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COVID-19 and Waste: Evidence from New York City and Taiwan

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Abstract

Existing literature broadly suggests that Coronavirus Disease (COVID-19) has many short-term benefits on the environment due to lockdown and factory shutdown. This paper examines the impact of COVID-19 on waste disposal, specifically metal, glass, and plastic output in the City of New York (NYC). We find a significant increase in waste output after the breakout of COVID-19 in NYC. In particular, the waste increases are concentrated on the more wealthy communities. An additional difference-in-differences analysis, using Taiwan as a control group, further confirms our findings. Our results shed new light on the potential long-term implications of COVID-19 due to changes in human consumption behavior.

Keywords: COVID-19, Waste Output, Difference-in-Differences, City of New York, Taiwan

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1. Introduction

Coronavirus Disease (COVID-19), a novel infectious disease, has caused huge disruptions to the whole world since its initial outbreak in the last quarter of 2019. With over 218 million confirmed cases and 4.5 million deaths, regions were going in and out of lockdown to stop the spread of pathogens (Lau 2020). Consequently, supply chains collapsed, economic activity stalled, and municipal systems slowed. Among these, the environment has shown promising signs of recovering as current environmental indicators continue to show a better outlook than before (Saadat et al. 2020).

While current literature broadly suggests that COVID-19 has many short-term benefits, our paper argues the contrary. Observing trends and current literature on digitalisation, our paper suggests impacts from COVID-19 may not be as short-term as implied in current literature. The pandemic has forced many cities into lockdown, which induced a new workstyle: working from home. This workstyle is part of a larger trend towards a more home-based economy and a more digitalised world. These trends can be seen across the globe through the increasing numbers of online shopping platforms, transforming towards online banking services, increasing usage of artificial intelligence, and more. However, this paradigm shift is accompanied by many unforeseeable consequences.

Our paper uses COVID-19 as a scope to investigate one of the many consequences of an increasingly home-based economy. This paper examines the influences of COVID-19 on waste disposal, specifically Metal, Glass, and Plastic (MGP) output. As COVID-19 foreshadows a move towards a more digitalised, home-based economy, environmental influences may also have long-term implications (Bick et al., 2020). In our analysis, we use waste data provided by The City of New York Department of Sanitation (DSNY) and The Environmental Protection Administration (EPA) of Taiwan.

In the first part of our analysis, we construct an Ordinary Least Squares (OLS) regression model to find the relationship between MGP output and COVID-19 outbreak, using three different indicators: lockdown, case number, and outbreak dates. Following this, we provide a cross-sectional analysis of income, differentiating between differences in output in high-income and low-income households. Finally, we use a Difference-in-Differences (DID) specification to make causal inferences about the relationship between COVID-19 and MGP growth. Although in general MGP levels are seen to increase, our final subgroup DID analysis attributes this increase mainly towards high-income households. This phenomenon can be understood from the fact that higher-income households would be the first to access and afford more frontline services, thus marking a more drastic change in lifestyle and transfers in waste output. Finally, we provide policy recommendations for different stakeholders in an attempt to address possible environmental externalities in the future.

Through our findings, we evaluate potential policies that could prolong the environmental benefits brought by the exogenous shock of COVID-19 and how they can be implemented in the future. We highlight the importance of adapting to the developing home economy that primarily utilizes delivery services for food, commerce, and utilities. The resulting packaging poses a great opportunity to develop long-lasting municipal recycling systems; however, if dedicated efforts are not made, the entire waste management system faces collapse. We also reference innovative solutions to the problems caused by throwaway culture. Finally, we propose harsher punitive measures upon firms who refuse to change production to cleaner methods of manufacturing. As a result, the incentive to switch to biodegradable plastics and higher recycling rates should help close the gap to a circular economy.

This research could be improved if there were explicit links between COVID-19 and the home-based economy. However, at this stage, it is only possible to observe current trends to make inferences about future possibilities. Nevertheless, an increasing amount of evidence and literature reveals that this paradigm shift towards a digitalised world is imminent. Our research could have been improved with more nuanced data, which is not currently available, and with investigations into other environmental factors. Even so, our research provides valuable insight into long-term implications, which isn't mentioned in the current literature, of COVID-19, and highlights the downfalls of COVID-19.

2. Background

Following the environmental revolution in the late 1960s, economists have been increasingly concerned with environment-related market failures, specifically Climate Change (Cropper and Oates, 1992; UNFCCC, 1992). Whether for personal, economic, or political aims, governments have been working to regulate anthropogenic pollution, as seen in the Clean Air Act (CAA, 1970), Paris Agreement (PA, 2015), and more. Furthermore, capital investors have begun to take notice of a firm's environmental, social, governance (ESG) ratings, emphasizing the current trend towards a more environmentally-conscious society driven by the increasingly imminent global warming situation (UNFCCC, 1992; Lee. 2011) .

In addition to Climate Change, another ongoing trend is the shift towards a more remote lifestyle, which includes working from home, online shopping, and reliance on delivery services (Bick et al., 2020; Lissitsa and Kol, 2016; Limayem et al., 2000). The recent outbreak of the coronavirus disease (COVID-19) in 2020, only served to fuel this embryonic lifestyle as commuting between work and home was eradicated. Enforced lockdowns imposed restrictions on many industries, resulting in stagnating levels of economic activity. As a result, firms are forced to shut down to cut losses thereby increasing unemployment rates (Gangopahyaya and Garett, 2020). On the other hand, tech companies such as Zoom Inc. and Webex thrived, as lockdown socialisation was reduced to being held remotely (BBC, 2021). On a wider scale, the COVID-19 situation is just a turning point that foreshadows the possible extent of globalisation, where technologically developed markets dominate the economy (Degryse, 2016).

