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Mobility and economic activity around the world during the Covid-19 crisis

Tea Gamtkitsulashvili and Alexander Plekhanov

Abstract

This paper traces the relationship between quarterly estimates of economic activity and people's mobility during the Covid-19 crisis in a sample of 53 economies. Over time, the estimates of elasticity of value added with respect to mobility have been declining, to around 20 percent at the start of 2021, attesting to the gradual adjustment of global economic activity to social distancing. Yet this adjustment appears to be modest, with economic recovery driven primarily by greater mobility. The analysis relies on country-specific estimates of potential economic growth consistent with normal mobility. The paper also proposes a simple approach to combining various aspects of mobility in a single index using country-specific weights. Out-of-sample forecasts of growth derived from mobility estimates perform well relative to random walk, medium-term potential growth and other benchmarks.

Keywords: economic growth, nowcasting, Covid-19, mobility index

JEL Classification Number: C53, O40

Contact details: Alexander Plekhanov, European Bank for Reconstruction and Development, One Exchange Square, London, EC2A 2JN, UK. Email: plekhana@ebrd.com.

Tea Gamtkitsulashvili and Alexander Plekhanov are at the EBRD.

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1 Introduction

Social distancing aimed at containing the spread of the Covid-19 has constrained both demand and supply across economies resulting in the greatest disruption to global economic activity since the Second World War. The drop in people's movements relative to the normal state of the economy has been a good predictor of economic activity since the early months of the crisis (see, for instance, Sampi and Jooste, 2020). Economic activity partially recovered towards the end of 2020 and the start of 2021 notwithstanding new waves of infections, leading to a perception of economic activity becoming less sensitive to the mobility deficit. The April 2021 World Economic Outlook, for instance, notes that adaptation to pandemic life has enabled the global economy to do well despite subdued overall mobility (IMF, 2021). This paper revisits this perception using quarterly growth data from a cross-section of 53 advanced economies, emerging markets and lower-income economies with timely releases of seasonally adjusted quarterly GDP growth rates (approximately half of these are advanced economies and half are emerging markets including Argentina, India and Russia). Using quarterly observations since the first quarter of 2020, it estimates the relationship between individuals' mobility and economic activity and tracks this relationship over time.

Widely watched measures of people's activity during the Covid-19 crisis draw on mobility indices provided by Google daily starting from 15 February 2020. They express people's movements to places of recreation, work, retail shops, transit stations or parks relative to the average levels observed in the five-week period up to 6 February 2020. They reflect well the driving force of the downturn – widespread social distancing, whether mandated by regulations or voluntary.

The lack of baseline before the onset of the Covid-19 crisis complicates the analysis. In particular, normal (100 per cent) mobility may imply different rates of economic growth in different economies. During the Covid-19 crisis, mobility patterns differed considerably from economy to economy depending on commuting habits, availability of infrastructure supporting work from home or shopping habits (online versus on-site). And we do not have information about seasonal patterns of mobility indices or the relationship between mobility and changes in value added (GDP).

We follow a multi-step estimation approach to deal with the lack of baseline information about mobility levels. First, for each economy we estimate a medium-term rate of potential growth, a rate assumed to be compatible with "normal" mobility levels. Second, we construct a single mobility index based on seven-day moving averages of daily observations for four separate mobility indices. Indices that are characterized by higher volatility relative to trend are assigned a lower weight since changes in such indices produce a noisier signal. As a result, composite mobility index combines its four parts in ways that are specific to each economy. This enables us to derive meaningful estimates of elasticity of output with respect to mobility from single-quarter cross-sections of data, starting with the first quarter of 2020 when social distancing measures were first introduced.

Over time, the estimates of elasticity of value added with respect to mobility have been declining, to around 0.2 at the start of 2021, attesting to the gradual adjustment of global economic activity to social distancing. Yet this adjustment appears to have been modest, with economic recovery driven primarily by greater mobility. We report tentative evidence that during the very early weeks of lockdown (in the first quarter of 2020) the elasticity of economic activity with respect to mobility was much higher, close to 0.4, falling to close to 0.2 already in the second quarter of 2020. In other words, adjustment of global economic activity to social distancing has been slow once the low-hanging fruit of improved IT systems supporting remote working has been harvested.

We further use the insights from this analysis to derive out-of-sample forecasts of economic growth based solely on information available at a given point in time, starting from the first quarter of 2020. To do so, country-specific estimates of elasticity of changes in value added with respect to changes in mobility are updated based on a combination of a country's own experience and an average experience of all other countries, in line with Stein (1956). The out-of-sample forecasts perform well relative to random walk (an assumption that the last observed realization of economic growth is repeated going forward), medium-term potential growth and other benchmarks.

The paper's main contribution is to review the relationship between mobility during the Covid-19 crisis and economic performance in a systematic way in a broad sample of economies. It also contributes to the literature by bringing together various forecasting techniques to build a simple forecasting model relying on highly relevant series that cannot be calibrated using historical data.

The rest of the paper is structured as follows. Section 2 outlines the main challenges of using mobility indices and produces estimates of countries' potential growth consistent with "normal" mobility. Section 3 discusses the estimates of elasticity of economic activity with respect to mobility indices. Section 4 presents out-of-sample economic forecasts based on this relationship. Concluding remarks follow.

2 Obtaining estimates of potential growth

2.1 Mobility indices and potential growth

The first challenge in using mobility indices is to calibrate the normal level of mobility in each economy. For instance, before the Covid-19 crisis income per capita in China had been growing at the rate of around 7 per cent in the long term while in Italy it had been near-stagnant. It may or may not be the case, however, that individuals in China have been moving ever more and in Italy less. In other words, each economy may have a rate of growth consistent with full mobility (this assumption is similar to each economy having a rate of unemployment consistent with low and constant inflation, for instance).

The next subsection discusses a simple way to build and update such estimates of medium-term potential growth based on each economy's historical growth record, its demographics and fundamental characteristics such as income per capita (growth tends to decelerate as economies grow richer).

2.2 Medium-term growth

The estimates of medium-term growth potential can be derived from panel data for a large number of countries over the long term. Real growth of output per worker g in country i in year t (using logarithmic transformation, $ln(1 + g_{it})$ can be regressed lagged growth of output per worker, a number of explanatory variables Z lagged by a year as well as a set of country fixed effects and year fixed effects:

$$g_{it} = \alpha + \lambda g_{i,t-k} + \beta Z_{i,t-1} + \delta_t + u_i + \epsilon_{it} \tag{1}$$

The estimated coefficients (inclusive of the estimated economy fixed effects u_i) could then be used to forecast annual growth of output for a given country based on the expected values of explanatory variables. The estimates of economy fixed effects can be interpreted as average long-term growth rates of every economy in the sample. The time effect can be set to be equal to the average of observed average time effect (δ_t).

