CHAPTER 2

ONLINE ANNEX

Annex 2.1. Data Sources and Sample Coverage

Annex Table 2.1.1 lists the data sources used in the analysis. The sample coverage for the different sections of the analysis is reported in Annex Table 2.2.2, with the selection of economies included in the analysis being driven by data availability. For the cross-country analysis, the sample varies between 22 and 52 countries based on data availability. In the case of the analysis relying on high-frequency indicators, the sample includes 22 countries when job postings are used and 128 countries when mobility is used. When subnational data on mobility is employed, the sample consists of 422 units for 15 G20 countries. Vodafone data is limited to Italy, Spain, and Portugal. Finally, the analysis of infections is based on a sample of 89 countries for which information on temperature, humidity, public information campaigns, testing, and contact tracing is available. At the subnational level, the sample consists of 373 units for G20 15 countries.

Annex Table 2.1.1. Data Sources

Indicator	Source
Altruism	Global Preference Survey
Contact tracing	Oxford COVID-19 Government Response Tracker
COVID-19 cases	Oxford COVID-19 Government Response Tracker
Humidity	Air Quality Open Data Platform
Industrial production	Haver Analytics
Lockdown measures	Oxford COVID-19 Government Response Tracker
Lockdown stringency index	Oxford COVID-19 Government Response Tracker
Mobility indicators	Google Community Mobility Reports, Baidu for China
Monetary policy rate	Haver Analytics
Percent of people moving by age and gender	Vodafone
PMI manufacturing	Haver Analytics
PMI services	Haver Analytics
Population	World Economic Outlook database, April 2020
Population density	World Economic Outlook database, April 2020
Public information campaigns	Oxford COVID-19 Government Response Tracker
Real consumption	Haver Analytics
Real consumption forecasts	World Economic Outlook database, January 2020
Real GDP	Haver Analytics
Real GDP forecasts	World Economic Outlook database, January 2020
Real investment	Haver Analytics
Real investment forecasts	World Economic Outlook database, January 2020
Retail sales	Haver Analytics
Rule of law	World Governance Indicators
Stock of job postings	Indeed
Temperature	Air Quality Open Data Platform
Testing	Oxford COVID-19 Government Response Tracker
Trust	Global Preference Survey
Unemployment rate	Haver Analytics

Source: IMF staff compilation.

Annex Table 2.1.2. Economies Included in the Analysis

Economy	Samples	Economy	Samples	Economy	Samples	Economy	Samples	Economy	Samples
Afghanistan	*Mn, In*	Croatia	*CE, Mn, In*	Iran	*In*	Mozambique	*Mn*	Slovak Republic	*CE, Mn, In*
Algeria	*In*	Czech Republic	*CE, Mn, In*	Iraq	*Mn, In*	Myanmar	*Mn, In*	Slovenia	*CE, Mn*
Algeria	*In*	Côte d'Ivoire	*Mn, In*	Ireland	*CE, Mn, In, Jp*	Namibia	*Mn*	South Africa	*CE, Mn, Ms, In, Is*
Angola	*Mn*	Cyprus	*In*	Israel	*CE, Mn, In*	Nepal	*Mn, In*	Spain	*CE, Mn, In, Jp, GA*
Argentina	*Mn, Ms, In, Is*	Denmark	*CE, Mn, In*	Italy	*CE, Mn, Ms, In, Is, Jp, GA*	Netherlands	*CE, Mn, In, Jp*	Sri Lanka	*Mn, In*
Aruba	*Mn*	Dominican Republic	*Mn*	Jamaica	*Mn*	New Zealand	*Mn, In, Jp*	Sweden	*CE, Mn, In, Jp*
Australia	*CE, Mn, Ms, In, Is, Jp*	Ecuador	*Mn, In*	Japan	*CE, Mn, Ms, In, Is, Jp*	Nicaragua	*Mn*	Switzerland	*CE, Mn, In, Jp*
Austria	*CE, Mn, In, Jp*	Egypt	*Mn*	Jordan	*Mn, In*	Niger	*Mn*	Taiwan Province of China	*CE, Mn*
Bahrain	*Mn, In*	El Salvador	*Mn, In*	Kazakhstan	*Mn, In*	Nigeria	*Mn*	Tajikistan	*Mn, In*
Bangladesh	*Mn, In*	Estonia	*CE, Mn, In*	Kenya	*Mn*	Norway	*CE, Mn, In*	Tanzania	*Mn*
Barbados	*Mn*	Ethiopia	*In*	Korea	*CE, Mn, In*	Oman	*Mn*	Thailand	*CE, Mn, In*
Belarus	*Mn*	Fiji	*Mn*	Kosovo	*In*	Pakistan	*Mn, In*	Togo	*Mn*
Belgium	*CE, Mn, In, Jp*	Finland	*CE, Mn, In*	Kuwait	*Mn, In*	Panama	*Mn*	Trinidad and Tobago	*Mn*
Belize	*Mn*	France	*CE, Mn, Ms, In, Is, Jp*	Kyrgyz Republic	*Mn, In*	Papua New Guinea	*Mn*	Turkey	*CE, Mn, In*
Benin	*Mn*	Gabon	*Mn*	Lao P.D.R.	*Mn, In*	Paraguay	*Mn*	Uganda	*Mn, In*
Bolivia	*Mn, In*	Georgia	*Mn, In*	Latvia	*CE, Mn*	Peru	*CE, Mn, In*	Ukraine	*CE, Mn, In*
Bosnia and Herzegovina	*Mn, In*	Germany	*CE, Mn, Ms, In, Is, Jp*	Lebanon	*Mn*	Philippines	*CE, Mn, In*	United Arab Emirates	*Mn, In, Jp*
Botswana	*Mn*	Ghana	*Mn, In*	Libya	*Mn*	Poland	*CE, Mn, In, Jp*	United Kingdom	*CE, Mn, Ms, In, Is, Jp*
Brazil	*CE, Mn, Ms, In, Is, Jp*	Greece	*CE, Mn, In*	Lithuania	*CE, Mn, In*	Portugal	*CE, Mn, In, GA*	United States	*CE, Mn, In, Jp*
Bulgaria	*Mn, In*	Guatemala	*Mn, In*	Luxembourg	*Mn*	Puerto Rico	*Mn*	Uruguay	*Mn*
Burkina Faso	*Mn*	Guinea	*In*	Macao SAR	*In*	Qatar	*Mn*	Uzbekistan	*In*
Cambodia	*Mn*	Haiti	*Mn*	Malaysia	*CE, Mn, In*	Romania	*CE, Mn, In*	Venezuela	*Mn*
Cameroon	*Mn*	Honduras	*Mn*	Mali	*Mn, In*	Russia	*CE, Mn, In*	Vietnam	*CE, Mn, In*
Canada	*CE, Mn, Ms, In, Is, Jp*	Hong Kong SAR	*CE, Mn, In, Jp*	Mauritius	*Mn*	Rwanda	*Mn*	Yemen	*Mn*
Chile	*CE, Mn, In*	Hungary	*CE, Mn, In*	Mexico	*CE, Mn, Ms, In, Is, Jp*	Saudi Arabia	*Mn, Ms, In, Is*	Zambia	*Mn*
China	*CE, Mn, Ms, In, Is*	Iceland	*In*	Moldova	*Mn*	Senegal	*Mn*	Zimbabwe	*Mn*
Colombia	*CE, Mn, In*	India	*CE, Mn, Ms, In, Is*	Mongolia	*Mn, In*	Serbia	*CE, Mn, In*		
Costa Rica	*Mn, In*	Indonesia	*CE, Mn, Ms, In, Is*	Morocco	*Mn*	Singapore	*CE, Mn, In, Jp*		

Source: IMF staff compilation.

Note: *CE* = cross-country regressions of economic indicators; *Mn* = national-level regressions of mobility; *Ms* = subnational-level regressions of mobility; *In* = national-level regressions of infections; *Is* = subnational-level regressions of infections; *Jp* = job postings; *GA* = gender-age mobility regressions.

