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Mitigation measures, prevalence response and public mobility during the COVID-19 emergency

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Mitigation measures, prevalence response and public mobility during the COVID-19 emergency

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WP/03/2021

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Abstract

In response to the rapid spread of the COVID-19 pandemic, national governments have implemented a range of mitigation measures designed to limit the transmission of the novel virus. In order to estimate the effects of these "non-pharmaceutical" policies, one needs to properly account for prevalence responses; self-imposed restrictions of individuals who trade-off the utility derived from social interactions against the risk of infection. We study the determinants of community mobility across the European Union during the COVID-19 crisis, focusing on government and self-imposed restrictions. Results indicate that time-series breaks in all types of mobility were clustered across time and EU states, with the most discretionary types falling first and by the largest amounts. Mobility measures fall only after the escalation of government containment measures, with school closures and cancellation of public events preceding falls in all types of mobility across all EU states. This indicates that these two policies have led to an overall risk re-assessment by the general public leading to self-imposed yet not self-initiated falls in mobility. Finally, self-imposed restrictions occurring independently of government measures are responsible for a significant part in the fall of post-pandemic mobility in the EU.

JEL Classification: I12, I18, D70, D80

Keywords: COVID-19, Mobility, Government mitigation measures, Government response

1 Introduction

In response to the rapid spread of the COVID-19 outbreak, national governments have implemented a range of mitigation measures designed to limit the transmission of the coronavirus. These policies range from outright strict lockdowns implemented in parts of Asia and in some European states to less stringent but focused approaches. As infection rates started to slow down, national authorities started to ease these emergency policies, before re-instating them once again through the last two months of 2020.

Existing literature shows that these so-called "non-pharmaceutical" interventions are usually very effective at limiting societal mobility and the spread of pandemics (Litvinova et al., 2019). Indeed changes in human mobility and related policy interventions have been extensively studied in literature as critical factors in explaining changes in the extent of the spread of past epidemics such as the Spanish Influenza of 1918 and the SARS epidemic of 2003 (see Hatchett et al., 2007 and Bajardi et al., 2011).

When estimating the effectiveness of restrictions in reducing the spread of a pandemic, it is important to properly capture the self-imposed reduction in mobility. Gersovitz and Hammer (2003) and Farboodi et al. (2020) argue that when deciding on the level of social interaction to maintain during a pandemic, individuals will choose to trade off the utility benefit of social interactions against the risks that come with such interactions. This gives rise to possible self-imposed restrictions which are part of a behavioural trait normally referred to as "prevalence response". This term is used in literature to refer to the change in the behaviour of individuals intent at protecting themselves or their families from the pandemic over and above any other restrictions which might be imposed by health and government authorities.

This behavioural trait has also been discussed extensively in empirical studies which have demonstrated that the decline in individual mobility that occurs during a pandemic is a combination of self-restraint and policy induced factors (Bennett et al., 2015). Chou et al. (2004) show that the 2003 SARS epidemic significantly reduced individual mobility to both discretionary type of activities such as restaurants and shopping spaces, but have also heavily contracted people's demands for health care. Similar shifts in behaviour that are not directly linked to restrictive policies implemented by local authorities are predominant in other epidemics such as the HIV epidemic (Lakdawalla et al., 2006 and Ahituv et al., 1996). Moreover, other studies have shown

that mobility shifts stemming from prevalence response also have important effects (both positive and negative) on the spread of an infectious disease (see Meloni et al., 2011 and Zhu et al., 2017).

Moreover, the study of individual mobility during pandemics is important as it could serve to better understand the sudden and unexpected changes in economic activity. During the pandemic, forecasting economic activity has become increasingly complex as the combined impact of supply-side restrictions resulting from government mitigation measures, as well as the repercussions of sudden drops in aggregate demand are difficult to measure. Indeed, Sampi et al. (2020) show that mobility indices can be used as leading indicators to forecast industrial production in a number of Latin American economies.

Evidence surrounding the effects of government policies on social distancing during the COVID-19 pandemic is concentrated around the United States. Gupta et al. (2020) shows that stay at home orders were only responsible for a small share in the decline of mobility. On the other hand the declaration of a state of emergency, together with the date of the first COVID-positive case and COVID-related death explain a larger share in the early drops in individual mobility across the US. Similar conclusions are reached by Cronin and Evans (2020) who argue that up to 80% of the decline in discretionary mobility (with restaurants, hotels entertainment and nonessential retail defined as being discretionary) were self-imposed. Qualitatively similar results highlighting the contribution of personal choices in the fall in mobility in US are found by Maloney and Taskin (2020), Goolsbee and Syverson (2020) and Brzezinski et al. (2020).

Studies focusing on the determinants of community mobility across the European Union are less common mainly due to data limitations. Most US studies make use of SafeGraph (or similar) cellular use data to track individual mobility, data which is generally only available for the US and Canada. A notable exception in this case is the study by Santamaria et al. (2020) which utilises cellular data collected under the initiative of the Joint Research Centre and the European Commission in an effort to study mobility developments in the EU during the Covid-19 pandemic. More recently, Mendolia et al. (2020) conduct a global study which covers 21 countries, including some EU nations, which makes use of Google's Mobility database. This data allows for a more detailed analysis of different types of mobility in a uniformly consistent way. This dataset has also been used in an EU-focused studies commissioned by the Joint Research Centre of the European Commission (Athanasios, 2020).

This paper contributes to this growing strand of literature by analysing the main drivers behind the drop in individual mobility in the EU, focusing on mobility dynamics recorded in Malta between the start of the pandemic and November 2020. Unlike other EU-focused studies (Athanasios, 2020 and Santamaria et al., 2020) we control for the prevalence response of individuals when estimating the effects that restrictive policies implemented by national authorities have had on EU-wide mobility. Moreover, we use an exhaustive list of government stringency policies, unlike most literature which mainly looks at Stay at Home measures and State of Emergency announcements. Moreover, unlike earlier studies on mobility we look at a much longer sample period, thus allowing us to understand whether the extent of the prevalence response has diminished over time as individuals become accustomed to a sense of urgency, and how the response of mobility measures vary after the initial implementation of mitigation measures. Finally, we focus on the determinants of mobility of the small island state of Malta, thus shedding light for the first time on the effectiveness of public and private mobility restrictions enacted in Malta during the COVID-19 pandemic.

All our analysis is based on mobility data computed by Google for six place categories, retail and recreation, groceries and pharmacies, parks, transport, workplaces, and residential. Mitigation measures taken by government and health authorities across EU states are measured through the Oxford COVID-19 Government Response Tracker, ensuring maximum comparability across EU states.

Our analysis highlights four main points. First, the timing of the structural breaks in mobility were concentrated across different categories of mobility, indicating an immediate fall in activity across all types considered. Second, we show that in the most discretionary types of mobility, there was significant concentration of mobility breaks across EU states. However contrary to US-based evidence, the vast majority of mobility breaks, occur only after the intensification of national mitigation measures. Thus, while in the US case, individuals have been found to react to news concerning the extensiveness of the pandemic in other states, individuals across EU states have most probably only reacted to what has been happening within their own borders. To this end, mitigation measures enacted at a national level have been instrumental in reducing mobility in individual states.

Third, looking more closely at the different containment measures, one notes that all mobility types have fallen substantially across all EU states, including those that were not specifically targeted by the containment measures put forward at that point in time. This points to the fact

that while instrumental in directly reducing mobility during the early stages of the pandemic, government containment measures were possibly indirectly affecting mobility by triggering self-restraining behaviour in individuals. Mitigation measures enacted by local authorities could have helped raise the general awareness of the disease, leading to an overall risk re-assessment of the situation by the general public, thereby leading to a precautionary reduction in mobility. These findings are confirmed by our panel estimates as well as by a timeseries analysis of Maltese data, both of which indicate that a significant proportion of the variation in post-pandemic mobility is driven by government measures. Most notably, results indicate that measures concerning the closing up of schools have affected in a disproportionate way mobility towards retail and recreation establishments and workplaces despite the fact that such a policy is not aimed at reducing these types of mobility.

Finally, results suggest that community responses that occur independently of mitigation measures introduced by national authorities are also responsible for a significant part of the fall in post-pandemic mobility. We find that at the EU-level, the number of COVID-19 related deaths and infections have a relatively large effect on the precautionary response of individuals. We also find that the magnitude of prevalence response following news of COVID-19 cases, for both EU and Maltese data peaks before the maximum transmission numbers have been reached, providing some evidence of pandemic fatigue in citizen's reaction to the COVID-19 infection numbers.

Maltese data on the other hand suggest that a prevalence response is only triggered as response to an escalation in the number of new on COVID-19 infections, with the number of new COVID-19 deaths featuring statistically insignificant responses.

This paper is structured as follows. The next section describes the data used in the study while section 3 conducts basic time-series analysis on the data. Sections 4 and 5 look at the estimation of the main empirical models for the EU and Malta and section 6 concludes.

2 Data

Data on government mitigation measures is sourced from the Oxford COVID-19 Government Response Tracker. This tracker collects information on several different common policy responses that governments have taken to respond to the pandemic. This government tracker is particularly detailed as it can capture both the extent of the mitigation measures as well as their regional coverage. In our case, our analysis is focused on a subset of these indicators, more precisely those that record containment measures: Closure of schools, workplaces, the cancellation of public events, restrictions on public gatherings, closure of public transport, internal travel restrictions and international travel restrictions. These indices can be aggregated into an overall stringency index that measures the strictness of the mitigation measures.

When focusing on the Maltese case, apart from the stringency indicator¹, we also focus on how specific mitigation policies, that have been introduced by local authorities, have affected individual mobility in Malta. Data on the introduction of these policies are sourced from an internal database maintained by the Central Bank of Malta and enter our empirical specification in the form of categorical dummies.

This study utilises Google’s COVID-19 Community Mobility data which measures changes in mobility by geography and different categories, such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. All mobility data is compared to a baseline, estimated as the median value of visits over a five week period between January 3rd and February 6th. Data is created with aggregated, anonymised sets of data from users who have turned on the Location History setting on their Google devices. This data is updated and made available regularly by Google. Since the data is published only in terms of percentage changes from a given baseline, it is important for any analysis to account for events that can change the mobility for specific dates (such as weekends and public holidays) as well as for seasonal changes, especially during the summer months. On the flip-side, this data set is particularly well-suited for these kind of semi-experimental studies, since it is available with virtually no time lag and is relatively easy to compare across nations.

¹For more information on the development of a COVID-19 government response tracker for Malta, see Sant (2021)

3 Breaks in mobility and stringency levels

In this section we take a purely time series approach towards establishing a relationship between an escalation of COVID-19 mitigation measures and the drop in mobility that has been most notable between March and May 2020.

3.1 Graphical Approach

Figure 1: Stringency indicators in the EU-28

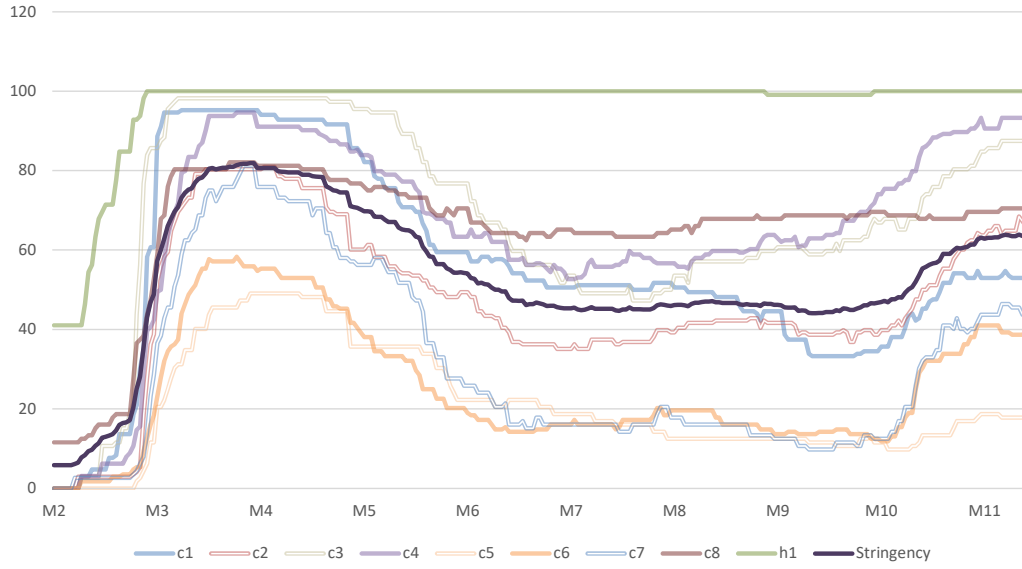


Chart 1 looks at the evolution of the indices making up the stringency indicator for the EU.² The data shows that the information campaign launched by the national and international health authorities, (h1), has been the first mitigation measure adopted across the EU . All other indicators (c1-c8), capturing the containment measures enacted by the governments of the EU-28 bloc, show an almost instantaneous increase in their stringency levels between March and April. The strongest increases in stringency levels were registered in the cancelling of public events, in restrictions to public gatherings and the closing down of schools. On the other hand, the closing down of public transport and stay at home orders (or strict lockdowns) show a lower level of stringency at an EU level, reflecting the relatively small number of countries that have enacted a full and strict lockdown.

²Data for the EU is estimated as a simple average across the 28 countries making up the EU block up till the end of 2020.

