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**Working Paper**

## COVID-19 lockdown policy and heterogeneous responses of urban mobility: Evidence from the Philippines

ADB Economics Working Paper Series, No. 659

**Provided in Cooperation with:**

Asian Development Bank (ADB), Manila

*Suggested Citation:* Jiang, Yi; Laranjo, Jade R.; Thomas, Milan (2022) : COVID-19 lockdown policy and heterogeneous responses of urban mobility: Evidence from the Philippines, ADB Economics Working Paper Series, No. 659, Asian Development Bank (ADB), Manila, <https://doi.org/10.22617/WPS220217-2>

This Version is available at:

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# COVID-19 LOCKDOWN POLICY AND HETEROGENEOUS RESPONSES OF URBAN MOBILITY

## EVIDENCE FROM THE PHILIPPINES

*Yi Jiang, Jade R. Laranjo, and Milan Thomas*

**NO. 659**

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May 2022

**ADB ECONOMICS  
WORKING PAPER SERIES**

ADB Economics Working Paper Series

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Yi Jiang, Jade R. Laranjo, and Milan Thomas

No. 659 | May 2022

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The authors thank Gilles Duranton, Lei Lei Song, Rana Hasan, and participants at the ADB Economists' Forum 2022 for constructive comments and discussions. Marjorie Villanueva Remolador and Sanjeev Parmanand provided excellent research assistance.



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[www.adb.org](http://www.adb.org)

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ISSN 2313-6537 (print), 2313-6545 (electronic)  
Publication Stock No. WPS220217-2  
DOI: <http://dx.doi.org/10.22617/WPS220217-2>

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## **ABSTRACT**

Throughout 2020, national and subnational governments worldwide implemented nonpharmaceutical interventions (NPIs) to contain the spread of coronavirus disease (COVID-19). These included community quarantines, also known as lockdowns, of varying length, scope, and stringency that restricted mobility. To assess the effect of community quarantines on urban mobility in the Philippines, we analyze a new source of data: cellphone-based origin–destination flows made available by a major telecommunication company. First, we demonstrate the impulse responses of mobility to lockdowns of varying stringency levels over six months starting in March 2020. Then we assess the heterogeneous effects of lockdowns by city characteristics, focusing on employment composition. This analysis reveals that the effect of lockdowns was strongest in cities where a high share of workforce was employed in work-from-home-friendly sectors or medium to large enterprises. We compare our findings with cross-country evidence on lockdowns and mobility, discuss the economic implications for containment policies in the Philippines, and suggest additional research that can be based on this novel dataset.

*Keywords:* mobility, employment, lockdowns, nonpharmaceutical interventions, remote work

*JEL codes:* I18, J61, K32, O18

## I. INTRODUCTION

To control the spread of coronavirus disease (COVID-19), national and subnational governments in nearly all countries instituted nonpharmaceutical interventions (NPIs) over 2020–2021 (Hale et al. 2021). These public health measures were imposed and enforced most strongly in high-density urban centers, and included closing schools and other public venues, instituting curfews, and limiting business activities and size of social gatherings. The primary goal of such policies is to reduce mobility of people and contain the pandemic by limiting human contact.

The effects of those lockdown policies on mobility in cities have been studied for several high-income countries. Those studies typically use big data sources to analyze how policies of differing stringency levels affect vehicular and non-vehicular mobility over time and by locational characteristics.<sup>1</sup> This mobility-focused research agenda is highly relevant because many studies have confirmed that mobility is closely associated with public health outcomes such as infection, hospitality, and mortality (e.g., Glaeser, Gorbach, and Redding 2020; Hadjidemetriou et al. 2020). On the other hand, mobility restrictions have been found to adversely affect economic activity (e.g., Sampi Bravo and Jooste 2020; Chen et al. 2020; Béland, Brodeur, and Wright 2020).

However, there is less empirical evidence on how mobility has responded to lockdowns in lower-income countries, where lockdowns have often lasted longer, entailed higher enforcement costs, and caused greater damage to the economy. One reason for missing evidence in these countries is lack of frequent, high-quality data on people’s travel. However, big data collected through information technology platforms has emerged as a good substitute. In this paper, we attempt to fill the gap by utilizing cellphone-based hourly flow data from a major local telecommunications service provider, combined with detailed city-level employment data, to investigate how mobility responded to lockdown policies in the Philippines.

Our study focuses on work-related mobility encompassing commuting and business trips for four reasons. First, work-related mobility accounts for a majority share of daily travel and is the primary target of many NPIs. Assessing how it has changed in response to lockdown policies can inform us of the effectiveness of the policies to a large extent. Second, the lockdown policies are designed to treat industries differently. Combining detailed spatial distribution of industries and firms of various sizes with work-related mobility, we can learn whether the differential treatments have worked or channels through which lockdown affected mobility. Third, work-related travel is directly associated with employment and production. Focusing on it could give us a better understanding of the adverse impacts of lockdown on the economy. Lastly, responses of work-related and nonwork-related trips to lockdown could be distinct. Not distinguishing between them could lead to uninformative, washed-out measurement of the impacts of lockdown.

In sum, we find that the lockdown reduced work-related mobility substantially across the country, with reasonably persistent effects. When the stringency of lockdown was lowered, mobility partially recovered. Moreover, there were evident spatial heterogeneities in the effects of lockdown arising from different industrial compositions and firm size compositions across localities. While this implies policies largely achieved the expected goals, this also reminds us that certain areas and

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<sup>1</sup> Please see next section for a comprehensive review of the literature.



populations require special policy attention, as the impacts of policies vary over space. As far as we know, we are among the first to present evidence and analysis on the topic for a lower-income country.

The rest of the paper is structured as follows. After surveying the emergent literature on NPIs and mobility in Section II, we introduce the data used in this study, including the proprietary cellphone-based dataset in Section III. Section IV provides detailed descriptions of the lockdown policies adopted by Philippine local governments over the study period. Then, we examine how mobility responses to lockdowns varied over time in Section V and how responses differed by cities' sectoral composition in Section VI. We conclude by discussing policy implications of the main findings and drawing possible lessons in Section VII.

## II. LITERATURE REVIEW

There is a large literature on COVID-19 containment policies, which continues to expand quickly. Here, we focus on surveying studies that examine the proximate response to NPIs: changes in human mobility.

Many studies conducted in the first year of the global pandemic identify large mobility responses to lockdown measures. For the United States, Lee et al. (2020) find that stay-at-home mandates between January and April 2020 were effective, based on mobile phone location data. However, that response was highly context specific. Hu et al. (2021) also use mobile device location data and show that the effect of NPIs on mobility (measured by average number and length of trips per person) decreased over time and depended on locations' average income, industry structure, and demographic composition.

A similar picture has emerged from studies of European cities and countries. Pullano et al. (2020) assess the impact of nationwide lockdown in France using origin–destination flows captured by mobile phone data. Mobility fell by 65%, with the largest decline in regions that had a high burden of COVID-19 cases, large economically active populations, and workers heavily employed in sectors that either shut down entirely (e.g., restaurants and hospitality) or could allow them to work remotely (e.g., financial services). Aloï et al. (2020) document that after quarantine was imposed in Spain in March 2020, mobility as measured by traffic counters and cameras fell by 76% in the city of Santander. The largest decline was in use of public transport, consistent with the finding by Heiler et al. (2020) that volume of commuters at metro stations fell by 80% in Austria following government lockdown. Milder restrictions in Sweden reduced density of commercial and industrial areas by 33% relative to the previous year, according to mobile phone data analyzed by Dahlberg et al. (2020). Hadjidemetriou et al. (2020) use driving, walking, and transit real-time data to show that mobility declined gradually in the United Kingdom in response to government policy, and then stabilized at around 80% of the pre-lockdown norm, significantly reducing COVID-19-related deaths.

More recent studies have been able to assess the extent of recovery after removal of restrictions. Caselli, Fracasso, and Scicchitano (2020) analyze imposition and removal of government lockdowns in Italy. Using a spatial discontinuity approach and Google Community Mobility Reports data, they find that measures lowered mobility by 33% and recovery to pre-lockdown mobility was stronger in areas where work-from-home was less prevalent. Hara and Yamaguchi (2021) use mobile phone location data to identify behavioral changes under COVID-19 “state of emergency” declarations

in Japan and find that significant reductions in travel were achieved without strong government restrictions, but that recovery of mobility after removal of restrictions was incomplete and slow.

Turning to cross-country evidence, after analyzing Apple mobility reports of 83 countries from across the income spectrum, David and Pienknagura (2020) show that controlling for a wide range of factors, walking and driving trip declines were relatively small after imposition of NPIs in countries with high informality, low share of remote work friendly jobs, and low government effectiveness. Askitas, Tatsiramos, and Verheyden (2020) use a multiple-events model using data from 135 countries to show that canceling public events, imposing restrictions on private gatherings, and school closures had largest effect on reducing COVID-19 incidence, with population mobility as a mediating factor. Camehl and Rieth (2021) use a mobility index based on daily Google visit data for transit stations, retail, shopping centers, and other recreational centers from 44 countries. Based on a Bayesian panel vector autoregression, they conclude that restrictions reduce mobility immediately, reduce cases with a one-week lag, and reduce deaths with a three-week lag.

Cross-country regression-based studies also show deteriorating effects of lockdowns over time. Wang et al. (2021) use Google mobility data from 33 countries and show that while the response to restrictions (as measured by a stringency index) was quick, it was not persistent. Goldstein, Yeyati, and Sartorio (2021) find that strict lockdowns lost their effectiveness (in terms of reducing case load and deaths) after four months based on mobility data from 152 countries, likely due to rising noncompliance.

In summary, mobility fell substantially in response to NPIs, but the effects of those lockdowns were heterogeneous by country and typically waned over time. Furthermore, there is within-country evidence that the magnitude of the decline and extent of recovery in mobility depended on locational economic characteristics (notably, the ability of local workforce to work from home). We investigate these issues in the Philippine context after describing the data source in Section III.