Annex 2.2. Cross-Country Evidence of the Impact of Lockdowns on Economic Activity

This annex provides technical details about the cross-country analysis presented in the chapter. Panel 1 of Figure 2.1 of the chapter displays the correlation between the average lockdown stringency and the GDP growth forecast error in the first half of 2020.[1] The forecast error is defined as the deviation of real GDP growth from the January 2020 World Economic Outlook projections, which are the latest ones before the COVID-19 outbreak.[2] The figure indicates that there is a clear negative correlation between the stringency of the lockdown measures and the real GDP growth forecast error, suggesting that countries with a tigher lockdown stringency experienced larger output losses.

The analysis then looks at the correlation between lockdowns and economic activity more systematically. To do that, the following specification is estimated:

$$y_i = \alpha + \beta lock_i + \gamma cases_i + \varepsilon_i \quad (2.1)$$

where y_i is, alternatively, one of the following economic activity indicators for country i: the forecast error of real GDP, real consumption, and real investment in the first half of 2020; the average growth of industrial production and retail sales; and the average change in the level of manufacturing purchasing manager index (PMI) and services PMI in the first three months after a country's epidemic started; $lock_i$ is the average lockdown stringency during the same period used for the y_i variable; and $cases_i$ is the log of per capita COVID-19 cases at the end of the period used for the y_i variable.

Annex Table 2.2.1 and panel 2 of Figure 2.1 of the chapter report the results of the estimations. To compare the lockdown estimates across economic activity indicators, the figure shows the coefficient β multiplied by the ratio of the standard deviation of lockdowns to the standard deviation of the relevant economic activity indiciator. The results suggest that lockdown are associated with lower economic activity, and that the impact is significant whether or not the spread of the virus is controlled for.

[1] Data on lockdown stringency come from the Coronavirus Government Response Tracker of the University of Oxford. The lockdown stringency index is constructed as a simple average of nine sub-indexes built from ordinal indicators where policies are ranked on a numerical scale. These indicators measure school closures, workplace closures, cancellations of public events, gathering restrictions, public transportation closures, stay-at-home requirements, restrictions on internal movement, controls on international traveling, and public information campaigns. Since public information campaigns have a direct impact on voluntary distancing, the analysis constructs the stringency index excluding those.

[2] The real GDP growth forecast error for the first half of 2020 is calculated by first taking the sum of real GDP in the first two quarters of 2020 and then calculating the growth of this sum relative to its counterpart a year ago.

Annex Table 2.2.1. The Impact of Lockdown on Economic Activities

	GDP forecast error in Q1	Consumption forecast error in Q1	Investment forecast error in Q1	Industrial production	Retail sales	PMI, manufacturing	PMI, services	Unemployment rate
				A. Without controlling for COVID-19 cases				
Lockdown stringency	-0.205***	-0.235***	-0.566**	-0.421***	-0.210**	-0.134***	-0.277***	0.0602*
	(0.0588)	(0.0479)	(0.273)	(0.0970)	(0.0908)	(0.0435)	(0.0632)	(0.0347)
Observations	52	33	33	45	40	40	22	43
R-squared	0.220	0.287	0.203	0.230	0.068	0.128	0.248	0.077
				B. Controlling for COVID-19 cases				
Lockdown stringency	-0.197***	-0.237***	-0.569**	-0.458***	-0.239**	-0.134***	-0.225**	0.0789*
	(0.0549)	(0.0559)	(0.270)	(0.114)	(0.107)	(0.0487)	(0.0877)	(0.0429)
COVID-19 cases	-0.362	-0.341	-0.483	1.747	0.577	0.00636	-1.113	-0.489
	(0.288)	(0.513)	(1.762)	(1.067)	(1.368)	(0.381)	(0.893)	(0.417)
Observations	52	33	33	45	40	40	22	43
R-squared	0.246	0.299	0.207	0.282	0.074	0.128	0.286	0.131

Source: IMF staff calculations.

Note: All regressions include a constant. Heteroskedasticity and autocorrelation robust standard errors in parentheses. * $p < .10$; ** $p < .05$; *** $p < .01$.

Annex 2.3. Impact of Lockdowns on Economic Activity using High-Frequency Indicators

This annex describes the methodology to assess the impact of lockdowns on economic activity using high-frequency data. The first indicator to proxy economic activity is an average of the mobility indexes provided by Google.[1] The advantage of this indicator is that it is available for over 130 countries (including many emerging market and developing economies) and at daily frequency since early February. The second indicator employed in the analysis is the number of job postings from the online platform Indeed, which is available for 22 countries, among which 18 advanced economies and 4 emerging market and developing economies.

Mobility

The Impact of Lockdowns on Mobility

To assess the dynamic response of mobility to the implementation of a lockdown, the analysis relies on local projections (Jordà, 2005). Specifically, the following panel regressions are estimated with data on 128 countries since early February until mid-July, 2020:

$$mob_{i,t+h} = \alpha_i^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h ln\Delta cases_{i,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + \sum_{p=1}^{P} \rho_p^h mob_{i,t-p} + \varepsilon_{i,t+h} \quad (2.3)$$

where $mob_{i,t+h}$ denotes mobility for country i at time $t+h$, with h being the horizon; $ln\Delta cases_{i,t-p}$ is the log of daily COVID-19 cases, which is used to track the stage of the pandemic, with p being the lag length;[2] and $lock_{i,t-p}$ is the index measuring lockdown stringency. The specification also features lags of the dependent variable to account for pre-existing trends, and country and time fixed effects to control for country characteristics and global factors. The estimation includes a week worth of lags. Standard errors are clustered at the country level.[3]

Lockdowns are generally imposed when the country's epidemic is entering an acute phase. At that time, people are also more likely to voluntarily reduce social interactions because they fear being infected or infecting others. This complicates the assessment of the extent to which the decline in mobility after lockdowns is driven by government restrictions or by people's behavioral changes. By controlling for the stage of the pandemic, the coefficient δ_0^h isolates the impact of lockdown measures. At the same time, for a given level of lockdown stringency, the coefficient β_0^h should reveal the extent of voluntary social distancing.

The results of the estimations are reported in Figure 2.2 of the chapter. As shown in panel 1, in response to a full lockdown, mobility declines after a week by almost 25 percent relative to the level prior to the lockdown. The effect dies off over a month, as restrictions are gradually eased

[1] The mobility index used in the analysis is constructed as the average of the mobility indexes for groceries and pharmacies, parks, retails and recreation, transit stations, and workplaces. In the case of China, the mobility index is based on data from Baidu.

[2] Replacing the log of daily COVID-19 cases with the log of daily COVID-19 deaths does not change the results.

[3] Similar results are obtained if the standard errors are corrected for cross-sectional dependence following Driscoll-Kraay (1998).

as shown in Figure 2.3.1. Panel 2 of Figure 2.2 of the chapter shows the impact of daily COVID-19 cases on mobility. A doubling of COVID-19 cases leads to a decline in mobility of about 2 percent after 30 days. The results are similar when COVID-19 cases are replaced with COVID-19 deaths. In this case, mobility declines by 28 percent a week after the introduction of a lockdown; and a doubling of COVID-19 deaths leads to a reduction in mobility by 1.2 percent after 30 days.

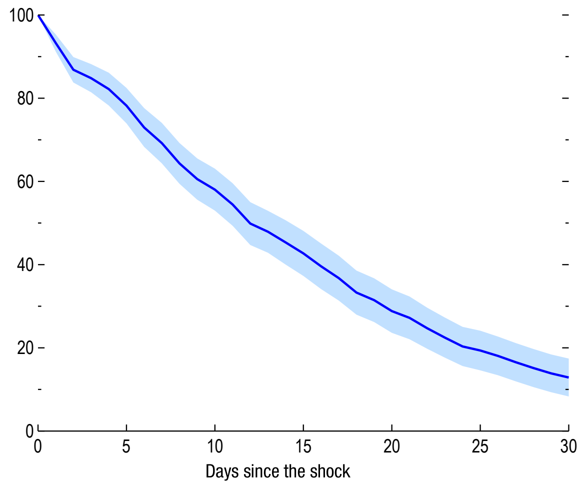
The analysis also proposes an alternative identification strategy that takes advantage of the sub-national disaggregation of the mobility data from Google. Some countries imposed national lockdowns in reaction to localized outbreaks in highly affected regions. Therefore, these national lockdowns were largely exogenous to the conditions in regions with less COVID-19 infections. Moreover, voluntary social distancing was likely weaker in regions with less COVID-19 cases. Thus, by focusing on countries that adopted national lockdowns (instead of different measures for each region) and examining the impact on mobility in regions that were less affected by COVID-19, the analysis should uncover the causal effect of lockdowns in curbing mobility.

