Unexpected Shocks to Movement and Job Search: Evidence from COVID-19 Policies in Singapore using Google Data

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Abstract

This paper uses Google data in Singapore to study the impact of COVID-19 policies. First, I find differences in the efficacy of the two movement controls, and that their announcements led to same-day increases in foot traffic. Second, I find evidence that online job search either stayed the same or has fallen. With a larger pool of potential candidates, this implies a drop in average search per worker. Finally, the data suggests that movement restrictions affected job search intensity, the implication being that while stay-home mandates are necessary to flatten the curve, it potentially creates another shock to labour supply which is more hidden than the demand side.

I Introduction

This paper examines the impact of COVID-19 related policies in Singapore, an institution that offers variation in two sets of policies—movement controls and COVID-19-specific fiscal stimulus. Using data from Google, I find a number of insights on how COVID-19 policies affected local movement and job search.

First, Singapore had two movement controls with clear differences in their degrees of restriction. Using data from Google's Community Mobility Reports (Google LLC, 2020), I make three observations on local movement. First, I find the expected drop in visits to non-residential places after the movement controls. The timing of this drop however, is not uniform across places, with the drop in workplace and

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grocery visits occurring only after the second stricter movement control. Second, there are same-day increases in park visits and grocery visits after the movement control announcements, relative to visits to other places with a similar pre-trend. Third, the drop in parks and retail visits is smaller on weekdays than on weekends, suggesting that individuals do substitute foot traffic across places and days when under movement control. A related study is Briscese et al. (2020), who find that the timing of announcements is important in managing public expectations.

Data on real-time online job search offer some insights into the potential impact of COVID-19 on the labour market. While most studies look at the impact on the labour demand side, such as a fall in vacancies (Kahn et al., 2020; Bartik et al., 2020), this paper provides evidence that a negative shock also occurs in the labour supply side. In particular, there is a conspicuous lack of change in total daily job search early in the COVID-19 fallout. Given first wave of job losses and withdrawn offers (Tang, 2020; Kahn et al., 2020), the lack of increase in job search implies that average search per worker has decreased. This is consistent with a procyclical model of job search (Krueger et al., 2011; Hensvik et al., 2020).

Total daily job search then had a persistent dip during the weeks of 6 April–4 May. With a larger pool of potential candidates in the labour market, this constitutes a further decrease in average search per worker. While COVID-19-specific fiscal stimulus might seem like the more obvious cause, I find that the timing of the drop in job search does not match the timing of the fiscal stimulus announcements nor the actual disbursement of cash payouts. Instead the drop which begins in the week of 6 April coincides with the start of the stay-home mandate. This behaviour is not present in part-time job searches nor in job search patterns over the same period in the previous year.

This paper relates to the literature on the importance of government responses in the COVID-19 crisis (Briscese et al., 2020; Fetzer et al., 2020), and the impact of COVID-19 on the labour market (Bartik et al., 2020; Coibion et al., 2020; Hensvik et al., 2020; Kahn et al., 2020). Hensvik et al. (2020) use user-level data from the government-operated online Swedish job board, while Coibion et al. (2020) use U.S. survey data. Both find a contraction in labour supply. This paper contributes by finding similar evidence of an exogenous labour supply shock, with suggestive evidence that the stay-home mandate further exacerbated this shock. If local movement restrictions indeed introduced additional frictions in job search, then COVID-19 induced not just a well-documented contraction in labour demand, but also a more hidden negative shock to labour supply.