### III. DATA

From one of the major telecommunication companies in the Philippines, we obtain nationwide data of flows of its cellphone users between barangay pairs for every hour from January to September 2020.<sup>2</sup> A barangay is the smallest administrative division in the Philippines. For our purpose, we aggregate the barangay-level flows to city- and municipality-level flows.<sup>3</sup>

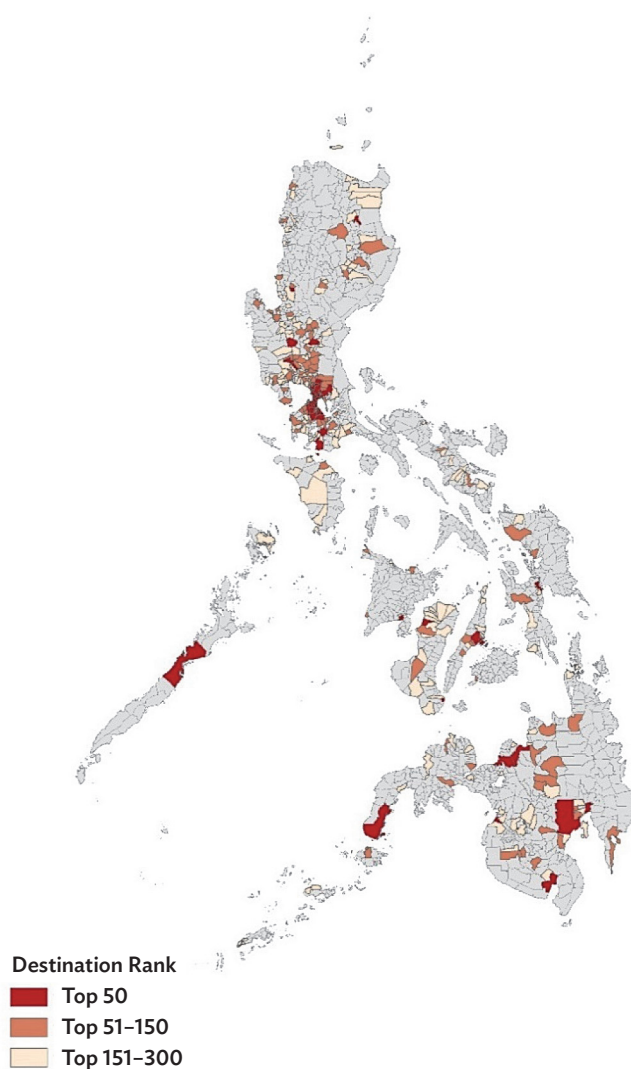
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<sup>2</sup> Google Community Mobility Report (CMR) data is a daily measure available at region level or for eight metropolitan areas in the Philippines. In contrast, our mobility data covers the whole country with higher time frequency as well as space granularity. On the other hand, Google CMR data distinguishes mobility by location type, which may allow better identification of work-related mobility.

<sup>3</sup> City and municipality belong to the same level of administrative divisions in the Philippines with cities more populated in general. There were 1,634 cities and municipalities consisting of 42,046 barangays in the Philippines in 2019. As the primary subnational policy making body in the Philippines, city and municipality are of key interest in this study. A problem with the barangay-level flow data is that not every barangay has a cell site and the user information in those barangays will be counted for the barangay whose cell site captures it. Aggregating to city and municipality largely mitigates this data bias problem. Moreover, the other data used in the study—employment by sector and firm size—are only available at city and municipality level. For simplicity, we sometimes use city to refer to both.

Since we are interested in work-related mobility including commuting and business trips, we select the data based on following criteria. First, we focus on flows taking place from 4 a.m. to 10 a.m. on weekdays. We include 4 a.m. since people started to go to work in the early morning during lockdown to avoid delays at checkpoints. Second, to focus the analysis on urban areas hosting the majority of national employment, we restrict the sample to the most popular destination cities in terms of pre-lockdown morning trips. Specifically, we calculate sum of hourly flows into each city and municipality between 4 a.m. and 10 a.m. and average it across weekdays from 2 January 2020 to 13 March 2020. The 300 cities and municipalities with the highest average inflows are retained from the total 1,560. These top 300 cities and municipalities account for 78% of total morning flows, 57% of population, 86% of employment, and 21% of the area of the country. Figure 1 illustrates where these top 300 are located across the country. Third, we exclude all city pairs with road-based distance

**Figure 1: Top 300 Morning Destination Cities and Municipalities**



Note: Cities and municipalities are ranked based on the sum of inflows between 4 a.m. and 10 a.m. averaged over weekdays from 2 January 2020 to 13 March 2020.

Source: Authors.

exceeding 150 kilometers from the analysis, considering the excluded pairs to be too far apart for regular commuting trips. This leaves us with 1,387 cities and municipalities as origins and more than 39,000 origin–destination (OD) pairs.

We sum flows over the six morning hours and then average them across workdays for each week. The unit of observation is thus city-level OD pair per week. There are 40 weeks between January and September. Lockdown measures were imposed in most areas of the Philippines from the 12th week of 2020 (i.e., March 16–20). Upon checking, however, the hourly profiles of the nine weeks in May and June show patterns distinct from those of other weeks (Appendix). Absent a clear explanation for this irregularity, we exclude data of these weeks from analysis. Thus, the final dataset we work with covers 31 weeks, 20 of which coincided with the pandemic.

To validate that the cellphone-based OD flows we compiled are a good measure of work-related mobility, we compare them with the commuting flows across cities and municipalities derived from microdata from the 2010 Census of Population and Housing, the latest census available. The correlation coefficient between census-based commuting flows and average cellphone-based morning flows over all pre-pandemic weeks (weeks 1–11) is around 0.95, suggesting the latter is a valid work-related mobility measure.

Table 1A reports summary statistics of flows by week. Positive flows are observed for about 34,000 to 35,000 pairs of cities before the 12th week. The average flows ranged from 2,800 to 3,400 and median flows from 15 to 20 in the 11 pre-lockdown weeks. In the 12th week, the number of observed OD pairs dropped by 11% to 30,838, followed by another 11% drop in the 13th week as the pandemic unfolded. The median flow decreased from 18 in the preceding weeks to 11 in the 12th week and further down to 7 in the 13th week, although the mean flows declined at a slower pace. Over the period covered, we see the flow statistics including mean, median, and total remain in the trough until the 27th week and start to rebound from the 28th week when there is a nationwide relaxation of lockdown. Up till the 40th week, however, the total flows had only recovered to less than 90% of the pre-lockdown level. The patterns of flows and how they respond to different lockdown stringencies will be further explored and discussed in the following sections of the paper.

List of Establishments 2018 (LE2018 hereafter) data is the second main data source used in this study. The LE2018 obtained from Philippine Statistics Authority (PSA) contains total employment at province level and number of firms at city and municipality level by size category and sector.<sup>4</sup> To derive employment at city and municipality level, we first calculate total number of firms by size and sector for each province. Then, the total employment is divided by total number of firms to obtain mean employment by size and sector at province level. Assuming that the constituent cities and municipalities have the same mean employment for each combination of size and sector as their province does, the mean employment is multiplied with number of firms to reach total employment by size and sector at city and municipality level.

To focus the analysis, we create two firm size groups by lumping the micro and small firms together and medium and large firms together. The sectors are also grouped into seven categories based on similarity, share in the economy, and ease of working from home of the industries. For instance, one sector category encompasses power, utilities, and construction industries, another trade and transport industries, and a third hospitality and recreation industries. Other tertiary industries are

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<sup>4</sup> There are four firm size categories: micro with 1–9 employees, small 10–99, medium 100–199, and large 200 and over. The total employment is available at city and municipality level for metro Manila and at province level for the rest of the country.

allocated into work-from-home (WFH) -friendly and non-WFH-friendly categories, respectively, based on 3-digit industry codes and the classification system for skilled scalable services proposed by Eckert, Ganapati, and Walsh (2020), with some discretionary adjustments for the Philippines in the context of the pandemic (e.g., classifying call center jobs and teaching as WFH friendly).

**Table 1A: Summary Statistics of Morning Flows by Week**

Week	Observations	Mean	SD	Min	Median	Max	Total
1	33,954	3,190	57,431	1	15	5,664,627	108,321,048
2	35,186	3,378	66,768	1	20	7,037,750	118,869,752
3	34,289	3,252	62,899	1	17	6,213,362	111,507,556
4	34,794	3,350	67,365	1	19	6,811,825	116,576,438
5	34,938	3,233	64,694	1	19	6,603,484	112,949,349
6	34,697	3,090	60,498	1	18	6,127,628	107,206,550
7	34,732	3,072	61,589	1	18	6,464,194	106,708,683
8	34,748	3,022	61,169	1	18	6,385,326	105,000,276
9	33,807	3,053	59,745	1	16	6,175,062	103,208,129
10	34,662	2,886	56,009	1	18	5,628,076	100,047,743
11	34,924	2,772	52,062	1	18	5,194,160	96,798,810
12	30,838	2,733	45,395	1	11	3,849,394	84,271,812
13	27,416	2,694	42,101	1	7	3,365,286	73,859,958
14	26,705	2,615	40,119	1	7	3,232,383	69,821,185
15	25,022	2,881	42,949	1	6	3,417,396	72,080,578
16	28,041	2,620	41,183	1	8	3,422,339	73,471,670
17	28,016	2,515	39,268	1	7	3,235,731	70,473,324
27	28,363	1,932	30,595	1	9	2,617,903	54,788,292
28	33,490	2,595	45,650	1	14	4,298,624	86,909,641
29	33,770	2,669	47,001	1	14	4,484,620	90,148,082
30	33,474	2,557	44,549	1	14	4,157,871	85,597,684
31	32,721	2,776	48,429	1	13	4,650,929	90,833,347
32	32,377	2,760	47,594	1	13	4,336,184	89,344,579
33	32,461	2,802	48,141	1	13	4,367,758	90,959,328
34	31,966	2,873	49,375	1	12	4,537,778	91,840,516
35	33,177	2,776	48,909	1	14	4,739,307	92,099,492
36	32,103	2,765	47,972	1	12	4,539,652	88,769,274
37	33,234	2,623	46,078	1	14	4,427,404	87,161,264
38	33,155	2,602	45,570	1	14	4,296,799	86,268,066
39	33,425	2,620	46,674	1	14	4,380,945	87,573,912
40	31,470	2,762	47,474	1	11	4,293,096	86,916,676

SD = standard deviation.

Notes: 1. Morning refers to 4 a.m. to 10 a.m.

2. Weekly data is average of daily morning flows over weekdays.

3. Each observation is weekly average flow between a pair of cities or municipalities with one of the top 300 cities and municipalities as destination.

Source: Authors' calculations.

The literature often quantifies the WFH propensity by occupation (Dingel and Neiman 2020). In the absence of spatial distribution data of occupations, industry-based categorization likely provides a second-best measurement of how different cities are amenable to WFH. Moreover, from a public policy perspective, understanding how cities with different industrial compositions respond to lockdown measures differently is important as it would be easier for policy interventions to be targeted at industries than at occupations.