Figure 2: Stringency index in EU countries

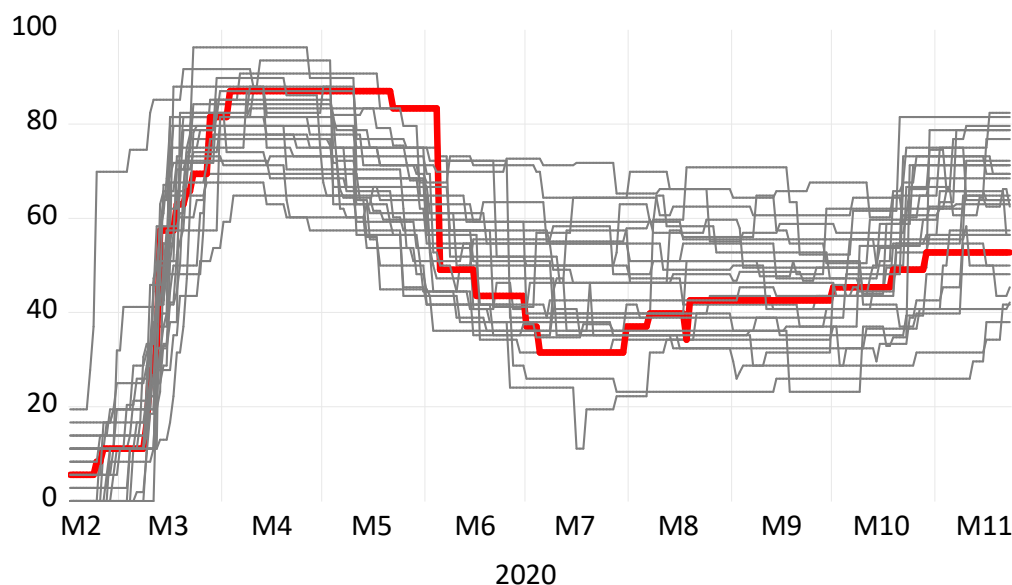


Figure shows stringency levels across all EU states as reported by the Oxford COVID-19 Government Response Tracker. Red line shows data from Malta.

All containment measures were partially lifted during the summer months, as the number of new COVID-19 cases across the EU slowed down substantially. Fuelled by a second wave of COVID-19 infections, most containment measures have been tightened gradually between October and November. Despite a surge in COVID-19 cases across Europe during the autumn, the overall stringency indicator has remained below the maximum level reached at the height of the first wave.

Despite being highly significant on their own, aggregated data hides a considerable degree of heterogeneity in the strength of the containment measures adopted by the different authorities across the EU. Data in figure 2 shows that in the first wave of COVID-19 infections, there has been a sudden and almost contemporaneous escalation of containment measures across all EU countries. Still, even at the height of the first COVID-19 wave, the data shows an element of heterogeneity both in the speed of the adoption as well as in the strictness of the containment measures adopted by individual states. These differences reflect both the different timings with regards to the start of the infection within each country as well as different approaches adopted by each individual state in controlling the pandemic. Being the first country to be hit by the pandemic, Italy has been the first nation to raise its containment measures. However, data shows that its stringency index has been increasing relatively slowly as health authorities grappled with how best to counteract the novel virus. Responding to the difficulties encountered in Italy, the

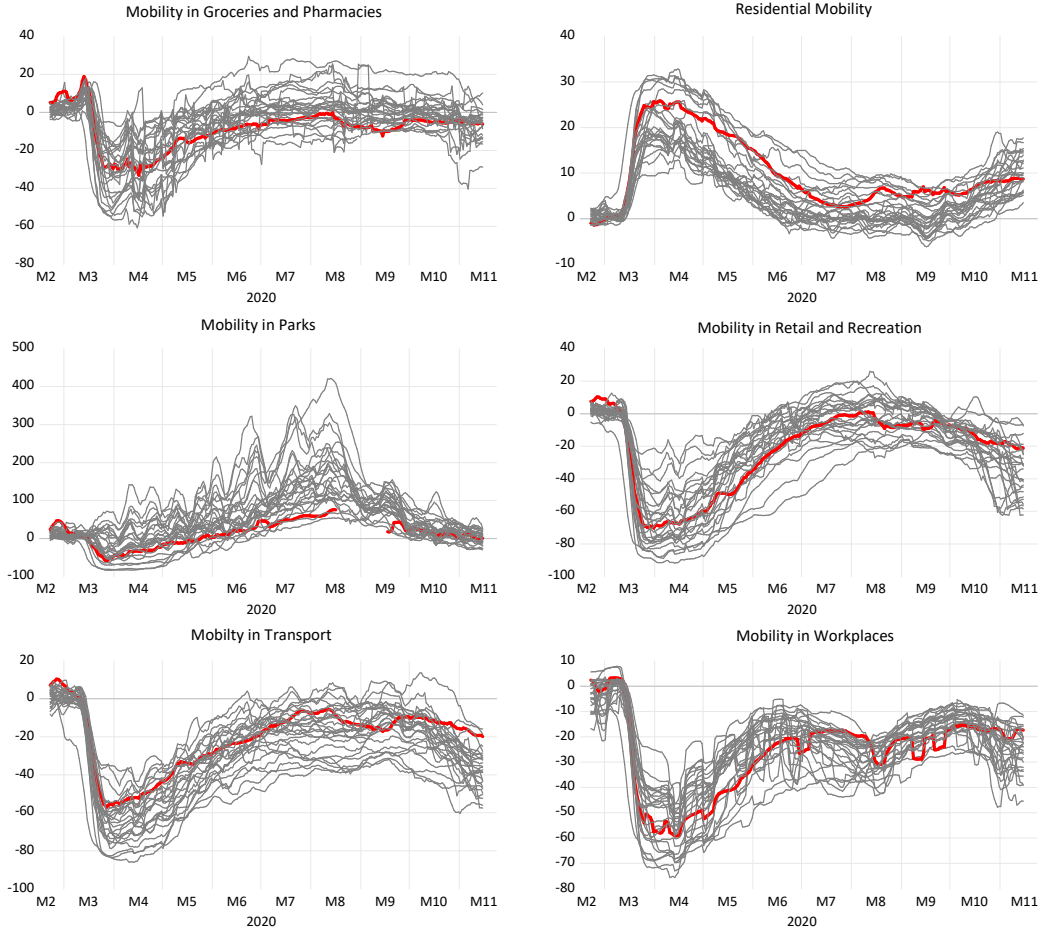
vast majority of states have increased their containment measures abruptly and in a decisive way. The only exceptions to this trend can be seen in the United Kingdom, which has raised its containment measures considerably after the rest of the EU, and the Nordic states (Finland, and Sweden) in which containment measures have been raised significantly less and relatively more slowly than the other states.

Even higher degrees of heterogeneity in the approach adopted by national authorities can be found in the subsequent stages of the pandemic. Most countries exhibit a gradual lifting-off of containment measures during the summer months, with varying speeds and degrees of relaxation. Even more heterogeneity is found when looking at the subsequent escalation in the containment measures. Authorities in some countries, such as those in Austria, France, Italy, Bulgaria, the Czech Republic and Slovakia, have re-introduced almost the same level of containment measures as those enacted in spring of 2020. On the other hand, most of the other states have kept containment measures well below the maximum levels reached in April.

Chart 3 looks at changes in all types of mobility across all EU states.³ EU level data show that all types of mobility levels across the union have dropped suddenly and significantly during mid-March 2020. At the height of the first wave, the most prominent decrease, has been registered in the Retail and Recreation category, which has on average dropped by almost 70% when compared to baseline levels. This is considerably more pronounced than the average falls registered in less discretionary types of mobility, such as workplace mobility (which has dropped by around 45%) and mobility to groceries and pharmacies (24% drop over baseline levels). Interestingly, footfall into groceries and pharmacies have experienced a short-lived increase as soon as the first mitigation measures were being introduced across Europe. This reflects a significant degree of stockpiling of main necessities, as individuals reacted to fears that the pandemic, as well as the containment measures enacted globally, could result in scarcity of the daily groceries and pharmaceuticals. Transport related mobility has roughly followed the trajectory of mobility to retail and accommodation establishments, albeit with slightly lower maximum levels registered on average across Europe. The drops in all types of mobility registered across the first wave of COVID-19 infections have contributed to a considerable increase in residential mobility which has on average climbed by 19%. All mobility measures (with the exception of mobility to parks) have slowly returned to baseline levels by mid-summer of 2020, as the situation across all EU countries slowly returned to their pre-pandemic states. Mobility levels have then started to drop

³All analysis includes the United Kingdom but excludes Cyprus, for which there is no availability of mobility data.

Figure 3: Mobility data in EU countries



Charts show Google Mobility data for all EU countries for 6 different mobility measures. Red lines show data for Malta. All data are shown as 7-day moving averages to remove day-of-the-week effects.

again in autumn 2020 as the second wave of pandemic hit the continent.

Contrary to the Stringency index, mobility measures exhibit a considerably lower level of cross-country heterogeneity.⁴ Chart 3 shows that while the absolute drops in mobility differ from one country to another, they do exhibit a very similar profile, contrary to the different profiles that can be seen in the stringency indicators. More precisely, after the first wave of infections was controlled, the cross-country heterogeneity in national stringency levels is considerably more pronounced than that found in mobility levels. This observation is the first indication that apart from the containment measures enacted by national governments, individual mobility in the COVID-19 pandemic has also been affected by other factors, especially throughout summer and autumn.

⁴The only exception to this is Mobility in Parks. The extreme heterogeneity in the results concerning mobility to parks could stem from the definition of what constitutes a park. Google Mobility Data defines a park as a National Park and therefore countries that do not have a large number of National Parks, but instead have other open spaces would not be correctly represented in this data.

3.2 Cross-sectional and time-series analysis

In this section we formalise our argument by first analysing whether the timing of the escalation of national containment measures coincides with the fall in individual mobility. This is an important point because as argued in literature, drops in mobility could very well be a reaction of the general public to news surrounding the pandemic, thus triggering a 'prevalence response'.

We proceed in the spirit of Cronin and Evans (2020) and estimate the break points for all types of mobility, the stringency index as well as all containment indicators for all EU states. To this end, we fit the following two models to find the dates c and \tilde{c} when different mobility and stringency values break:

$$y_t = \alpha + \sum_{d=1}^6 [DOW_{d,t}(1 - M_t^c)\theta_{b,d} + DOW_{d,t}M_t^c\theta_{a,d}] + \sum_{k=1}^3 time^k [(1 - M_t^c)\beta_{b,k} + (M_t^c)\beta_{a,k}] + \epsilon_t \quad (1)$$

$$x_t = \gamma + S_t^{\tilde{c}} + \omega_t \quad (2)$$

where y_t and x_t are mobility and stringency indicators, DOW_t is a day of the week dummy, and $time$ is a linear dummy such that equation 1 is cubic in time.

We then generate dummies M_t^c , $S_t^{\tilde{c}}$ that take the value of one if $t \geq c$ and $t \geq \tilde{c}$ and zero otherwise. We then vary the break point across a range of alternative break points spanning 22nd February till the 21st April 2020 and find $t \geq c$ and $t \geq \tilde{c}$ that maximise the F-statistic.⁵

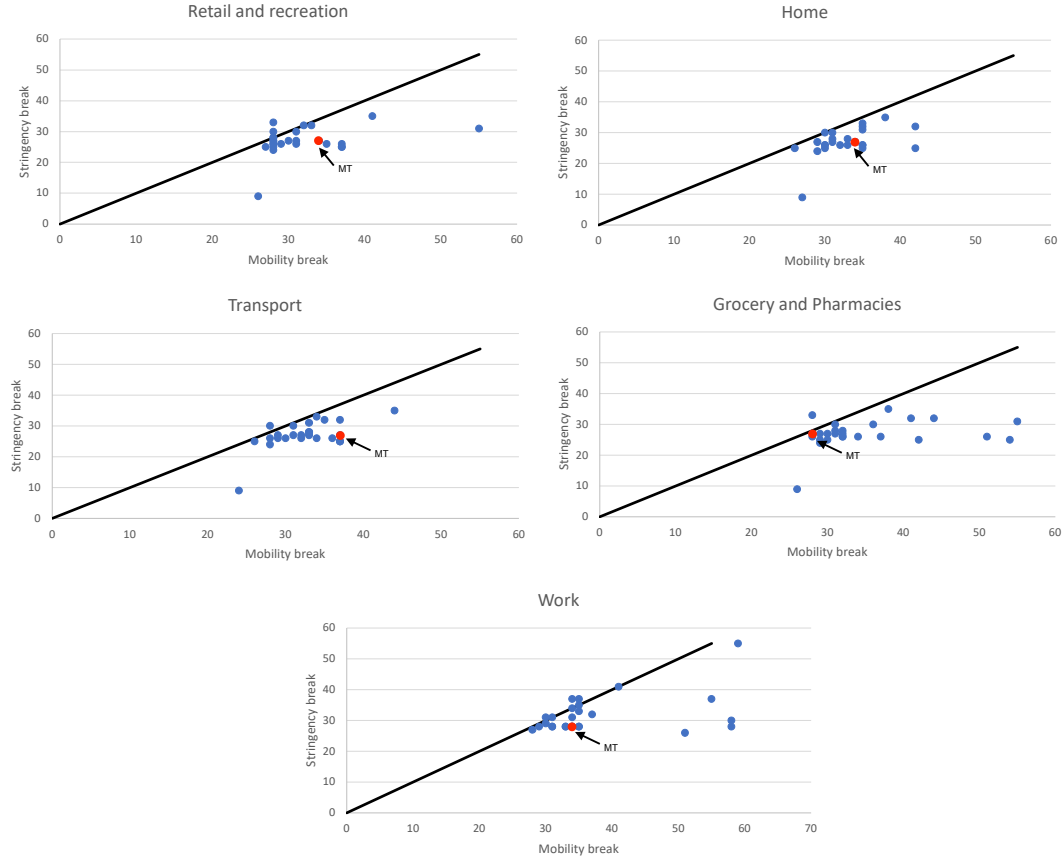
Chart 4 plots the break points (measured in terms of days after 22nd February) of our mobility indicators against those for the overall stringency index of all EU states. Each subplot therefore provides information on the timing of the breaks in series of a specific type of mobility indicator against the timing of the break in the stringency indicator for all EU states.⁶

There are three main conclusions that can be derived from these EU-wide estimates. First, the timing of the breaks indicates that mobility categories that can be regarded as discretionary in

⁵The starting date was chosen as the earliest date with which we could run equation 1 without incurring in issues of multicollinearity.