Fundamental industrial and behavioral changes of this inevitable paradigm shift can be inferred from that of the recent COVID-19 pandemic, including permanently working from home and online video conferences, (Bick et al., 2020; LSC, 2021; Degryse, 2016). However, some of the often overlooked aspects of globalisation are the environmental implications, as human pollution may change from one form to another. As shopping takes an online form, does wasteful packaging increase? Should government regulations adapt to these changes? These questions are best answered by investigations into how COVID-19, an insight into a more digitalised, remote economy, impacts anthropogenic environmental outputs, and how governments can respond to these changes.

Current literature primarily revolves around the impact of lockdown measures on air quality. According to Bashir et al. (2020a), the implementation of mandatory lockdown in urban environments has resulted in drastic reductions in environmental pollution. El Zowalaty et al. (2020) find that social distancing directives and quarantines have led to substantial decreases in commuting and Wang et al. (2020) confirms that this helped air quality in urban neighbourhoods.

Research also shows that urban neighbourhoods experience the economic growth and other effects of digitalisation far more than rural communities (Maiti et. al 2019). Sarfraz et al. (2020), a study focused on New York, finds notable reductions in pollution levels; Bashir et al. (2020a) coincide with these results, reaching a similar conclusion in California. However, Zangari et al. (2020) argue that positive benefits are just continuations of the improvements over the years, and are sceptical about the true positive impacts of COVID-19 on the environment.

Challenges in solid waste management have gotten worse since the first outbreak as citizens' reliance on plastics for safety and hygienic purposes have increased (Vanapalli. et al 2020). Saadat et al. (2020) and Bashir et al (2020b) both find that mandatory preventive measures, such as enforced mask-wearing, have resulted in the generation of mass medical waste. Research calls for innovation to figure out more sustainable waste management techniques as the current rebound of single-use plastic production is unsustainable (Silva et al. 2020). A gap exists within the literature on the long term impacts of the pandemic on waste generation as no studies have progressed into this year.

Furthermore, other studies conducted on worldwide preventive measures have expanded to explore more wide-reaching environmental impacts, such as energy implications. As stated by Klemeš et al. (2020), the energy and related emissions of the vaccine life cycle are reaching significant figures.

As seen above, current literature is largely focused on air quality, energy consumption, and medical waste and offers a variety of explanations for improved environmental quality. There is a clear paucity of literature investigating the impact of the pandemic on waste production, specifically plastics, which our paper focuses on. Furthermore, consistent conjecture papers find that GHG impacts of COVID-19 are fleeting, whereas our paper suggests long-term policy implications of the more permanent remote lifestyle.

The paper most closely linked to us is Sarkodie et al. (2020)'s paper, which examines the impacts of COVID-19 on waste management in the first few months of the pandemic. Sarkodie et al. (2020) find that the quantity of waste increases across regions under lockdown. In an attempt to halt the global proliferation of cases, all types of protective equipment were under high demand. A monthly global expenditure of 1.6 million plastic-based protective goggles, 76 million plastic-based examination masks and 89 million plastic-based medical masks was predicted by the World Health Organisation (WHO) (Andersen 2020). Sarkodie et al. (2020) attributed the observed increases in single-use plastic products to panic buying behaviours, implying that these observations are restricted to medical waste and short term. This paper differs from Sarkodie et al. (2020) as we now have sufficient lockdown data collected, and no assumptions are needed in our empirical analysis. Furthermore, our paper discusses long-lasting policy implications for the digitalisation trend, brought by an increasing work from home environment, which is not included in the current literature.

We chose New York City (NYC) as our subject of interest. As the pandemic proliferated in the United States of America (USA), NYC became a hotspot for infections in the USA (Zangari et al. 2020). It is also a global financial hub, the ideal place for the effects of digitalization to be consistently present. Since the initial confirmed case on March 1st 2020, the government has implemented multiple lockdowns and strengthened social distancing measures.

For our Difference-in-Differences (DID) model, Taiwan was chosen as the control group because it is highly developed, digitalised, and most importantly, has suffered limited impacts from the COVID-19 pandemic in our study period.[1] Taiwan's information and communications technology sector ranks as the largest in the world as a share of GDP, with the nation's export market share in computer, electronics, and optical industry ranking among the top as well. The first 5G network in the nation was set up in June 2020 and over 90% of the population have access to the internet. The market in Taiwan benefits from the high penetration and connectivity.

While being composed of totally different geographies, Taiwan and New York both reflect upon the developed, modern world where digitalization is expected to dramatically change societies more than anywhere else. The two economies are heavily reliant on exports in the services sector meaning changes to job dynamics will impact both.

3. Data

For the purpose of our investigation, NYC was chosen as the subject of interest as it was one of the first cities to experience a breakout in the United States of America. Since then, over 1.03 million cases have been confirmed as of August 30th 2021, providing us with a longer study period and more extreme results, theoretically making it easier to observe differential changes. Furthermore, the city's community board and borough system allow us to investigate changes between demographics within the city. Other than providing a correlational link between NYC's COVID-19 situation and waste output, we were interested in establishing a causal relationship. This relationship was established with a Difference-in-Differences (DID) approach as represented in Section 4.3. Taiwan was chosen as our control group as it was one of the few places in the world that had a consistently low case count, meaning COVID-19's

[1] Taiwan had been a pandemic success story until the outbreak of COVID-19 in late May of 2021.

influence should be minimal. (CNBC. 2020) The breakup of Taiwan into its 22 different districts also allows for investigation in urban, suburban and rural areas.

Our main source of NYC data comes from NYC government departments and NYC open data, which is published by official agencies for the public. Our Taiwan data comes from the Ministry of the Interior open statistics and the Environmental Protection Administration (EPA) of Taiwan, both of which are either published by reliable official government partners or government departments.[2]

3.1 Criterion variables

In this paper, we use two ways to identify our criterion variable. In our Ordinary Least Squares Regression (OLS), as seen in sections 4.1 and 4.2, we directly use data from The Department of Sanitation in New York[3] (DSNY). Data is given in tons per day for each community district[4] in New York City, and is adjusted to a monthly standard.