Table 1B shows that employment by micro and small firms accounts for 73% of total employment across the top 300 cities and municipalities on average, with individual cities' shares ranging from 13% to 100%. Medium and large firms hire from 0% to 87% across cities, with the average a little more than one quarter.

**Table 1B: Summary Statistics of City Employment Shares for Top 300 Destination Cities and Municipalities**

Classification	Category	Observations	Mean	SD	Min	Median	Max
Firm size	Micro and small	300	0.732	0.202	0.125	0.772	1.000
	Medium and large	300	0.268	0.202	0.000	0.228	0.875
Sector	Manufacturing	300	0.179	0.155	0.017	0.121	0.820
	Primary	300	0.040	0.074	0.000	0.013	0.489
	Power, utilities and construction	300	0.039	0.036	0.000	0.028	0.229
	Trade and transport	300	0.351	0.113	0.047	0.353	0.748
	Hospitality and recreation	300	0.132	0.070	0.016	0.124	0.599
	WFH-friendly tertiary	300	0.133	0.071	0.005	0.121	0.550
	Non-WFH-friendly tertiary	300	0.126	0.070	0.012	0.113	0.513

SD = standard deviation, WFH = work-from-home.

Notes: 1. Total employment is divided by total number of firms for each firm size and sector combination to get mean employment by firm size and sector in each province.

2. The city-level total employment equals the product of provincial mean employment and city-level number of firms in each firm size and sector combination.

Source: Philippine Statistics Authority. List of Establishments 2018. Manila.

Philippine cities vary considerably in terms of industrial composition. On average, trade and transport combined is the largest sector category, followed by manufacturing, hospitality and recreation, and WFH-friendly tertiary. On one end of the sector distribution spectrum, manufacturing employment accounts for 82% of total employment. On the other end, trade and transport account for 75%. There are other cities dominated by hospitality and recreation sectors, WFH-friendly tertiary sectors, or non-WFH-friendly tertiary sectors, which are likely to respond to mobility restrictions differently.

Other data used in the study are lockdown policies from the *Official Gazette* of the Government of the Philippines and daily COVID-19 infection cases from the Department of Health. Both are processed to the city- and municipality-week level.<sup>5</sup>

<sup>5</sup> Lockdown policies data is available at <https://www.officialgazette.gov.ph/section/laws/other-issuances/inter-agency-task-force-for-the-management-of-emerging-infectious-diseases-resolutions/>, and COVID-19 cases data is available at <https://doh.gov.ph/covid19tracker>.

## IV. COVID-19 LOCKDOWN POLICIES IN THE PHILIPPINES

Faced with the threat of COVID-19 in the Philippines, the government introduced “community quarantine” as a restriction policy to contain the rapid transmission of the virus. The policy has four levels: enhanced community quarantine (ECQ), modified enhanced community quarantine (MECQ), general community quarantine (GCQ), and modified general community quarantine (MGCQ). Among levels, ECQ is the most stringent while MGCQ is the most lenient.

According to Inter-Agency Task Force for the Management of Emerging Infectious Diseases (2020), the mobility in cities and municipalities placed under ECQ is generally restricted, with public transportation suspended. Only those individuals accessing basic goods and services and workers in industries permitted to operate are authorized to leave their residences. Essential industries, particularly hospitals and frontline health services, manufacturers of essential goods, agriculture, forestry, fishing, and logistics and delivery service providers of essential goods, are allowed to operate with full on-site capacity. Industries providing essential retail trade and services, food preparation (for take-out and delivery), and media outlets are also allowed but should operate at 50% of maximum workforce on-site and the remaining through WFH or other flexible work arrangements.

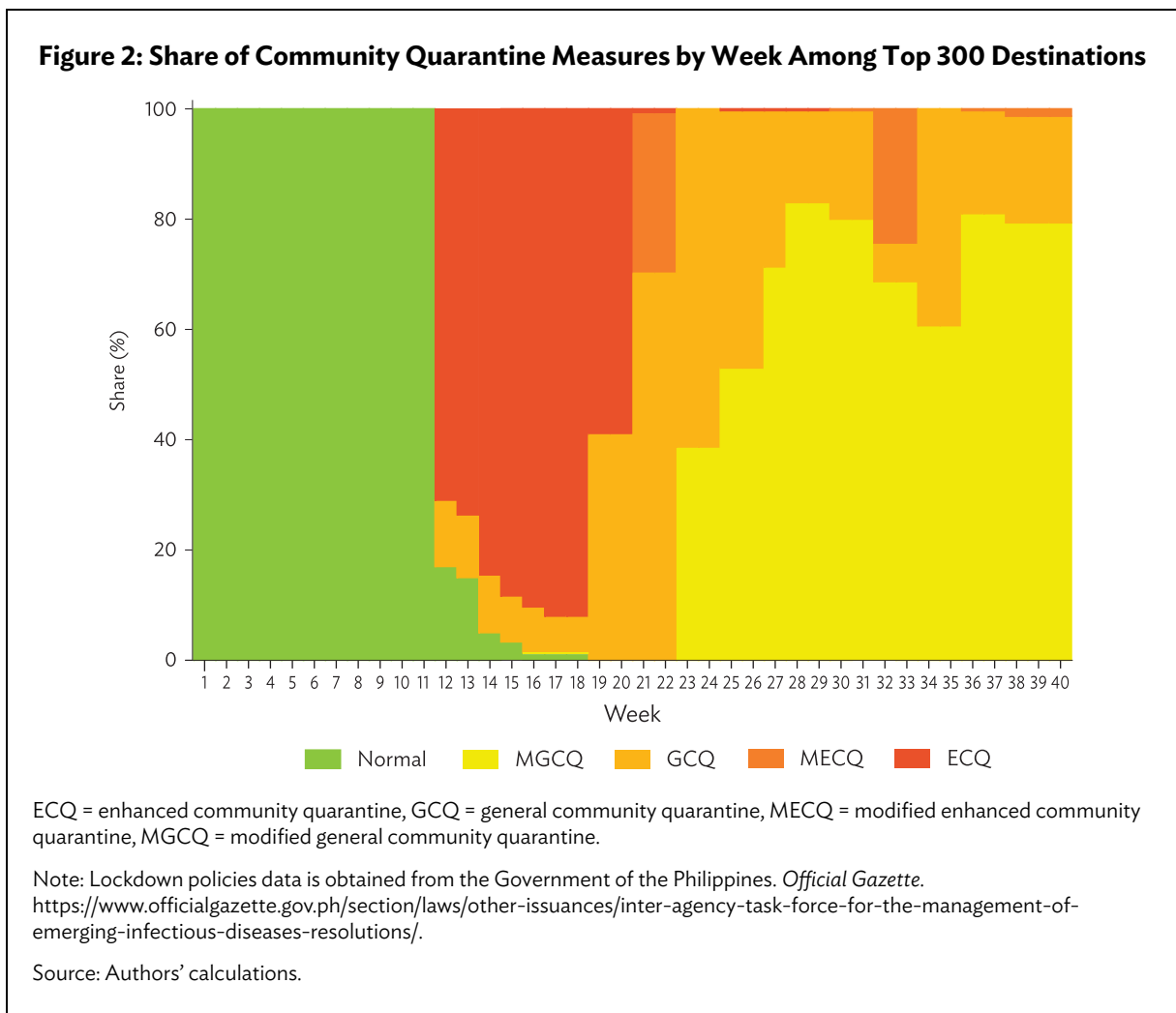
Non-essential businesses are permitted with skeleton on-site capacity during ECQ. This includes other health-related businesses, financial institutions, water facilities and sanitary services, the energy sector, information technology and telecommunication companies, and aviation and maritime industries. In addition, skeleton arrangement is also enforced for other manufacturing companies, business process outsourcing (BPO), export-oriented, mining and quarrying businesses, construction companies of priority projects, repair and maintenance establishments, property renting businesses, employment agencies for permitted sectors, and other essential services. Similarly, government offices function with skeleton staff and through alternative work arrangements. On the other hand, hospitality industries are not allowed to operate, except those accommodation establishments accredited to cater guests and clients for legitimate purposes under a state of public health emergency, and they should only provide basic services through skeleton employees. Also, all recreation industries are prohibited to operate during ECQ.

While MECQ is the less stringent variation of ECQ, the population is still required to stay at home. Public transportation remains unavailable, and travel is limited to authorized persons going to work or acquiring essential goods and services. However, more industries are permitted to operate with full on-site capacity. The additional industries include the media, BPOs, export-oriented establishments, e-commerce companies, property renting businesses, employment agencies for permitted sectors, and housing services. All other industries previously operating with skeleton workers, including establishments providing professional, scientific, and technical services, are permitted with 50% personnel. Government offices continue to operate with minimum capacity under MECQ. Hospitality and leisure establishments follow the same restriction as for ECQ.

For cities and municipalities under GCQ, public transportation is permitted at reduced capacity with strict health protocols. But the guideline on the movement of individuals is the same as for the more stringent measures. For industries, full operational capacity is extended to energy, water, other utilities, health-related, information technology, and telecommunications industries. Likewise, mining, quarrying, other manufacturing, repair and maintenance, and housing and office services are permitted at an operational capacity of 50% to 100%. Under GCQ, other permitted industries must follow the same capacity and work arrangements as under MECQ. The same limitation is imposed on hospitality and leisure industries as for previous measures.

Relaxed restriction is imposed during MGCQ. Those government and private offices and industries previously allowed can operate at a capacity of 50% to 100% with an option of flexible working. Hospitality and recreational establishments are also allowed at a maximum of 50% capacity. However, for accommodation businesses, only those accredited may operate. Furthermore, all forms of transportation are generally allowed but should follow health protocols. Physical non-contact activities are also permitted within place of residence under MGCQ.

Figure 2 presents the share of the top 300 city and municipality destinations under the various stringency measures by week. Although COVID-19 was first detected in the Philippines in the last week of January 2020 (week 5), the lockdown measures were imposed beginning in the third week of March 2020 (week 12). As shown in the chart, the country was in normal state (i.e., unrestricted) from weeks 1 to 11 before 71% of the areas were placed under ECQ in week 12. By week 18 (last week of April) ECQ covered 92% of the top 300 cities and municipalities. There was an easing of lockdown to GCQ in some areas during the first half of May (weeks 19 and 20). However, 60% remained under ECQ, particularly Metro Manila and surrounding provinces, Metro Cebu, and Metro Davao due to prevailing high-risk COVID-19 infections. Subsequently, 70% total areas shifted to GCQ in the second half, whereas Metro Manila and other high-risk areas moved to MECQ.