⁶A point to the right of the identity (45°) line indicates that for a particular country the break point of the mobility indicator under analysis has occurred after the escalation of the containment measures.

Figure 4: Mobility vs Stringency breaks



nature, such as mobility to retail and recreation establishments, have fallen before other less discretionary items (such as groceries and pharmacies). Indeed, the median break in mobility towards recreation and retail establishments occurred on the 22nd of March while the median break in work mobility has occurred 5 days later.

Second, there is a considerable amount of clustering in the fall of most types of mobility. Clustering in mobility breaks is more prominent in mobility to transit places and retail and recreation establishments both of which exhibit less than half the standard deviation of the rest of the mobility types. Focusing on mobility to retail and recreation establishments, all mobility breaks for the retail and recreation category (except for the United Kingdom and Sweden, two countries that exhibit considerable heterogeneity when compared to the rest of the sample) have occurred in an 11-day period spanning the 11th and the 22nd of March. Moreover, 10 countries have exhibited breaks in this type of mobility exactly on the 13th of March 2020, 28 days after the start of our sample period. The significant amount of clustering in this type of mobility might suggest that individuals across member states might have been reacting to a similar information set, thereby indicating that the response of individuals especially for the most discretionary types

of mobility have been subject to a prevalence response as people started reacting to COVID-19 related news across the union.

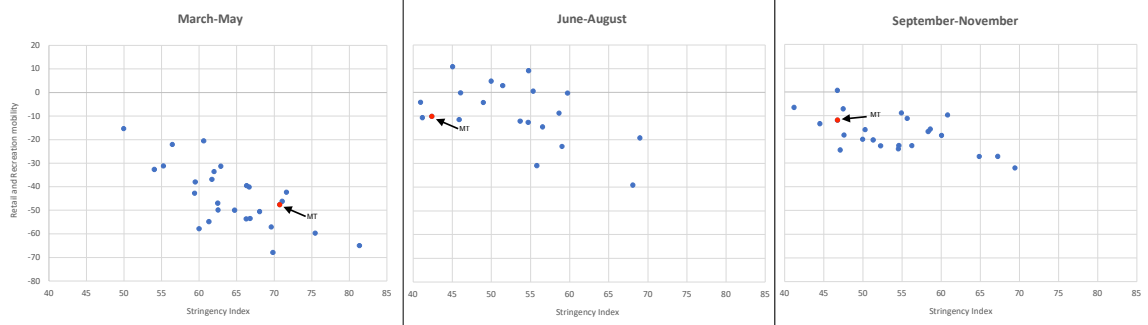
Finally, almost all mobility breaks (especially those in non-discretionary categories) have occurred after countries have intensified their mitigation measures. Thus despite the evidence of clustering in the most discretionary types of mobility points at a degree of cross-country prevalence response, this analysis indicates that the mitigation measures implemented by national authorities were instrumental in limiting social mobility and consequently the extent of COVID infections in the EU especially at the start of the pandemic. This evidence goes counter to the findings of Cronin and Evans (2020) for the US, which indicate that most breaks in mobility across American states have occurred well before any meaningful stringency measures were implemented by either national or federal authorities.

Comparing the timing of mobility breaks with those of specific stringency indicators (See Appendix A), is particularly informative in order to understand which specific policies have caused mobility measures to break. Results indicate that most mobility breaks recorded across the vast majority of EU states have been preceded by public events prohibitions and school closings. This result is especially interesting when considering that a-priori, neither of these two policies is expected to directly affect mobility to retail and recreation establishments. In fact, those policies which are expected to directly cut this type of mobility, such as the closure of inessential retail and recreation establishments, are measured under the sub-index workplace closure. Comparing the timings of the breaks in recreation mobility and the intensification of workplace closures shows a less clear cut result with around a third of the countries experiencing cuts in mobility to recreation establishments before the intensification of work closures. This result could indicate an element of prevalence response in discretionary mobility in a number of countries. Similarly, residential mobility which records the duration of stay in residential places indicate that in most countries individuals have increased their presence at home even before stay at home orders started to be announced in their respective states.

All-in-all, these results paint a mixed picture on whether the falls in individual mobility measures are directly and entirely due to the mitigation measures put forward by national authorities. On the one hand, looking at the stringency index as a whole, we note that most mobility measures, especially those of a discretionary type, have fallen considerably only after the escalation of mitigation measures by national authorities. However policies relating to public events prohibitions and school closings seem to be preceding the majority of falls in most mobility measures, even

in those which, a-priori, are not directly affected by these two policy measures. This suggests that individuals across the EU, were not reducing their mobility as a direct consequence of the restrictions but were rather reacting to the heightened sense of risk brought about by these policies. Moreover, these results might also be an indication that while the restrictions imposed by governments do seem to be effective at reducing individual mobility, there are other factors which have been driving mobility dynamics during the first wave of the COVID-19 epidemic.

Figure 5: Mobility in Retail and Recreation and Stringency index



These charts plot the average drops in mobility to retail and recreation establishments across the EU with the change in stringency level for three different periods

The latter point can be seen more clearly, by looking at how the relation between the stringency indicator and mobility changes have evolved throughout 2020. The first panel of chart 5 plots the average drop in mobility registered in recreation and retail between March and May 2020 across all EU countries against the average stringency level in effect in the same period.⁷ These three months coincide with the first wave of COVID-19 infections in Europe and is characterised by a sharp increase in COVID-19 cases and the roll-out of a number of mitigation measures. Results show a very clear relation between the level of stringency and the drop in retail and recreation mobility. This clear relation cannot be seen however, if we repeat the analysis for the periods spanning June-August and September-November 2020.⁸

The second and third panels of chart 5 indicate that on average the stringency levels across most EU countries during the periods June-August and September-November have fallen when compared to the March-May period. Mobility to and from recreation and retail establishments between June and August have on average increased to their baseline levels despite non trivial containment restrictions. On the other hand mobility between September and November has fallen considerably despite only a moderate increase in stringency levels. Moreover, the clear cross-country relation that existed between high stringency and low levels of mobility during the

⁷Data for mobility is smoothened using a 7-day moving average to remove day-of-the-week effects

⁸The cutoff date for all data is the 23rd of November. Therefore, the last period covers the 1st of September till the 23rd of November 2020.

March-May period, is not evident in the two subsequent periods.

These results indicate that while clearly successful at reducing individual mobility, government mitigation measures were not the only factor behind the changes in mobility that have taken place in Europe during this pandemic, especially in its later phases. Indeed, the general sense of insecurity that was so widespread during the first months of the pandemic and that re-emerged during the second wave, can be seen to play a non-trivial role in the dynamics of individual mobility. The changing relationship between government stringency levels and changes in mobility measures could also be a result of a general sense of fatigue that reduces the extent of prevalence response and adherence to national policies.

4 Main estimations

To study the effect that mitigation measures have had on public mobility during the COVID crisis, it is therefore important to isolate other factors that have had an effect on mobility. As argued by the previous sections this implies that we need to control for the response of the public to news that COVID-19 was spreading in their communities. Empirically, it is very challenging to separate the effects of policies from those relating to self-restrictions, especially since there is considerable correlation between heightened risk factors that trigger prevalence responses and policy induced restrictions (Manski, 2000). In order to better separate these two effects, we rely on a panel dataset. Timing differences between changes in national stringency levels and the number of COVID-19 cases and deaths across countries should help isolate the effects of mitigation measures.

We propose two model specifications which differ in the amount of detail surrounding national mitigation measures. The first specification uses the overall Stringency Index, while the second model uses 7 sub-indicators that measure the strength of containment measures enacted by national authorities.⁹ The two specifications share the same functional form:

$$y_{i,t} = \gamma_i + \sum_{c=1}^7 \beta_{i,c} cases_{i,c,t} + \sum_{h=1}^6 \gamma_{i,h} deaths_{i,h,t} + \sum_{p=1}^P \xi_{i,p} P_{i,p,t} + \sum_{j=1}^3 \delta_{i,j} t^j + \sum_{d=1}^6 \theta_{i,d} DOW_{i,d,t} + \phi_i temp_{i,t} + \sigma_{i,t} \quad (3)$$

$y_{i,t}$ measures the change in the mobility measure under analysis across countries i and time t , γ_i are country fixed effects. We specify $cases_{i,c,t}$ $deaths_{i,h,t}$ as dummy variables that record the number of COVID-19 cases and deaths per million, unlike other studies such as Mendolia et al. (2020) which specify the number of cases and deaths in absolute numbers. In particular we specify 7 dummy variables for cases, which take the value of 1 if new reported cases per million in a given country are between 0 and 5, 5 and 10, 10 and 20, 20 and 40, 40 and 80, 80 and 160 or greater than 160. For COVID-19 related deaths we specify 6 dummy variables that take the

⁹The Stringency Index is made up of 9 sub indices capturing the strength of containment measures: Closure of schools, workplaces, the cancellation of public events, restrictions on public gatherings, closure of public transport, stay at home orders, internal travel restrictions and international travel restrictions as well as a health promotion measure capturing public information campaigns. The first 8 capture the containment measure of national authorities.

value of 1 if new daily deaths per million in a given country are between 0 and 1, 1 and 2, 2 and 5, 5 and 10, 10 and 20 or larger than 20. In our first specification we test for the overall stringency indicator, thus setting $P = 1$. Our second specification looks at 8 sub-indicators that measure the level of containment across each country i , thus setting $P = 8$.¹⁰

In all specifications we control for day of the week effects and a third degree polynomial in time measured in days since the first COVID-19 case is registered in each country. This means that the time trend variable takes the same value for all time periods before the first case of each country, helping to properly distinguish between the pre- and post- pandemic periods in each country. Moreover, since Google Mobility data is published in terms of deviations from a baseline level estimated between January and February, we control for seasonality effects by including temperature data for the capital cities of all countries in our sample.

Table 1: Panel regression results - Stringency indicator

	Home		Park		Retail		Transport		Groceries		Work	
0 < Cases < 5	0.04		-2.98		-1.67	*	-0.71	**	1.84	**	0.66	
5 ≤ Cases < 10	1.05	***	-0.28		-4.94	***	-3.12	***	-0.20		-2.24	***
10 ≤ Cases < 20	1.71	***	0.26		-5.69	***	-4.42	***	-0.99	*	-3.42	***
20 ≤ Cases < 40	1.97	***	0.47		-6.95	***	-5.15	***	-2.34	***	-4.14	***
40 ≤ Cases < 80	2.35	***	-13.18	***	-8.02	***	-6.93	***	-3.65	***	-4.82	***
80 ≤ Cases < 160	2.76	***	-12.01	***	-9.23	***	-6.68	***	-4.51	***	-4.76	***
160 ≤ Cases	1.86	***	12.21	***	-4.18	***	-3.67	***	-1.09		-4.12	***
0 < Deaths < 1	-0.13		-6.16	***	-0.47		-0.38		0.01		0.14	
1 ≤ Deaths < 2	0.88	**	-10.54	***	-4.60	***	-1.69	***	-0.68		-2.33	***
2 ≤ Deaths < 5	1.60	***	-6.84	***	-5.74	***	-1.84	***	-0.53		-4.63	***
5 ≤ Deaths < 10	2.56	***	2.98		-7.11	***	-2.37	***	-2.30	***	-8.06	***
10 ≤ Deaths < 20	5.32	***	4.68		-15.42	***	-9.23	***	-8.99	***	-16.39	***
20 ≤ Deaths	5.76	***	-7.75		-17.67	***	-9.86	***	-2.11		-14.32	***
Stringency Index	0.23	***	-0.35	***	-0.76	***	-0.67	***	-0.41	***	-0.55	***
Temperature	-0.22	***	5.10	***	0.43	***	0.41	***	0.24	***	-0.08	**
Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Cubic trend	Yes		Yes		Yes		Yes		Yes		Yes	
D-o-W dummies	Yes		Yes		Yes		Yes		Yes		Yes	
R-squared	0.83		0.68		0.82		0.82		0.46		0.69	

Table shows panel regression results. Variables "Cases" and "Deaths" are dummy variables and are specified in per million terms. Asterisk denote statistical significance, * = $p < 0.10$, ** = $p < 0.05$ and *** = $p < 0.01$.

The stringency index is found to affect all types of mobility in a statistically significant way.

Moreover, both sign and the relative magnitude of the effects were found to be in line with

¹⁰This panel regression with time dummies and fixed effects can be interpreted as a staggered Difference-in-Differences (DiD) specification. As argued in Brzezinski et al. (2020), the staggered DiD estimates give an unbiased estimate of the weighted average causal effect assuming that, conditional on controlling for the progression of the pandemic, as well as country and time-invariant effects, treatment assignment is indeed random. In other words, assuming random treatment effects and no time-varying treatment effects, countries that, at any point in time, have not implemented any policy, can be seen as a viable counterfactual for those that have. To try to combat the bias arising from non-random or time-varying treatment effects we control for the stage of the pandemic in each state using the number of country-specific COVID-19 cases and deaths as well as trends in time since the first COVID case in each country. Apart from helping in the identification of the causal effect of national government policies on community mobility, these two control variables will also help identify the extent of the prevalence response in the different stages of the pandemic.

a-priori expectations. In particular, an increase in the stringency index is estimated to reduce mobility to parks, retail and recreation establishments, transport, groceries and workplaces while increasing residential mobility. Moreover, the stringency index was found to affect to a larger extent, mobility in discretionary types of mobility, that is retail and recreation. In fact, mobility related to transport, place of residence, work and groceries were found to be less affected by changes in the government stringency level.