Taiwan data used in Section 4.3 is retrieved from the Taiwan EPA, which is recorded in kilograms per month. Data is adjusted for seasonal fluctuations and growth rates by specifying the criterion variable with yearly growth[5]. This marks our second way of specifying the criterion variable. This specific adjustment is needed to fulfil the assumption of parallel trends. As seen in Table 1 below, the original Taiwan metal, glass, and plastics (MGP) growth rate is significantly higher than that of NYC's, therefore, we will adjust the data to represent

[2] LienJiang County refers to a group of small islands offshore from Taiwan island, known as "Matsu Islands". These islands are omitted because their data points are anomalous.
[3] The Department of Sanitation NY is the world's largest sanitation department and collects more than 10,500 metric tons of residential and institutional waste each day.
https://www1.nyc.gov/assets/dsny/site/resources/statistics/monthly-dsny-curbside-collections (Last accessed 01/06/2021)
[4] New York City's 59 community districts were created by local law in 1975, each representing a community board. These create opportunities for active participation in the political process and provision of services.
[5] Data is cleaned by yearly growth rates, each month is compared to the months in the previous year. For example, March 2019 and March 2018. This absorbs any fluctuations in waste, such as sudden spikes in waste during holidays.

growth of MGP instead. The adjusted growth rates are presented in Table 2. The benefit of this adjustment is that it not only accounts for seasonal fluctuations, caused by differing consumption patterns in holidays, but also accounts for the differences in measuring units[6].

Figure 1: Comparing MGP in NYC and Taiwan
(Jan 2016 - May 2021)

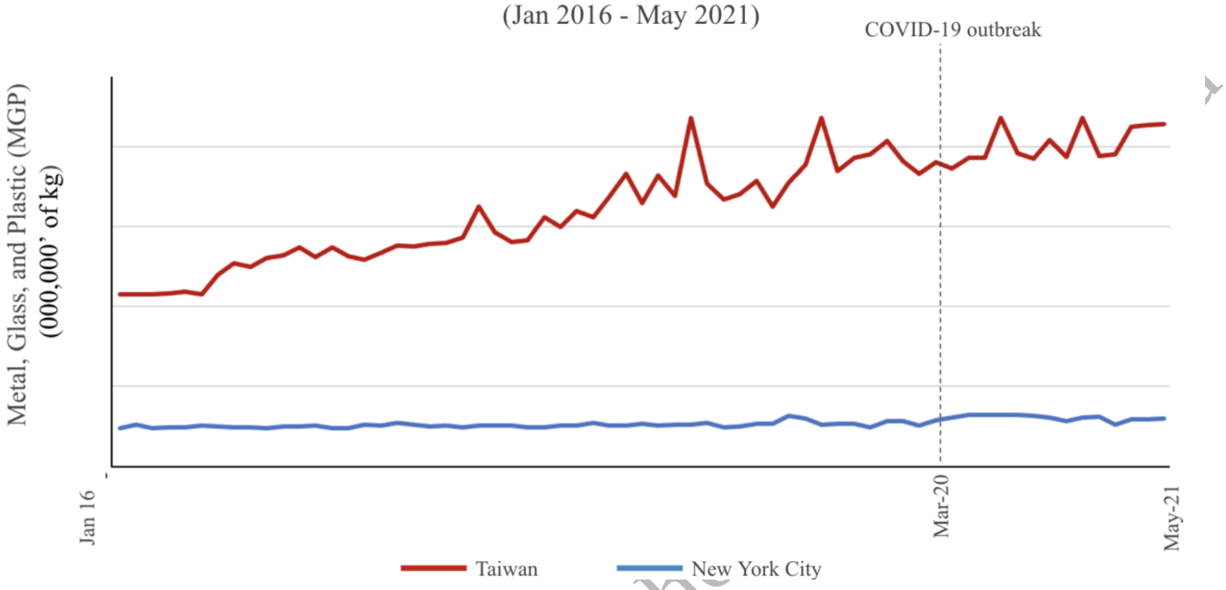
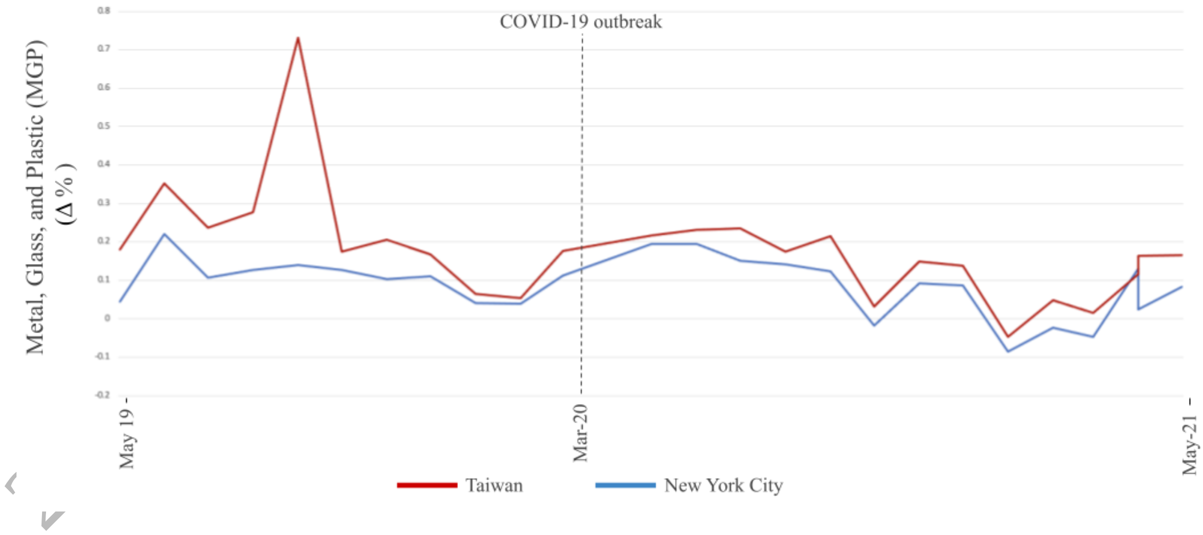


Figure 2: Comparing MGP Growth Rates in NYC and Taiwan
(May 2019 - May 2021)



[6]New York City data is measured in tons per day; Taiwan data is measured in kilograms per month. Adjustments are made to tons per month before proceeding to adjust for growth rates.