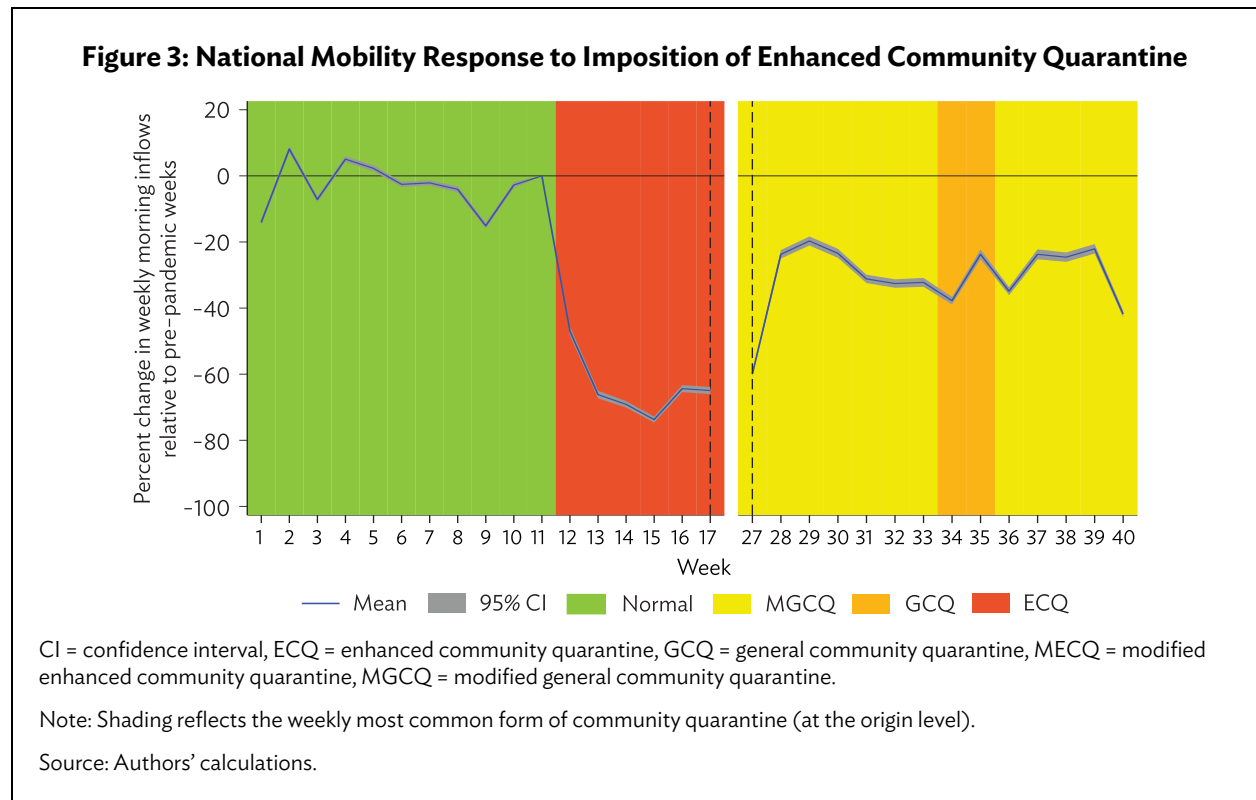
Many cities and municipalities gradually transitioned to less stringent measures in the following months. In the first week of June (week 23) 61% were under GCQ, and by the end of July (week 31) 80% had eased to MGCQ. At the same time, Metro Manila and nearby provinces, and other metropolitan areas shifted to GCQ. However, MECQ was reimposed in Metro Manila and neighboring provinces for two weeks in August (weeks 32 and 33). This was after medical frontliners appealed to the government for a break to prevent the collapse of the healthcare system amid the continuous surge in COVID-19 cases in those areas. Since then, Metro Manila and neighboring areas reverted to GCQ, with most of the country in MGCQ.

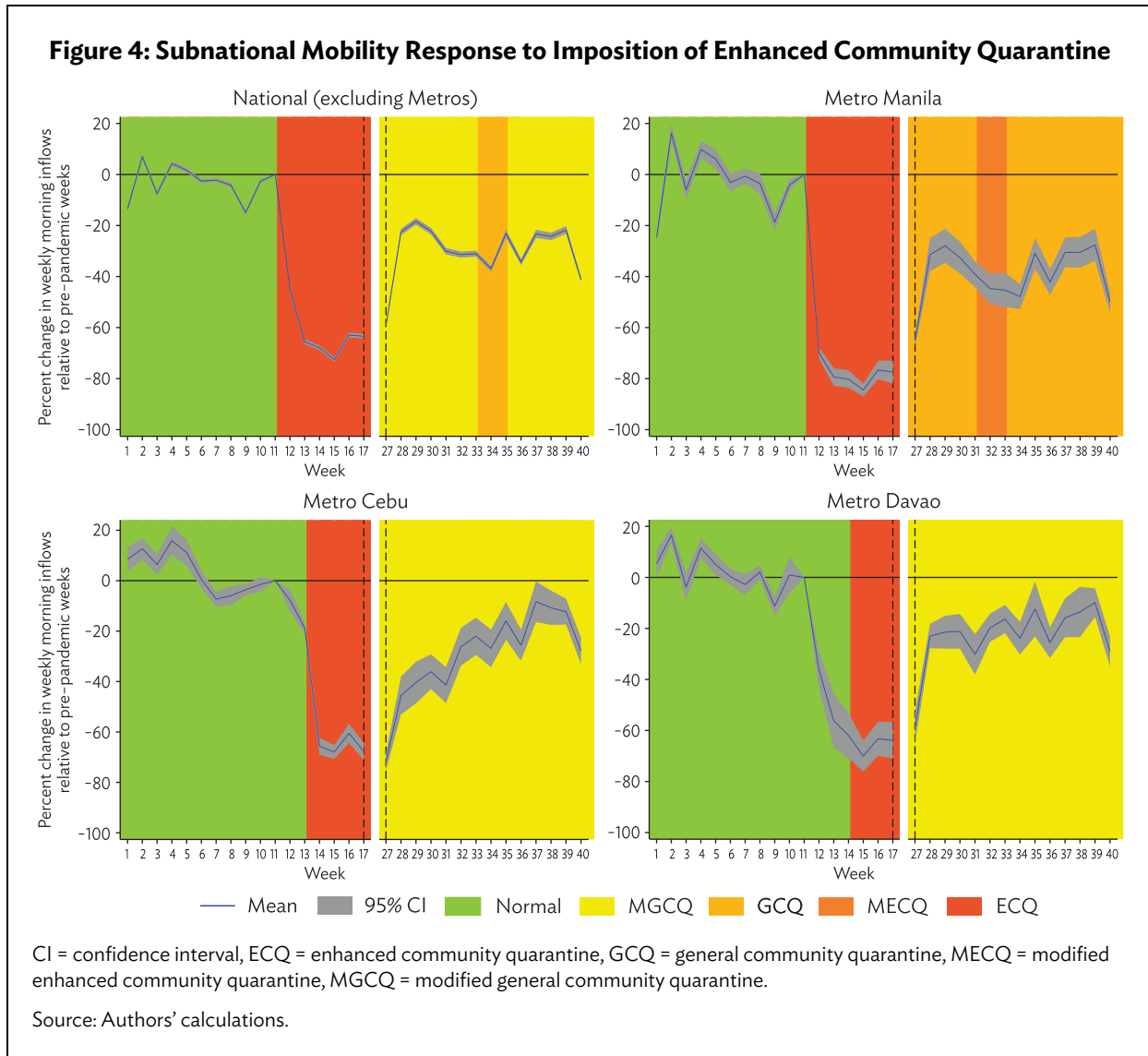
## V. TIME PROFILE OF MOBILITY RESPONSE TO LOCKDOWN POLICIES

To assess how mobility evolved over the first six months of the COVID-19 pandemic in the 300 most active Philippine cities, we regressed change in OD flows relative to the pre-lockdown baseline (the first 9 weeks of 2020) on weeks elapsed since first national imposition of ECQ, with destination city fixed effects ( $\alpha_d$ ) and standard errors clustered at the destination city-week level ( $\varepsilon_{od,w}$ ):

$$\% \text{ change in flows relative to baseline}_{od,w} = \alpha_d + \sum_{x=0}^{30} \beta_x [ECQ \text{ imposed } x \text{ weeks ago}]_w + \varepsilon_{od,w}$$

The resulting impulse response regression coefficients ( $\beta_x$ ) are shown in Figure 3 for the country (change in flows based on 1,001,955 OD pairs), and then in Figure 4 separately for non-metro cities (871,932 OD pairs), Metro Manila (104,681 OD pairs), Metro Cebu (13,444 OD pairs), and Metro Davao (11,989 OD pairs).





Mobility relative to the pre-lockdown norm declined precipitously in the month following ECQ imposition, reaching a low of 26% in the fourth week after ECQ before recovering somewhat and stabilizing at around 70% of the pre-lockdown level of flows when most of the country was under MGCQ in August and September 2020.

The mobility response was most pronounced for Metro Manila, where flows fell to as low as 15% of the pre-lockdown norm. The recovery in the second half of 2020 was also weakest for Metro Manila, which remained in GCQ while the rest of the country was largely in MGCQ. The response was similar among non-metro cities, Metro Cebu, and Metro Davao, where the low was only around 30% of the pre-lockdown norm and recovery to previous levels of mobility in the second half of 2020 was stronger than for Metro Manila (though there was a notable dip in flows in the last week of our data).

While the picture is interrupted due to the data issues for May and June noted in Section III, this analysis shows that urban mobility in the Philippines was highly responsive to community quarantines and appears to have tracked stringency levels in the expected manner, with the largest declines experienced during ECQ and recovery experienced during MGCQ. Overall, the quarantine

policies have been effective persistently, which should have had significant impacts on the economy as well as containing COVID-19 spread.