These results also confirm the role of prevalence response in reducing individual mobility across the EU. Indeed, the two sets of dummy variables capturing the precautionary response of individuals, that is the number of per million COVID-19 cases and COVID-19 related deaths are seen to have statistically significant effects on all types of mobility. As expected, the strongest response to the number of COVID-19 cases and deaths have been estimated in the most discretionary type of mobility, that pertaining to Retail and recreation activities. Mobility to workplaces is relatively less sensitive to news relating to COVID-19 cases, but is especially responsive to news regarding COVID-19 deaths. As expected, results are less significant with regard to the prevalence response in mobility to parks and groceries and pharmacies. With regards to the latter, the effect of prevalence response on mobility to groceries is not known a-priori. Indeed, at the start of the COVID-19 pandemic, mobility towards groceries and pharmacies has increased across all EU countries, as individuals reacted to uncertainty regarding supplies of the main necessities. This effect might be reflected in our estimates as mobility to groceries and pharmacies is estimated to increase when the number of cases stand between 1 and 5 in per million terms, figures that were only registered at the start of the pandemic. Results for mobility to parks do not paint a clear picture. News relating to COVID-19 cases only seem to exert a negative effect on mobility towards park when the number of per million cases hovered between 40 and 160. Similarly reports on COVID-19 deaths reduce mobility to parks only when deaths per million were between 1 and 5.¹¹

Results also indicate that the precautionary motive behind changes in mobility is positively related to the progression of the pandemic. As the number of reported cases and deaths per million increase, the effect on mobility is also expected to increase considerably. For instance our estimates show that when the number of daily COVID-19 cases stood between 1 and 5,

¹¹Results pertaining to mobility to parks should be treated with caution. First, Google Mobility data defines a park specifically as a National Park and does not necessarily including open rural spaces. Second, it is very complicated to form a-priori expectations on how a pandemic might affect mobility to parks. On the one hand, people might choose to go to parks to reduce their proximity to others in their society. On the other hand, some national authorities have suggested that in the interest of safety, people should not visit parks as human contact might not be avoidable especially if the number of visitors increases during the pandemic.

there is a drop of 1.67% in mobility to retail and recreation outlets. This drop climbs gradually to more than 9% when daily cases stood between 81 and 160. The increase in the prevalence response of individuals is more pronounced for news relating to COVID-19 deaths, ranging from no significant effect at the lowest levels of reported deaths to a drop of almost 18% when COVID-19 related per million deaths exceed 20.

Finally, these estimations reveal an interesting result. The precautionary effects following news relating to COVID-19 cases, peak before the number of cases reported in each country reach their maximum. This could suggest that as the number of COVID-19 cases start to stabilise at very high levels, the general public starts to acclimatise to this new normal thereby reducing the degree of prevalence response. For the majority of EU countries, per million cases in excess of 160 have only been reported in the second wave of the pandemic, that is more than 6 months since the first cases of COVID-19 were reported in Europe. The lower sensitivity of general mobility to the number of COVID cases in excess of 160 could therefore be a sign that in the second part of the pandemic, EU nationals started to reassess their risk perceptions surrounding the pandemic. The reassessment of one's risk profiles and the subsequent demotivation to engage in protective behaviours during a prolonged period of crisis is a very well documented phenomenon, known as pandemic fatigue (WHO, 2020).

Similar conclusions are derived from our second specification which provides a more detailed disaggregation of the types of mitigation measures that have been imposed by national governments. News regarding the number of per million cases and deaths exert considerable downward pressures on all type of mobility while increasing time spent at home. This precautionary effect intensifies as the number of cases and deaths start to climb. Again we see an element of pandemic fatigue that becomes apparent when the number of per million cases stabilise at very high levels.

Turning to the effects of different mitigation measures, results indicate that almost all types of containment measures exert a negative effect on all types of mobility. Policies relating to the closure of schools seem to exert the largest effects on all types of mobility (with the exception of mobility to parks). In this respect, the result pertaining to mobility to retail and recreation establishments and to workplaces are especially striking. Estimates in fact show that these two types of mobility have been significantly more affected by school closures than by workplace closures (with the latter including the forced shutdown of non-essential retail outlets and recreation establishments) and stay at home orders (which capture outright lockdowns).

This confirms the general tendency outlined in section 3, that is, that all mobility measures throughout the EU have seen strong breaks that have occurred exactly after or concurrently with school closures. This result can be explained in two ways. First, school closures, imply that parents had to find alternative ways in which to tend for their children, in a period when visits to other members of the family were either not permitted or else highly not recommended. This would have negatively impacted the ability of working parents to continue travelling to their workplace. Moreover, this result could be capturing the reaction of the general population to a heightened sense of risk that follows the closure of schools. This point seems to be better at explaining the results regarding the most discretionary types of mobility, mainly those relating to retail and recreation.

Table 2: Panel regression results - Restriction indicators

	Home		Park		Retail		Transport		Groceries		Work	
0 < Cases < 5	0.32		-4.08	*	-2.4	***	-1.07		1.17		0.41	
5 ≤ Cases < 10	1.27	***	-1.66		-5.45	***	-3.29	***	-0.77		-2.3	***
10 ≤ Cases < 20	1.84	***	-1.79		-6	***	-4.46	***	-1.34	*	-3.26	***
20 ≤ Cases < 40	2.14	***	-2.25		-7.39	***	-5.38	***	-2.81	***	-4.05	***
40 ≤ Cases < 80	2.65	***	-15	***	-8.86	***	-7.56	***	-4.39	***	-5.2	***
80 ≤ Cases < 160	3.25	***	-13.2	***	-10.7	***	-7.67	***	-5.25	***	-5.61	***
160 ≤ Cases	2.13	***	12.73	***	-4.81	***	-4.14	***	-1.74		-4.56	***
0 < Deaths < 1	-0.2	*	-4.82	***	-0.09		-0.03		0.13		0.35	
1 ≤ Deaths < 2	0.56	**	-8.88	***	-3.53	***	-0.95		-0.44		-1.67	***
2 ≤ Deaths < 5	1.05	***	-7.13	*	-3.98	***	-0.74		-0.31		-3.24	***
5 ≤ Deaths < 10	1.87	***	1.36		-5.1	***	-1.32		-1.77	*	-6.43	***
10 ≤ Deaths < 20	4.26	***	-3.24		-12.4	***	-7.63	***	-8.49	***	-13.4	***
20 ≤ Deaths	4.59	***	-13.7		-13.9	***	-7.44	***	-1.58		-11.3	***
School Closing	0.06	***	-0.01		-0.19	***	-0.17	***	-0.07	***	-0.16	***
Workplace Closing	0.03	***	0.22	***	-0.1	***	-0.05	***	-0.05	***	-0.09	***
No Public Events	0	*	-0.21	***	-0.03	***	-0.04	***	-0.02	***	0	
No gatherings	0.03	***	-0.09	***	-0.08	***	-0.07	***	-0.05	***	-0.06	***
Close of Public Transp	0.03	***	-0.19	***	-0.09	***	-0.07	***	-0.09	***	-0.06	***
Stay At Home	0.02	***	0.15	***	-0.07	***	-0.05	***	-0.02		-0.06	***
National travel restr	0.03	***	-0.2	***	-0.09	***	-0.08	***	-0.05	***	-0.04	***
Inter travel restriction	0.01	***	0.07		-0.05	***	-0.08	***	-0.06	***	-0.05	***
Temperature	-0.22	***	5.11	***	0.45	***	0.41	***	0.24	***	-0.07	
Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Cubic trend	Yes		Yes		Yes		Yes		Yes		Yes	
Day of the week dummies	Yes		Yes		Yes		Yes		Yes		Yes	
R-squared	0.84		0.69		0.83		0.82		0.47		0.7	

Table shows panel regression results. Variables "Cases" and "Deaths" are dummy variables and are specified in per million terms. Asterisk denote statistical significance, * = p<0.10, ** = p<0.05 and *** = p<0.01.

4.1 Persistence in changes in mobility

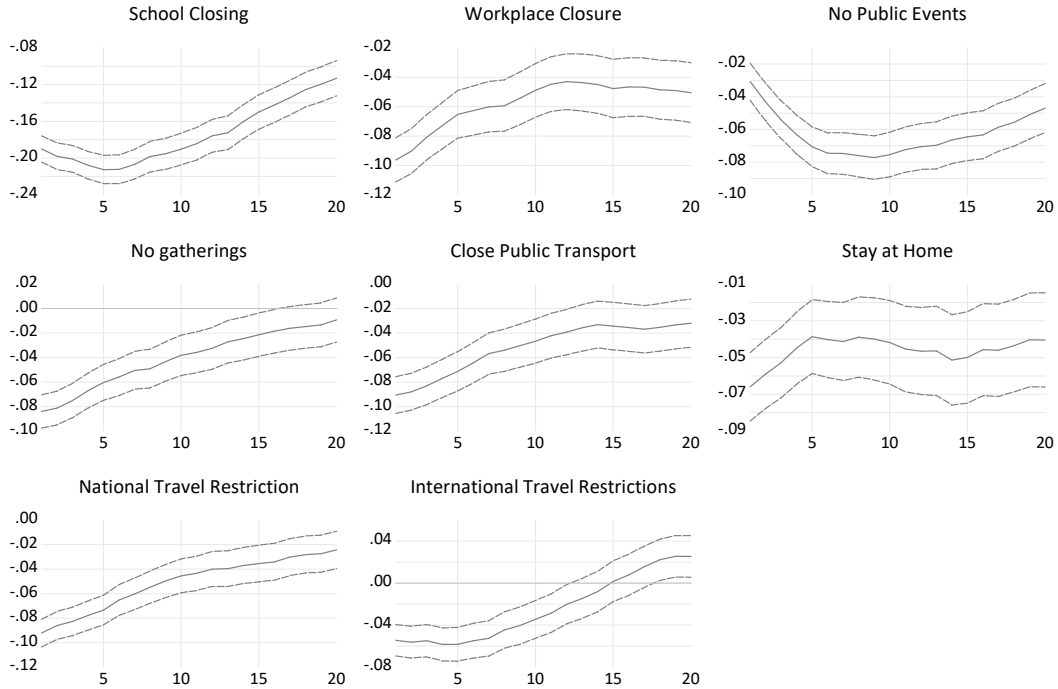
Despite being quite detailed, the specifications described in equation 3 do not provide any information with regards to the persistence of the mobility measures after a change in either

the state of the pandemic or a change in the mitigation measures adopted by governments. To account for this I run a local projections specification in line with Jordà (2005). Such a framework is flexible enough to easily accommodate a panel structure (as in David et al., 2019) and is quite robust to mis-specification especially since it does not recursively estimate impulse responses and does not therefore restrict their shape. The estimating equations take the following form:

$$y_{i,t+h} = \gamma_i + \sum_{c=1}^7 \beta_{i,c} cases_{i,c,t} + \sum_{h=1}^6 \gamma_{i,h} deaths_{i,h,t} + \sum_{p=1}^P \xi_{i,p} P_{i,p,t} + \sum_{j=1}^3 \delta_{i,j} t^j + \sum_{d=1}^6 \theta_{i,d} DOW_{i,d,t} + \phi_i temp_{i,t} + \sigma_{i,t+h} \quad (4)$$

where all variables are defined as before and h denotes the time horizon considered. For space considerations, I restrict local projection estimates to the specification considering the different stringency subindices. Also, for brevity, I discuss results pertaining to the dynamic effects different mitigation measures have on mobility in retail and recreation establishments, while results for all other mobility types are shown in Appendix B.¹²

Figure 6: Panel Local Projection estimates for cases, deaths and stringency index



Impulse responses from Panel Local Projection estimates. Dashed lines show 95% confidence bands.

¹²Results of the dynamic responses following mitigation measures are fairly similar across mobility types.

Results show that all mitigation measures have persistent and statistically significant negative effects on mobility to retail and recreation measures. Moreover, I find two types of dynamic responses, hump-shaped responses where the peak effect of a mitigation measure occurs after its introduction, and monotonically decaying effects where the peak effect of the measure is found on impact. In line with static results, school closures have the strongest and most persistent effect on mobility to retail and recreation establishments. The peak effect is estimated after 5 days since the schools are closed, and while the effect decays over the horizon considered, it still has considerably stronger effects than other government mitigation measures 20 days after introduction. Restrictions on public events also has considerably strong and persistent effects which peak after more than a week since their introduction. Throughout the horizon under consideration, stay at home measures have also very persistent effects on the mobility to retail and recreation establishments, even though they are marginally smaller than the effects we see on impact in our static analysis.

Finally, restrictions on public gatherings, public transport and national as well as international travel all have similar dynamic effects on mobility to retail and recreation establishments. For all these mitigation measures, effects peak on impact and decay monotonically. Moreover, the effects of the introduction of restrictions on gatherings and international travel go down to zero after 20 days, implying that this specific type of mobility goes back to its pre-restriction levels 20 days after the introduction of these two types of mitigation measures.

