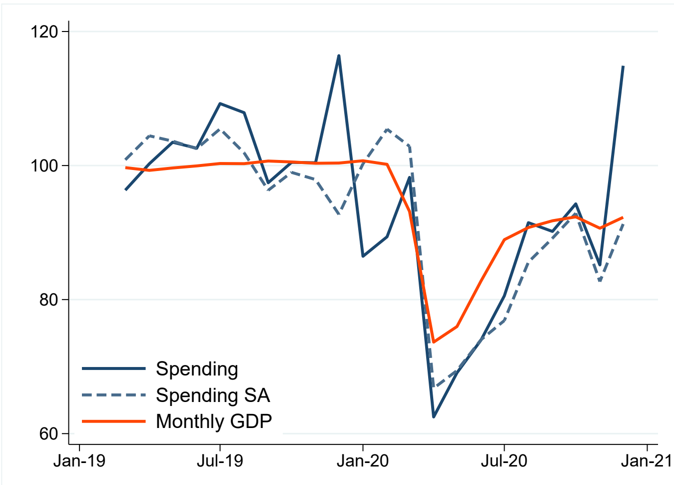

Figure 1: Monthly GDP, in-store spending and in-store spending seasonally adjusted (2019=100).

Given the results of this model, I explore the relationship between our ISX and RRM indices further, by fitting bivariate VARs and panel VARs, i.e.,

$$y_t = Ay_{t-1} + \epsilon_t, \quad (2)$$

$$y_{it} = \mu_i + Ay_{it-1} + \epsilon_{it}. \quad (3)$$

Lag lengths are selected using conventional criteria, and impulse response functions are reported for both of the possible Cholesky decompositions.

3. Results

First, as a validation exercise, I evaluate how our spending series performs vis a vis national accounts data. Thus, monthly GDP series released by the UK Office for National Statistics are plotted with the in-store spending series in figure 1, with data indexed to 2019. From figure 1 one can observe that the spending series clearly tracks the pattern of GDP between 2019 and 2020, and closely captures the pandemic recession in April 2020.

I proceed to evaluate the effectiveness of mobility as a proxy for spending. I first concentrate on the series aggregated at national level, and visually inspect the correlations with spending data expressed as a deviation from the pre-pandemic median. In the upper panel of figure 2 one can see that ISX and RRM are strongly correlated (0.86) in the entire sample. In the lower panel I plot GPM and ISG. Relative to the previous case, the correlation is weaker (0.30) but still positive.

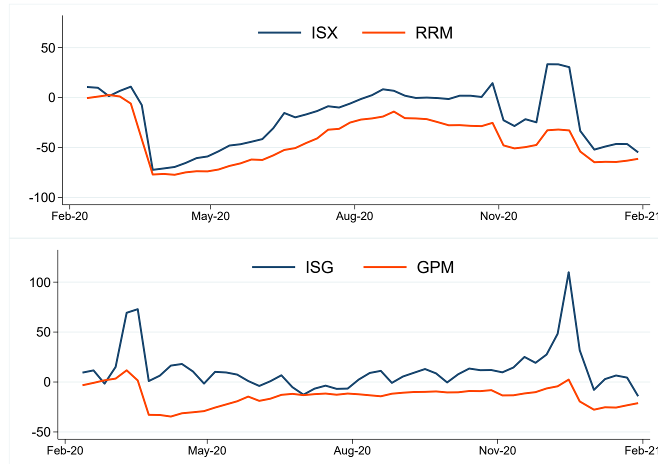

Figure 2: The upper panel displays Spending Excluding Groceries and Pharmacies (ISX), expressed as deviation from pre-pandemic median, and Retail and Recreational Mobility (RRM). The lower panel display Spending in Groceries and Pharmacies (ISG), expressed as deviations from pre-pandemic median, and Groceries and Pharmacies Mobility (GPM).

The strong correlation between ISX and RRM is confirmed as we move from aggregate to panel data. Figure 3 displays the correlation coefficients and confidence intervals for each district in the panel. We notice that about 90% of the units in our sample display a correlation coefficient greater than 0.5, and 46% display a coefficient greater than 0.75.

In figure 4 I provide a more comprehensive overview of this relationship by estimating the elasticity of spending with respect to mobility using model 2 and the entire set of indices. The results are grouped by explanatory variable (labeled at the top of each panel) and the outcome variables are the logarithms of our spending series (labeled in the legend). In line with expectations, mobility appears to be a significant explanatory variable for in-store spending. The largest estimates are associated with ISX, and range from approximately -4% for residential mobility to approximately +1.2% for Groceries and Pharmacies. On the other hand, perhaps surprisingly, none of the mobility indicators are significant when online spending is the outcome variable.

Given these results, I further explore the relationship between ISX and RRM by looking at the dynamic responses from our VAR models. Figure 5 depicts the orthogonalized impulse response functions from the estimated VAR model. The figure shows the impact on the logarithm of ISX to a standard deviation shock to RRM, over a period of sixteen weeks.