## VI. GEOGRAPHIC PROFILE OF MOBILITY RESPONSE TO LOCKDOWN

### A. Empirical Models and Conjectures

It is expected that there is significant variation across cities in mobility responses to lockdown measures based on the nature of their pre-pandemic economic activity. To assess this heterogeneity, we focus on two aspects of workplace cities: industrial composition and firm size composition. We focus on these because lockdown policies treat or affect industries differently as necessity, human contact intensity, and remote workability vary across industries and lockdown enforcement cost could be closely related to firm size, which is related to formality.

We employ the following gravity regression to examine this:

$$y_{odt} = \alpha_0 + \sum_l \gamma_l Z_{dt}^l + \sum_l \sum_e \gamma_{el} X_{ed} Z_{dt}^l + \beta_1 dist_{od} + \beta_2 nwd_t + \beta_3 stricter_{odt} + \beta_4 looser_{odt} + \beta_5 cases_{dt-1} + \beta_6 cases_{ot-1} + \beta_7 cases_{dt-2} + \beta_8 cases_{ot-2} + \theta_o + \theta_d + \varepsilon_{odt}$$

where  $y_{odt}$  is the ratio of average flow between origin city  $o$  and destination city  $d$  of week  $t$  to the average pre-lockdown flow,  $Z_{dt}^l$  is a dummy equal to 1 if city  $d$  adopted lockdown measure  $l$  in week  $t$  and 0 otherwise,<sup>6</sup>  $X_{ed}$  is the share of employment in industrial category  $e$  or share of employment in medium and large firms of city  $d$ . The parameters  $\gamma_l$ 's measure benchmark effects of lockdown policies on mobility without considering differences in the destination city's industrial characteristics. Of main interest are  $\gamma_{el}$ 's, which measure the heterogenous effects of lockdown varying by city industrial characteristics. Specifically, we expect that: (i) cities with larger shares in tertiary industries would have experienced a more pronounced decrease in mobility while those with more employment in manufacturing and trade and transport industries experienced smaller declines; (ii) when lockdown stringency was reduced, more mobility rebound would have been observed in cities with more non-WFH-friendly industries as compared to those with more WFH-friendly industries; and (iii) mobility would have declined more in cities with a greater share of workers in medium and large firms.

To obtain consistent estimates of  $\gamma_l$ 's and  $\gamma_{el}$ 's, we control for a set of variables including the road-based distance between the origin and destination ( $dist_{od}$ ), number of working days in each week ( $nwd_t$ ), whether the origin city's lockdown was more or less stringent than that of destination city ( $stricter_{odt}$  and  $looser_{odt}$ ), numbers of cases in destination and origin cities in the past two weeks ( $cases_{dt-1}$ ,  $cases_{ot-1}$ ,  $cases_{dt-2}$ , and  $cases_{ot-2}$ ) as well as origin and destination dummies ( $\theta_o$  and  $\theta_d$ ). While the pandemic spread and lockdown rollout were inextricably linked, controlling for lagged

<sup>6</sup> Here  $l = ECQ + MECQ, GCQ$  or  $MGCQ$ . MECQ accounts for a very small share in the sample, so we combine ECQ and MECQ (ECQ+MECQ) in the analysis for simplicity. Pre-lockdown weeks are the omitted category.

local COVID-19 cases separates the response to lockdown policy from the response to perceived risk of infection as much as the data allow.

The lockdown stringency was adjusted by the government mainly based on the pandemic situation. While it is unlikely to have reverse causality whereby the observed mobility led to change in lockdown policies, the omitted variables such as utilization of intensive care unit beds could be correlated with both mobility and lockdown stringency. To address this, we include lagged mobility variable as regressor in a second specification. Furthermore, we replace separate origin and destination dummies with origin–destination pair dummies in a third specification. Results reported below show estimates from these three specifications. Stable coefficient estimates would suggest that the model is not subject to severe endogeneity arising from omitted variables.

## B. Baseline Results

Tables 2A and 2B report estimates of  $\gamma_l$ 's and  $\gamma_{el}$ 's with  $X_{ed}$  being share of employment in industrial category and share in medium and large firms, respectively. Other coefficients are suppressed to save space. Across three model specifications, the estimates are qualitatively similar while some diminish slightly after controlling for lagged mobility. Hence, we focus on results from the third specification hereafter since it minimizes the potential endogeneity.

First, Table 2A shows that the benchmark effects decline from 47% reduction in mobility under the combined ECQ and MECQ (ECQ+MECQ) to around 16% under GCQ or MGCQ. This confirms again that ECQ+MECQ as the most stringent lockdown policy had the largest impacts on mobility. It is notable that GCQ and MGCQ had almost the same effects if not accounting for industrial differences across cities.

The coefficients of interaction terms suggest that cities with more employment in power, utilities and construction, hospitality and recreation, and WFH-friendly or non-WFH-friendly tertiary industries have experienced greater declines in mobility, regardless of lockdown stringency. For instance, should the employment share of WFH-friendly tertiary sectors increase by 10 percentage points in a destination city, the expected morning inflows would decrease by additional 2.8%, 4.2%, and 4.2% when the city moves from normal period to the respective ECQ+MECQ, GCQ, and MGCQ scenarios.<sup>7</sup>

In contrast, cities with larger employment in trade and transport industries have in general experienced smaller declines in mobility. Compared with the benchmark, a 10 percentage-point increase in employment share of trade and transport industries would predict 2.4% less decrease in morning flows into the city under ECQ+MECQ. Primary sector employment had similar dampening effects on the lockdown measures.

Furthermore, we see varying effects of industrial shares under different lockdown measures, which are in line with our second conjecture. Figure 5 plots the estimated  $\gamma_{el}$ 's for four industrial categories with additional adverse effects from lockdowns. With implementation of GCQ and MGCQ, the decrease in mobility (relative to the benchmark) in cities with larger power, utilities and construction, and non-WFH-friendly tertiary industries shrank towards the benchmark suggesting considerable job and business rebound in these sectors.

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<sup>7</sup> Note that the estimates measure marginal effects of employment in WFH-friendly sectors on top of benchmark effect, so they could be larger under less stringent lockdown. The overall reduction in mobility is still bigger under more stringent lockdown.

**Table 2A. Effects of Lockdown Measures by Destination City Industrial Composition (Baseline)**

Variables	Model 1		Model 2		Model 3	
	$\beta$	SE	$\beta$	SE	$\beta$	SE
<b>Benchmark effects</b>						
ECQ+MECQ	-0.599***	(0.020)	-0.459***	(0.018)	-0.474***	(0.018)
GCCQ	-0.284***	(0.023)	-0.153***	(0.020)	-0.165***	(0.020)
MGCQ	-0.281***	(0.020)	-0.146***	(0.017)	-0.162***	(0.017)
<b>ECQ+MECQ dummy × Employment share of industry category</b>						
Primary	0.393***	(0.071)	0.315***	(0.058)	0.320***	(0.060)
Power, utilities, construction	-0.441***	(0.108)	-0.335***	(0.085)	-0.366***	(0.087)
Trade, transport	0.316***	(0.038)	0.212***	(0.030)	0.241***	(0.031)
Hospitality, recreation	-0.126	(0.066)	-0.107	(0.056)	-0.121*	(0.057)
WFH-friendly tertiary	-0.342***	(0.052)	-0.249***	(0.043)	-0.276***	(0.044)
Non-WFH-friendly tertiary	-0.345***	(0.065)	-0.202***	(0.054)	-0.247***	(0.055)
<b>GCCQ dummy × Employment share of industry category</b>						
Primary	0.159	(0.093)	0.040	(0.079)	0.050	(0.080)
Power, utilities, construction	-0.376**	(0.127)	-0.323**	(0.108)	-0.344**	(0.110)
Trade, transport	0.058	(0.048)	0.015	(0.041)	0.024	(0.041)
Hospitality, recreation	-0.126	(0.088)	-0.109	(0.073)	-0.125	(0.074)
WFH-friendly tertiary	-0.511***	(0.052)	-0.395***	(0.046)	-0.420***	(0.046)
Non-WFH-friendly tertiary	-0.297***	(0.077)	-0.109	(0.066)	-0.130	(0.066)
<b>MGCQ dummy × Employment share of industry category</b>						
Primary	0.264***	(0.069)	0.169**	(0.058)	0.186**	(0.060)
Power, utilities, construction	-0.246*	(0.098)	-0.143	(0.083)	-0.157	(0.083)
Trade, transport	0.233***	(0.035)	0.129***	(0.031)	0.146***	(0.031)
Hospitality, recreation	-0.097	(0.072)	-0.094	(0.063)	-0.095	(0.064)
WFH-friendly tertiary	-0.534***	(0.059)	-0.403***	(0.052)	-0.417***	(0.052)
Non-WFH-friendly tertiary	-0.168**	(0.056)	-0.116*	(0.048)	-0.128**	(0.048)
Origin and destination dummies		Yes		Yes		No
AR(1)		No		Yes		Yes
Origin destination dummy		No		No		Yes
Observations		931,233		902,924		902,924
Adjusted R-squared		0.265		0.322		0.386