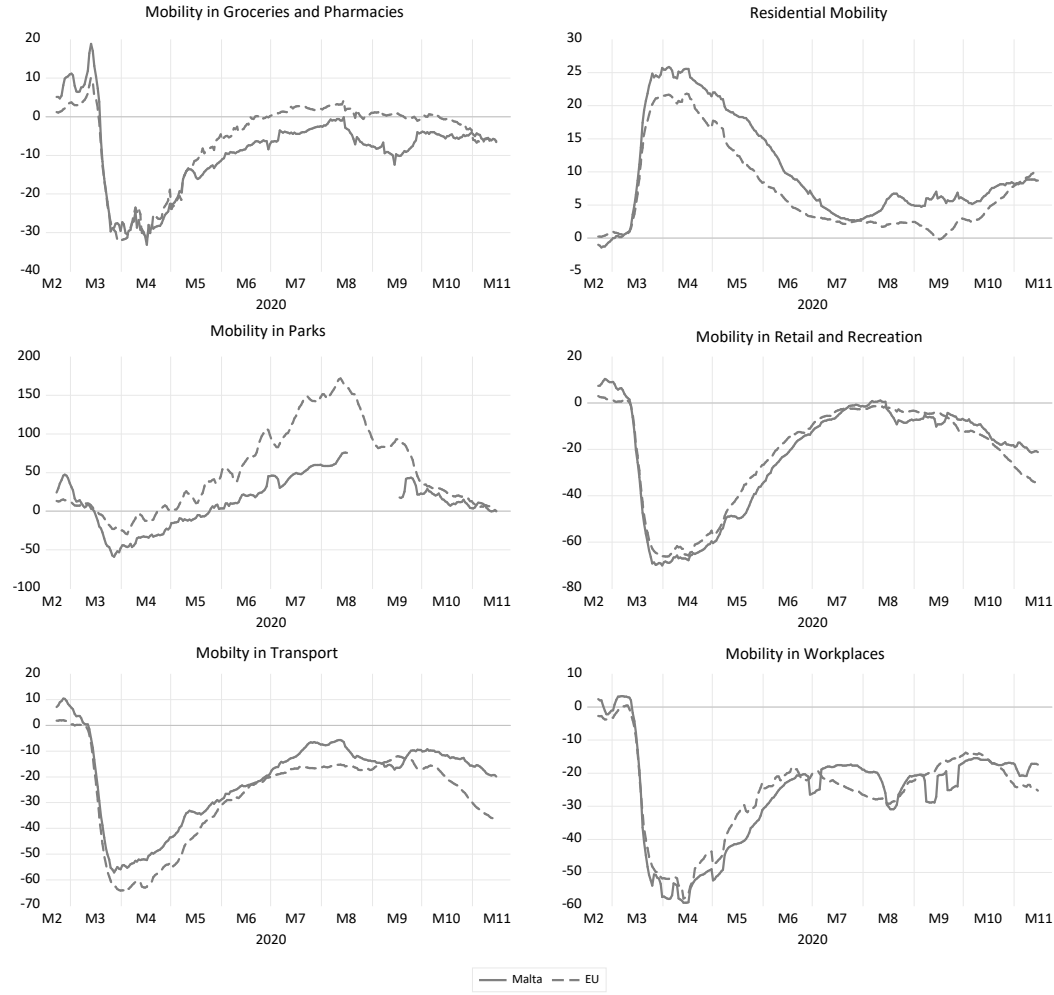
5 Individual Mobility in Malta during the pandemic

Broadly speaking, Malta's dynamics for individual mobility, follow those exhibited in all EU countries. Figures 3 and 7 indicate that Malta has experienced a sudden and significant drop in all types of mobility during mid-March 2020. The only exception is obviously residential mobility which has climbed considerably during the same period. The magnitudes of the fall in mobility are roughly equivalent to those exhibited by the rest of the EU. The peak drops in mobility have been registered between the second part of March and the first half of April 2020. As expected, and in line with EU-wide data, retail and recreation establishments in Malta have witnessed the largest drops in mobility, peaking at roughly 70% less mobility when compared to the baseline in January and February of the same year. These were followed by mobility to workplaces and transport hubs, with falls of almost 60%. The lowest falls in mobility were recorded in parks and groceries and pharmacies. Despite the fact that Maltese authorities have never enforced a full-blown lockdown or stringent stay-at-home orders, the increase in Maltese residential mobility has been significantly higher than the average registered across the EU.

Stringency measures in Malta have also followed the trajectories found in the rest of the EU. Between the first and third weeks of March, in line with the steps taken by other national authorities across Europe, the Maltese authorities have rapidly imposed significant restrictions targeted at reducing public mobility, with the aim of controlling the transmission of the disease. Estimates documented in section 3.2 show that Malta's overall stringency index features a sudden break that happened on the 13th of March 2020. The main containment indicators that drive this break relate to the following subindices: Public event cancellations, School closures as well as National and International travel restrictions, all of which exhibit statistically significant breaks between the 11th and 13th of March 2020. In this period, Maltese authorities have closed all education institutions (13th March 2020), prohibited all major events from taking place (12th March 2020) and have enacted a number of policies aimed at reducing the risk of importing active COVID-19 cases, namely the cancellation of all flights from Italy and Sicily (11th March 2020), and the introduction of obligatory quarantine to all individuals returning from overseas (13th March 2020).

In line with results pertaining to the rest of the EU, breaks in all types of mobility in Malta have occurred after the spike of the overall stringency indicator. This confirms the general tendency exhibited across the EU, that government action was instrumental in reducing mobility and

Figure 7: Mobility in Malta and EU



Charts show Google Mobility data for the EU average (estimated as a simple average) and for Malta for 6 different mobility measures. All data are shown as 7-day moving averages to remove day-of-the-week effects.

control the transmission of COVID-19 in the local community. Delving deeper into the sub-categories of containment and mobility measures for Malta, we can confirm another general tendency exhibited at the EU-level. While government action has been instrumental in triggering the drops in general mobility, the first wave of containment measures introduced by the Maltese authorities have brought about a drop in all types of mobility measures, including those that were not directly targeted by the containment measures that had been enacted till that point.

Indeed, the break-point analysis for Malta indicates that most mobility measures feature a break in series between the 14th and 20th of March 2020. The first mobility indicator to feature a break in series corresponds to mobility towards groceries and pharmacies which features a first positive break on the 14th of March, two days after the imposition of travel restrictions

from Italy and the closing off of schools. On the same date, mobility to restaurants and other entertainment establishments have plummeted, even though no policies directed at closing or limiting capacity of recreation and food establishments had been introduced at the time.¹³ This shows that the closure of schools, the cancellation of public events and the imposition of mandatory quarantine to anyone returning from international travel have served to trigger a prevalence response within the Maltese population. Similarly, residential mobility features a positive and statistically significant break on the 20th March 2020, even though shielding orders prohibiting vulnerable people from leaving their place of residence were only enacted on the 28th March 2020.¹⁴

Similar conclusions are derived from figure 8, which portrays changes in mobility in Malta juxtaposed to the introduction of the main mitigation measures in Malta. This graphical analysis shows that most mobility breaks have occurred after the closing of schools, well after the recording of the first COVID case in Malta, but before the imposition of restrictions related to the closing of workplaces and of stay at home orders to vulnerable individuals and their immediate family members.

These findings confirm the point that the way government containment measures have affected public mobility in Malta is not in line with what one would expect a-priori. Indeed, despite the fact that the first government measures that were introduced have not been actively seeking to reduce mobility by closing establishments or workplaces, they have caused a systemic shift in the population's risk assessment of the general situation, prompting a sudden drop in mobility across all spheres of society. This in turn points to the fact that apart from restrictions imposed by local authorities, people's assessment of the risk level associated with the pandemic has a profound role to play in determining levels of mobility and consequently of economic activity.

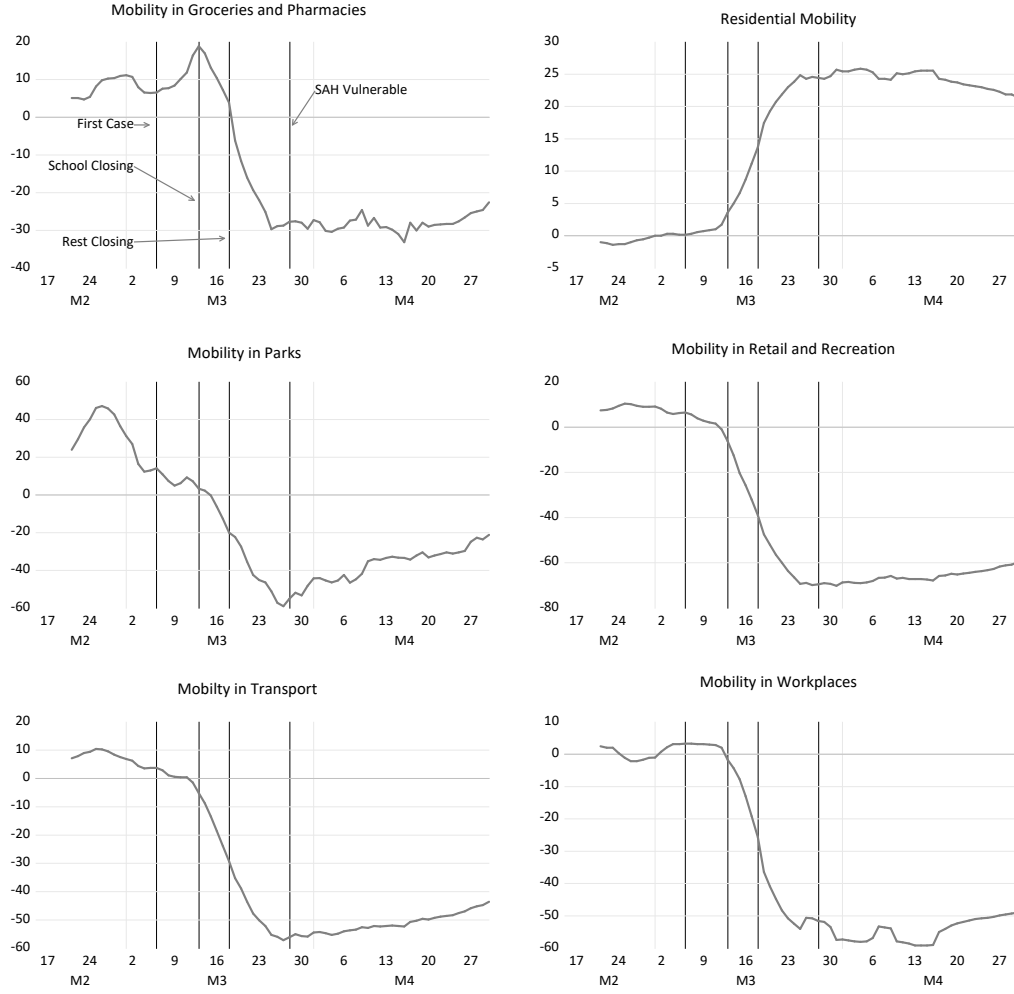
These conclusions are also confirmed by the times series estimates shown in tables 3 and 5.¹⁵ Results show a significant precautionary response of Maltese individuals which is triggered when the number of daily cases hover between 10 and 160 in per million terms. Results turn insignificant

¹³The closing of restaurants and non-essential retail establishments became effective from the 18th and 23rd March respectively.

¹⁴Malta has never enacted a full blown mandatory lockdown. However Maltese authorities have repeatedly encouraged the general population not leave home for no valid reasons before legally obliging the elderly and those with underlying health conditions not to leave their residency.

¹⁵Contrary to the previous analysis which benefited from the panel dimension of the available data set, the timeseries analysis undertaken for the Maltese scenario is unable to properly identify between effects related to the prevalence response (proxied by the number of COVID-19 cases and deaths) and the effects of government policies. Moreover, given the unavailability of suitable instruments (such as the data on the number of ventilators which are correlated with government interventions but are not directly observed by the general public), these results should be interpreted with caution.

Figure 8: Mobility in Malta and mitigation measures



Charts show Google Mobility data for the for Malta between mid-February and the end of April juxtaposed with the introduction of three key mitigation measures and with the first COVID case. All data are shown as 7-day moving averages to remove day-of-the-week effects.

(though still negative) when the number of cases increase beyond 160 per million. The fact that these transmission numbers have been only found in the second wave starting in the autumn of 2020, suggests that Maltese individuals' behaviour started to be affected by an element of policy fatigue . No prevalence response seems to be triggered in Malta with news of COVID related deaths. In line with the results for the EU, Malta's mobility has been significantly impacted by the authorities' stringency measures (with both magnitude and sign of the coefficients for all mobility measures being in line with those of the EU).