Thus, to ensure the reliability of the results based on national data, the following specification is estimated on data for 422 subnational units of 15 G20 countries:[4]

$$mob_{j,t+h} = \alpha_j^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h \, ln\Delta cases_{j,t-p} + \sum_{p=0}^{P} \delta_p^h \, lock_{i,t-p} + \sum_{p=1}^{P} \rho_p^h \, mob_{j,t-p} + \varepsilon_{j,t+h} \quad (2.4)$$

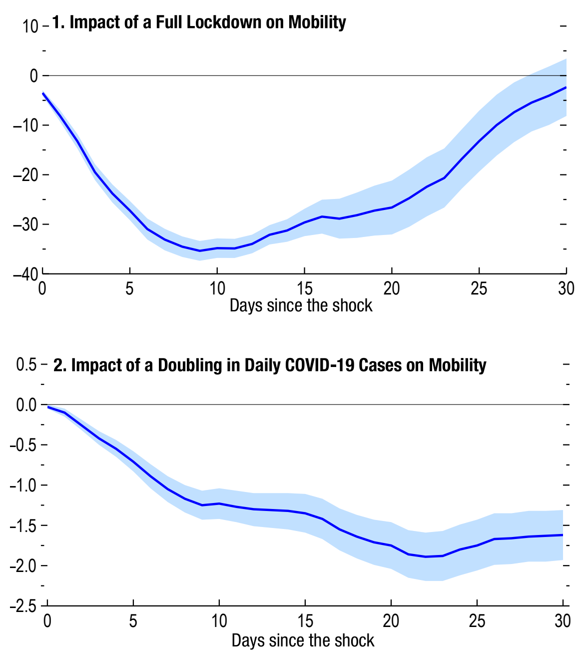
where j is the subnational unit, excluding the unit in each country with the largest number of

Annex Figure 2.3.1. Persistence of a Full Lockdown
(Index)



Source: IMF staff calculations.
Note: The shaded area corresponds to 90 percent confidence interval computed with standard errors clustered at the country level.

Annex Figure 2.3.2. The Impact of Lockdowns and Voluntary Social Distancing on Mobility, Subnational Data
(Percent)



Source: IMF staff calculations.
Note: The shaded areas in panels 1 and 2 correspond to 90 percent confidence intervals computed with standard errors clustered at the subnational level.

[4] For this exercise the sample is restricted to G20 countries for which subnational level data on mobility and COVID-19 cases are available. The level of geographical disaggregation is determined by Google mobility data and it varies across countries. For the US, state-level mobility data are available, but since policies are determined at the state level, all US observations are excluded from the sample.

cases. The analysis also excludes units that had more than 20 percent of the country's total COVID-19 cases.

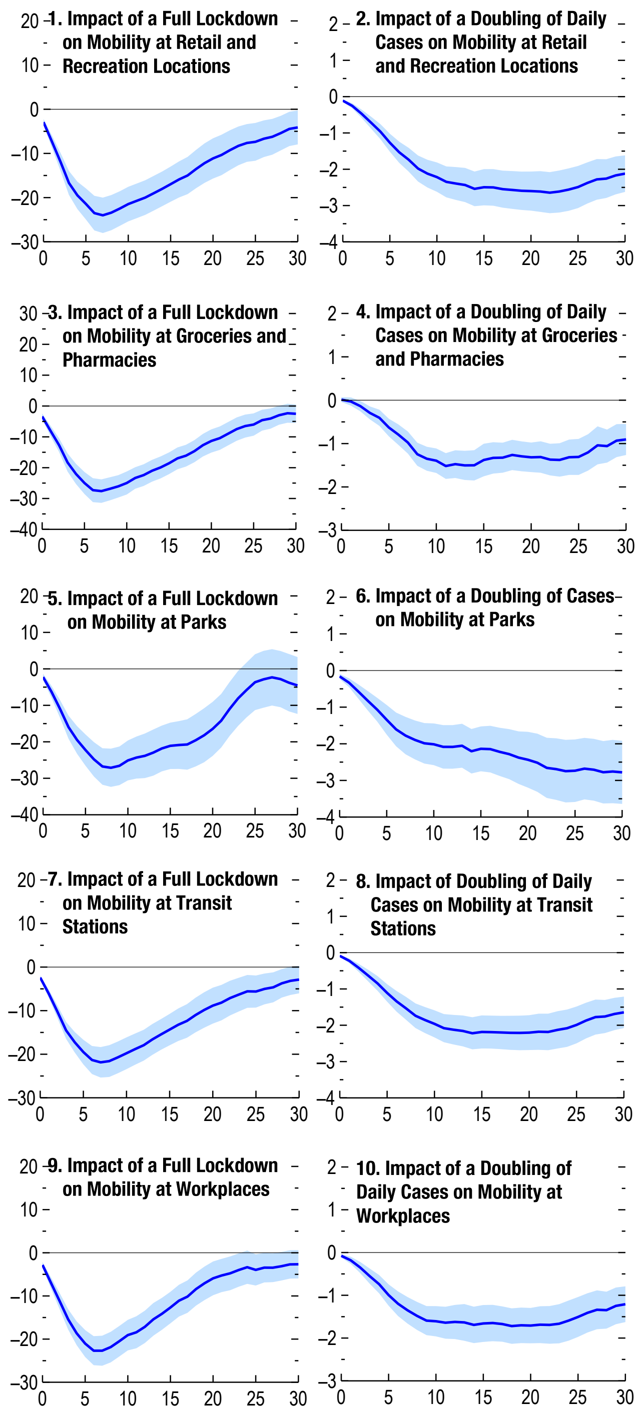
The estimates reported in panel 1 of Figure 2.3.2 corroborate the negative effect of lockdowns on mobility. While the shape of the mobility response is similar to the one obtained with national data, the magnitude is about 10 percentage point larger. Yet, differences may be related to the sample coverage. Symmetrically, Panel 2 of Figure 2.3.2 shows the impact of COVID-19 on mobility. The results are in line with the ones obtained at the national level: a doubling of COVID-19 cases leads to a contraction in mobility of 1.7 percent after 30 days.

Robustness

This section presents several robustness exercises. First, to ensure that the results are not driven by the dynamics in mobility at specific locations, the analysis replaces the average mobility indicator in equation (2.3) with the mobility at retail and recreation, groceries and pharmacies, parks, transit stations, and workplaces.[5] The results in Figure 2.3.3 suggest that the decline in mobility in response to a full lockdown and in response to a doubling of COVID-19 cases are in line with the ones presented in panels 1 and 2 of Figure 2.2 of the chapter. That is, across all locations a full lockdown leads to a reduction in mobility between 23 and 28 percent about a week after the introduction of the lockdown; and a doubling in COVID-19 cases leads to a decline in mobility between 1 and 2.8 percent after 30 days.

