COVID-19 Mobility and Spending Dynamics in the UK: A Time-Series Analysis

Introduction

COVID-19 ushered in an era of sweeping change once it became widespread within the United Kingdom in 2020. Although some of these changes were temporary, others, such as the adoption of working from home (WFH), have become a permanent part of society after the pandemic. Reuschke and Felstead (2020) find that in 2020, there was an eight-times increase in the number of people who reported working entirely from home. The pandemic changed the very basic nature of everyday life for millions of people. In the UK most of the population was subjected to a mandatory lockdown. This severely restricted individuals' mobility and consumption patterns because they were confined to their homes. To investigate these effects I explore data from Google COVID-19 Community Mobility Reports and data from the Office for National Statistics using the 2021 edition *UK spending on credit and debit cards* dataset. In this analysis I show that credit card spending in the UK was highly correlated with mobility to places. Specifically, I look to see how changes in mobility to different places as tracked by Google affect credit/debit spending, focusing on different spending categories to analyse the heterogeneity across spending categories.

I begin by outlining my underlying data and then present the analysis performed. Finally I conclude with some limitations and areas of further research.

Data

To implement my analysis I utilize two datasets. The Google mobility dataset tracks how visits to places, such as grocery stores and parks changes within a region compared to a baseline from a five week period in early 2020 (Google LLC, n.d.). The regions are divided into principal subdivisions using ISO 3166-2 codes which is part of the International Organization for Standardization (ISO). The six places tracked are grocery and pharmacy, parks, transit stations, retail and recreation, residential, and workplaces.

Meanwhile the credit/debit card spending data tracks payments on an electronic system called Clearing House Automated Payment System (CHAPS). The spending is divided into five categories: aggregate, delayable, social, staple, and work related. The data is tracked by the ONS and released annually. The data is a backward looking seven-day rolling average, that is non-seasonally adjusted indicating nominal prices with a baseline indexed from February 2020 (baseline value equals 100) (Office for National Statistics, 2024).

Results

I begin by taking the moving average of all the time-series mobility data because its quite useful to model population-level health intervention impacts while considering underlying trends, autocorrelation, and seasonality (Schaffer, Dobbins, and Pearson, 2021). It also helps to smooth out any short term fluctuations in the data, providing a better overview of long-term trends. To illustrate the relationships over time, I graph a mobility and credit/debit card spending over time. Figure 1 shows that credit/debit card spending tracks quite similarly to mobility patterns in the selected period. For example the work mobility changes data appear to be moving in unison with aggregate spending. This indicates that the majority of individuals in the UK have potentially travel costs or other financial costs borne on them when they commute to a traditional office. Overall, it seems as though mobility patterns are quite a reasonable and reliable of aggregate expenditure. Indeed this is also confirmed by the correlation matrix seen in Figure 2.