The projected growth rate ($\hat{y}_{it}$) is then obtained as a sum of the estimated potential growth of output per worker ($\hat{g}_{it}$) and the labour force growth ($\hat{l}_{it}$) as well as their interaction term. The labour force growth is estimated based on recent trends and the UN population growth projections.

$$\hat{y}_{it} = \hat{g}_{it} + \hat{l}_{it} + \hat{g}_{it}\hat{l}_{it} \tag{2}$$

The set of controls reflects findings of earlier studies of economic growth in a cross-country context (see, for instance, Levine and Renelt, 1992, and Sala-i-Martin, 1997) that conceptually follow the income convergence theory. In this framework the potential rate of growth in output per worker is a function of physical capital accumulation, human capital accumulation and technological change as well as other factors affecting total factor productivity – the efficiency with which factors of production are combined.

The logarithm of GDP per capita at purchasing power parity in 2011 constant US dollars (richer countries tend to grow slower) is included to capture slower average growth of richer economies (the negative relationship between GDP per capita and growth rates is perhaps the most robust in the growth literature; see Barro, 1991). The logarithm of the purchasing power parity coefficient (the ratio of GDP per capita at PPP to the ratio of GDP per capita at market exchange rates) controls for the level of the exchange rate (see Ravallion, 2013, for a discussion of PPP adjustments). Countries with undervalued currencies and hence higher PPP coefficients tend to enjoy a comparative advantage in labour-intensive manufacturing industries and hence grow faster.

Growth in output per worker also tends to be faster in countries with a higher investment rate, measured in percentage points of GDP (see, for instance, Krugman, 1994, and Young, 1995). Fast growth further tends to be sustained for longer in countries with higher current account balance (also measured in percentage points of GDP; see Berg et al., 2012, and Hong and Tornell, 2005, on lasting negative effects of currency crises on growth).

Higher quality of economic institutions tends to be associated with faster long-term economic growth (see for instance, Mauro, 1995). The quality of economic institutions is captured by the average of the Worldwide Governance Indicators of rule of law, control of corruption, regulatory quality and government effectiveness (see Kaufmann et al., 2009). The impact of higher quality of democratic institutions on long-term growth is debated but is typically found to be positive (see Barro, 1996; Acemoglu et al., 2004) or neutral, whereby stronger democratic institutions reduce dispersion of growth outcomes rather than boost the averages (see Besley and Muller, 2017, for a discussion). The quality of political institutions is proxied by the average of the Worldwide Governance Indicators of voice and accountability and political stability and lack of violence. Both measures have been extrapolated for years in which they are not available.

The level of financial development is captured by the credit to the private sector expressed as a percentage of GDP. While financial development may be an important driver of growth (as suggested by Levine, 1997, and a number of other studies) recent studies found a negative relationship between credit-to-GDP ratios and growth in recent times (see, for instance, Plekhanov and Stostad, 2018) as high credit-to-GDP ratios have increasingly become tantamount to excessive debt (see, for instance, Reinhart and Rogoff, 2010; Reinhart et al., 2012). Various other variables such as measures of educational attainment based on Barro and Lee (2013); measures of capital account openness (Chinn and Ito, 2006) and measures of inequality (Barro, 2000) have been evaluated but not necessarily included in the final specification if they don't improve the fit of the model to limit loss of efficiency or significantly reduce the number of observations available. Time fixed effects are included to control for the features of global economic environment simultaneously affecting all economies in a given year, such as the global financial crisis.

The model is estimated by fixed effects. Using relatively long time horizons somewhat mitigates the Nickel (1981) bias in estimates due to the lack of strict exogeneity of explanatory variables (for example, past values of economic growth) as the bias is inversely proportional to the number of years in the panel. Alternative estimation methods such as Arellano and Bond (1991) and Blundell and Bond (1998) can be applied with the view to obtain unbiased estimates, albeit at a cost of lower efficiency. In the evaluation exercise in this paper the long-term forecasts are obtained by averaging GMM-based and fixed-effects-based forecasts (see Pesaran et al., 2009, for a discussion of the rationale behind model averaging).

The estimates are presented in Table 1. The quarterly rate of potential growth (derived from the annual rate) averages 0.8 percentage points, exceeding 1.3 percent in India and falling short of 0.4 percent in Ukraine.

3 The relationship between mobility and economic activity

3.1 Constructing a composite mobility index

Second, we combine individual mobility indices (tracking trips to recreation venues such as restaurants or retail shops, trips to grocery stores, trips to mass transit stations and trips to workplaces) into a single index. One approach is to average the most relevant indices, for instance, those related to travel to work and recreation (Woloszko, 2020). An alternative approach is to attach a lower weight to indices that are likely to send a noisier signal in a given country – based on the observed movement patterns, which may, in turn, have to do with shopping habits or the ability to work from home.

We start by taking a seven-day moving average of each mobility index to smooth out patterns within each week. We then fit a constant rate-of-change trend based on the first and last observed values of the index. Next, we compute daily deviations of each index from its constant-rate-of-change trend. The weights of each index are assigned to be proportional to the inverse of the standard deviation of the detrended value of each index. Thus a change in mobility to, say, workplaces is assigned a greater weight if mobility to workplaces follows a relatively stable trend in a given country.

The weights are generally close to one quarter each but with substantial differences across countries (see Table 2). For instance, the weight of the index tracking travel to places of work ranges from 17 percent in Denmark, Japan, Singapore and Sweden to 30 percent in Thailand (where movement to workplaces has been relatively more stable over time). The index tracks mobility daily: as daily observations are added, weights get recalculated.

Globally, mobility dropped by around 45 per cent in March-April 2020. Mobility in Emerging Europe, Central Asia and Southern and Eastern Mediterranean ("the EBRD regions") recovered more quickly in the summer of 2020 but recorded a sharper drop in December, to around 70 per cent of its baseline level. By end-May 2021, mobility in the EBRD regions recovered to baseline levels while average global mobility remained around 10 per cent below the reference point. Overall, the quarterly mobility index averaged 87 in 2020 (see Table 3), ranging from 33 in Peru in the second quarter of 2020 to 104 in Brazil in the last quarter of the year. Figure 1 shows the trajectory of the mobility index calculated for the global economy, where country-specific mobility indices are weighed by GDP at purchasing power parity (PPP). By construction, the composite index drops slightly less steeply than the simple average of mobility sub-indices (as movement to grocery stores, being more stable over time, tends to have a higher weight, for instance).

During the same period, quarterly growth averaged -0.5 percent, oscillating between -27 percent (in Peru in the second quarter) and 31 percent (again in Peru in the subsequent quarter, see Table 1) making forecasting particularly challenging.