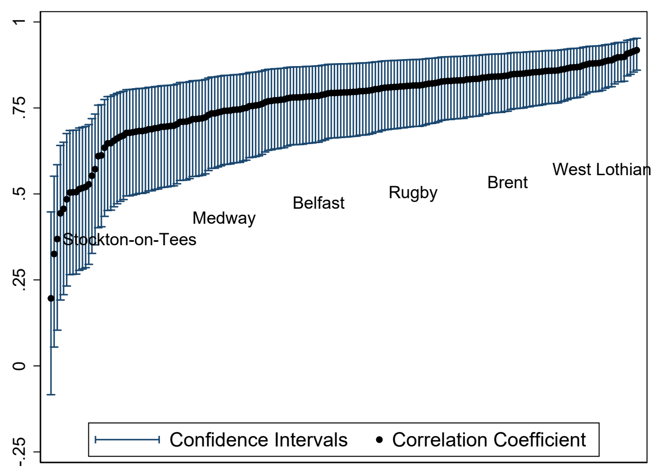

Figure 3: Estimated correlation coefficient and confidence intervals between the log(ISX) and RRM in each local authority, with a subsample of units' names displayed

The left panel of figure 5 displays the country-level results. Independently of the Cholesky ordering, the model yields very similar hump shaped patterns with positive responses that peak after one or two weeks at about 13% and 20%, and then converge to zero after 7 or 8 weeks. These results are highly similar to the panel VAR impulse responses shown on the right hand side of figure 5. For the latter we employ both the fixed-effects least square estimator (LSDV) and generalized method of moments (GMM) to take into account potential Nickell's bias (Nickell, 1981, Abrigo and Love, 2016).

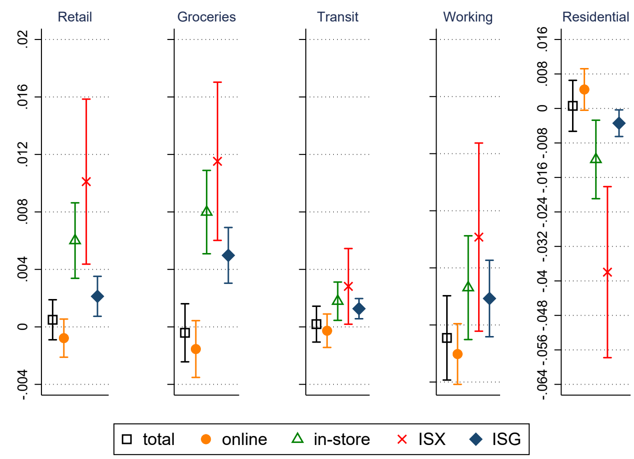

Figure 4: Estimates of β from a TWFE model $Y_{it} = \alpha_i + \delta_t + \beta X_{it} + \epsilon_{it}$ where Y_{it} is one of the five spending indices, and X_{it} is one of the five mobility indices. Confidence Intervals are based on Driscoll-Kraay standard errors.

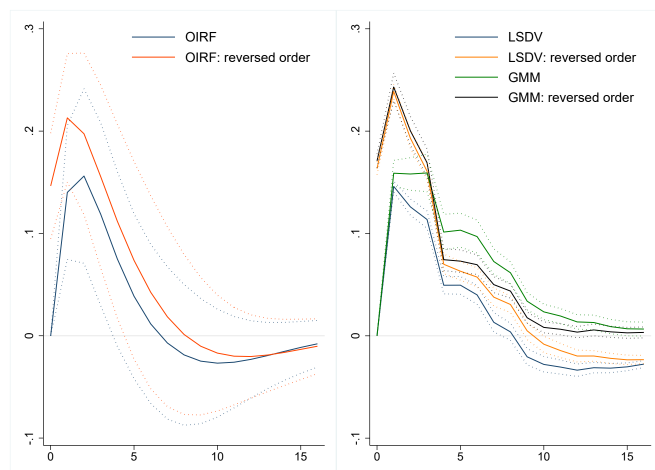

Figure 5: The figure plots the orthogonalized impulse response functions (straight lines) and confidence intervals (dotted lines) of the impact on the logarithm of ISX to a standard deviation shock to RRM, over a period of sixteen weeks, for a two lags country-level VAR on the left hand side, and a six lags panel VAR on the right hand side. Reversed order indicates the reversed order of the Cholesky decomposition.

Furthermore, in line with the TWFE results, there is no evidence that shocks to mobility have any significant effect on online spending in the VAR models, independently of the mobility index used (please refer to the online appendix, where robustness checks and tables of descriptive statistics can also be found). This suggests that online shopping does not substitute for in-store spending, even when constraints on the latter are legally enforced.

4. Summary

The results of this study underscore the reliability of mobility data, specifically trips to retail and recreational venues sourced from the Google Mobility report, as a robust proxy for measuring retail spending. This suggests that the literature using mobility to proxy for consumption (discussed in section 1), is a reliable guide to policy.

Moreover, the analysis presented in this paper reveals no discernible correlation between mobility and online shopping, suggesting that negative shocks to mobility should lead to falls in overall spending. This is consistent with previous works such as Chen et al. (2021) and Andersen et al. (2020).

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