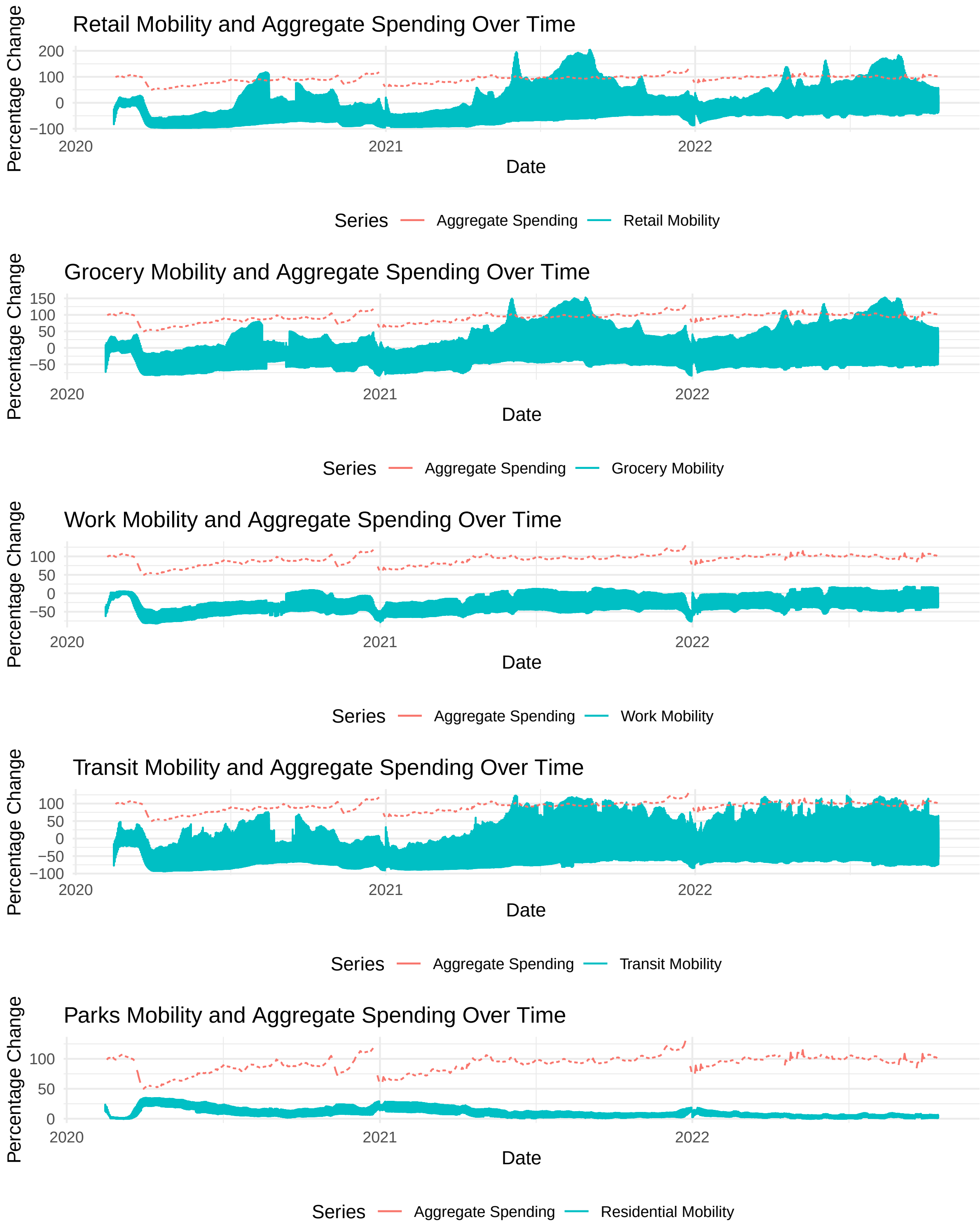

Figure 1: Time-Series of Credit/Debit Card Spending and Mobility Data

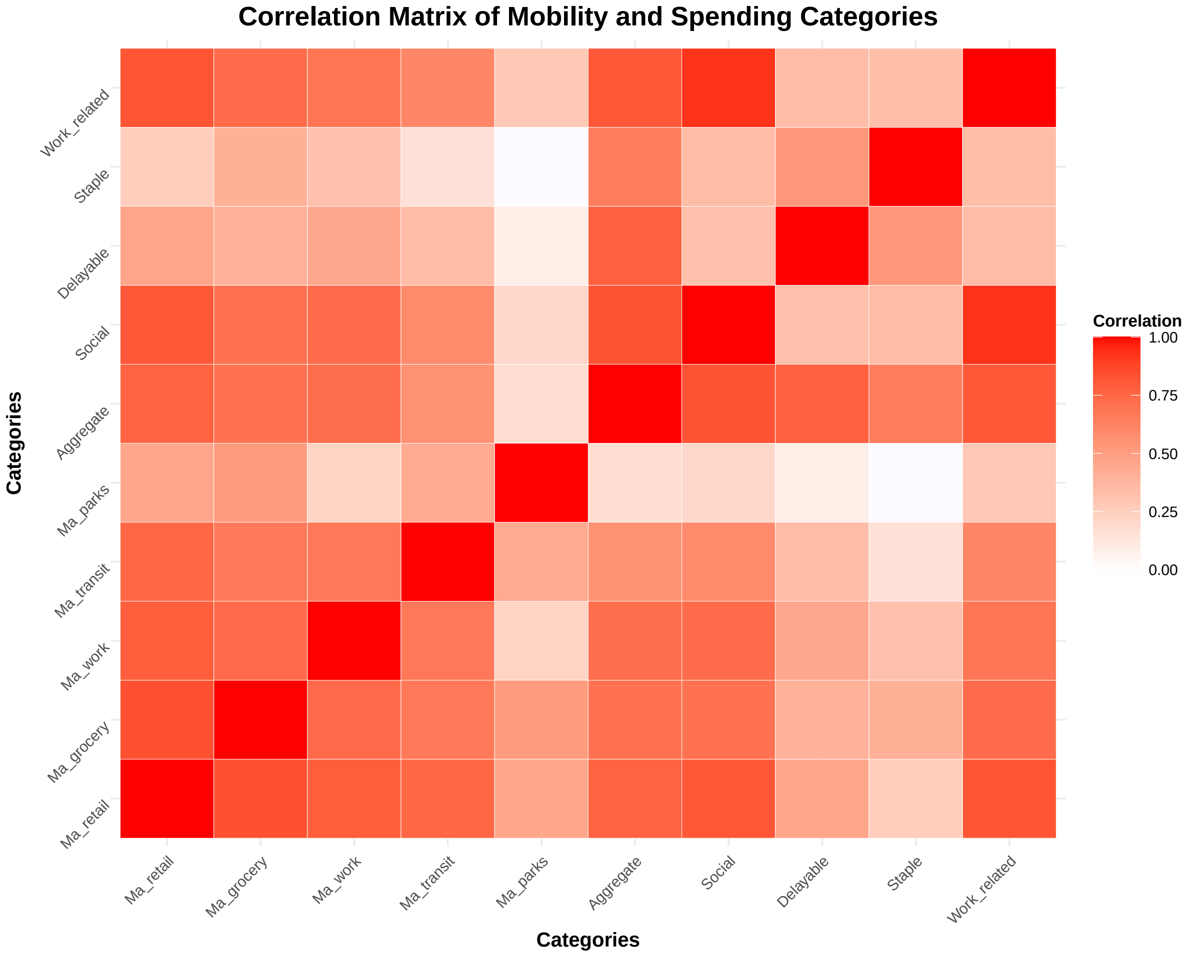

Figure 2: Correlation Matrix between Credit/Debit Card Spending Variables and Mobility Variables in the UK

To test the significance of this relationship I run an OLS model on every category of credit/debit card spending using the mobility data variables as my independent variables. Table 1 displays the results of the corresponding regressions. Every single regressor is significant in all of the models at the 1% level except changes in work in Model 5. Model 1 takes aggregate credit/debit card spending as the outcome variable with all variables significant at the 1% significance level. All but changes in transit and parks are positive. This is most likely because during the imposed lockdown measure individuals significantly cut their time spent at public transport hubs thus spending would decrease as a result of the savings. Similarly, engaging in areas like local parks generally bears no costs for an individual wishing to spend time there. Model 2 analyses the effects of changes in mobility on social-related spending. Again every regressor has a positive coefficient except transit and parks potentially due to reasons similar to those just mentioned. Model 3 exhibits delayable expenditures related to clothing, household goods, or vehicles.

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	105.65***	101.97***	102.12***	109.46***	121.88***
	(0.06)	(0.10)	(0.13)	(0.06)	(0.12)
MA_retail	0.31***	0.66***	0.26***	−0.08***	0.82***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MA_grocery	0.25***	0.22***	0.08***	0.43***	0.38***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
MA_work	0.18***	0.26***	0.25***	0.07***	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MA_transit	−0.04***	−0.05***	−0.02***	−0.05***	−0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MA_parks	−0.07***	−0.10***	−0.06***	−0.05***	−0.09***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.67	0.71	0.25	0.26	0.70
Adj. R^2	0.67	0.71	0.25	0.26	0.70
Num. obs.	184502	184502	184502	184502	184502

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 1: Regression Results from Credit/Debit Card Spending and Mobility Data