3.2 Independent variables

We will use two different measures to explore the impact of COVID-19, including lockdown and confirmed case number of infection. Our case number data is collected from the source of the NYC state health website, a GitHub[7] repository. Lockdown data is constructed using official NYC announcements, including the "New York State on PAUSE[8]" and "Micro-clustering policy[9]", and through analysing case rate, hospitalised rate, death rate, and hospital capacity according to these announcements. These are our independent variables for the OLS analysis in Section 4.1.

3.3 Control variables

Control variables included in this research are used to control for any socio-economic conditions, which may influence or bias our results, including population, population density, poverty rates, income, total housing units, and zonings. Note that some control variables are only used for analysis in Sections 4.1 and 4.2, and are replaced or omitted as Taiwan data is not available or comparable.

In our OLS regressions, our variables include population, population density, poverty rates, income, total housing units, and zonings. We collected poverty rate data from NYC Economic Opportunity[10]; total housing units, population[11] and population density data are retrieved from NYC Planning[12]; zoning[13] data is collected from the NYC GitHub Repository; income data is retrieved from Citizens' Committee for Children.

Our DID model omits poverty rates as these are not recorded or calculated in Taiwan. The changes are then attributed towards a similar measure: income. Zoning data is needed only

[7]Github is the largest source code host in the world with more than 28 million public repositories. https://github.com/nychealth/coronavirus-data (Last accessed 01/06/2021)

[8]"New York State on PAUSE" was a ten-point policy by Mayor Cuomo which restricted all dining to only take out or delivery, closed all non-essential businesses, and more. Adopted from March till July, 2020.

[9]"Micro-cluster policy" is a policy that aggressively responds to micro-clusters in order to limit COVID spread in a defined geographic area, and by doing so prevent broader viral transmission that would result in widespread economic shutdowns. Adopted from August, 2020 till May, 2021. https://www.governor.ny.gov/sites/default/files/atoms/files/MicroCluster_Metrics_10.21.20_FINAL.pdf

[10] NYC Economic Opportunity is an agency centered to develop policies and evaluate budgeting decisions. https://www1.nyc.gov/site/opportunity/poverty-in-nyc/poverty-measure.page (Last accessed on 01/06/2021)

[11]Note that population was adjusted for growth rates in the recent year as data has not been released to the public.

[12] NYC Planning is NYC's primary land use agency which is responsible for designing the city's physical and socioeconomic framework. https://www1.nyc.gov/site/planning/planning-level/nyc-population/nyc-population.page (Last accessed on 01/06/2021)

[13] Zoning refers to the major function of the sector, sections include residential, manufacturing and commercial. This is an important factor

in the OLS analysis to investigate changes in sectors for our treatment group, since there should be no changes to our control group, this is omitted in our DID model.This means that our DID specification only uses total housing units, income, population and population density as controls. We retrieved total housing units, population, and population density data from Taiwan's Ministry of the Interior; income data is retrieved from Census and Economic Information Center.

We analyse data including and excluding these control variables to ensure that differential changes are not caused by changes in these variables. Our results show that the regression is robust excluding and including the control variables, suggesting that changes are not due to differences in the control groups.

Table 3 illustrates all summary statistics. Panel A represents the summary statistics for NYC; panel B represents the summary statistics for Taiwan.

Table 1: Summary Statistics
Panel A: NYC

	N	Mean	S.D.	Min	50th	Max
MGP	1180	533.34	226.37	147.00	498.00	2820.0
MGP Growth	1180	7.23	29.69	-26.34	5.40	956.18
Income	1180	11.13	0.56	10.05	11.11	13.32
Housing Units	1180	10.96	0.33	9.86	10.96	11.83
Population	1180	11.82	0.34	10.88	11.83	12.45
Population Density	1180	10.54	0.63	8.78	10.51	11.65
Zoning	1135	1.01	0.32	0.00	1.00	2.00
Poverty Rate	1180	19.65	7.28	6.30	19.60	37.10

Panel B: Taiwan

	N	Mean	S.D.	Min	50th	Max
MGP	440	9107.04	9887.37	45.00	5075.00	95988.00
MGP Growth	440	10.32	43.57	-75.14	4.56	755.61
Income	440	7.30	0.73	6.91	7.04	9.68
Housing Units	440	12.10	1.45	7.90	12.05	14.24
Population	440	13.24	1.30	9.48	13.13	15.21
Population Density	440	6.36	1.56	2.40	6.62	9.19

4. Methodology

4.1 COVID-19 outbreak and lockdown in New York City (NYC)

We will begin by exploring New York City's (NYC) waste output in relation to COVID-19. We attempt to create a more holistic indicator by including different measures: lockdown, cases, outbreak dates and the interaction term of lockdown and cases, as impacts are often highly dependent. This analysis provides us with an indicator of COVID-19's influence on waste. The initial regression model is as following,

$$Y_{im} = \beta_1 \, PostCOVID19 + X_{im} + T_m + D_i + \varepsilon_i \tag{1}$$

Our dependent variable Y_{im} represents the amount of metal, glass, and plastics (MGP) disposed of in the m months in i districts. *PostCOVID19* is a dummy variable that contains our coefficient of interest β_1, indicating whether the date is after the outbreak of COVID-19 in NYC (March 2020). X_{im} represents all social and economic controls, including poverty rates, zoning, income, population, population density, and total housing units. T_m and D_i are monthly and borough fixed effects respectively, which control for variations in time and geographical location. We will fix for robust standard error, hence fulfilling the homoscedasticity assumption.