3.2 Empirical approach and data

The value of the mobility index can be averaged across a quarter (assuming that mobility index averaged 100 in the last quarter of 2019 and the first weeks of 2020 for the purpose of the subsequent analysis). The log-difference in value added of economy i between quarter $t-1$ and quarter t (equivalent to the logarithmic transformation of the quarterly seasonally adjusted rate of economic growth, $ln(1+y_{it})$ relative to that economy's potential quarterly rate of growth, $ln(1+\hat{y_i})$) is then assumed to be a linear function of the log-difference in mobility index, $lnM_{it} - lnM_{i,t-1}$.

$$ln(1+y_{it}) - ln(1+\hat{y_i}) = \alpha_i + \beta[lnM_{it} - lnM_{i,t-1}] + \delta_t \tag{3}$$

This equation can be estimated as a cross-section in each quarter or as a fixed-effect model on several quarters of data (with quarter fixed effects δ_t).

The model is evaluated on a sample of 53 economies for which data on quarterly seasonally adjusted rates of growth is available in a timely manner. These include most advanced economies as well as emerging markets such as Argentina, India or Russia. We use data from the last quarter of 2019 onward. Growth rates are expressed in quarter-on-quarter (non-annualized) terms. Mobility indices are provided by Google Analytics. They cover most economies in the world with the exception of countries where Google has limited or no presence (notably China).

3.3 Results

The results are summarized in Table 4 and Figure 2. The initial estimate obtained from the first-quarter cross section (of around 0.38) matches closely the views expressed early in the Covid-19 crisis according to which around 40 per cent of economic activity relied on close personal contact (see, for instance, EBRD, 2020, and *The Economist* of 14 March 2020). With the exception of the first-quarter cross-section, the estimates are close to 0.2.

In other words, a 10 per cent drop in mobility is associated, on average, with 2 percentage points lower GDP growth. These elasticities do not appear to vary systematically across advanced economies and emerging markets (see Table 5), although explanatory power of mobility tends to be better in advanced economies reflecting, in part, higher quality of early releases of national accounts data.

The elasticity of output with respect to mobility appears to decline over time, but fairly gradually. This trend could reflect adjustments in economic activity over time, such as increased working from home, online retail, take-away meals and shifts in economic activity toward less mobility-intensive sectors (such as construction). The analysis suggests that the bulk of this adjustment took place in the first weeks of social distancing, with modest further adjustment since the second quarter. This suggests that stronger-than-expected economic performance in the late months of 2020 and the first half of 2021 can be largely attributed to higher mobility (compared with the second quarter of 2020). Economies' adaptation to social distancing has played a smaller role in delivering stronger growth outcomes.

4 Using mobility to forecast economic growth out-of-sample

4.1 Approach

Significant advances have been made in nowcasting – forecasting economic performance in the short run, several weeks or months ahead of the official data release (see Evans, 2005, Nunes, 2005, and Giannone et al., 2008, for early applications). Nowcasts typically rely on principal component analysis of a large number of data series available with a short lag, such as market movements or survey-based indicators of consumer and investor confidence (Stock and Watson, 2002). They typically account for a large number of global variables such as commodity prices (see, for instance, Andreini et al., 2020, for the case of Germany). Nowcasting models have generally performed well at horizons of up to a quarter ahead (see, for instance, Ruenstler et al., 2009; Havrlant et al., 2016).

Yet their performance deteriorates during the times of major upheaval, such as the Covid-19 economic crisis. Including a larger number of concurrent indicators, including financial variables, does not tend to improve the precision of principal-component-based forecasts (Boivin and Ng, 2006; Bai and Ng, 2008; Reichlin et al., 2020). Averaging of various nowcasting models does not appear to improve the performance either (Andreini et al., 2020). Workarounds during the time of exceptional economic turbulence include appending forecast errors obtained during the previous major crisis (Forini et al., 2020). Reliability of these corrections is uncertain since every crisis is different. An alternative approach deploys machine learning to spot a break in the trends based on, for instance, Google trends (see Woloszko, 2020). Its disadvantage is the difficulty of building a narrative of forecasts based on a black-box algorithm.

The insights about elasticity of output with respect to mobility can be used to obtain simple and easy-to-interpret estimates of economic activity in near-real time. Consider such nowcasting conducted out-of-sample at the end of every quarter, when mobility data are available but first official estimates of growth are weeks away.

At the end of the first quarter (31 March 2020), little information was available to estimate parameters of the equation linking mobility and output. This calls for a certain rule of thumb needs to be applied to all economies. As discussed above, early estimates suggested that around 40 percent of consumption in a modern economy relies on close personal contact. This enables us to derive nowcasts of output based on mobility by assuming the elasticity of 0.4 for all economies and using Equation 3, including country-specific estimates of potential growth, as a basis for calculations.

At the end of the second quarter (30 June 2020), we observe the realization of mobility as well as early estimates of economic growth in the first quarter. These could be used to update the above estimates of elasticity of value added with respect to mobility. In principle, these estimates can be specific to each economy, although such estimates derive one parameter from a single observation with no degrees of freedom. These estimate can be updated, however, based on experiences of other economies. The Stein (1956) principle suggests that the best estimate of a country-specific elasticity of output with respect to mobility is given by a weighted average of a country-specific estimate of elasticity and one obtained by using data on all other economies. The latter can be obtained by estimating equation 3 in a cross-section of economies.

For each economy, the elasticity $\hat{\beta_{it}}$ is calculated by assigning a weight of w_t to the country-specific elasticity and a weight of $1 - w_t$ to the cross-sectional estimate β_t^s.

$$\hat{\beta_{it}} = w_t \beta_{it}^c + (1 - w_t)\beta_t^s \tag{4}$$

Initially the weights have to be assigned based on a prior judgment. We start by using $w_1 = 0$ and $w_2 = 0.1$ given scarcity of country-specific data. In addition, country-specific estimates of elasticity are windsorised at 0.1 and 0.6, respectively. Once estimates of growth during the Covid-19 crisis become known, country-specific estimates gain precision and the weights can be updated, for instance, with the view of minimizing the root mean square error (RMSE) of forecasts produced for the earlier quarters. Updated weights are then applied going forward; the estimate of the weight of country-specific indicator stabilizes at 0.4. In subsequent quarters, equation 3 can be re-estimated in a panel. The average composite estimate of elasticity across economies declines over time, in line with the results of estimations discussed above (see Table 6).

4.2 Evaluation

The forecasting is performed in every quarter as of the first week of the following quarter when mobility data for the entire quarter become available. In sample, the predictive power of the composite mobility index is relatively high. It explains between 21 and 61 percent of variance in growth outcomes across economies and up to 89 percent of the overall variance of quarterly growth outcomes in 2020 (see Table 4).

The results of out-of-sample forecasts are presented in Table 8. The mobility-based model outperforms random walk (see Table 7), the estimate of potential growth for each economy as well as other "naive" forecasts assuming reversion of economic activity to a certain level or trend. The first of these alternative benchmarks assumes a constant rate of growth equal to the estimated medium-term potential growth rate. Another one assumes that output reverts to its pre-crisis level (adjusted by the potential growth rate). In other words, a contraction of 20 percent can be expected to be followed by a growth of 25 percent in an economy with zero potential growth. Yet another one assumes reversal to the pre-crisis level of output irrespective of trend growth observed before the Covid-19 crisis.