Annex Figure 2.3.3. The Impact of Lockdowns and Voluntary Social Distancing on Mobility at Different Places

(Percent; days since the shock on x-axis)

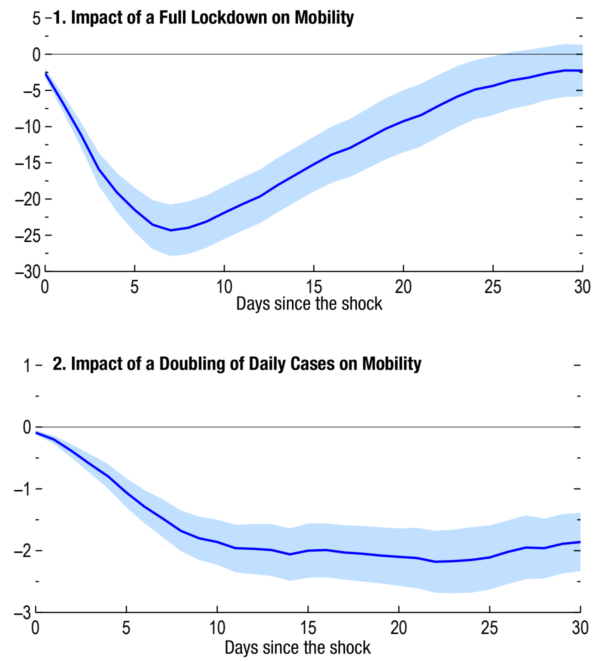


Source: IMF staff calculations.
Note: The shaded areas in panels 1–10 correspond to 90 percent confidence intervals computed with standard errors clustered at the country level.

[5] When the average mobility indicator is substituted with mobility observed at specific locations China drops from the sample.

Second, public information campaigns, contact tracing, and massive testing may lead people to re-assess the risk of getting infected (and infecting others) and therefore could contribute to a decline in mobility. The analysis estimates the specification in equation (2.3) including these controls (and their lags). The results presented in Figure 2.3.4 are consistent with the ones in panels 1 and 2 of Figure 2.2 of the chapter: a full lockdown reduces mobility by 24 percent after a week, and a doubling of COVID-19 cases leads to a reduction in mobility by 1.9 percent after 30 days.

Annex Figure 2.3.4. The Impact of Lockdowns and Voluntary Social Distancing on Mobility, Controlling for Public Information Campaigns, Testing, and Contact Tracing
(Percent)



Source: IMF staff calculations.
Note: The shaded areas in panels 1 and 2 correspond to 90 percent confidence intervals computed with standard errors clustered at the country level.

Third, there are several country characteristics that could potentially affect the magnitude of the impact of lockdowns on mobility. These include population density and governance variables such as rule of law, among others. The test if these factors determine the impact of lockdowns on mobility, the analysis estimates the following specification:

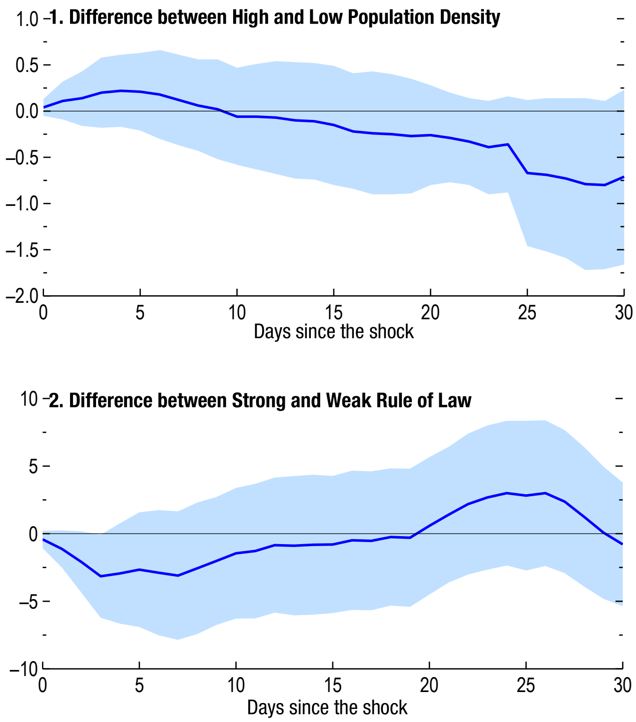
$$mob_{i,t+h} = \alpha_i^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h ln\Delta cases_{i,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + \sum_{p=0}^{P} \gamma_p^h lock_{i,t-p} \times x_{i,t-p} + \sum_{p=1}^{P} \rho_p^h mob_{i,t-p} + \varepsilon_{i,t+h} \quad (2.5)$$

where $x_{i,t-p}$ is, alternatively, population density as of 2019 or rule of law as of 2018. Similarly, social capital could change the impact of voluntary social distancing on mobility. The analysis then tests if trust and altruism affect the results by estimating the following specification:

$$mob_{i,t+h} = \alpha_i^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h ln\Delta cases_{i,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + \sum_{p=0}^{P} \gamma_p^h ln\Delta cases_{i,t-p} \times x_{i,t-p} + \sum_{p=1}^{P} \rho_p^h mob_{i,t-p} + \varepsilon_{i,t+h} \quad (2.6)$$

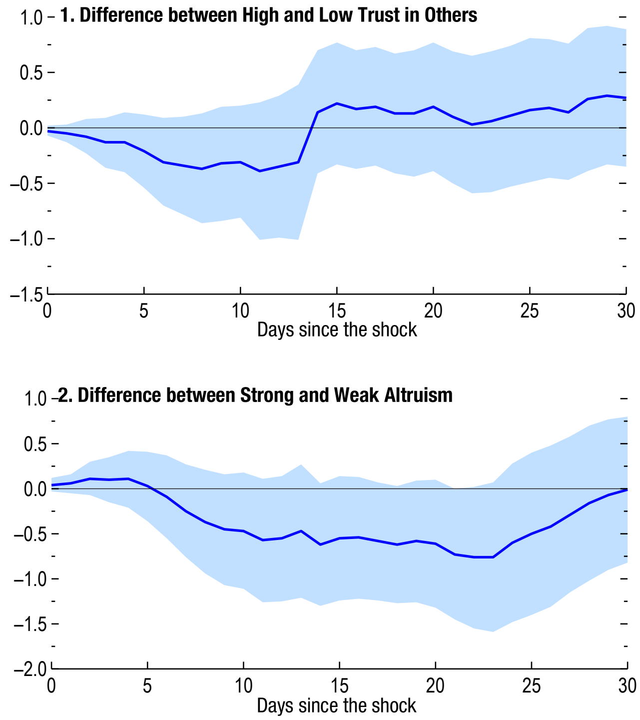
where $x_{i,t-p}$ now is, alternatively, an indicator of trust or altruism as of 2012. The results in Figure 2.3.5 and Figure 2.3.6 indicate that the impact of lockdowns and voluntary social distancing are not statistically different in countries with different population densities, strength of rule of law, and levels of trust and altruism. Thus, the results presented in the chapter extend to countries that are different in these characteristics.

Annex Figure 2.3.5. Differences in the Impact of Lockdowns on Mobility
(Percent)



Source: IMF staff calculations.
Note: The shaded areas in panels 1 and 2 correspond to 90 percent confidence intervals computed with standard errors clustered at the country level.

Annex Figure 2.3.6. Differences in the Impact of Social Distancing on Mobility
(Percent)



Source: IMF staff calculations.
Note: The shaded areas in panels 1 and 2 correspond to 90 percent confidence intervals computed with standard errors clustered at the country level.

Contributions

The analysis decomposes the decline in mobility due to the tightening of lockdown measures and to voluntary distancing during the first 90 days of the pandemic. Lockdowns and voluntary distancing are likely to have a different impact depending on many factors, including the prevalence of teleworking, the share of people that do not depend on labor income (e.g., retirees), the presence of contactless delivery services, the amount of personal savings, among others. To capture some of these nuances, the specification in equation (2.3) is amended to allow the coefficients of the variables of interest (i.e., the lockdown stringency index and the stage of the pandemic) to depend on the country group:

$$mob_{i,t+h} = \alpha_i^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h ln\Delta cases_{i,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + AE_i \times \left(\sum_{p=0}^{P} \beta_p^{h,AE} ln\Delta cases_{i,t-p} + \sum_{p=0}^{P} \delta_p^{h,AE} lock_{i,t-p}\right) + EM_i \times \left(\sum_{p=0}^{P} \beta_p^{h,EM} ln\Delta cases_{i,t-p} + \sum_{p=0}^{P} \delta_p^{h,EM} lock_{i,t-p}\right) + \sum_{p=1}^{P} \rho_p^h mob_{i,t-p} + \varepsilon_{i,t+h} \quad (2.7)$$

where AE_i and EM_i are dummy variables identifying advanced economies and emerging markets, respectively, with low-income countries being the omitted category. Thus, the impact of lockdowns on mobility for advanced economies can be obtained as $\delta_0^h + \delta_0^{h,AE}$, for emerging markets as $\delta_0^h + \delta_0^{h,EM}$, and for low-income countries as δ_0^h.