When specifying our equation in terms of separate restriction indicators (see table 4), we find a general increase in the standard errors estimates for the coefficients measuring the impact of the number of COVID cases across all mobility types, resulting in a considerable drop in

Table 3: Results for Malta - Stringency indicator

	Home	Park	Retail	Transport	Groceries	Work
0 < Cases < 5	0.43	-4.02	-1.48	-0.53	3.26 **	0.10
5 ≤ Cases < 10	1.74	-7.91	-3.69	-2.09	0.57	-0.35
10 ≤ Cases < 20	3.47 ***	-15.55 ***	-10.55 ***	-8.81 ***	-4.02 **	-7.41 ***
20 ≤ Cases < 40	3.66 ***	-17.09 ***	-10.80 ***	-9.78 ***	-2.83	-6.73 ***
40 ≤ Cases < 80	3.41 ***	-5.06	-6.20 **	-7.82 ***	1.76	-8.61 ***
80 ≤ Cases < 160	3.91 ***	-12.64 **	-8.91 ***	-7.67 ***	0.89	-7.82 ***
160 ≤ Cases	3.68 ***	6.05	-6.18	-3.13	3.19	-8.14 **
0 < Deaths < 5	-0.27	0.31	0.21	1.35	0.98	0.82
5 ≤ Deaths < 10	-1.02	4.55	1.13	0.86	-0.57	0.87
10 ≤ Deaths	-1.92	4.35	2.02	2.31	-1.57	-0.07
Stringency Index	0.22 ***	-0.51 ***	-0.66 ***	-0.38 ***	-0.36 ***	-0.50 ***
Temperature	-0.50 ***	4.52 ***	1.22 ***	1.32 ***	0.76 ***	0.28
Cubic trend	Yes	Yes	Yes	Yes	Yes	Yes
D-o-W dummies	Yes	Yes	Yes	Yes	Yes	Yes
Pub Hol dummies	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.93	0.8	0.91	0.86	0.69	0.87

Table shows panel regression results. Variables "Cases" and "Deaths" are dummy variables and are specified in per million terms. Asterisk denote statistical significance, * = $p < 0.10$, ** = $p < 0.05$ and *** = $p < 0.01$.

the number of statistically significant coefficients. This result could be driven by a high degree of multicollinearity between the explanatory variables, especially the number of cases and the mobility numbers.

In an effort to attenuate this problem we specify the model in terms of categorical dummy variables that take the value of one whenever a particular mitigation measure is in action.¹⁶ Estimates in table 5 show significant self-restrictive effects across all ranges of COVID cases, with the magnitude first increasing in absolute terms, before falling substantially with the maximum number of new daily cases. News about COVID deaths in Malta again fail to register statistically significant results. Finally, estimates regarding the effect of the mitigation measures enacted by Maltese authorities confirm our previous analysis. That is, policies aimed at closing off schools seem to have had the strongest effect on almost all types of mobility, even stronger than those related to the closure of non essential retail and restaurants. This result again points out that while government restrictions have been key in reducing mobility in Malta, the way this has been achieved is not exactly in line with a-priori expectations. Indeed, the initial measures taken by national authorities have most likely triggered a precautionary response by the majority of population as individuals reassessed the risk levels associated with the pandemic. This led to a drop in all types of mobility including those which at that particular point in time were still not being restricted through government measures.

¹⁶While such a specification reduces the collinearity with the other explanatory variables, it fails to capture the varying intensities in each of the policy instrument under consideration.

Table 4: Results for Malta - Restriction indicators

	Home		Park		Retail		Transport		Groceries		Work	
0 < Cases < 5	0.14		-1		0.92		1.58		2.13		-0.23	
5 ≤ Cases < 10	0.85		-2.26		0.67		1.96		1.11		0.22	
10 ≤ Cases < 20	1.85	***	-7.3	**	-3.63	**	-2.02		-2.34		-3.92	**
20 ≤ Cases < 40	1.76	***	-7.67	**	-2.56	*	-1.75		-1.74		-2.54	
40 ≤ Cases < 80	2.01	**	5.31		2.13		-0.33		1.26		-6.8	**
80 ≤ Cases < 160	2.64	***	-2.18		-1.06		-0.67		0.01		-6.81	**
160 ≤ Cases	2.38	**	13.75		1.19		3.05		2.53		-6.48	*
0 < Deaths < 5	-0.13		-0.14		-0.49		0.72		1.12		0.45	
5 ≤ Deaths < 10	-1.48	*	3.88		2.32		1.81		1.16		3.11	
10 ≤ Deaths	-1.68		-0.49		0.3		0.49		-2.88		0.2	
School Closing	0.09	***	-0.22	**	-0.27	***	-0.24	***	-0.17	***	-0.2	***
Workplace Closing	0.09	***	-0.18	*	-0.32	***	-0.25	***	-0.28	***	-0.33	***
No Public Events	0.04	***	-0.16	*	-0.19	***	-0.13	***	0.05		-0.07	*
No gatherings	0.02	*	-0.05		-0.1	***	-0.04		-0.07	**	0	
Close Public Trans- port	0.03	**	-0.17	*	-0.05		-0.06	**	-0.1	**	-0.08	*
Stay At Home	-0.02		0.19		0.2	*	0.12		0.04		-0.09	
National travel restr	-0.02		0.01		0.05		0.11	**	0.05		0.13	**
Inter travel restriction	0.02		-0.42	***	-0.13	**	-0.13	***	-0.05		-0.02	
Temperature	-0.5	***	3.75	***	1.19	***	1.12	***	0.77	***	0.52	**
Cubic trend	Yes		Yes		Yes		Yes		Yes		Yes	
D-o-W dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Pub Hol dummies	Yes		Yes		Yes		Yes		Yes		Yes	
R-squared	0.95		0.82		0.94		0.92		0.74		0.9	

Table shows panel regression results. Variables "Cases" and "Deaths" are dummy variables and are specified in per million terms. Asterisk denote statistical significance, * = p<0.10, ** = p<0.05 and *** = p<0.01.

Table 5: Results for Malta - Policy Dummies

	Home		Park		Retail		Transport		Groceries		Work	
0 < Cases < 5	1.06	*	-7.94	**	-4.19	**	-2.12	**	1.16		-1.1	
5 ≤ Cases < 10	2.78	***	-12.5	**	-8.4	***	-3.43	**	-1.71		-2.53	
10 ≤ Cases < 20	3.09	***	-16.9	***	-10.4	***	-5.55	***	-1.91		-4.6	***
20 ≤ Cases < 40	4.27	***	-20.7	***	-13.7	***	-7.24	***	-2.27		-5.63	***
40 ≤ Cases < 80	5.34	***	-13.1	**	-13.6	***	-7.14	***	0.81		-10.1	***
80 ≤ Cases < 160	6.4	***	-23.1	***	-17.9	***	-8.3	***	-0.41		-10.7	***
160 ≤ Cases	5.55	***	-4.01		-13.6	***	-4.22		1.51		-10.1	**
0 < Deaths < 5	0.3		-0.58		-1.71		0.7		0.05		-0.63	
5 ≤ Deaths < 10	-1.99	**	7.92		3.74		3.5	**	0.36		3.09	
10 ≤ Deaths	-5.56	**	13.58		12.31		9.96	**	2.35		8.43	
Restaurant L.down	2.23	**	-9.13	**	-7.51	***	-10.6	***	-8.77	***	-8.16	***
Airport L.down	2.97	***	-7.35	**	-6.11	**	-6.3	***	-8.66	***	-5.15	**
Airport Tier System	1.28		15.56	**	1.1		3.14		0.34		-4.4	
NE Retail Restrictions	2.96	***	-7.05		-12	***	-6.95	***	-9.48	***	-9.66	***
School Closure	5.32	***	-20.1	***	-15	***	-15.9	***	-5.76	***	-12.7	***
Temperature	-0.52	***	3.89	***	1.12	***	0.78	***	0.1		0.15	
Cubic trend	Yes		Yes		Yes		Yes		Yes		Yes	
D-o-W dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Pub Hol dummies	Yes		Yes		Yes		Yes		Yes		Yes	
R-squared	0.92		0.81		0.91		0.92		0.77		0.88	

Table shows panel regression results. Variables "Cases" and "Deaths" are dummy variables and are specified in per million terms. Asterisk denote statistical significance, * = p<0.10, ** = p<0.05 and *** = p<0.01.

6 Conclusion

The outbreak of the COVID-19 pandemic has seen national authorities around the world scramble to restrict public mobility in an effort to control the transmission of the novel coronavirus. Literature has repeatedly shown that apart from national and international restrictions, public mobility during pandemics is also significantly affected by self-imposed restrictions. This implies that when estimating the effectiveness of restrictions in reducing public mobility and consequently the spread of the pandemic, it is important to identify between the effects of this so-called prevalence response and of the mobility restrictions implemented at local, national or international levels.

This paper estimates the effects of the mitigation measures taken by government and health authorities across the EU by controlling for other effects including self-imposed restrictions. Results highlight four main points. First, in every EU country, the timing of the structural breaks in mobility were concentrated across all categories. Second, the vast majority of mobility breaks across the EU occur after the intensification of national mitigation measures implying that containment policies enacted at national levels have been instrumental in reducing the levels of mobility in individual states. Third, mitigation measures directed at school closures and cancellation of public events have affected all types of mobility including mobility towards retail and recreation establishments. Moreover, school closures and restrictions of public events also have a very persistent hump-shaped effect on all mobility measures, with the peak effect reached around a week after the introduction of such measures. This might indicate that such policies could have led to an overall re-assessment of the risk situation by the general public leading to widespread drops in mobility.

Finally, self-imposed restraints which occur independently of government measures have been responsible for a significant part of the fall in mobility with communities reacting to news relating to both COVID-19 cases and deaths. Moreover, results indicate a lower sensitivity of public mobility to reported cases and deaths when these go past the 160 cases and 20 deaths per million. This might indicate that at the later stages of the pandemic, as the number of cases and deaths stabilised at very high numbers, EU nationals started to reassess their risk perceptions leading to a demotivation to engage in self-restraining protective behaviour.

These conclusions have two important policy implications. First, some government policies

which are targeted at controlling a specific type of activity (such as school closures and cancellation of public events) might have strong and unintended effects on mobility types which are not specifically being targeted. Thus, when estimating the effectiveness of non-pharmaceutical interventions (most notably, school closures and the cancellation of public events) in reducing the transmission of the novel coronavirus, one needs to factor in the unintended fall in mobility types which are not necessarily due to specific stringency measures implemented by the local authority. Moreover, when planning the mitigation measures required to cut overall mobility by a given amount, government needs to internalise any unintended drops in mobility that particular policies (such as school closures) are likely to have.

Second, changes in community mobility should not be interpreted as being solely a function of government policies but are deeply affected by the state of the pandemic. More specifically, if current new COVID-19 related cases and/or deaths are particularly low, the extent of self-imposed precautionary reductions in mobility are considerably lower when compared to medium-high levels of COVID cases. This implies that any additional restraints on community mobility which are required during periods when cases are still relatively low, depend to a larger extent on the policies adopted by national authorities. Moreover, the lifting of any containment measures need to internalise the reduction in the prevalence response of the public which occurs naturally as new transmission and death numbers start to fall.

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A Breaks and Stringency Indicators