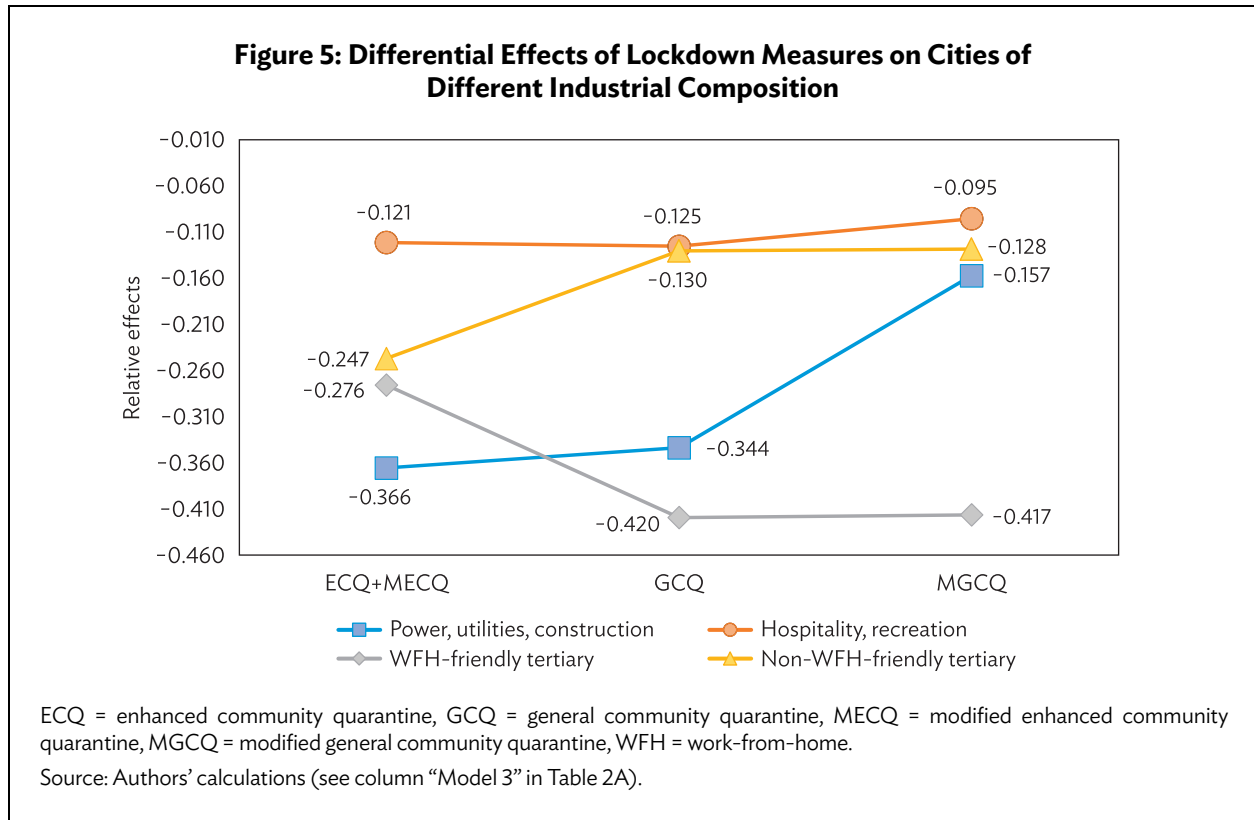
AR(1) = autoregressive term, lag 1; ECQ = enhanced community quarantine; GCCQ = general community quarantine; MECQ = modified enhanced community quarantine; MGCQ = modified general community quarantine.

Notes: 1. Other regressors not shown in the table include the road-based distance between the origin and destination (except model 3), number of working days in each week, whether the origin city's lockdown was more or less stringent than that of destination city, numbers of cases in destination and origin cities in the past two weeks.

2. Standard errors are clustered at the destination-week level.

3. \*\*\*, \*\*, \* indicate significant coefficients at 1%, 5%, 10%, respectively.

Source: Authors' calculations.



In contrast, the relative effects of WFH-friendly sectors become larger in magnitude under GCQ and MGCQ. A simple calculation shows that moving from ECQ to GCQ, the benchmark mobility will increase from 53% (= 100% - 47%) to 83% (= 100% - 17%) of the pre-pandemic level. Nonetheless, for a city with 20% employment in WFH-friendly sectors, the mobility will shift from 47% (= 100% - 47% - 28% × 20%) of pre-pandemic level under ECQ to 75% (100% - 17% - 42% × 20%) only under GCQ. Hence, a large share of employment in WFH-friendly sectors could help keep mobility low even when the lockdown policy is not highly restrictive.

Hospitality and recreation industries belong to the non-WFH-friendly tertiary category. However, they are separately analyzed because they were specially targeted by the lockdown policies. Only under the least stringent MGCQ were they allowed to operate with maximum of 50% capacity. These industries did perform differently from other non-WFH-friendly industries. Under the most stringent ECQ, the relative effect of lockdown for employment share in hospitality and recreation is just half of that for non-WFH-friendly industries. Driven by job recovery in non-WFH-friendly industries, the two estimates converge under GCQ. Only with implementation of MGCQ does the mobility due to hospitality and recreation rebound moderately, as suggested by the estimate changing from -0.121 to -0.095. The results observed here may be because hospitality- and recreation-related mobility is more sensitive to the threat of COVID-19 (proxied by numbers of new cases in the past two weeks) than to government regulations. To avoid infection, people self-regulated on entertainment activities such as dining out and attending parties more than they did for other, less discretionary economic activities.<sup>8</sup>

<sup>8</sup> We do find that the coefficients of interactions between lockdown and share of hospitality and recreation are larger in magnitude with uniform statistical significance in regressions without lagged number of cases.

In Table 2B, we show that cities with higher employment share in medium and large firms experienced a greater decline in morning inflows. An increase of 10 percentage points in employment share in large and medium firms led to 1.9% decrease in mobility on top of benchmark reduction when ECQ+MECQ was in place. Echoing the findings in the literature (David and Pienknagura 2020), this may be related to the lockdown enforcement cost or tendency to comply. It is easier for the government to monitor and enforce lockdown measures with larger employers and becomes much costlier when the firms are small and likely informal as well. It is also possible that larger firms chose to be more compliant with the lockdown policies. The differential effects, however, decreased considerably when the lockdown was relaxed to GCQ and MGCQ. This is expected as gaps in enforcement costs or compliance tendency closed under less stringent lockdown.

**Table 2B: Effects of Lockdown Measures by Destination City Firm Size Composition (Baseline)**

Variables	Models		
	1	2	3
<b>Benchmark effects</b>			
ECQ+MECQ	-0.534*** (0.007)	-0.417*** (0.009)	-0.427*** (0.008)
GCQ	-0.342*** (0.010)	-0.201*** (0.010)	-0.215*** (0.010)
MGCQ	-0.256*** (0.006)	-0.153*** (0.007)	-0.163*** (0.007)
ECQ+MECQ dummy × Employment share of medium and large firms	-0.241*** (0.020)	-0.162*** (0.016)	-0.186*** (0.017)
GCQ dummy × Employment share of medium and large firms	-0.161*** (0.026)	-0.107*** (0.021)	-0.119*** (0.021)
MGCQ dummy × Employment share of medium and large firms	-0.169*** (0.019)	-0.096*** (0.016)	-0.107*** (0.016)
Origin and destination dummies	Yes	Yes	No
AR(1)	No	Yes	Yes
Origin-destination dummy	No	No	Yes
Observations	931,233	902,924	902,924
Adjusted R-squared	0.262	0.321	0.384

AR(1) = autoregressive term, lag 1; ECQ = enhanced community quarantine; GCQ = general community quarantine; MECQ = modified enhanced community quarantine; MGCQ = modified general community quarantine; SE = standard errors; WFH = work-from-home.

Notes: 1. Other regressors not shown in the table include the road-based distance between the origin and destination (except model 3), number of working days in each week, whether the origin city's lockdown was more or less stringent than that of destination city, numbers of cases in destination and origin cities in the past two weeks.

2. Standard errors are clustered at the destination-week level.

3. \*\*\*, \*\*, \* indicate significant coefficients at 1%, 5%, 10%, respectively.

Source: Authors' calculations.

### C. Robustness Check

We consider three sensitivity analyses to test robustness of the results presented above. First, there was a large number of short-distance trips in the data, for instance those found moving within a barangay.

A considerable share of these trips may not have been related to work, even if they took place during peak hours. Thus, they may have different patterns in terms of responding to the lockdown measures. We excluded within-barangay flows, which account for 40% of total flows, to examine whether the baseline results are retained among the remaining flows. The estimates are reported in Tables 3A and 3B.

**Table 3A: Effects of Lockdown Measures by Destination City Industrial Composition (Excluding Within-Barangay Flows)**

Variables	Model 1		Model 2		Model 3	
	$\beta$	SE	$\beta$	SE	$\beta$	SE
<b>Benchmark effects</b>						
ECQ+MECQ	-0.599***	(0.020)	-0.460***	(0.018)	-0.476***	(0.018)
GCCQ	-0.284***	(0.023)	-0.153***	(0.020)	-0.166***	(0.020)
MGCQ	-0.279***	(0.020)	-0.146***	(0.017)	-0.162***	(0.017)
<b>ECQ+MECQ dummy × Employment share of industry category</b>						
Primary	0.386***	(0.071)	0.311***	(0.058)	0.316***	(0.060)
Power, utilities, construction	-0.443***	(0.109)	-0.336***	(0.085)	-0.367***	(0.087)
Trade, transport	0.316***	(0.038)	0.212***	(0.030)	0.241***	(0.031)
Hospitality, recreation	-0.131*	(0.067)	-0.110*	(0.056)	-0.125*	(0.057)
WFH-friendly tertiary	-0.342***	(0.052)	-0.249***	(0.043)	-0.276***	(0.044)
Non-WFH-friendly tertiary	-0.342***	(0.065)	-0.200***	(0.054)	-0.245***	(0.055)
<b>GCCQ dummy × Employment share of industry category</b>						
Primary	0.155	(0.093)	0.037	(0.079)	0.047	(0.080)
Power, utilities, construction	-0.378**	(0.126)	-0.324**	(0.108)	-0.345**	(0.110)
Trade, transport	0.057	(0.048)	0.014	(0.041)	0.022	(0.041)
Hospitality, recreation	-0.129	(0.088)	-0.111	(0.073)	-0.126	(0.074)
WFH-friendly tertiary	-0.511***	(0.052)	-0.395***	(0.046)	-0.420***	(0.046)
Non-WFH-friendly tertiary	-0.295***	(0.077)	-0.108	(0.066)	-0.129	(0.066)
<b>MGCQ dummy × Employment share of industry category</b>						
Primary	0.259***	(0.069)	0.165**	(0.058)	0.183**	(0.060)
Power, utilities, construction	-0.249*	(0.098)	-0.146	(0.083)	-0.159	(0.083)
Trade, transport	0.231***	(0.035)	0.127***	(0.031)	0.145***	(0.031)
Hospitality, recreation	-0.101	(0.072)	-0.097	(0.063)	-0.098	(0.064)
WFH-friendly tertiary	-0.537***	(0.059)	-0.405***	(0.052)	-0.419***	(0.052)
Non-WFH-friendly tertiary	-0.169**	(0.056)	-0.117*	(0.048)	-0.128**	(0.049)
Origin and destination dummies		Yes		Yes		No
AR(1)		No		Yes		Yes
Origin-destination dummy		No		No		Yes
Observations		931,233		902,924		902,924
Adjusted R-squared		0.266		0.323		0.386

AR(1) = autoregressive term, lag 1; ECQ = enhanced community quarantine; GCCQ = general community quarantine; MECQ = modified enhanced community quarantine; MGCQ = modified general community quarantine; SE = standard errors; WFH = work-from-home.

Notes: 1. Other regressors not shown in the table include the road-based distance between the origin and destination (except model 3), number of working days in each week, whether the origin city's lockdown was more or less stringent than that of destination city, numbers of cases in destination and origin cities in the past two weeks.