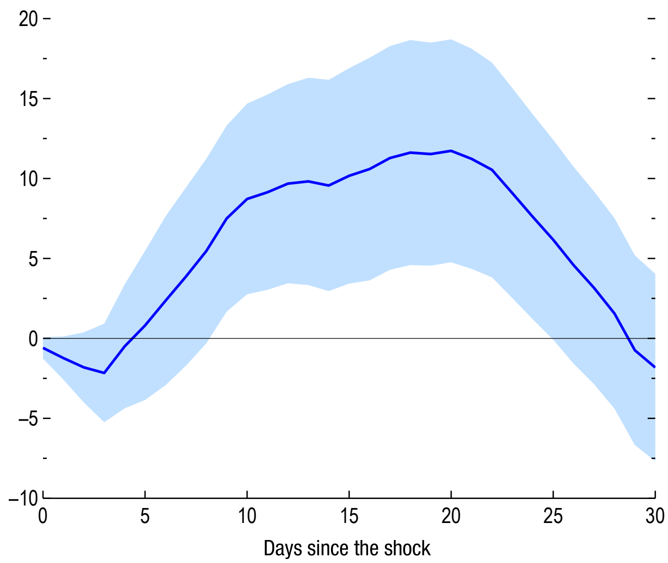
The contributions of lockdowns and voluntary distancing to the decline in mobility are then calculated as follows:

$$C_i^x = \bar{\Gamma}^{x,g}\bar{x}_i \quad (2.84)$$

where C_i^x is the contribution of variable $x = \{ln\Delta cases, lock\}$ to the decline in mobility observed in country i; $\bar{\Gamma}^{x,g}$ is the average coefficient over h horizons of variable x for country group $g = \{AE, EM, LIC\}$, with $i \in g$; and $\bar{x}_i$ is the average of the variable during the first 90 days of the epidemic. Contributions are then averaged across countries.

Panel 3 of Figure 2.2 of the chapter shows that lockdowns and voluntary social distancing played a similar role in reducing mobility. For the entire sample of 128 countries, the share of the decline attributed to lockdowns is comparable to the one attributed to voluntary distancing. The contribution of voluntary distancing is larger in advanced economies relative to emerging markets and low-income countries.

Annex Figure 2.3.7. Difference between High and Low National Cases
(Percent)



Source: IMF staff calculations.
Note: The shaded area corresponds to 90 percent confidence interval computed with standard errors clustered at the country level.

Informing the Recovery

The analysis also examines if the effect of lockdowns depends on the stage of the country's epidemic by estimating a specification featuring an interaction term between the lockdown stringency index and the number of daily COVID-19 cases:

$$mob_{i,t+h} = \alpha_i^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h ln\Delta cases_{i,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + \sum_{p=0}^{P} \gamma_p^h ln\Delta cases_{i,t-p} \times lock_{i,t-p} + \sum_{p=1}^{P} \rho_p^h mob_{i,t-p} + \varepsilon_{i,t+h} \quad (2.9)$$

where γ_0^h reveals the differential effect of a lockdown conditional on a given number of daily cases.

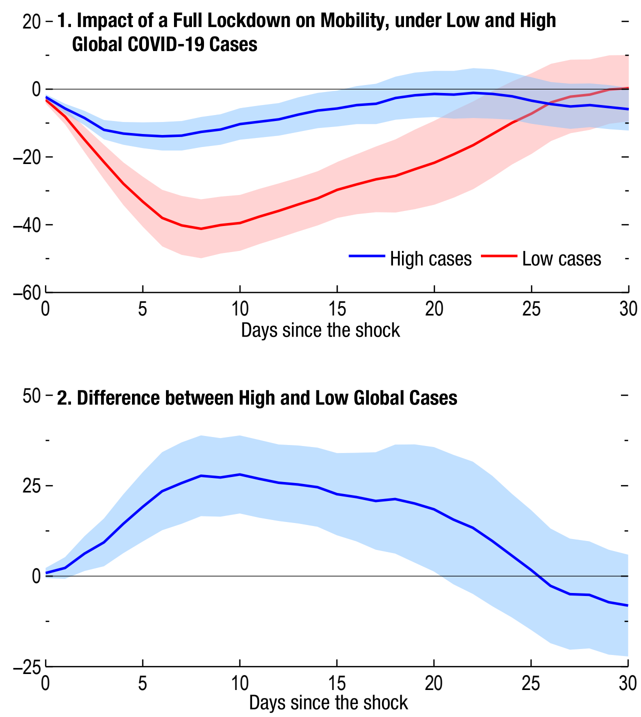
The results in panel 1 of Figure 2.3 of the chapter show that the impact of lockdowns on economic activity is smaller when cases are relatively higher. A possible interpretation is that, when cases are high, people's behavior is predominantly influenced by the fear of the virus reducing the impact of lockdowns. Figure 2.3.7 shows that the difference between the effects of lockdowns with high and low cases is statistically significant.

In some cases, people might be scrutinizing the spread of the virus at the global level, rather than at the domestic level. To account for that, the interaction term in equation (2.9) is replaced with the interaction term of the lockdown stringency index with global cases. Results in panel 1 of Figure 2.3.8 corroborate the findings for which lockdowns have a weaker impact on mobility when cases are relatively higher. Panel 2 of Figure 2.3.8 confirms that the interaction term is statistically significant.

Finally, the analysis examines if the effects on mobility from tightening and loosening lockdown restrictions are symmetric. To address this question, the specification in equation (2.3) is modified to allow for an interaction term between the lockdown stringency index and a dummy variable identifying periods in which restrictions were eased:

$$mob_{i,t+h} = \alpha_i^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h ln\Delta cases_{i,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + D_{i,t}^+ \times \sum_{p=0}^{P} \varphi_p^h lock_{i,t-p} + \sum_{p=0}^{p} \theta_p^h D_{i,t}^+ + \sum_{p=1}^{P} \rho_p^h mob_{i,t-p} + \varepsilon_{i,t+h} \quad (2.10)$$

Annex Figure 2.3.8. Impact of a Full Lockdown on Mobility
(Percent)



Source: IMF staff calculations.
Note: High and low cases in panel 1 correspond to the 75th and 25th percentile of the log of daily global COVID-19 cases, respectively. The shaded areas in panels 1 and 2 correspond to 90 percent confidence intervals computed with standard errors clustered at the country level.

where $D_{i,t}^+$ is a dummy that takes value one if the seven-day moving average of the change in lockdown stringency is positive and zero otherwise. All periods without a change in stringency following a tightening (loosening) are considered a tightening (loosening) period.[6] The impact of lifting restrictions can be obtained as $\delta_0^h + \varphi_0^h$.

The results in panel 2 of Figure 2.3 of the chapter illustrate that tightening and loosening lockdown measures have asymmetric effects on mobility. While the introduction of a full lockdown leads to decline in in mobility of about 26 percent one week after the tightening, lifting restrictions boosts mobility only by about 18 percent over the same period. Figure 2.3.9 confirms that the lockdown effects on mobility from tightening and loosening are statistically different from each other.