Similarly transit and parks are decreasing because there is no opportunity to spend on transit during lockdown and time at parks takes away from time that can be dedicated to purchasing goods of these nature. Purchases categorized as staple are shown in Model 4. In this case changes in retail, transit, and parks mobility all have negative effects. Retail may be negative because disposable income dedicated to retail shopping or recreation would otherwise go to purchasing goods that are necessitated. Finally, Model 5 show work-related expenses, of which only transit and parks mobility changes display negative associations. These results seem to be inline with patterns displayed in developed Western economies where spending declined overall but spending on necessities, such as food, experienced smaller declines (Baker et al., 2020; Chetty et al., 2020).

Discussion

Overall it appears as though expenditure decreased as a result of the mobility patterns seen during the pandemic. However, as Figure 1 shows, it seems as though the UK reverted to the old 'normal' by the end of 2022. The changes induced by mobility patterns appear to have inhibited usual spending patterns. As millions in the UK became furloughed it seems as though they opted to smooth their consumption paths, opting to save and lower their consumption in periods of reduced income, aligning with other consumer behavior exhibited in other major economies such as the U.S. (Horvath, Kay, and Wix, 2023).

Important areas for research in this area consist of models that employ a more robust time-series method to evaluate the relationship between credit/debit card spending and mobility patterns. Moreover, state specific effects were also crucial as lockdown measures varied in across different regions during the pandemic due to policies implemented by the local government in conjunction with variation in COVID-19 case numbers. Examining the aggregate shifts in consumer behavior are quite important for explaining a holistic overview of underlying trends, however analysis can be richer when examined on a granular level, accounting for details missed emphasizing a hierarchical approach.

References

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