2. Standard errors are clustered at the destination-week level.

3. \*\*\*, \*\*, \* indicate significant coefficients at 1%, 5%, 10%, respectively.

Source: Authors' calculations.



**Table 3B: Effects of Lockdown Measures by Destination City Firm Size Composition  
(Excluding Within-Barangay Flows)**

Variables	Models		
	1	2	3
<b>Benchmark effects</b>			
ECQ+MECQ	-0.536*** (0.007)	-0.418*** (0.009)	-0.429*** (0.009)
GCQ	-0.342*** (0.010)	-0.202*** (0.010)	-0.217*** (0.010)
MGCQ	-0.257*** (0.006)	-0.154*** (0.007)	-0.164*** (0.007)
ECQ+MECQ dummy × Employment share of medium and large firms	-0.240*** (0.020)	-0.162*** (0.016)	-0.186*** (0.017)
GCQ dummy × Employment share of medium and large firms	-0.160*** (0.026)	-0.107*** (0.021)	-0.118*** (0.022)
MGCQ dummy × Employment share of medium and large firms	-0.168*** (0.019)	-0.096*** (0.016)	-0.106*** (0.016)
Origin and destination dummies	Yes	Yes	No
AR(1)	No	Yes	Yes
Origin-destination dummy	No	No	Yes
Observations	931,233	902,924	902,924
Adjusted R-squared	0.264	0.322	0.385

AR(1) = autoregressive term, lag 1; ECQ = enhanced community quarantine; GCQ = general community quarantine; MECQ = modified enhanced community quarantine; MGCQ = modified general community quarantine; SE = standard errors; WFH = work-from-home.

Notes: 1. Other regressors not shown in the table include the road-based distance between the origin and destination (except model 3), number of working days in each week, whether the origin city's lockdown was more or less stringent than that of destination city, numbers of cases in destination and origin cities in the past two weeks.

2. Standard errors are clustered at the destination-week level.

3. \*\*\*, \*\*, \* indicate significant coefficients at 1%, 5%, 10%, respectively.

Source: Authors' calculations.

Second, Table 1A shows that a significant number of OD pairs disappeared completely from the data when COVID-19 broke out and some of them re-emerged in later weeks when the pandemic eased with relaxed lockdown. We constructed a balanced panel of city pairs to take into account these ODs. The flows are set at 0 when they are not observed in the data for certain weeks. The estimates with this balanced panel are reported in Tables 4A and 4B.

**Table 4A: Effects of Lockdown Measures by Destination City Industrial Composition (Balanced Panel of City Pairs)**

Variables	Model 1		Model 2		Model 3	
	$\beta$	SE	$\beta$	SE	$\beta$	SE
<b>Benchmark effects</b>						
ECQ+MECQ	-0.454***	(0.023)	-0.321***	(0.020)	-0.425***	(0.019)
GQC	-0.066**	(0.025)	-0.005	(0.020)	-0.078***	(0.020)
MGCQ	-0.082***	(0.022)	-0.009	(0.017)	-0.080***	(0.017)
<b>ECQ+MECQ dummy × Employment share of industry category</b>						
Primary	0.283***	(0.080)	0.244***	(0.068)	0.277***	(0.067)
Power, utilities, construction	-0.562***	(0.123)	-0.405***	(0.097)	-0.405***	(0.092)
Trade, transport	0.308***	(0.041)	0.212***	(0.033)	0.212***	(0.032)
Hospitality, recreation	-0.205**	(0.075)	-0.140*	(0.063)	-0.164**	(0.060)
WFH-friendly tertiary	-0.433***	(0.059)	-0.305***	(0.051)	-0.315***	(0.048)
Non-WFH-friendly tertiary	-0.332***	(0.076)	-0.202**	(0.064)	-0.209***	(0.061)
<b>GQC dummy × Employment share of industry category</b>						
Primary	-0.089	(0.099)	-0.146	(0.082)	-0.099	(0.084)
Power, utilities, construction	-0.382**	(0.138)	-0.259*	(0.104)	-0.292**	(0.107)
Trade, transport	0.050	(0.051)	0.006	(0.040)	-0.012	(0.040)
Hospitality, recreation	-0.321***	(0.092)	-0.212**	(0.073)	-0.202**	(0.071)
WFH-friendly tertiary	-0.692***	(0.058)	-0.472***	(0.048)	-0.526***	(0.048)
Non-WFH-friendly tertiary	-0.230**	(0.088)	-0.051	(0.069)	-0.098	(0.070)
<b>MGCQ dummy × Employment share of industry category</b>						
Primary	0.140	(0.072)	0.074	(0.056)	0.111	(0.061)
Power, utilities, construction	-0.361**	(0.114)	-0.210*	(0.086)	-0.218*	(0.085)
Trade, transport	0.176***	(0.039)	0.077*	(0.030)	0.105***	(0.030)
Hospitality, recreation	-0.208**	(0.080)	-0.137*	(0.061)	-0.151*	(0.064)
WFH-friendly tertiary	-0.578***	(0.064)	-0.395***	(0.051)	-0.463***	(0.051)
Non-WFH-friendly tertiary	-0.183**	(0.064)	-0.114*	(0.050)	-0.100*	(0.051)
Origin and destination dummies		Yes		Yes		No
AR(1)		No		Yes		Yes
Origin-destination dummy		No		No		Yes
Observations		1,149,138		1,108,514		1,108,514
Adjusted R-squared		0.213		0.303		0.356

AR(1) = autoregressive term, lag 1; ECQ = enhanced community quarantine; GQC = general community quarantine; MECQ = modified enhanced community quarantine; MGCQ = modified general community quarantine; SE = standard errors; WFH = work-from-home.

Notes: 1. Other regressors not shown in the table include the road-based distance between the origin and destination (except model 3), number of working days in each week, whether the origin city's lockdown was more or less stringent than that of destination city, numbers of cases in destination and origin cities in the past two weeks.

2. Standard errors are clustered at the destination-week level.

3. \*\*\*, \*\*, \* indicate significant coefficients at 1%, 5%, 10%, respectively.

Source: Authors' calculations.

**Table 4B: Effects of Lockdown Measures by Destination City Firm Size Composition  
(Balanced Panel of City Pairs)**

Variables	Models		
	1	2	3
<b>Benchmark effects</b>			
ECQ+MECQ	-0.410*** (0.007)	-0.287*** (0.007)	-0.399*** (0.007)
GCQ	-0.171*** (0.011)	-0.079*** (0.009)	-0.167*** (0.009)
MGCQ	-0.108*** (0.007)	-0.047*** (0.006)	-0.113*** (0.006)
ECQ+MECQ dummy × Employment share of medium and large firms	-0.280*** (0.022)	-0.194*** (0.018)	-0.179*** (0.018)
GCQ dummy × Employment share of medium and large firms	-0.180*** (0.027)	-0.102*** (0.021)	-0.107*** (0.021)
MGCQ dummy × Employment share of medium and large firms	-0.175*** (0.021)	-0.090*** (0.017)	-0.099*** (0.016)
Origin and destination dummies	Yes	Yes	No
AR(1)	No	Yes	Yes
Origin–destination dummy	No	No	Yes
Observations	1,149,138	1,108,514	1,108,514
Adjusted R-squared	0.211	0.303	0.355

AR(1) = autoregressive term, lag 1; ECQ = enhanced community quarantine; GCQ = general community quarantine; MECQ = modified enhanced community quarantine; MGCQ = modified general community quarantine.

Notes: 1. Other regressors not shown in the table include the road-based distance between the origin and destination (except model 3), number of working days in each week, whether the origin city's lockdown was more or less stringent than that of destination city, numbers of cases in destination and origin cities in the past two weeks.

2. Standard errors are clustered at the destination-week level.

3. \*\*\*, \*\*, \* indicate significant coefficients at 1%, 5%, 10%, respectively.

Source: Authors' calculations.

Third, certain degree of symmetry is expected in work-related mobility between morning inflows and afternoon outflows. Hence, we constructed an afternoon sample containing all flows leaving the 300 cities between 4 p.m. and 10 p.m. to any city within 150 kilometers road-based distance. In regressions, we replace the destination (origin) city's characteristics with those of the origin (destination) city. The estimation results are reported in Tables 5A and 5B.

**Table 5A. Effects of Lockdown Measures by Destination City Industrial Composition (Afternoon Flows Leaving the Top 300 Cities)**

Variables	Model 1		Model 2		Model 3	
	$\beta$	SE	$\beta$	SE	$\beta$	SE
<b>Benchmark effects</b>						
ECQ+MECQ	-0.622***	(0.008)	-0.536***	(0.010)	-0.555***	(0.011)
GCQ	-0.240***	(0.010)	-0.233***	(0.010)	-0.241***	(0.009)
MGCQ	-0.273***	(0.008)	-0.264***	(0.008)	-0.273***	(0.008)
<b>ECQ+MECQ dummy × Employment share of industry category</b>						
Primary	0.441***	(0.023)	0.394***	(0.022)	0.407***	(0.021)
Power, utilities, construction	-0.453***	(0.027)	-0.385***	(0.027)	-0.421***	(0.026)
Trade, transport	0.340***	(0.014)	0.302***	(0.013)	0.324***	(0.013)
Hospitality, recreation	-0.074***	(0.022)	-0.038	(0.020)	-0.040	(0.021)
WFH-friendly tertiary	-0.304***	(0.014)	-0.283***	(0.014)	-0.304***	(0.013)
Non-WFH-friendly tertiary	-0.314***	(0.018)	-0.303***	(0.017)	-0.335***	(0.016)
<b>GCQ dummy × Employment share of industry category</b>						
Primary	0.168***	(0.030)	0.106***	(0.030)	0.119***	(0.028)
Power, utilities, construction	-0.364***	(0.040)	-0.267***	(0.040)	-0.286***	(0.037)
Trade, transport	0.086***	(0.020)	0.101***	(0.020)	0.092***	(0.019)
Hospitality, recreation	-0.159***	(0.029)	-0.114***	(0.027)	-0.124***	(0.026)
WFH-friendly tertiary	-0.532***	(0.017)	-0.463***	(0.018)	-0.488***	(0.019)
Non-WFH-friendly tertiary	-0.310***	(0.031)	-0.325***	(0.032)	-0.335***	(0.030)
<b>MGCQ dummy × Employment share of industry category</b>						
Primary	0.177***	(0.026)	0.149***	(0.021)	0.154***	(0.020)
Power, utilities, construction	-0.373***	(0.029)	-0.269***	(0.029)	-0.297***	(0.028)
Trade, transport	0.199***	(0.014)	0.220***	(0.013)	0.223***	(0.013)
Hospitality, recreation	-0.101*	(0.042)	-0.090**	(0.027)	-0.101***	(0.028)
WFH-friendly tertiary	-0.475***	(0.019)	-0.425***	(0.018)	-0.437***	(0.018)
Non-WFH-friendly tertiary	-0.197***	(0.018)	-0.178***	(0.017)	-0.186***	(0.017)
Origin and destination dummies		Yes		Yes		No
AR(1)		No		Yes		Yes
Origin-destination dummy		No		No		Yes
Observations		906,864		875,839		875,839
Adjusted R-squared		0.263		0.307		0.369

AR(1) = autoregressive term, lag 1; ECQ = enhanced community quarantine; GCQ = general community quarantine; MECQ = modified enhanced community quarantine; MGCQ = modified general community quarantine; SE = standard errors; WFH = work-from-home.