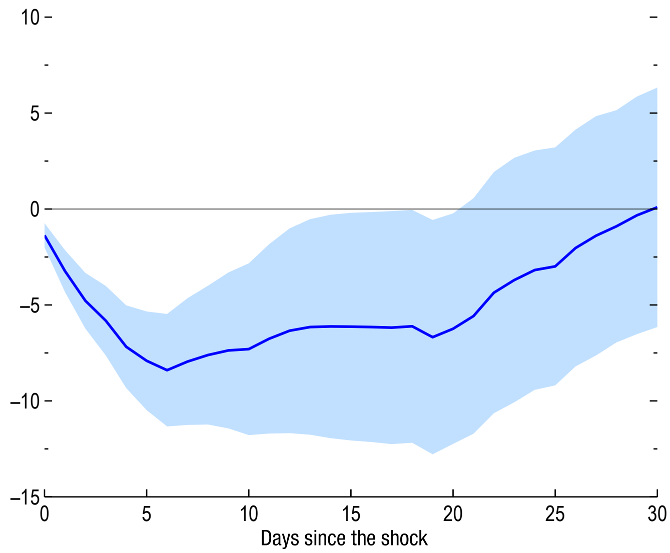
Job Postings

To analyze the dynamic response of job postings to the adoption of lockdowns, the analysis relies on the same empirical approach used in Section 2.3. The empirical specification mimics

[6] The use of a moving average should reduce the chances of interpreting a small increase (decrease) in the lockdown stringency index as a tightening (loosening) during a loosening (tightening) phase.

equation (2.3), but in this case the dependent variable is the log of the stock of job postings instead of mobility. The impulse response functions are estimated with data for 22 countries from January 1 to June 28, 2020. In line with the analysis of mobility, the specification includes 7 lags of the dependent and independent variables, and country and time fixed effects to control for time invariant country characteristics and global factors. Standard errors are clustered at the country level.[7] The identification assumption is that the coefficient on the number of COVID-19 cases captures the extent of voluntary social distancing, so that the coefficient on the index of lockdown stringency traces the effect of tighter lockdowns.

Annex Figure 2.3.9. Difference between Lockdown Tightenings and Loosenings
(Percent)



Source: IMF staff calculations.
Note: The shaded area corresponds to 90 percent confidence interval computed with standard errors clustered at the country level.

Figure 2.4 of the chapter shows that lockdowns have a negative and significant effect on job postings. The estimates in panel 1 suggest that a full lockdown is associated with a decline in job postings of about 12 percent two weeks after the introduction of the lockdown. The negative effect is robust to dropping one country at the time, but the point estimate declines materially if New Zealand is excluded. Voluntary social distancing also plays a role. Doubling COVID-19 cases leads to a 2 percent decline in job postings after 30 days, as shown in panel 2. Following the procedure explained in Section 2.3, these estimates can be used to compute the contributions of each variable to the decline in job postings observed during the first 90 days of the countries' epidemics. Panel 3 shows that both lockdowns and voluntary social distancing contributed to the drop in job postings. Consistent with the results based on mobility, the contribution of voluntary social distancing is particularly large since the sample is mostly based on advanced economies.

Analysis of Sectoral Job Postings

To shed further light on the role played by lockdowns and voluntary social distancing, the analysis compares the dynamics of job postings in contact-intensive sectors—food, hospitality and personal care—to that of less-contact intensive ones—manufacturing. To do that, an event study around the time of the introduction of national-stay-at-home orders is implemented. The sample considers all countries that introduced national stay-at-home orders.

[7] The results are robust to correcting the standard errors for cross-sectional dependence via the Driscoll-Kraay (1998) procedure.

Figure 2.5 of the chapter presents the results of the event study. In panel 1, the stock of job postings is normalized to 100 forty days before the introduction of stay-at-home orders, and time zero denotes the introduction of stay-at-home orders. Job postings in contact-intensive sectors started to decline a few weeks before the introduction of stay-at-home orders, suggesting the importance of fear and hence of voluntary social distancing in these segments of the economy. The decline of job postings in the manufacturing sector coincided instead with the introduction of stay-at-home orders, suggesting that in less-contact intensive sectors lockdowns have been the driving force behind the decline in activity.[8]

A second exercise focuses on the dynamics of job postings around the time of reopening. In panel 2, time zero denotes the time at which stay-at-orders are lifted. The chart shows that lifting lockdown restrictions led also to marginal recovery in job postings. This suggests that simply raising lockdown restrictions is unlikely to provide a sharp boost to the economy until the virus is successfully contained.

[8] Results are similar if the series are purged of the sector and country specific time-invariant characteristics.

Annex 2.4. The Unequal Effects of Lockdowns Across Gender and Age Groups

To test whether lockdowns have unequal effects across gender and age groups, a regression discontinuity (RD) approach is adopted in a similar spirit to Davis (2008), Anderson (2014), and Chetty et al. (2020). With respect to a standard cross-sectional RD setting, in this case the running variable is time, with the treatment date as threshold, making this approach akin to an event study exercise. As in more standard RDs, endogeneity is addressed by considering a narrow bandwidth (in this case a time window) around the introduction of the treatment. Within this interval, unobserved confounding factors affecting the outcome variable are likely to be similar.[1]

Gender

The analysis studies the impact of lockdowns across gender by focusing on the mobility of people aged 25-44, since they are more likely to have young kids and hence be affected by schools' closures. Specifically, the variable of interest is the share of Vodafone customers leaving their homes in a given day disaggregated by gender. The baseline analysis considers a window of 30 days. The series are orthogonalized with respect to day-of-week and province fixed effects.

Panel 1 of Figure 2.6 of the chapter reports a binned scatterplot where each dot represents the mean of the data calculated within 20 equally sized bins and the treatment is the introduction of national stay-at-home orders. The fitted lines are obtained for each group in the pre and post stay-at-home periods. The results suggest that the introduction of national-stay-at-home orders led to a sharp drop in the share of people moving both for men and women. Yet, the share of women moving dropped by a larger extent, with the difference being as large as 2 percent.

To test whether the difference in the mobility drop between men and women is statistically significant, the analysis uses the following local linear regression based on Anderson (2014):

$$PercPeopleMov_{pcgt}^{25-44} = \alpha_p + \tau_{dow} + \beta StayHome_{ct} + \gamma Date_t + \theta StayHome_{ct} * Date_t + \phi Female + \lambda Female * StayHome_{ct} + \nu Date_t * StayHome_{ct} + \psi Female * Date_t + \varepsilon_{pcgt} \quad (2.11)$$

where $PercPeopleMov_{pcgt}^{25-44}$ is the percent of people moving in the age group 25-44 in province p, in country c, for gender g, at time t; $StayHome_{tc}$ is the treatment variable, equal to one when the national stay-at-home orders are in place; $Date_t$ is the number of days since the beginning of the stay-at-home-order; and α_p and τ_{dow} are province and days of the week fixed effects. The coefficient β captures the effect for men, while $\lambda + \beta$ traces the effect for women. Standard errors are clustered at the province level.

Table 2.4.1 reports the results for the baseline model in Column (1). Consistent with the graphical evidence, mobility of women drops by 2 percent more than men, and the difference is statistically significant. The rest of Table 2.4.1 presents some robustness exercises. In Column (2), the estimation is restricted to the age group 45-64, which includes individuals that are less likely to have young kids. The effect is still significant, but smaller—equal to about 1 percent. In

[1] For a comprehensive review of RD in time see Hausman and Rapson (2018).

Column (3), the sample is restricted to Italy and Spain and the difference between men and women is equal to 3 percent. Finally, changing the bandwidth around the treatment to 20 days does not affect the results, as shown in Column (4).

Annex Table 2.4.1. Effect of Stay-at-Home Orders on Percent of People Moving by Gender – Linear Interacted Model

	(1)	(2)	(3)	(4)
	Percent of people moving	Percent of people moving	Percent of people moving	Percent of people moving
National stay at home	-0.180***	-0.174***	-0.198***	-0.148***
	(0.006)	(0.005)	(0.006)	(0.006)
Date	-0.002***	-0.002***	-0.002***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
National stay at home x Date	-0.002***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
National stay at home x Date x Female	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.035***	-0.036***	-0.035***	-0.036***
	(0.004)	(0.003)	(0.005)	(0.004)
National stay at home x Female	-0.023***	-0.014***	-0.024***	-0.026***
	(0.004)	(0.003)	(0.004)	(0.004)
Date x Female	-0.001***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	21,913	21,910	18,863	14,787
R-squared	0.830	0.830	0.808	0.834
NUTS3 FE	Yes	Yes	Yes	Yes
Days of week FE	Yes	Yes	Yes	Yes
Sample	25-44	45-64	25-44, no PRT	25-44, 20 days
Lockdown effect female	-0.203	-0.188	-0.222	-0.174
Lockdown effect male	-0.180	-0.174	-0.198	-0.148

Source: IMF staff calculations.