Different measures could be seen in the second regression equation represented by,

$$Y_{im} = \beta_1 \, Lockdown{*}Case + \beta_2 \, Lockdown + \beta_3 \, Case + X_{im} + T_m + D_i + \varepsilon_i \tag{2}$$

Lockdown is a dummy variable that indicates whether the district i is in lockdown on month m. This lockdown indicator will vary from the original *PostCOVID19* dummy variable, because of New York City's micro-clustering policy[14]. *Case* represents the number of cases in the community district in month m. *Lockdown*Case* is the interaction term that captures the non-linear impacts that lockdown may have dependent on case number. Our coefficients of

[14] For details, refer to Section 3.

interest are β_1, β_2, and β_3. The rest of the variables as specified in equation (1). Again, this regression is adjusted for robust standard errors.

Regressions are run with different combinations of *Lockdown*, *Case*, and *Lockdown*Case* to investigate differing impacts of each variable, as seen in Table 2. All combinations prove to be robust after adjusting for standard error, with and without demographic controls, this forms a strong correlation between COVID-19 and waste output.

4.2 Demographic analysis: Income

Income often has heterogeneous influences on waste output and a consumer's choice of goods; this could be seen in even the earliest of neo-classical economic theories (Gowdy and Mayumi, 2001). In this section, we attempt to tease out the differences in the response of richer consumers in comparison to poorer consumers. The regression model is as following,

$$Y_{im} = \beta_1 \, PostCOVID*Rich + \beta_2 \, PostCOVID*Poor + X_{im} + T_m + D_i + \varepsilon_i \tag{3}$$

Rich is a dummy variable indicating whether the district is the richest 30% of all districts. On the other hand, *Poor* is a dummy variable indicating whether the district is the poorest 30% of all districts. This methodology enables us to observe changes in the most extreme ends of the spectrum. All percentages are calculated using the NYC poverty rates. β_1 and β_2 represent our coefficients of interest, enabling us to observe differential changes in waste disposal between poorer districts and richer districts. For all other notations, please refer to equation (1). Since observations are likely to be correlated between districts, robust and clustered standard errors are adjusted at a community district level.

4.3 Difference-in-Differences: NYC and Taiwan

We will employ a difference-in-differences (DID) approach in an attempt to make a causal inference about the relationship between waste outputs, which may be influenced by an increasingly digitalised economy, and NYC after the outbreak (March 2020). The regression model can be written as,

$$\Delta Y_{im} = \beta_1 \, PostCOVID*NYC + X_{im} + T_m + D_i + \varepsilon_i \tag{4}$$

Our dependent variable ΔY_{im}, where Y_{im} represents the amount of metal, glass, and plastics (MGP) disposed of in the *m* month in district[15] *i*, captures the change in waste disposed. Δ compares changes in MGP disposal across a year, this accounts for apparent seasonal fluctuations. *PostCOVID* is a dummy variable that specifies whether month *m* is after the treatment outbreak (March 2020). *NYC* is the second dummy variable that specifies whether district *i* is in our treatment group: NYC. The interaction term *PostCOVID*NYC* presents our coefficient of interest β_1 , which illustrates the impact of COVID-19 on NYC in comparison to Taiwan. X_{im} represents social and economic controls for all *i* districts, including total housing units, log of income, population, and population density. These controls are needed as the changes to waste may be influenced by other social factors. T_m and D_i are monthly and borough fixed effects respectively, which control for variations in time and geographical location. We will adjust robust and clustered standard errors at a community district level, this again, fulfils the homoscedasticity assumption.

Following Section 4.2, a strong correlational relationship was found between high-income households' MGP output and COVID-19. In the following DID models we attempt to clarify this relationship. The regression is as following,

$$\Delta Y_{im} = \beta_1 \, PostCOVID*NYC + X_{im} + T_m + D_i + \varepsilon_i \tag{5}$$

The regression model is identical to the previous model; however, this DID was run strictly on households identified as $Rich_2$ in both Taiwan and NYC. We identified households in the top 30% of income, calculated in USD, as $Rich_2$; similarly, households in the bottom 30% of income, calculated in USD, were identified as $Poor_2$. Current literature explores relationships between online shopping, consumption and income (Gowdy and Mayumi, 2001;Milovic. 2021). This model allows us to expand on this by exploring how income may influence a household's MGP output during COVID-19, providing insight into behavior in a home economy centered society. For all other notations, please refer to equation (4).

[15] Districts refer to the 59 community districts in New York City and the 22 counties in Taiwan. For more detailed explanations, refer to Section 3.

To test the effect of the 2020 COVID outbreak, we ran regression models with robust standard errors on our panel data. The Hausman test was run to determine whether to use fixed-effect or random-effect models. The model's p-value was 0.4592, so a random effect model was applied. Results were run with and without demographic variables, as seen in Table 4 and 5, to ensure that coefficients are not biased by changes in control variables.

5. Empirical findings

In this section, we analyse and display the results of our regressions, including OLS and DID. Inspired to explore the relationship between MGP and COVID-19, we compared waste levels before and after COVID-19. The results displayed a positive relationship with robust results, with and without controls. However, this doesn't establish a particularly strong correlation between COVID-19 and MGP; therefore, several measures, including before and after COVID-19, lockdown, and case, were used to establish this positive correlational relationship. Table 1 presents the results, which are all consistent with our original hypothesis, that are robust and indicate an increase in MGP due to COVID-19.