The model performs well across economies with a notable exception of Russia as well as Greece and Ireland (see Table 8). In Russia, alternative models based on Google trends have also been shown to underperform relative to random walk or an autoregressive process (Woloszko, 2020). In Ireland, the estimate of long-term potential growth may be unrealistic on the back of recent very high growth readings (up to 26 percent per annum) driven by peculiarities of foreign direct investment accounting. In sum, the insights about the evolving relationship between mobility and value added yield a simple, tractable and relatively well-performing method of tracking economic activity during the period of reduced mobility. The gradual weakening of the model's performance over time is bad news for the power of the forecasting model going forward but good news for the economies.

The relationship between mobility and output can also be used to track an estimate of economic activity on a daily basis, using the composite index of mobility. The difference between the value of the index and its baseline value (100) can be adjusted by the country-specific estimate of elasticity of output with respect to mobility. The index can be further adjusted by the pro-rated estimate of potential economic growth. For instance, an expected growth of 4 percent per annum (corresponding to baseline mobility) translates into 0.011 percentage points of growth per day. Figure 3 presents an example of such an index of economic activity for Turkey, setting the level observed at the end of 2019 to 100.

5 Conclusion

The Covid-19 crisis involved unprecedented restrictions on people's movements across majority of economies. Together with voluntary social distancing, they resulted in a sharp drop in people's movements to places of work and recreation, on average by 45 per cent in March-April 2020. As major part of consumption in a modern economy relies on social contact, the drop in mobility coincided with the deepest recession since the Second World War. This paper used Google Analytics mobility measures to trace the relationship between mobility and economic activity over time in a broad sample of advanced and emerging market economies.

While the relationship between people's movements and economic activity appears to have been weakening over time as businesses and consumers partially adjusted to social distancing, this adjustment has only been partial. A 10 per cent drop in mobility is associated, on average, with 2 percentage points lower GDP growth, with no systematic differences observed between advanced economies and emerging markets. Stronger-than-expected economic performance in the second half of 2020 and the early months of 2021 can thus largely be attributed to higher mobility (compared with the second quarter of 2020). Economies' adaptation to social distancing has played a smaller role in delivering stronger growth outcomes.

These insights can, in turn, be used to obtain out-of-sample short-term forecasts (nowcasts) of economic activity. They perform well relative to simple alternative methods of forecasting and random walk. While their usefulness is likely to decline as mobility returns to normal levels, observed mobility can be incorporated as one of the inputs into standard principal-component models of nowcasting (see, for instance, Andreini et al., 2020; Evans, 2005).

To the extent that early estimates of quarterly GDP during major crises are subject to large subsequent revisions, a caveat applies to the results of our analysis based on early estimates of economic activity. Future research can revisit the estimates based on updated quarter-on-quarter GDP data.

References

Acemoglu, Daron, Suresh Naidu, Pascual Restrepo, James Robinson, 2004, "Democracy Does Cause Growth", NBER Working Paper 20004.

Andreini, Paolo, Thomas Hasenzagl, Lucrezia Reichlin, Charlotte Senftleben-König and Till Strohsa, 2020, "Nowcasting German GDP", Centre for Economic Policy Research Discussion Paper 14323.

Arellano, Manuel, and Stephen Bond, 1991, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Questions," *Review of Economic Studies*, Vol. 58, pp. 277–97.

Bai, Jushan, and Serena Ng, 2008, "Forecasting economic time series using targeted predictors," *Journal of Econometrics*, Vol. 146, pp. 304-317.

Barro, Robert, 1991, "Economic Growth in a Cross-Section of Countries", *Quarterly Journal of Economics*, Vol. 106, pp. 407–43.

Barro, Robert, 1996, "Democracy and growth", *Journal of Economic Growth*, Vol. 1, pp. 1–27.

Barro, Robert, 2000, "Inequality and Growth in a Panel of Countries", *Journal of Economic Growth*, Vol. 5, pp. 5–32.

Barro, Robert, and Jong Wha Lee, 2013, "A new data set of educational attainment in the world, 1950–2010," *Journal of Development Economics*, Vol. 104, pp. 184-198.

Berg, Andrew, Jonathan Ostry and Jeromin Zettelmeyer, 2012, "What Makes Growth Sustained?" *Journal of Development Economics*, Vol. 98, pp. 149-166.

Besley, Timothy, and Hannes Mueller, 2017, "Institutions, Volatility and Investment", London School of Economics Working Paper.

Blundell, R., and Stephen Bond, 1998, "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, Vol. 87, pp. 115-143.

Boivin, Jean, and Serena, Ng, 2006, "Are more data always better for factor analysis?" *Journal of Econometrics*, Vol. 132, pp. 169-194.

Chinn, Menzie, and Hiro Ito, 2006, "What matters for financial development? Capital controls, institutions, and interactions," *Journal of Development Economics*, Vol. 81, pp. 163-92.

EBRD, 2020, "Covid-19: From shock to recovery'", Regional Economic Prospects, April.

Evans, Martin, 2005. "Where Are We Now? Real-Time Estimates of the Macroeconomy," *International Journal of Central Banking*, Vol. 1

Foroni, Claudia, Massimiliano Marcellino and Dalibor Stevanović, 2020, "Forecasting the Covid-19 recession and recovery: lessons from the financial crisis", European Central Bank Working Paper 2468.

Giannone, Domenico, Lucrezia Reichlin and David Small, 2008, "Nowcasting: The real-time informational content of macroeconomic data," *Journal of Monetary Economics*, Vol. 55, pp. 665 676.

Havrlant, David, Peter Toth and Julia Woerz 2016, "On the optimal number of indicators – nowcasting GDP growth in CESEE", *Focus on European economic integration*, National Bank of Austria, pp. 54-72.

Hong, Kiseok, and Aaron Tornell, 2005, "Recovery from a Currency Crisis: Some Stylized Facts", *Journal of Development Economics*, Vol. 76, pp. 71-96.

IMF, 2017, World Economic Outlook, International Monetary Fund, April.

IMF, 2021, World Economic Outlook, International Monetary Fund, April.

Kaufmann, Daniel, Aart Kraay, and Massimo Mastruzzi, 2009, "Governance Matters VIII: Governance Indicators for 1996–2008", World Bank Policy Research Working Paper 4978.

Krugman, Paul, 1994, "The Myth of Asia's Miracle", *Foreign Affairs*, Vol. 73, pp. 62-76.

Levine, Ross, 1997, "Financial Development and Economic Growth: Views and Agenda", *Journal of Economic Literature*, Vol. 35, pp. 688-726.

Levine, Ross, and David Renelt, 1992, "A Sensitivity Analysis of Cross-Country Growth Regressions", *American Economic Review*, Vol. 82, No 4, pp. 942–63.

Mauro, Paolo, 1995, "Corruption and Growth", *Quarterly Journal of Economics*, Vol. 110, pp. 681–712.