Figure 1: Mobility vs Public events index

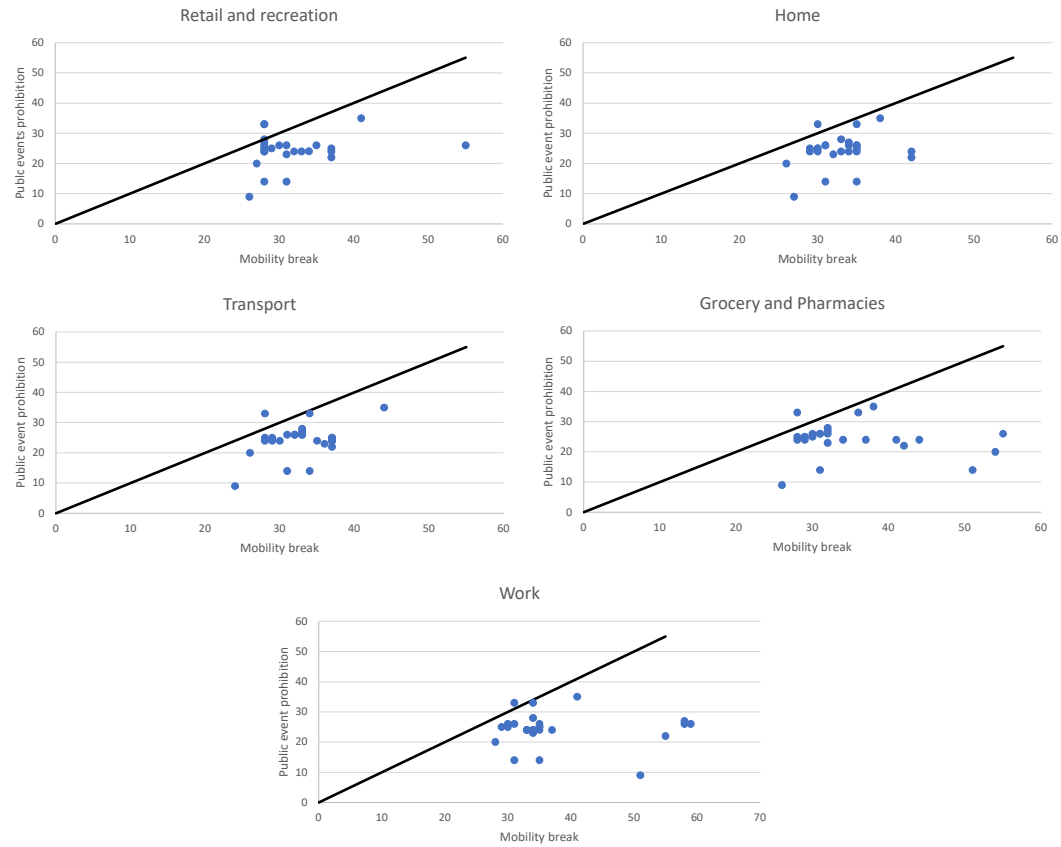


Figure 3: Mobility vs Public gatherings index

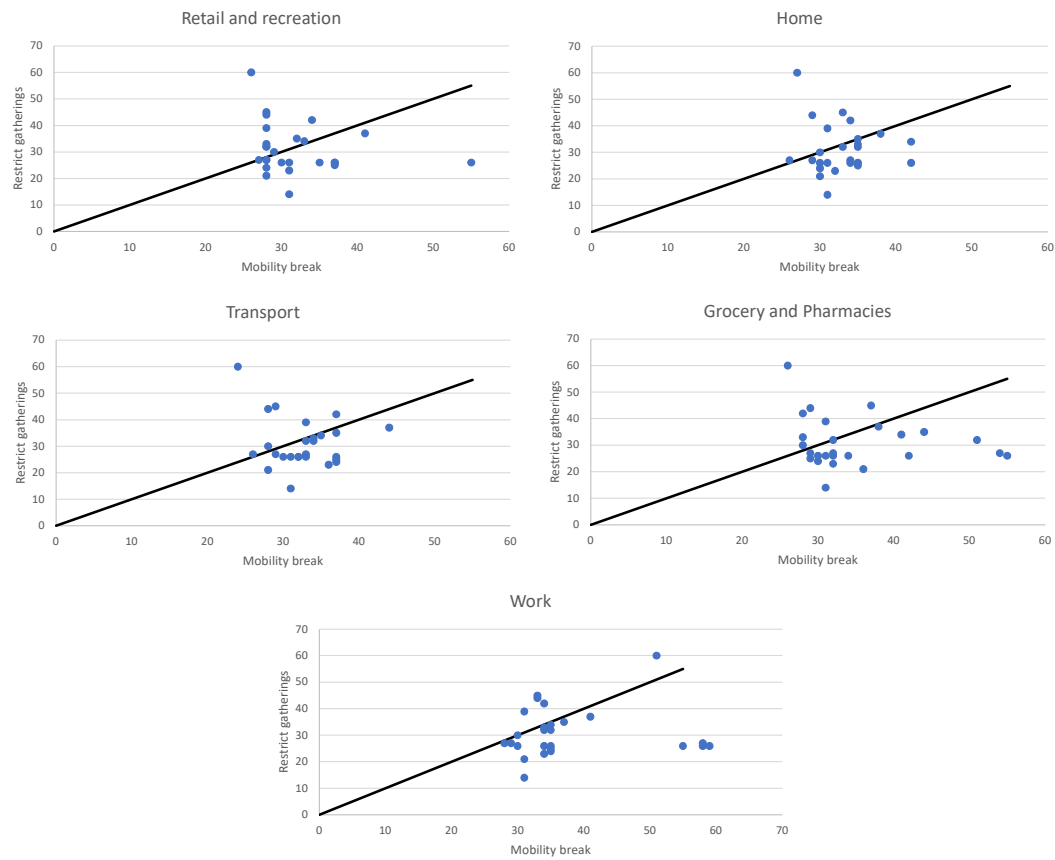


Figure 5: Mobility vs International travel restrictions index

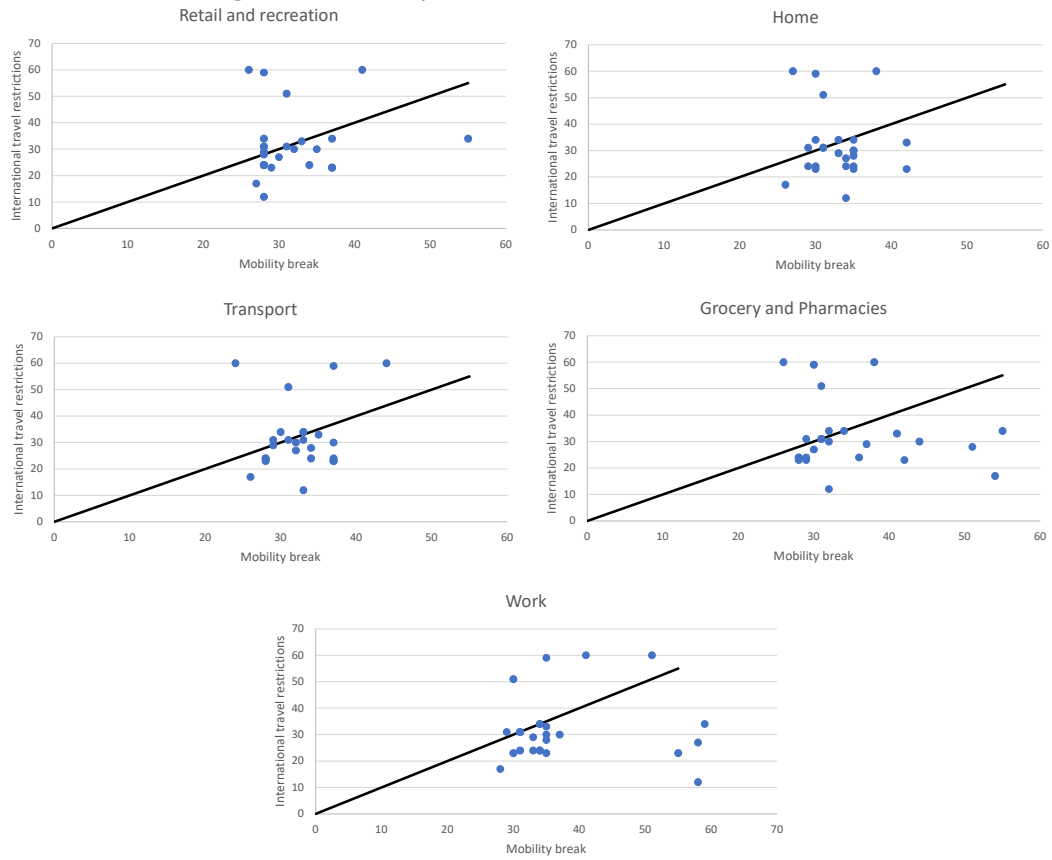


Figure 7: Mobility vs School closures index

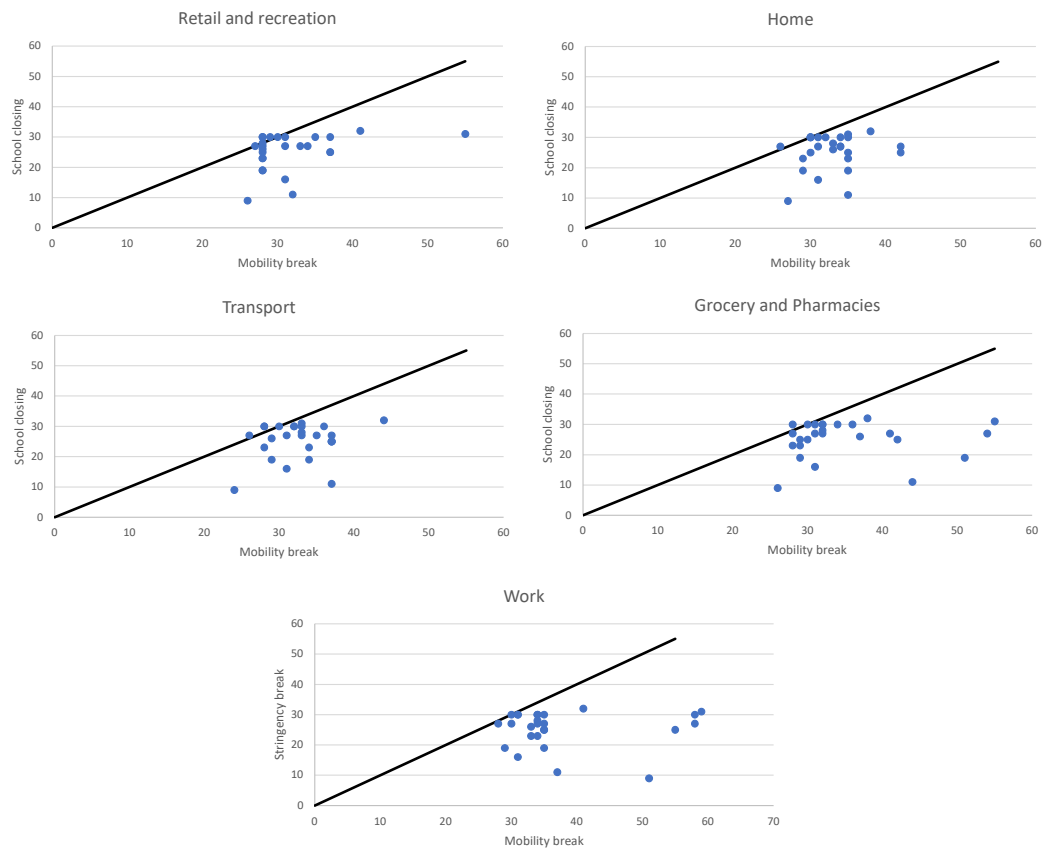


Figure 9: Mobility vs Stay at home index

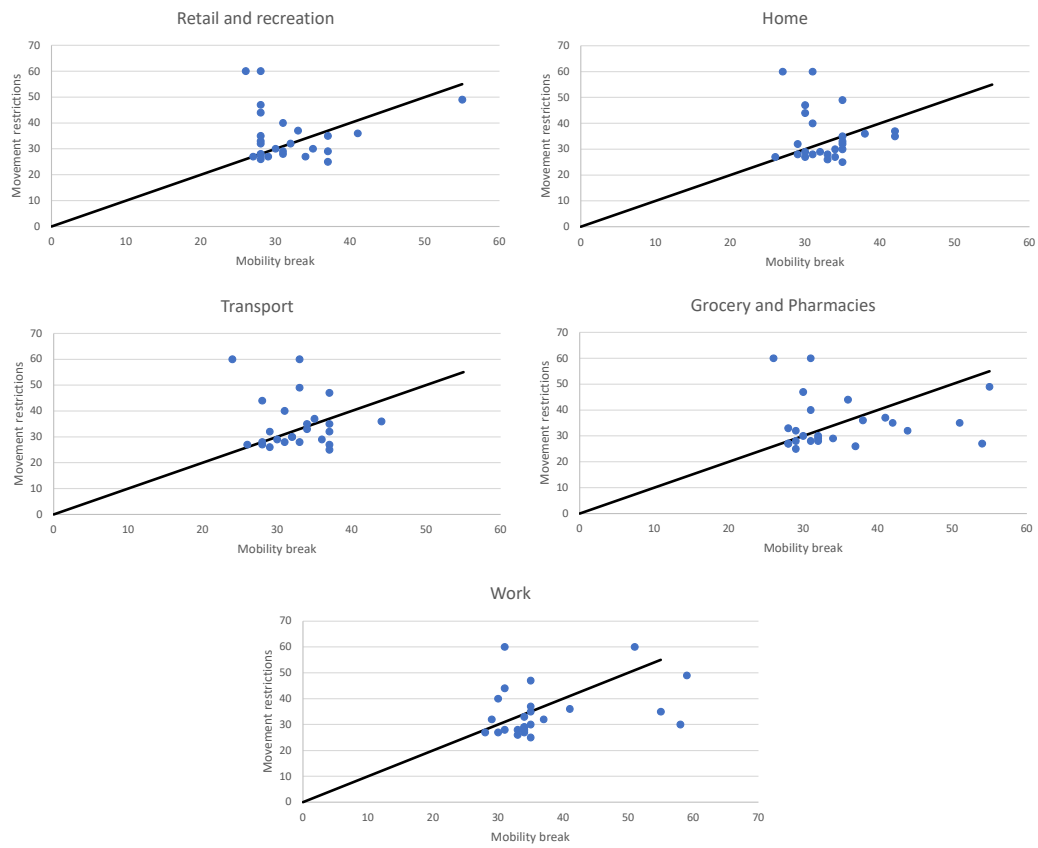


Figure 11: Mobility vs Internal travel index

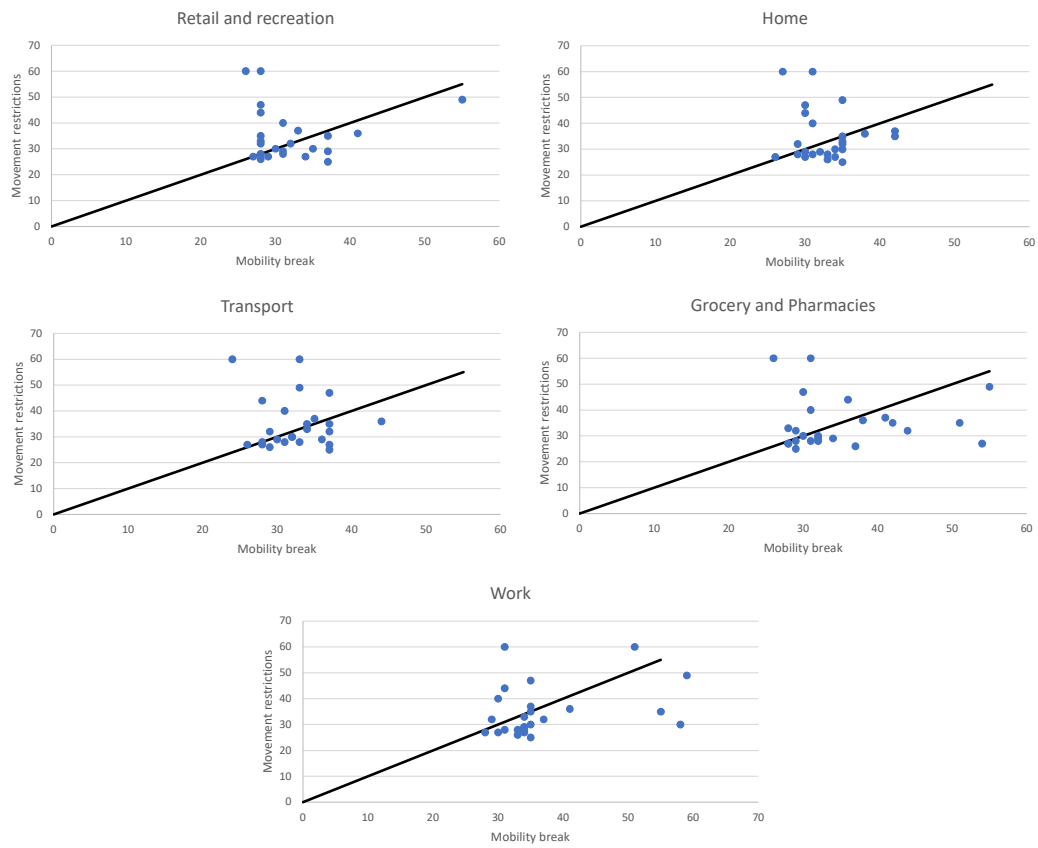
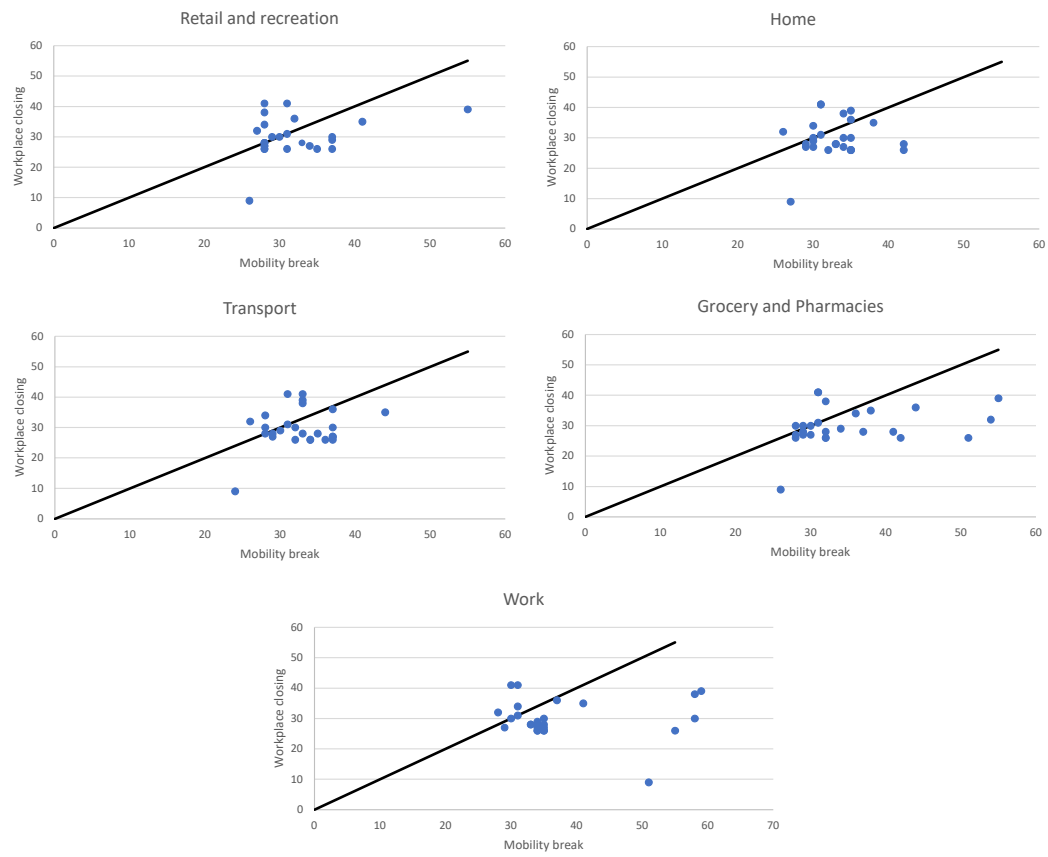


Figure 13: Mobility vs Work closure index



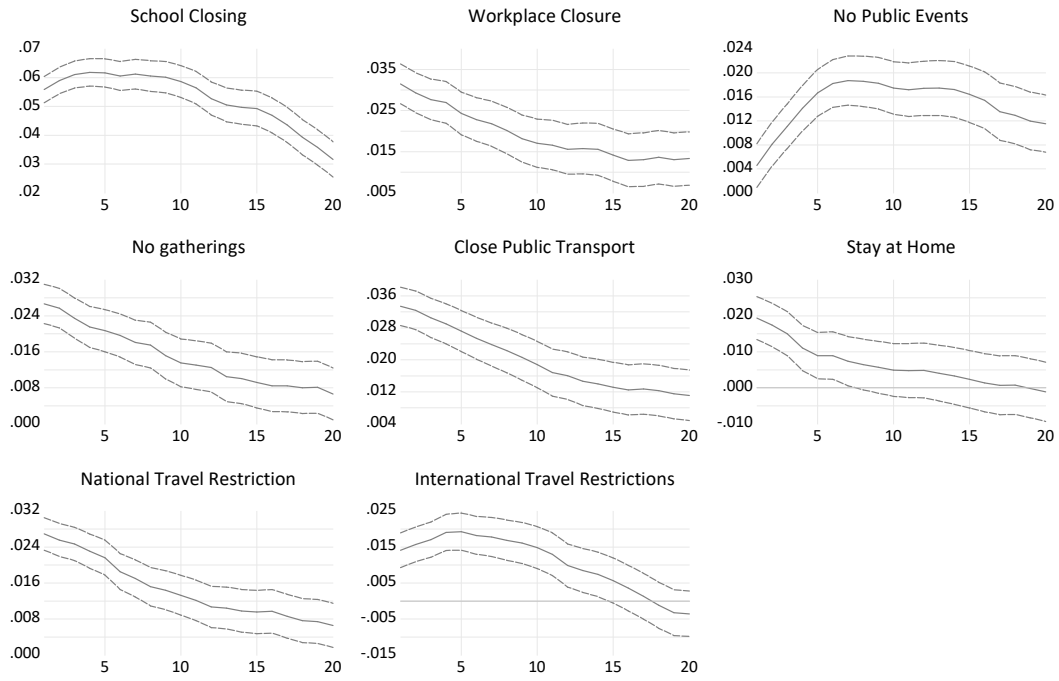
B Dynamic Responses for Mitigation Measures

Figure 1: Panel Local Projection estimates: Mobility in Groceries and Pharmacies



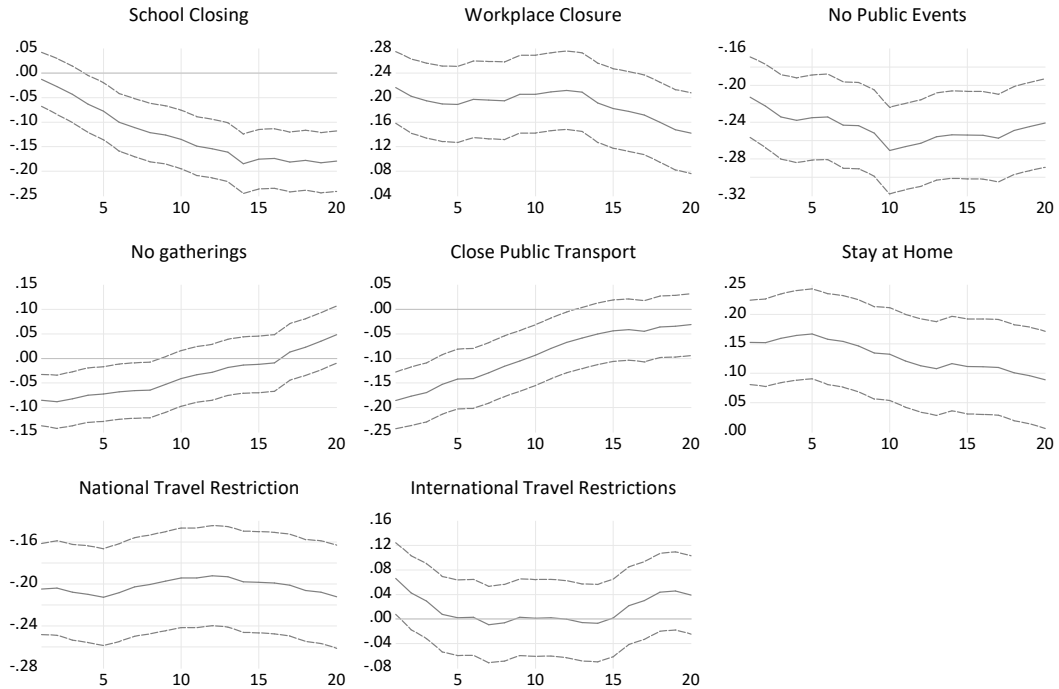