Our conjecture follows that online shopping, take-out, and delivery services increase as a result of lockdowns, hence the consequential change in MGP. Although previous analysis establishes a strong correlational relationship between COVID-19 and MGP, there is no detailed analysis providing more insight into the miniature changes. Following the expansive literature stating the relationship between income and consumption of online services, we create a regression model investigating how the difference in income may influence MGP output, thus providing insight into purchasing behavior. The results are presented in Table 2, and indicate that richer districts, on average, saw a higher increase in waste compared to poorer districts, which is consistent with the current literature.

However, the previous results may be confounded and biased by other events, so we seek to clarify this relationship using a more rigorous Difference-in-Differences (DID) specification. Following our conjecture, we are interested in the relationship between MGP growth and COVID-19 from a digitalised economic perspective. This means that our control group and our treatment group should be of similar technological and demographic measures, but most importantly, should be unaffected by COVID-19. These conditions narrowed our search, and Taiwan, a developed island, proved to be a perfect control group. DID results are displayed below in Table 3; these results prove to be consistent with our hypothesis and enable us to form a causal conclusion between the two variables.

Our most precise results include all controls and regional and month fixed effects, as seen in Table 1, Column (2), (4), (6), (8); Table 2, Column (5); Table 3, Column (2), (4). These will be the results which will be explained in more detail.

5.1 COVID-19 outbreak and lockdown in NYC

Column (1), (3), (5), and (7) represent our regression results of the four different measures of COVID-19, including variables *PostCOVID, Case, Lockdown,* and *Lockdown*Case.* The successive Columns (2), (4), (6), and (8) represent regressions of previous controls with region fixed effects, month fixed effects, and all controls. All results are significant at a 0.01 significance level ($p < 0.01$). The results suggest that after COVID-19, NYC saw an average increase in MGP of 69.212 tons per month for each district, indicating a strong correlation between COVID-19 and MGP output. This relationship is strengthened by results in Column (4) and (6), which indicate an average increase in MGP of 42.901 tons per month during lockdowns; in addition, an average increase in MGP of 0.028 tons per case. This means that during the peak of COVID-19, with 6,000 average cases, MGP increased by 168 tons per month, illustrating a 100% increase in MGP output. Finally, Column (8) illustrates results with the interaction term *Lockdown*Case*. The coefficient of 0.022 suggests that during lockdown, each confirmed COVID-19 case, increased MGP output by 0.022 tons per month. All results are completely consistent, implying a strong correlation between COVID-19, measured using lockdown, case, and outbreak date, and MGP output.

Table 2: COVID-19 outbreak and lockdown in NYC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MGP	MGP	MGP	MGP	MGP	MGP	MGP	MGP
PostCOVID	63.578***	69.212***						
	(11.840)	(6.650)						
Lockdown			33.346**	42.901***				
			(16.098)	(8.721)				
Case					0.060***	0.028***		
					(0.008)	(0.005)		
Lockdown*Case							0.047***	0.022***
							(0.008)	(0.005)
Housing Units		36.685		42.482		39.177		39.734
		(47.044)		(47.639)		(47.569)		(47.690)
Income		-1.755		0.982		0.803		1.089
		(9.665)		(10.433)		(10.318)		(10.450)
Population		428.504***		423.502***		412.944***		416.656***
		(46.236)		(46.756)		(46.648)		(46.722)
Population Density		-1.022		-1.996		2.017		0.830
		(11.113)		(11.468)		(11.441)		(11.514)
Zoning (Baseline: Commercial)								
Residential		-44.881**		-18.755		-13.969		-11.564
		(22.601)		(22.283)		(21.916)		(21.934)
Manufacturing		-87.562***		-62.066***		-56.046***		-53.380***
		(18.802)		(18.728)		(18.431)		(18.511)
Poverty Rate		-11.828***		-11.633***		-11.974***		-11.875***
		(0.998)		(1.048)		(1.044)		(1.053)
Constant	456.219***	-4741.453***	474.272***	-4777.825***	417.160***	-4673.459***	434.988***	-4708.497***
	(23.105)	(218.044)	(23.244)	(223.128)	(24.064)	(221.718)	(23.837)	(222.269)
Observations	1180	1135	1180	1135	1180	1135	1180	1135
R^2	0.277	0.720	0.264	0.706	0.289	0.708	0.278	0.706

Robust standard errors in parentheses. All models are with region and month fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Cross-sectional analysis

Column (5) contains our most rigorous regression results, which include region fixed effects, time fixed effects and all controls. In general, the coefficients of *PostCOVID*Rich* are all statistically significant at a 0.05 significance level ($p < 0.05$) and positive; the coefficients of *PostCOVID*Poor,* on the other hand, are all statistically insignificant and inconsistent. These results clearly indicate a strong correlational relationship between a household's income and their post-COVID-19 MGP output. The coefficient 109.818 in Column (5) indicates that, on average, a "rich" household that is in the top 30% of lowest poverty rates in NYC saw an increase of 109.818 tons in MGP after the COVID-19 outbreak (March 2020). The difference between the *PostCOVID*Poor* and *PostCOVID*Rich* coefficients are 86.583, highlighting the differential impact on the two groups. This suggests that in a digitalised economy, high-income households will have the ability to transfer towards a more online and extravagant lifestyle, while low-income households stay constant. (Melovic. 2021) This conclusion regarding low-income households is supported by the fluctuation between coefficients and the statistically insignificant results.