Nickell, Stephen, 1981, "Biases in Dynamic Models with Fixed Effects", *Econometrica*, Vol. 49, pp. 1417–26.

Nunes, Luis, 2005, "Nowcasting quarterly GDP growth in a monthly coincident indicator model", *Journal of Forecasting*, Vol. 24, pp. 575-592.

Pesaran, M. Hashem, Christoph Schleicher and Paolo Zaffaroni, 2009, "Model averaging in risk management with an application to futures markets", *Journal of Empirical Finance*, pp. 280-305.

Plekhanov, Alexander, and Morten Stostad, 2018, “Modern growth in perspective: Relative growth performance since the global financial crisis”, EBRD Working Paper, Forthcoming.

Ravallion, Martin, 2013, “Price levels and economic growth: making sense of revisions to data on real incomes”, *Review of Income and Wealth*, Vol. 59, pp. 593-613.

Reichlin, Lucrezia, Giovanni Ricco and Thomas Hasenzagl, 2020, “Financial variables as predictors of real growth vulnerability”, Centre for Economic Policy Research Discussion Paper 14322.

Reinhart, Carmen, and Kenneth Rogoff, 2010, “Growth in a Time of Debt,” *American Economic Review*, Vol. 100, pp. 573-78.

Reinhart, Carmen, Vincent Reinhart and Kenneth Rogoff, 2012, “Public debt overhangs: Advanced economy episodes since 1800”, *Journal of Economic Perspectives*, Vol. 26, pp. 69-86.

Rünstler, G., K. Barhoumi, S. Benk, R. Cristadoro, A. Den Reijer, A. Jakaitiene, P. Jelonek, A. Rua, K. Ruth and C. Van Nieuwenhuyze, 2009, ”Short-term forecasting of GDP using large datasets: a pseudo real-time forecast evaluation exercise,” *Journal of Forecasting*, Vol. 28, pp. 595-611.

Sala-i-Martin, Xavier, 1997, ”I Just Ran Two Million Regressions,” *American Economic Review*, Vol. 87, pp. 178–83.

Sampi, James, and Charl Jooste, 2020, “Nowcasting Economic Activity in Times of COVID-19: An Approximation from the Google Community Mobility Report”, World Bank Policy Research Working paper 9247.

Stein, Charles, 1956, “Inadmissibility of the Usual Estimator for the Mean of a Multivariate Normal Distribution”, *Proceedings of the Third Berkeley Symposium on Mathematical Statistics and Probability*, Vol. 1, pp. 197—206.

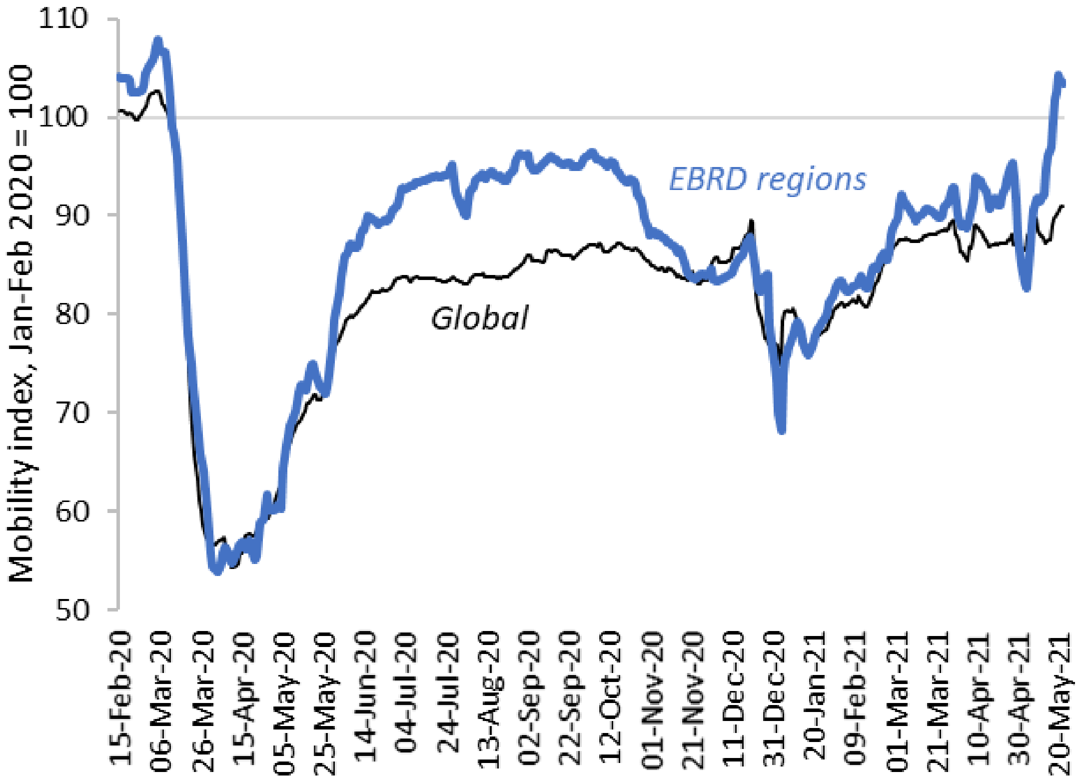
Stock, J., and M. Watson, 2002, “Forecasting Using Principal Components From a Large Number of Predictors”, *Journal of the American Statistical Association*, Vol. 97, pp. 1167-1179.

Woloszko, Nicolas, 2020, “Tracking activity in real time with Google trends”, OECD Economics Department Working Paper 1634.

Young, Alwyn, 1995, “The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience,” *Quarterly Journal of Economics*, Vol. 110, pp. 641-680.

Figures and Tables

Figure 1: Global mobility index, daily values



Sources: Authors' calculations based on Google Analytics.
Mobility index of economies representing more than 80 percent of world GDP, with values weighted by GDP at purchasing power parity. Weighted average of mobility indices for groceries, recreation, workplaces and transit, with endogenously determined weights. Six-week period up to 6 Feb 2020 = 100.

Table 1: Estimates of medium-term potential quarterly growth

Country	Potential	Country	Potential
Argentina	0.95	Australia	0.65
Austria	0.66	Belgium	0.75
Brazil	0.67	Bulgaria	0.68
Chile	0.75	Colombia	
Czech R.	0.76	Denmark	0.66
Estonia	0.76	Finland	0.80
France	0.72	Germany	0.80
Greece	0.46	Hungary	0.92
India	1.26	Indonesia	1.07
Ireland	1.18	Israel	0.94
Italy	0.57	Japan	0.59
Kazakhstan	0.86	Kenya	1.01
Latvia	0.85	Lithuania	0.90
Luxembourg	0.61	Malaysia	0.89
Malta	0.72	Mexico	0.90
Morocco	0.95	Netherlands	0.68
New Zealand	0.55	Norway	0.67
Peru	1.03	Philippines	1.11
Poland	0.89	Portugal	0.60
Romania	0.83	Russia	0.43
Serbia	0.92	Singapore	0.64
Slovak R.	0.72	Slovenia	0.72
South Africa	0.74	Spain	0.63
Sweden	0.88	Switzerland	0.51
Thailand	0.55	Turkey	0.89
Ukraine	0.38	UK	0.90
US	0.74		

Source: National authorities and authors' calculations.