Impulse responses from Panel Local Projection estimates. Dashed lines show 95% confidence bands.

Figure 2: Panel Local Projection estimates: Residential Mobility



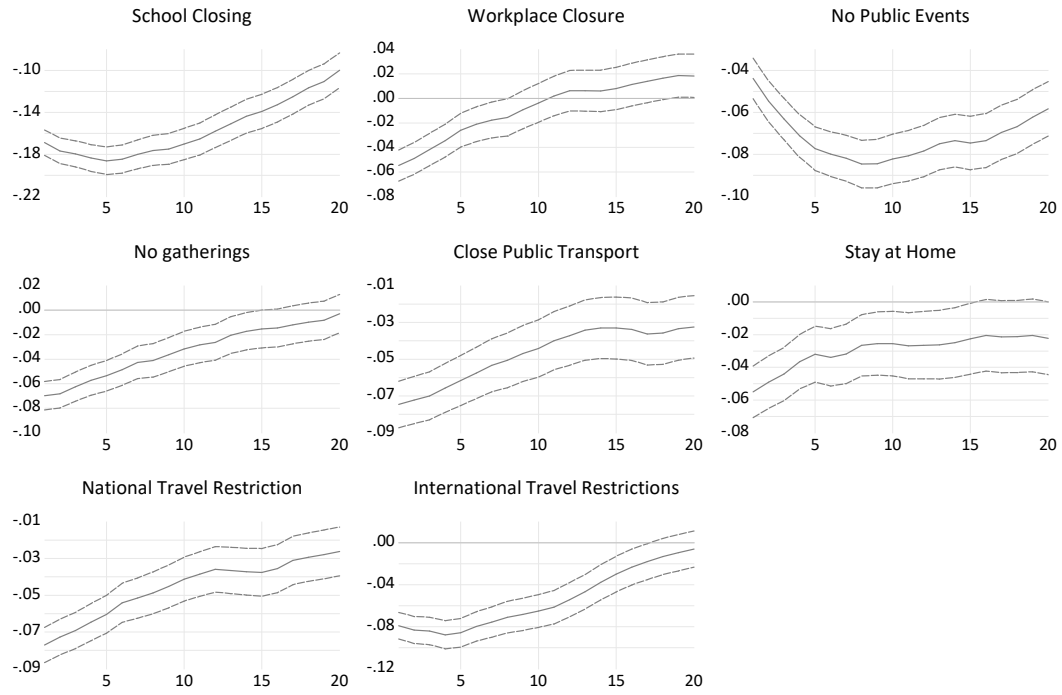
Impulse responses from Panel Local Projection estimates. Dashed lines show 95% confidence bands.

Figure 3: Panel Local Projection estimates: Mobility in Parks



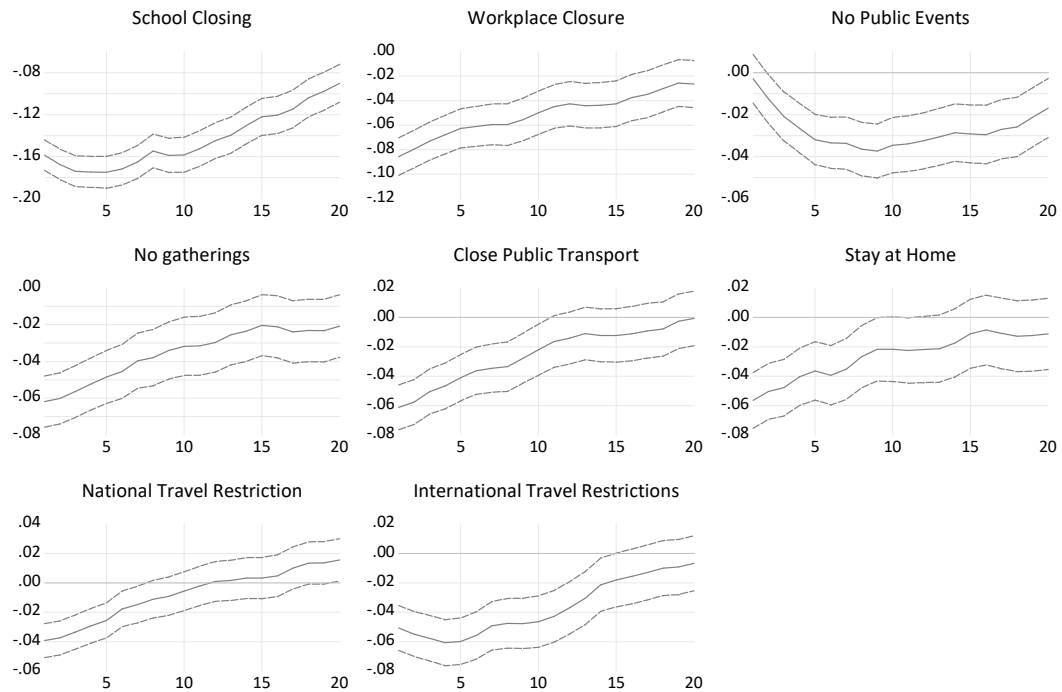
Impulse responses from Panel Local Projection estimates. Dashed lines show 95% confidence bands.

Figure 4: Panel Local Projection estimates: Mobility in Transport



Impulse responses from Panel Local Projection estimates. Dashed lines show 95% confidence bands.

Figure 5: Panel Local Projection estimates: Mobility in Workplaces



Impulse responses from Panel Local Projection estimates. Dashed lines show 95% confidence bands.