Table 3: Cross-sectional analysis - income difference

	(1) MGP	(2) MGP	(3) MGP	(4) MGP	(5) MGP
Poor*PostCOVID	-75.717		-36.342	14.676	23.235
	(51.509)		(41.585)	(32.940)	(18.509)
Rich*PostCOVID		130.239**	118.125***	93.324***	109.818***
		(48.708)	(38.669)	(31.140)	(26.049)
Housing Units					319.733*
					(178.190)
Population					165.372
					(171.346)
Population Density					-52.458
					(39.518)
Zoning (Baseline: Commercial)					
Residential					22.830
					(94.876)
Manufacturing					-89.494
					(109.298)
Constant	530.400***	478.911***	491.025***	462.089***	-4447.960***
	(39.288)	(34.808)	(34.779)	(94.851)	(746.790)
With Controls	N	N	N	N	Y
Region Fixed Effects	N	N	N	Y	Y
Month Fixed Effects	N	N	N	Y	Y
Observations	720	720	720	720	675
R-Squared	0.019	0.056	0.060	0.251	0.679

Robust and clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Difference-in-Differences (DID)

Two DID models were run for causal inferences, Table 4 indicates the change in MGP growth due to COVID-19; whereas, Table 5 illustrates the impact of COVID-19 on different income households' MGP output growth rate over COVID-19.

All results in Table 4 were statistically significant at a 0.01 significance level ($p < 0.01$) and consistently positive. Column (2) illustrates our most rigorous regression model, including all fixed effects and controls. The coefficient of interest indicates that there was a 7.467% increase in MGP output in NYC due to COVID-19. This is consistent with our original hypothesis.

Furthermore, results in Table 5 indicate that this drastic increase was mostly attributable towards high-income households. Column (2) and Column (6) illustrate the most rigorous models in Table 5. The coefficient of interest for $Rich_2$ (Rich Subgroup) is statistically significant at a 0.1 significance level ($p < 0.10$) and positive. This suggests an increase of 11.681%, on average, in $Rich_2$ households after COVID-19. On the other hand, consistent with results from Section 5.2, changes in MGP output in $Poor_2$ are insignificant but drastically less than those of $Rich_2$ households. The decrease in significance level from our OLS analysis to our DID level, from 0.05 to 0.1, could be explained by the change in identification methods. As poverty rate data was unavailable in Taiwan, our DID specifications were done with income data. This difference could have, in turn, influenced the significance of our results.

Although slightly less significant, our results still lie consistent with our original hypothesis and further our findings. In general, we find that COVID-19 significantly contributed to MGP growth, suggesting implications for an increasingly digitalised economy. In addition, these contributions were not evenly distributed among different income groups. As shown in our results, most of the increase in growth rates could be attributed towards high-income households. This is consistent with current literature, as the relationship between online shopping and income is positively correlated.

Table 4: The Effect of COVID-19 on changes in Metal, Glass and Plastic (MGP) - DID Estimates of NYC and Taiwan

	(1) MGP Growth	(2) MGP Growth	(3) MGP Growth	(4) MGP Growth
PostCOVID	-7.073***	-7.227***		
	(1.948)	(1.869)		
NYC	-6.739*	10.784		
	(4.077)	(9.261)		
PostCOVID*NYC	7.288***	7.467***	7.288***	7.436***
	(2.578)	(2.509)	(2.601)	(2.486)
Housing Units		2.407		2.462
		(5.365)		(5.203)
Income		-2.252		-0.499
		(2.005)		(2.468)
Population		1.215		-1.267
		(5.893)		(5.417)
Population Density		-1.084		1.345
		(1.665)		(1.368)
Constant	13.859***	-7.920	0.541	-21.335
	(3.631)	(39.573)	(1.615)	(44.873)
With Controls	N	Y	N	Y
Region Fixed Effects	N	N	Y	Y
Month Fixed Effects	N	N	Y	Y
Observations	1620	1620	1620	1620
Within R2	0.003	0.003	0.045	0.045
Between R2	0.023	0.097	0.363	0.388
Overall R2	0.005	0.010	0.068	0.069

Robust and clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The Effect of COVID-19 on changes in Metal, Glass and Plastic (MGP) - Income Subgroup analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rich Subgroup				Poor Subgroup			
PostCOVID	-11.172*	-11.710*			-9.191	-9.575		
	(6.346)	(6.313)			(8.888)	(8.929)		
NYC	-15.722**	-10.466			-6.858	-4.632		
	(6.319)	(10.077)			(11.411)	(35.047)		
PostCOVID*NYC	11.176*	11.681*	11.176	11.864*	4.406	4.564	4.406	4.621
	(6.793)	(6.800)	(7.001)	(7.207)	(10.289)	(10.260)	(10.570)	(10.627)
Housing Units		-0.482		8.803		29.271		81.226*
		(4.216)		(6.844)		(30.128)		(48.007)
Income		2.138		3.073		-1.515		4.057
		(1.877)		(2.318)		(6.455)		(10.123)
Population		5.040		-5.400		-34.450		-79.266
		(4.733)		(6.548)		(31.058)		(48.506)
Population Density		-0.000***		-0.000**		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Constant	19.194***	-61.456***	1.947	-68.045**	19.127*	128.961**	0.119	5.236
	(6.268)	(10.448)	(4.725)	(27.725)	(10.248)	(57.270)	(3.218)	(78.970)
With Controls	N	Y	N	Y	N	Y	N	Y
Region Fixed Effects	N	N	Y	Y	N	N	Y	Y
Month Fixed Effects	N	N	Y	Y	N	N	Y	Y
Observations	380	380	380	380	500	500	500	500
Within R2	0.029	0.029	0.061	0.064	0.003	0.003	0.056	0.056
Between R2	0.461	0.694	0.778	0.885	0.026	0.171	0.560	0.758
Overall R2	0.078	0.105	0.143	0.158	0.005	0.012	0.083	0.094

Robust and clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6. Discussion

6.1 Policy implications and recommendations

As remote working becomes the norm in the rapidly digitalizing world, the importance of maintaining and improving environmental conditions becomes more pertinent than ever. Our literature review highlights that the indirect benefits brought along by the pandemic are purely temporary and policies must adapt to prevent levels of pollution from rising once again. Before the start of the pandemic, waste management was deemed to be a major environmental issue with growing concerns about its impact on natural ecosystems (Rajmohan. 2019). COVID-19 only exacerbated this situation as the usage of protective gear amongst patients and healthcare workers generate excessive amounts of waste. Our results confirm this, as the correlation between different measures of COVID-19 and waste consumption is robust and positive, as seen in Sections 5.1 and 5.3.