Note: Growth expressed in percentage points, quarter-on-quarter, non-annualized. Estimates of medium-term potential growth are derived from panel regressions of annual growth on a number of indicators estimated by fixed effects and generalized method of moments.

Table 2: Weights assigned to mobility sub-indices

Country	Recreation	Groceries	Transit	Work
Argentina	0.203	0.335	0.222	0.240
Austria	0.160	0.372	0.207	0.260
Australia	0.248	0.367	0.172	0.213
Belgium	0.167	0.410	0.198	0.225
Brazil	0.187	0.407	0.186	0.220
Bulgaria	0.169	0.364	0.184	0.283
Canada	0.209	0.364	0.203	0.224
Chile	0.218	0.293	0.221	0.268
Colombia	0.242	0.295	0.226	0.238
Czech Republic	0.142	0.403	0.191	0.265
Denmark	0.172	0.501	0.152	0.175
Estonia	0.183	0.369	0.212	0.236
Finland	0.177	0.428	0.178	0.217
France	0.192	0.336	0.203	0.269
Germany	0.159	0.398	0.194	0.249
Greece	0.156	0.408	0.187	0.249
Hungary	0.184	0.351	0.206	0.259
India	0.216	0.270	0.244	0.271
Indonesia	0.227	0.359	0.172	0.242
Ireland	0.163	0.436	0.194	0.206
Israel	0.168	0.354	0.224	0.254
Italy	0.185	0.323	0.220	0.273
Japan	0.185	0.507	0.138	0.170
Kazakhstan	0.224	0.301	0.217	0.259
Kenya	0.232	0.286	0.222	0.260
Latvia	0.209	0.354	0.200	0.236
Lithuania	0.200	0.313	0.209	0.278
Luxembourg	0.194	0.333	0.226	0.246
Malaysia	0.209	0.326	0.208	0.257
Malta	0.170	0.372	0.232	0.226
Mexico	0.195	0.394	0.186	0.225
Morocco	0.206	0.277	0.249	0.268
Netherlands	0.175	0.451	0.166	0.208
New Zealand	0.188	0.399	0.205	0.208
Norway	0.207	0.378	0.198	0.217
Peru	0.228	0.290	0.229	0.253
Philippines	0.225	0.295	0.236	0.244
Poland	0.186	0.317	0.203	0.294
Portugal	0.202	0.327	0.212	0.259
Romania	0.196	0.303	0.214	0.287
Russia	0.204	0.352	0.202	0.242
Serbia	0.207	0.322	0.212	0.259
Singapore	0.185	0.455	0.187	0.173
Slovak Republic	0.159	0.352	0.200	0.289
Slovenia	0.176	0.308	0.226	0.290
South Africa	0.222	0.327	0.215	0.236
Spain	0.195	0.315	0.220	0.270
Sweden	0.198	0.452	0.172	0.177
Switzerland	0.139	0.437	0.198	0.227
Thailand	0.175	0.356	0.169	0.301
Turkey	0.204	0.343	0.204	0.248
Ukraine	0.197	0.328	0.213	0.262
United Kingdom	0.178	0.375	0.222	0.225
United States	0.201	0.386	0.198	0.215

Source: Authors' calculations.

Note: Weights are assigned in proportion to the inverse of the standard deviation of the difference between seven-day moving average of a given index and a constant-rate-of-change trend fitted for that index, based on daily data. Weights calculated using data up to mid-March 2021 are shown, average across five calculations at the end of every quarter. Weights add up to 1 for every economy.

Table 3: Descriptive statistics

Variables	Mean	St. dev.	Median	Min	Max
GDP growth, pp, qoq, non-annualized	-0.538	8.617	-0.297	-26.893	31.228
Potential growth, pp, qoq, non-annualized	0.774	0.184	0.752	0.379	1.259
Mobility index, quarterly average	86.811	13.443	90.326	32.835	103.605

Source: National authorities, Google analytics and authors' calculations.

Note: Based on 53 economies and 54quarters of data.

Table 4: Cross-country estimates of elasticity of value added with respect to mobility

Dep. var: Log-change in value added	Data from Q1 up to				
	Q1	Q2	Q3	Q4	Q1 2021
Mobility index, log difference	0.380***	0.199***	0.244***	0.206***	0.202***
	(0.048)	(0.038)	(0.046)	(0.034)	(0.033)
R^2	0.444	0.854	0.889	0.872	0.866
R^2 between	0.444	0.599	0.280	0.154	0.193
Observations	53	106	159	211	253

Source: Authors' calculations.

Note: Robust standard errors in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively. Estimated by fixed effects with time dummies included. The dependent variable is the change in logarithm of value added.

Table 5: Cross-country estimates of elasticity of value added with respect to mobility

Dep. var: Log-change in value added	Emerging markets		Advanced economies	
	Full panel	Last 3 quarters	Full panel	Last 3 quarters
Mobility index, log difference	0.208***	0.149**	0.237***	0.188***
	(0.054)	(0.063)	(0.031)	(0.041)
R^2	0.843	0.683	0.911	0.795
R^2 between	0.084	0.179	0.360	0.623
Observations	118	66	135	81

Source: Authors' calculations.

Note: Robust standard errors in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively. Estimated by fixed effects with time dummies included. The dependent variable is the change in logarithm of value added.