Notes: 1. Other regressors not shown in the table include the road-based distance between the origin and destination (except model 3), number of working days in each week, whether the origin city's lockdown was more or less stringent than that of destination city, numbers of cases in destination and origin cities in the past two weeks.

2. Standard errors are clustered at the destination-week level.

3. \*\*\*, \*\*, \* indicate significant coefficients at 1%, 5%, 10%, respectively.

Source: Authors' calculations.

**Table 5B: Effects of Lockdown Measures by Destination City Firm Size Composition  
(Afternoon Flows Leaving the Top 300 Cities)**

Variables	Models		
	1	2	3
<b>Benchmark effects</b>			
ECQ+MECQ	-0.530*** (0.004)	-0.454*** (0.007)	-0.468*** (0.008)
GCQ	-0.296*** (0.005)	-0.271*** (0.006)	-0.287*** (0.006)
MGCQ	-0.273*** (0.003)	-0.242*** (0.004)	-0.253*** (0.005)
ECQ+MECQ dummy × Employment share of medium and large firms	-0.247*** (0.007)	-0.222*** (0.007)	-0.242*** (0.006)
GCQ dummy × Employment share of medium and large firms	-0.160*** (0.009)	-0.153*** (0.010)	-0.155*** (0.009)
MGCQ dummy × Employment share of medium and large firms	-0.132*** (0.007)	-0.134*** (0.007)	-0.138*** (0.006)
Origin and destination dummies	Yes	Yes	No
AR(1)	No	Yes	Yes
Origin-destination dummy	No	No	Yes
Observations	906,864	875,839	875,839
Adjusted R-squared	0.261	0.306	0.368

AR(1) = autoregressive term, lag 1; ECQ = enhanced community quarantine; GCQ = general community quarantine; MECQ = modified enhanced community quarantine; MGCQ = modified general community quarantine.

Notes: 1. Other regressors not shown in the table include the road-based distance between the origin and destination (except model 3), number of working days in each week, whether the origin city's lockdown was more or less stringent than that of destination city, numbers of cases in destination and origin cities in the past two weeks.

2. Standard errors are clustered at the destination-week level.

3. \*\*\*, \*\*, \* indicate significant coefficients at 1%, 5%, 10%, respectively.

Source: Authors' calculations.

Patterns of heterogeneous mobility reduction emerging from these exercises are qualitatively the same as those from the baseline case despite significant data variations. Lockdown effects on work-related mobility vary across cities with different industrial and firm size compositions. Cities with higher industrial concentration in utilities, construction, and tertiaries and with larger employers were more adversely affected. Moreover, mobility responses to lockdown measures of varying stringency also depended on the employment characteristics of a city. When less stringent lockdown was in place, more mobility recovery occurred in cities heavy in non-WFH-friendly and power, utilities, and construction sectors, and less so in cities with more WFH-friendly sectors.<sup>9</sup>

<sup>9</sup> There are a couple of noteworthy differences between the results of the sensitivity and baseline analyses. The relative effects for share of hospitality and recreation employment and share of WFH-friendly employment increase significantly in magnitude when the balanced panel is used to include disappeared city pairs. This suggests that industries in these two categories (e.g., restaurants and call centers) served as the major economic connectivity between some cities, which could have been cut down during lockdowns. Besides, we find larger benchmark effects of mobility reduction under all three lockdown policies with afternoon outflows than morning inflows. This may be because the working hours were shortened and some commuters left their workplaces early.

## VII. DISCUSSION AND CONCLUSION

While NPIs have proved to be effective in reducing mobility to control COVID-19 spread in advanced countries, there is little evidence on whether and how similar measures have worked in lower-income countries. An equally important question is how they have impacted the economy. This study sheds light on these questions through studying the lockdown policies within 6 months since the breakout of COVID-19 in the Philippines.

Consistent with findings from advanced countries, community quarantines were an effective policy for reducing urban mobility in the Philippines during crises, and mobility was highly responsive to different degrees of lockdown stringency. By design and in practice, lockdown measures were less effective in limiting mobility for manufacturing-based cities. This could be economically rational as Furceri, Kothari, and Zhang (2021) find that keeping the industrial sector open lessens economic costs without worsening health outcomes because industrial activities are less contact intensive.

As main target of lockdown policies, the tertiary sector was more severely affected (aside from trade and transport industries). However, given the diversity of jobs and businesses within the tertiary sector, we see distinct policy impacts on cities that have a higher share of workforce in industries amenable versus not amenable to working from home. Low-skilled service workers could still suffer from the aftereffects of lockdowns when returning to the workplace, as they were dependent on demand from workers who have shifted to home office and stayed there even under less stringent lockdown (Althoff et al. 2021). Policy makers may want to take this into account in designing assistance programs or deciding allocation of resources within their jurisdictions. More livelihood support may be needed for cities and municipalities that have a larger population share working in non-WFH friendly tertiary industries.

Cities relying on tourism wherein hospitality and recreation workers cluster also need special policy attention. Although our results suggest these cities were subject to moderate additional mobility reduction due to lockdown, the actual loss of business could be substantial as people are sensitive to pandemic threat more than to policy restrictions, and long-distance (including international) travelers are not captured in our data. Programs that help these workers to transfer to other sectors that reopened or newly developed may be warranted to mitigate the adverse impacts of COVID-19 and lockdown policies.

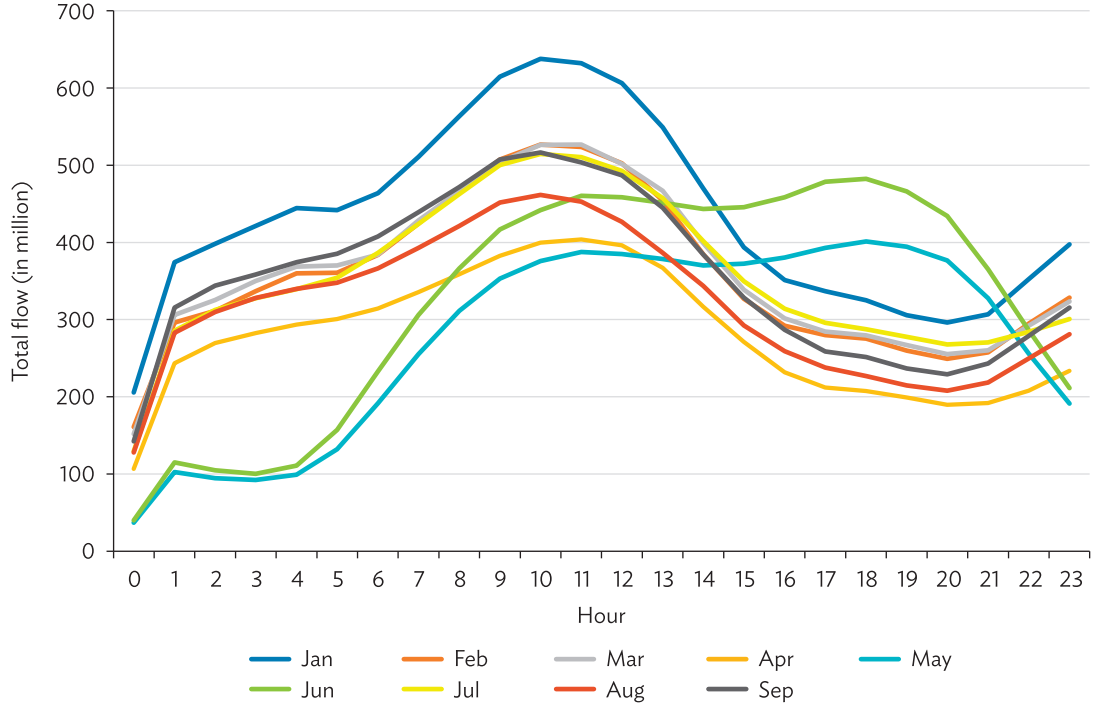
The finding that lockdown measures were less effective in cities dominated by micro and small firms is also informative. Employees of these firms have lower income and limited access to health and social security services in general. They are thus exposed to greater health and financial risks when continuing to work under lockdown. Supplementary NPIs may be needed to protect them from infection and financial support to ensure their access to necessary health services.

Looking ahead, as health and climate-related disasters increase in prevalence, public interventions including social safety nets need to be designed more proactively. An understanding of the implications of emergency measures for cities of differing economic profiles can contribute to efficient utilization of public resources.

Finally, our study demonstrates the usefulness of big data for understanding policy impacts and supporting informed policy making. Its granularity in space and time complements traditional data, such as those based on large-scale household or firm surveys, which often contain better measures of economic outcomes. Linking the two types of data allows for more meaningful and relevant analyses, for instance on the cost-effectiveness of these lockdown policies.

# APPENDIX

**Figure A1: Hourly Profiles of Total Flows by Month**



Source: Authors' calculations.

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# COVID-19 Lockdown Policy and Heterogeneous Responses of Urban Mobility

*Evidence from the Philippines*

To assess the effect of community quarantines on urban mobility in the Philippines after the initial outbreak of coronavirus disease, this paper analyzes a new source of data: cellphone-based origin-destination flows. The analysis of 2020 data reveals that the impact of lockdowns was strongest and most persistent in cities where a high share of workforce was employed in work-from-home-friendly sectors or medium and large enterprises. The paper compares findings with cross-country evidence on lockdowns and mobility, discusses the economic implications for containment policies in the Philippines, and suggests directions for additional research.

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