Consequently, the rising home economy has disrupted food purchasing and consumption habits, forcing many consumers to do more cooking and eating at home. With lockdowns, an increase in demand for home delivery has been observed as more households choose to utilize this service for food, groceries, and other goods. Online food ordering saw an increase in usage as digital orders increased by 135% since June 2020. Consequently, this led to an increase in packaging waste (Tenenbaum. 2020). Governments should specifically look into the implications of the growing home economy sector as it will continue to expand and poses a threat to a future circular economy Romagnoli. (2020)

Of the 78 million metric tons of plastic packaging produced globally each year, only 14% is recycled. Most packaging waste from the delivery of food, groceries and other products are recyclable however, throwaway culture fueled by consumerism is greatly hindering this potential. Companies still believe that it is cheaper to pay emissions taxes than to change production practices to become more sustainable. This must be disincentivised otherwise, throwaway culture will continue to hinder recycling capacity. Levies and taxes should be set on non-recyclable plastic to deter the customer from purchasing them. Furthermore, tax reductions or rebates can be offered to firms that use biodegradable plastics in their packaging process. This places importance on long-lasting design, manufacturing and reusability. Legislation and corporate governance can also be tightened to encourage the high-polluting industries to employ more sustainable practices. These have been proven to work in the past with a group of majority stakeholders demanding for Nestlé, the Swiss food giant to make all its plastic packaging 100% recyclable or reusable by 2025 (UNEP 50., 2018). Until then, the use of plastics that allow better recycling rates should be promoted. Containers must be biodegradable or made of thermoplastic so heat sterilization can be done before reusing them. On the other hand, social media campaigns can be used to raise awareness about recyclable packaging with people becoming conscious of the benefits of reusable plastic, thereby making informed purchases accordingly.

Researchers, designers and biologists should strive to develop packaging that falls within the circular economy's mandate. Following this model supply chains should continuously cycle old materials back to be remade into products of value. RISE, a Swedish research institute has developed a cellulose-based container that can be used as soup bowls. They are fully compostable and grown from strands of mycelium, a vegetative compound. Other research institutes are looking into bioplastics that are almost completely compostable. The most successful of this kind belongs to Harvard's Wyss Institute where silk protein from shrimp shells can be used to make a thin film and rigid shapes. To maximize the collection of compostable materials, universal access to municipal compost systems where organic materials can be redistributed are important (Jiang 2021).

When lockdowns were being enforced, the United States halted recycling programs due to the fear of contaminated waste in recycling centres (Kaufman and Chasan, 2020). The reduction in recycling and increase in waste further endanger the contamination of physical spaces and increase total waste. New York City embodies this issue as the available material far exceeds the capacity of local processors. Governments should restart the collection of reusable materials when it is deemed safe and must ensure that there are a sufficient number of collection points that are accessible to the public to make recycling more convenient.

6.2 Further Research

This research can be improved by evaluating multiple environmental indicators to see comprehensively the effect of the pandemic on the environment. A higher number of observations for the MGP waste data would increase the degree of accuracy of our investigation; however, it was not available in more frequent intervals. Furthermore, control variable data was stagnant at times due to availability, and we did not adjust for fiscal changes to the economy, such as inflation. Further research could look to provide a more holistic picture of environmental influences of COVID-19, and seek to form a more concrete relationship between COVID-19 and long term trends, such as digitalisation.

7. Conclusion

This paper examines the effect of COVID-19 on MGP output. We use OLS and DID analysis to clarify the relationship between COVID-19 and MGP output. We find that COVID-19 results in a drastic increase in MGP output. However, through subgroup studies with high-income and low-income groups, these increases are attributed mostly to high-income households. These results have long-term implications for government environmental policies as influences of COVID-19 are argued to be not only short-term.

Current literature marks an increase in digitalisation, and the COVID-19 situation only served to exacerbate this. The pandemic has forced many cities into lockdown, which induced a new workstyle: working from home. This workstyle is part of a larger trend towards a more home-based economy and a more digitalised world. These trends can be seen across the globe through the increasing numbers of online shopping platforms, transforming towards online banking services, increasing usage of artificial intelligence, and more. However, this paradigm shift is accompanied by many unforeseeable consequences.

Our paper uses COVID-19 as a scope to investigate one of the many consequences of an increasingly home-based economy. As seen in our results, waste disposal levels increased exponentially, especially the MGP levels. Furthermore, the MGP output of the high-income households were much more significant than those of the low-income households. This phenomenon can be understood from the fact that higher-income households would be the first to access and afford more frontline services, thus marking a more drastic change in lifestyle and transfers in waste output. Finally, we provide policy recommendations for different stakeholders in an attempt to address possible environmental externalities in the future.

This research could be improved if there were explicit links between COVID-19 and the home-based economy. However, at this stage, it is only possible to observe current trends to make inferences about future possibilities. Nevertheless, an increasing amount of evidence and literature reveals that this paradigm shift towards a digitalised world is imminent. Our research could have been improved with more nuanced data, which is not currently available, and with investigations into other environmental factors. Even so, our research provides valuable insight into long-term implications, which isn't mentioned in the current literature, of COVID-19, and highlights the downfalls of COVID-19.

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