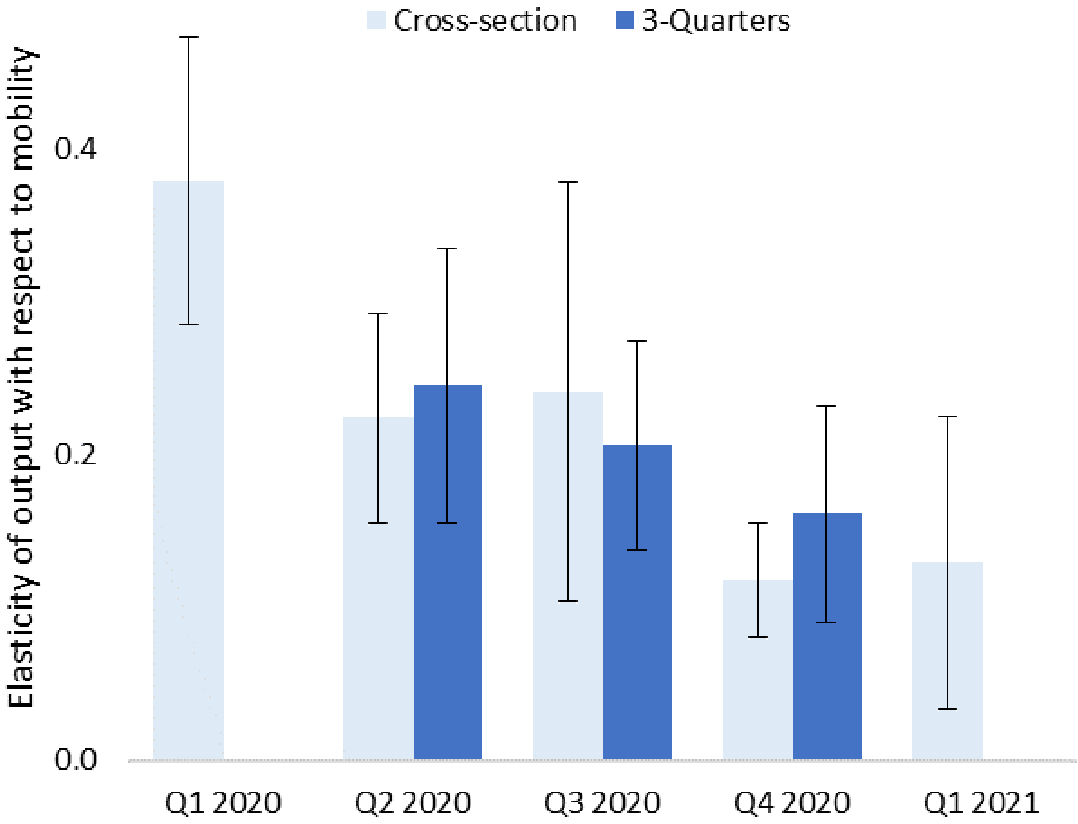
Table 6: Country-specific estimates of elasticity of value added with respect to mobility used in nowcasting

Country	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021
Argentina	0.40	0.40	0.24	0.30	0.29
Australia	0.40	0.40	0.23	0.27	0.26
Austria	0.40	0.38	0.33	0.34	0.31
Belgium	0.40	0.39	0.29	0.34	0.32
Brazil	0.40	0.40	0.25	0.29	0.27
Bulgaria	0.40	0.35	0.36	0.28	0.24
Chile	0.40	0.35	0.23	0.24	0.23
Colombia	0.40	0.38	0.20	0.24	0.22
Czech Republic	0.40	0.40	0.36	0.38	0.25
Denmark	0.40	0.37	0.36	0.38	0.32
Estonia	0.40	0.37	0.32	0.23	0.20
Finland	0.40	0.37	0.22	0.24	0.22
France	0.40	0.40	0.25	0.31	0.30
Germany	0.40	0.39	0.36	0.37	0.31
Greece	0.40	0.35	0.36	0.27	0.18
Hungary	0.40	0.37	0.36	0.37	0.34
India	0.40	0.35	0.36	0.38	0.35
Indonesia	0.40	0.40	0.21	0.23	0.22
Ireland	0.40	0.40	0.16	0.24	0.22
Israel	0.40	0.38	0.32	0.38	0.36
Italy	0.40	0.38	0.30	0.29	0.28
Japan	0.40	0.40	0.36	0.38	0.37
Kazakhstan	0.40	0.39	0.23	0.22	0.21
Kenya	0.40	0.35	0.25	0.25	0.24
Latvia	0.40	0.40	0.34	0.33	0.23
Lithuania	0.40	0.36	0.36	0.25	0.22
Luxembourg	0.40	0.36	0.20	0.24	0.22
Malaysia	0.40	0.37	0.32	0.31	0.30
Malta	0.40	0.39	0.34	0.31	0.30
Mexico	0.40	0.40	0.29	0.35	0.32
Morocco	0.40	0.40	0.19	0.22	0.21
Netherlands	0.40	0.38	0.36	0.37	0.34
New Zealand	0.40	0.39	0.21	0.28	0.27
Norway	0.40	0.37	0.36	0.32	0.27
Peru	0.40	0.40	0.24	0.29	0.28
Philippines	0.40	0.40	0.18	0.23	0.22
Poland	0.40	0.36	0.36	0.27	0.25
Portugal	0.40	0.39	0.25	0.28	0.27
Romania	0.40	0.36	0.32	0.26	0.24
Russia	0.40	0.35	0.16	0.18	0.17
Serbia	0.40	0.37	0.19	0.20	0.19
Singapore	0.40	0.37	0.27	0.28	0.27
Slovak Republic	0.40	0.40	0.22	0.31	0.27
Slovenia	0.40	0.40	0.28	0.32	0.26
South Africa	0.40	0.37	0.26	0.29	0.27
Spain	0.40	0.39	0.27	0.29	0.28
Sweden	0.40	0.38	0.36	0.38	0.37
Switzerland	0.40	0.38	0.32	0.33	0.30
Thailand	0.40	0.39	0.33	0.34	0.31
Turkey	0.40	0.36	0.25	0.28	0.27
Ukraine	0.40	0.37	0.36	0.32	0.30
United Kingdom	0.40	0.40	0.27	0.32	0.30
United States	0.40	0.40	0.28	0.35	0.33
Total	0.40	0.38	0.28	0.30	0.27

Source: Authors' calculations.

Note: Estimates of elasticity of value added with respect to the composite mobility index, by country and quarter, as used to generate out-of-sample forecasts.

Figure 2: Estimates of elasticity of output with respect to mobility



Sources: Authors' calculations. Based on cross-sectional and fixed effect estimates of elasticity of oputput with respect to mobility in a sample of 53 economies based on quarter-on-quarter GDP growth between Q1 2020 and Q1 2021.

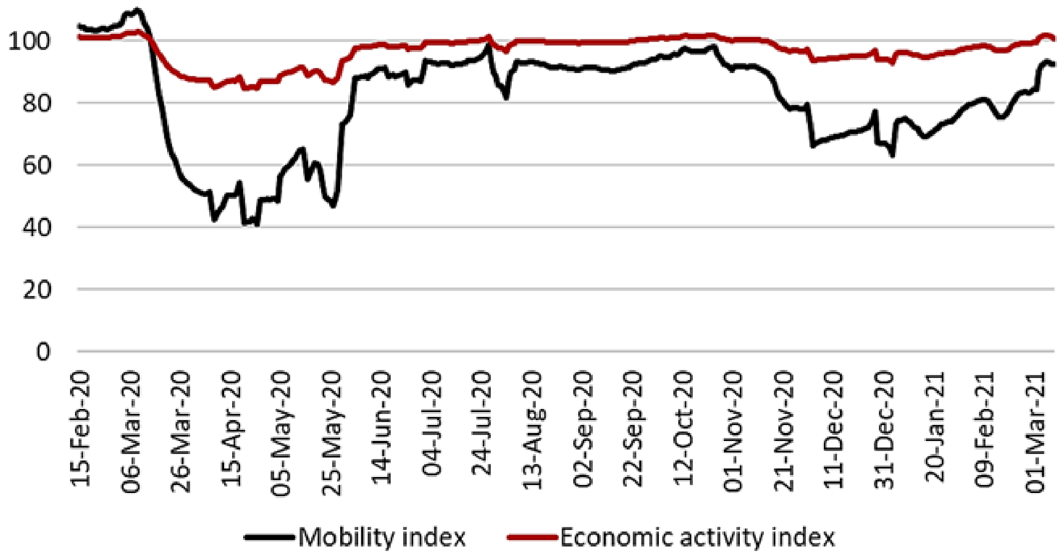
Table 7: Forecast evaluation (root mean square error)

Country	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021	All
Mobility-based	1.49	4.25	4.65	3.41	2.11	3.52
Random walk	3.35	10.52	22.96	10.10	2.44	12.57
Potential growth	3.24	12.86	10.46	2.56	1.86	7.16
Reversion to the trend	3.24	15.66	9.25	7.30	7.77	9.62
Reversion to the pre-crisis level	2.66	14.15	6.83	4.44	4.63	7.80

Source: Authors' calculations.