Note: Standard errors clustered at the province level in parentheses. * p < .10; ** p < .05; *** p < .01.

The analysis then re-examines the difference in mobility between men and women by restricting the sample to five northern Italian regions where local schools closed before stay-at-home orders. Panel 2 of Figure 2.6 of the chapter presents the results of this exercise, where the first discontinuity is set on February 23rd, the date of the local schools' closure, and the second one on March 10th, when the national lockdown is implemented. The divergence in mobility between men and women starts to appear around the time of school closures, consistent with the idea that women carry a greater share of childcare responsibilities.

Age Groups

Finally, the analysis looks at the differential effects of lockdowns across age groups. Panel 3 of Figure 2.6 in the chapter shows that the mobility of all age groups drops at the time of the national stay-at-home orders, however the drop for individuals aged 18-24 is particularly sharp. It also reveals that the mobility of individuals aged 65+ was already significantly lower prior to lockdowns. To test more formally the impact of lockdowns on age groups, the following specification is estimated separately for each age group, with standard errors clustered at the province level:

$$PercPeopleMov_{pct}^{age} = \alpha_p + \tau_{dow} + \beta StayHome_{ct} + \varepsilon_{pct} \quad (2.12)$$

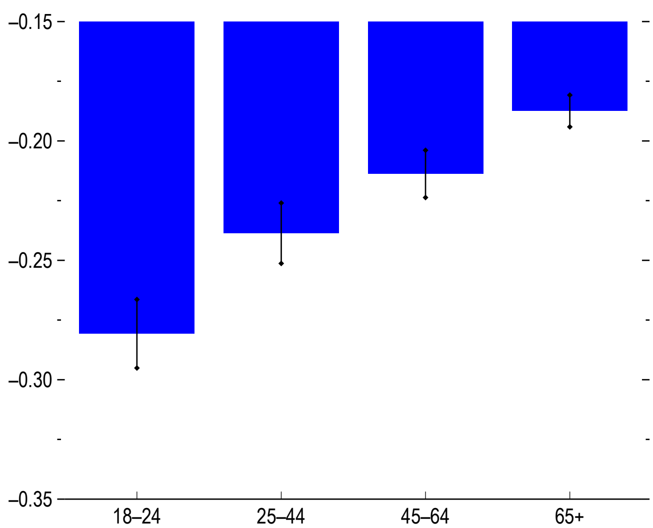
The findings in Table 2.4.2confirm that people in the age group 18-24 experienced the largest drop in mobility because of lockdowns, close to 30 percent. People in both age groups 25-44 and 45-64 also experienced declines in mobility as large as 20 percent, whereas people aged 65+ saw their mobility decline by 19 percent. The coefficient estimates on the treatment variable are also reported in Figure 2.4.1, which shows that the magnitude of the negative effect becomes smaller for older age groups.

Annex Table 2.4.2. Impact of Stay-at-home Orders on Different Age Groups

	(1)	(2)	(3)	(4)
	Percent of people moving	Percent of people moving	Percent of people moving	Percent of people moving
National stay at home	-0.281***	-0.239***	-0.214***	-0.187***
	(0.007)	(0.006)	(0.005)	(0.003)
Observations	60,175	60,563	60,543	55,951
R-squared	0.760	0.732	0.723	0.615
NUTS3 FE	Yes	Yes	Yes	Yes
Days of week FE	Yes	Yes	Yes	Yes
Sample	18-24	25-44	45-64	65+

Source: IMF staff calculations.
Note: Standard errors clustered at the province level in parentheses. * p < .10; ** p < .05; *** p < .01.

Annex Figure 2.4.1. Impact of Stay-at-Home Orders on Different Age Groups
(Percent)



Source: IMF staff calculations.
Note: The blue bars denote the point estimates and the black lines correspond to the 90 percent confidence intervals computed with standard errors clustered at the province level.

Annex 2.5. Infections

The Impact of Lockdowns on COVID-19 Infections

The final section of the chapter examines if countries that adopted lockdown measures experienced less COVID-19 infections. Formally, the following specification is estimated with data for 77 countries since the beginning of January:

$$lncases_{i,t+h} - lncases_{i,t-1} = \alpha_i^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h X_{i,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + \sum_{p=1}^{P} \rho_p^h \Delta lncases_{i,t-p} + trend_i^h + trend_i^{2,h} + \varepsilon_{i,t+h} \quad (2.13)$$

where $X_{i,t-p}$ is a vector of controls including the average temperature and humidity in the country, as well as indicators for whether public information campaigns are carried out and if massive testing and contact tracing policies are in place; and $trend_i^h$ and $trend_i^{2,h}$ are the country-specific linear and quadratic trends.

The results in panel 1 of Figure 2.7 of the chapter indicate that COVID-19 cases start declining 3 to 4 weeks after the adoption of a lockdown, relative to a no-lockdown scenario. This time lag between the tightening of the lockdown measures and the decline in cases is consistent with the incubation period, the testing, and the time needed to obtain and record the test results. After a month, cases are about 38 percent lower.

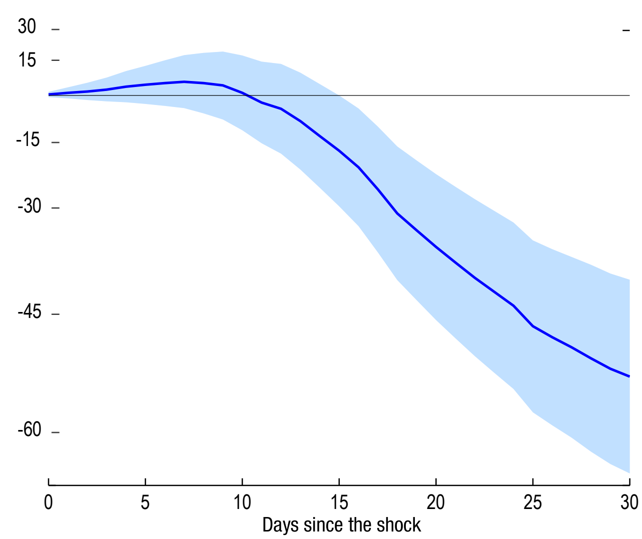
To improve the identification of the impact of lockdowns, the analysis employs subnational data for 339 units in 15 G20 countries, mimicking the approach described for mobility:[1]

$$lncases_{j,t+h} - lncases_{j,t-1} = \alpha_j^h + \tau_t^h + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + \sum_{p=1}^{P} \rho_p^h \Delta lncases_{j,t-p} + trend_j^h + trend_j^{2,h} + \varepsilon_{j,t+h} \quad (2.14)$$

where controls are dropped as they are not available at the subnational level. It should be noted that, as in the analysis of mobility with subnational data, subnational units with the largest number of cases per country and those that had more than 20 percent of the country's total COVID-19 cases are excluded from the sample.

The results based on subnational-level data in Figure 2.5.1 corroborate the results

Annex Figure 2.5.1. Response of COVID-19 Infections to a Full Lockdown, Subnational Data
(Percent)



Source: IMF staff calculations.
Note: The shaded area corresponds to 90 percent confidence interval computed with standard errors clustered at the subnational level.