Note: Root mean square error of forecasts made out-of-sample based on mobility data available at the end of each quarter or 16 March 2021 in the case of Q1 2021. Potential growth assumes a constant rate of growth equal to the estimated medium-term potential rate. Reversion to the trend assumes regaining pre-crisis level of output, adjusted by the potential rate of growth. Reversion to the pre-crisis level assumes regaining the level of output observed in the last quarter of 2019.

Figure 3: Turkey: Activity index, daily values



Sources: Authors' calculations based on Google Analytics.
Economic activity index for Turkey, end-2019 = 100. Calculated based on mobility indices, the estimated potential growth rates and the estimated country-specific elasticity of output with respect to mobility.

Table 8: Out-of-sample growth forecasts

Country	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021	RMSE ratio	RMSE ratio (RW)
Argentina	-2.95	-18.93	5.95	5.67	1.90	0.41	0.24
Australia	0.21	-9.41	2.17	2.67	0.04	0.36	0.22
Austria	-3.29	-9.38	8.47	-5.57	-1.14	0.27	0.14
Belgium	-3.20	-10.54	7.30	-1.70	1.38	0.31	0.17
Brazil	-1.50	-10.37	6.36	4.20	-1.50	0.19	0.11
Bulgaria	-2.65	-5.59	8.20	-1.77	-0.42	0.76	0.43
Chile	-1.80	-20.50	4.28	7.83	0.77	0.62	0.33
Colombia	-2.71	-23.15	7.63	8.01	-0.47	0.52	0.32
Czech R.	-2.11	-2.84	6.27	-6.04	-1.11	0.83	0.49
Denmark	-2.07	-1.86	3.72	-2.10	-4.74	0.73	0.42
Estonia	-1.90	-4.54	7.03	-1.15	-1.43	0.95	0.64
Finland	-1.79	-6.43	4.04	-0.68	-0.60	0.50	0.31
France	-4.33	-13.53	10.91	-3.45	0.28	0.37	0.20
Germany	-1.81	-6.29	6.70	-3.13	-3.49	0.44	0.24
Greece	-3.02	-4.13	9.15	-5.56	-1.31	1.11	0.66
Hungary	-1.32	-7.62	9.22	-3.09	-0.43	0.50	0.27
India	-2.09	-18.11	12.71	9.22	3.51	0.40	0.22
Indonesia	-0.39	-10.59	4.84	1.46	-0.52	0.56	0.36
Ireland	-1.98	-13.52	5.28	-0.13	-2.97	1.13	0.73
Israel	-2.56	-7.00	3.99	-1.18	-1.50	0.53	0.29
Italy	-6.83	-12.63	13.12	-2.42	-0.78	0.16	0.09
Japan	-0.21	-4.12	2.63	1.56	-2.25	0.54	0.33
Kazakhstan	0.20	-9.68	5.29	2.00	-0.34	0.60	0.37
Kenya	0.04	-10.04	7.04	4.87	1.42	0.21	0.11
Latvia	-0.87	-3.95	6.93	-5.84	-2.87	0.83	0.48
Lithuania	-2.26	-5.01	9.60	-3.92	-2.41	0.70	0.37
Luxembourg	-3.96	-13.68	7.60	-0.59	-1.03	0.66	0.39
Malaysia	-3.21	-14.28	14.00	-2.88	-1.40	0.25	0.13
Malta	-2.20	-10.46	9.76	-0.23	-0.41	0.38	0.22
Mexico	-0.30	-15.32	6.03	4.26	-0.57	0.35	0.19
Morocco	-3.31	-23.51	13.37	3.77	1.25	0.58	0.34
Netherlands	-2.09	-6.59	4.64	-2.95	-2.02	0.44	0.24
New Zealand	-0.78	-14.89	7.30	2.63	-0.71	0.63	0.38
Norway	-2.26	-2.21	3.75	-2.22	-2.39	0.63	0.36
Peru	-4.04	-32.24	14.47	8.15	-1.77	0.47	0.27
Philippines	-3.75	-25.73	7.79	4.89	1.92	0.64	0.42
Poland	-2.39	-7.15	10.61	-3.56	-0.01	0.44	0.23
Portugal	-3.69	-15.39	10.19	-0.82	-6.07	0.20	0.11
Romania	-2.10	-10.18	10.41	-2.01	0.48	0.70	0.42
Russia	0.58	-8.80	4.14	-0.87	-0.98	2.31	1.64
Serbia	-1.80	-18.36	11.95	0.34	0.13	0.99	0.55
Singapore	-1.38	-14.03	8.65	2.72	0.92	0.11	0.06
Slovak R.	-3.19	-8.39	6.36	-4.98	-3.23	0.55	0.32
Slovenia	-3.75	-8.97	7.75	-8.49	0.72	0.58	0.32
South Africa	-1.13	-18.02	9.59	4.41	-1.70	0.23	0.12
Spain	-4.73	-17.72	13.16	0.50	-1.58	0.15	0.08
Sweden	-0.51	-2.68	2.16	-2.63	-2.05	0.75	0.40
Switzerland	-2.55	-6.07	5.23	-1.79	-1.58	0.36	0.20
Thailand	-1.33	-7.35	5.53	1.01	0.25	0.21	0.12
Turkey	-0.83	-13.04	10.22	-1.41	-1.19	0.40	0.21
Ukraine	-1.22	-6.75	8.26	-2.01	-3.10	0.36	0.19
UK	-1.99	-19.75	9.94	-0.36	-4.69	0.28	0.15
US	-0.93	-8.63	3.24	-0.36	-0.77	0.42	0.23
Average	-2.11	-11.32	7.64	-0.11	-0.99	0.54	0.32

Source: Authors' calculations.

Note: Forecasts made out-of-sample based on mobility data available at the end of each quarter. RMSE ratio is the ratio of root mean square error of the forecast relative to that of potential medium-term growth assumed in every quarter or (in the last column) random walk.