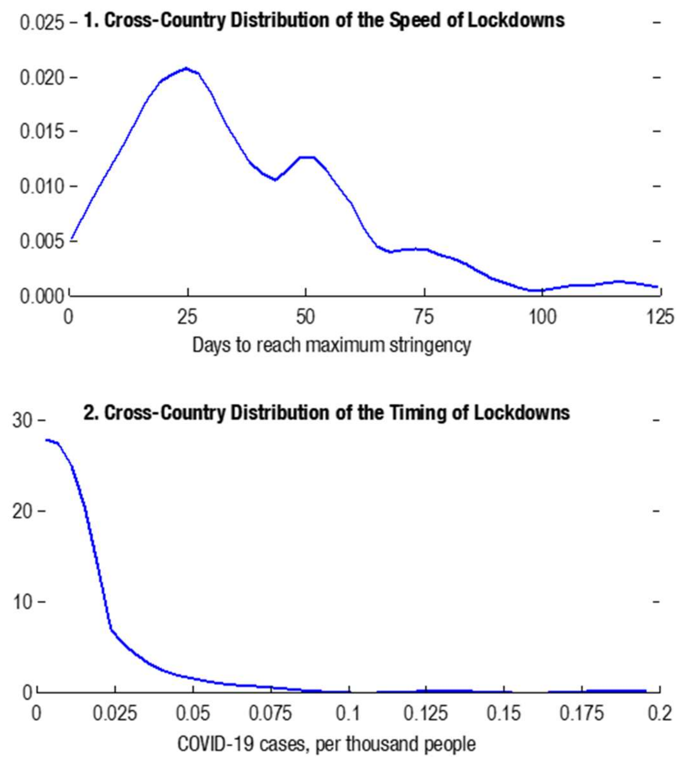
[1] The sample is restricted to G20 countries that adopted national lockdown measures and that provide regionally disaggregated data. The analysis considers only subnational entities that experienced at least one COVID-19 case."

using national-level data, albeit estimates are larger. After a month since the adoption of a lockdown, COVID-19 cases in subnational units under a national lockdown are 58 percent lower than in subnational units without a lockdown.

Early and Late Lockdowns

From a policy perspective, it is relevant to understand if countries that adopted lockdown measures early in the pandemic managed to control the spread of the virus better than countries that waited until the number of cases was higher. To differentiate across early and late adopters, the analysis employs two alternative criteria. The first criterion looks at the number of days that went by since the country registered the first COVID-19 case until the moment in which the country reached its maximum lockdown stringency. The second criterion is based on the number of weekly cases at the time in which the maximum lockdown stringency was reached.

Annex Figure 2.5.2. Speed and Timing of Lockdowns
(Density)



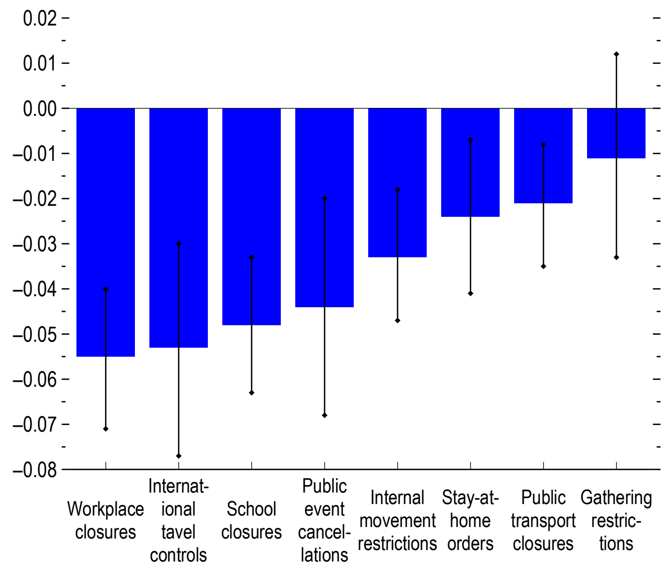
Source: IMF staff calculations.
Note: The *x*-axis in panel 1 denotes the number of days between the first COVID-19 case and the day in which maximum lockdown stringency was reached. The *x*-axis in panel 2 denotes the COVID-19 cases the day in which maximum stringency was reached.

As shown in panel 1 of Figure 2.5.2, there is a large cross-country heterogeneity in terms of how quickly lockdown measures were tightened. One fourth of the countries tightened lockdown measures within 20 days and half of the countries within a month. It took between a month and a half and four months to tighten lockdown measures for the rest of the countries. However, this also reflects how quickly the virus spread in the population. Panel 2 of Figure 2.5.2 shows that virtually all countries reached the maximum stringency before daily cases reached 0.1 cases per thousand people.

The analysis then compares the epidemiological outcomes of early and late lockdown adopters 90 days after the first COVID-19 case, splitting the sample of countries with respect to the median of the distributions in Figure 2.5.2. The results in panels 2 and 3 of Figure 2.7 in the chapter indicate that countries that tightened lockdown measure early in the pandemic—both with respect of the time needed to reach the maximum stringency and the number of cases at the time in which maximum stringency was reached—had considerably less COVID-19 infections per thousand people than countries that waited until the number of cases was higher to adopt lockdowns.

Annex 2.6. Individual Lockdown Measures and Nonlinear Effects

Annex Figure 2.6.1. Impact of Lockdown Measures on Mobility
(Percent)



Source: IMF staff calculations.
Note: The bars report the largest negative coefficients over a 30-day projection horizon. The vertical lines correspond to 90 percent confidence intervals computed with standard errors clustered at the country level.

The stringency index from the University of Oxford combines a broad range of measures, including school closures, workplace closures, stay-at-home orders, public event cancellations, gathering restrictions, public transportation closures, internal movement restrictions, and international traveling controls. As shown in panel 1 of Figure 2.8 in the chapter, these measures are often introduced in a rapid succession, and this complicates the assessment of the effectiveness of each individual measure due to collinearity.

A regression specification that features all the lockdown measures as independent variables would generally capture the marginal effects of a measure conditional on those that have been adopted beforehand. For example, replacing the lockdown stringency index in equation (2.3) with the (rescaled) indices for each individual lockdown measure produces the results in Figure 2.6.1.[1] As expected, measures that are introduced later (e.g., stay-at-home orders or transportation restrictions) display a smaller impact on mobility, while the measures that are introduced first (e.g., international movement restrictions or school closures) are associated with a larger impact.[2]

The analysis proceeds to examine nonlinearities in the effects of lockdowns on mobility. This is done by introducing in equation (2.3) quadratic terms of the lockdown stringency:

$$mob_{i,t+h} = \alpha_i^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h ln\Delta cases_{i,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + \sum_{p=0}^{P} \omega_p^h lock_{i,t-p}^2 + \sum_{p=1}^{P} \rho_p^h \Delta lncases_{i,t-p} + \sum_{p=1}^{P} \rho_p^h mob_{i,t-p} + \varepsilon_{i,t+h} \quad (2.15)$$

The results shown in panel 2 of Figure 2.8 in the chapter suggest that introducing new lockdown measures (or tightening existing ones) when other measures are already in place has a weaker effect on mobility compared to introducing them when there are less (or looser)

[1] The indices of the lockdown measures provided by the Oxford COVID-19 Government Response Tracker are ordinal indicators where policies are ranked on a numerical scale. Since different indicators have different maximum values in their ordinal scales, each index is rescaled between zero and 100.

[2] This framework could in principle allow for interaction terms across all measures to better capture the impact on mobility of a given measure conditional on the others being in place or not. However, the regression becomes cumbersome and the results are inconclusive.

lockdown measures in place. The quadratic term is positive and statistically significant at various horizons.

The analysis then examines the same question with respect to epidemiological outcomes. Equation (2.13) is modified to include the squared term of lockdown stringency:

$$lncases_{i,t+h} - lncases_{i,t-1} = \alpha_i^h + \tau_t^h + \sum_{p=0}^{P} \beta_p^h X_{i,t-p} + \sum_{p=0}^{P} \delta_p^h lock_{i,t-p} + \sum_{p=0}^{P} \omega_p^h lock_{i,t-p}^2 + \sum_{p=1}^{P} \rho_p^h \Delta lncases_{i,t-p} + trend_i^h + trend_i^{2,h} + \varepsilon_{i,t+h} \quad (2.16)$$

The results presented in panel 3 of Figure 2.8 in the chapter indicate that lockdown measures have an impact on infections if they are introduced on top of existing ones. The quadratic term is negative and statistically significant at various horizons.

Taken together, these results suggest that tighter lockdowns appear to entail modest additional economic costs while bringing considerable benefits in containing the virus.