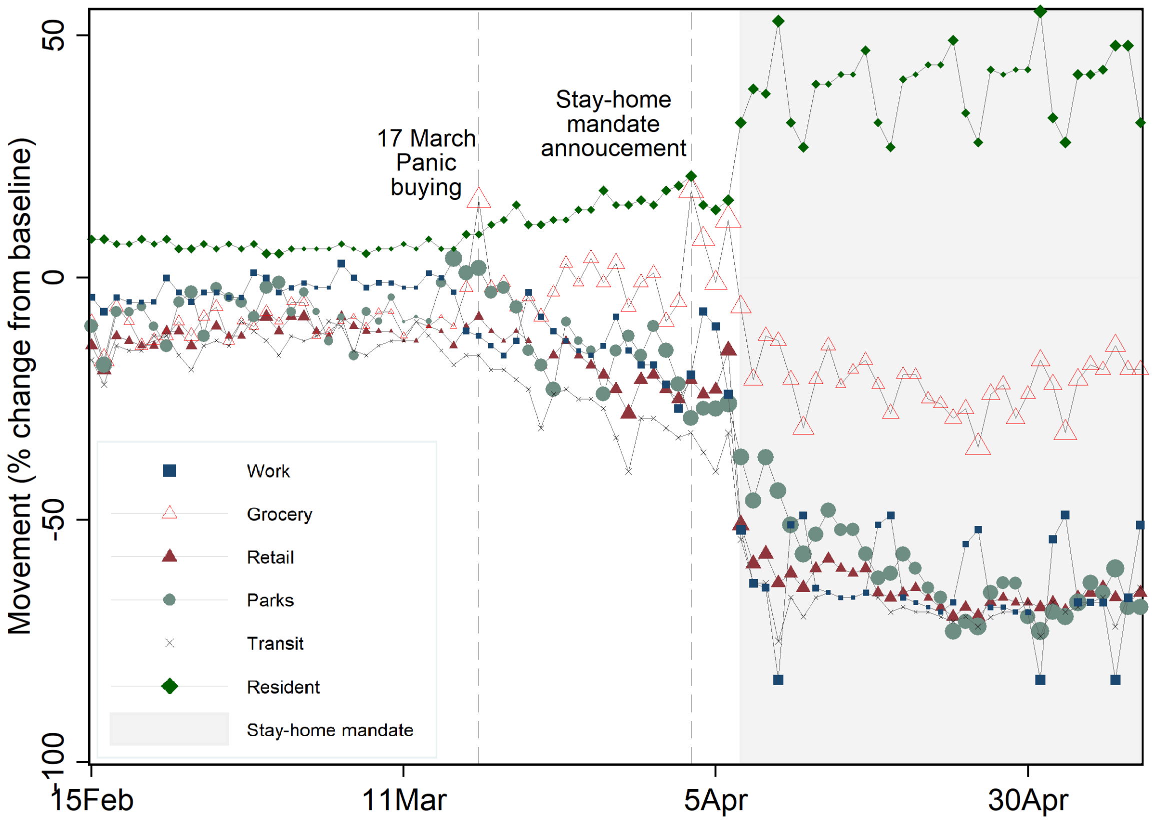


Figure I: Changes in Movement

Notes. Scatterplot of the Google Community Mobility data for Singapore, 15 Feb to 9 May, 2020. Observation markers are weighted by anomaly scores from the *isolation forest* algorithm, with larger markers implying greater anomaly. The first vertical line indicates the panic buying on 17 March. Second vertical line indicates the date of annoucment for stay-home mandate which begins 7 April, indicated by the grey areas.

The next section describes the data. Section III documents the expected changes in movement. Section IV shows the unexpected changes in movement and job search. Section V concludes.

II Data and Description

Community Mobility Reports. To measure local visits to points of interests, I use the publicly available data from Google's COVID-19 Community Mobility Reports (Google LLC, 2020),[1] which categorises six points of interests as shown in Table A2. The measure for a place in a given day is the percentage deviation from the median value of visit to that place for that corresponding day of week during the 5-week period from 3 Jan–6 Feb 2020. The data shared from Google is aggregated

[1] Yilmazkuday (2020) uses the same mobility data to study the cross-country effectiveness of stay-home policies on the number of confirmed cases and deaths.

Table I—*Summary of Events*

Event	Description	Additional notes
17 Feb	1st GDP growth forecast downgrade	Official downgrade from 0.5–2.5% (Nov 2019) to -0.5–1.5% due to the COVID-19 outbreak.
18 Feb	1st stimulus package	"Unity Budget". New *Jobs Support Scheme* to offset 8% of local wages for three months. 100–300 SGD (70–211 USD) one-time payout. Plus other alleviating measures.
17 Mar	Panic buying	Wave of panic buying after Malaysia announced its lockdown on 17 March, which begins 18 March.
24–26 Mar	1st movement control	10-people social gathering limit, and closure of entertainment venues. Announced on 24 March, implemented on 26 March.
26 Mar	2nd stimulus package 2nd GDP growth forecast downgrade	"Resilience Budget". *Jobs Support Scheme* broadened to last 9 months, and subsidise 25–75% of local wages. "One-off" cash payout of 3,000 to low-income workers (Jul and Oct). *Self-Employed Person Income Relief Scheme* grants 1,000 a month, for 9 months, to freelancers/ self-employed persons. Plus other alleviating measures. Also, GDP forecast downgraded further to -1 to -4%.
3 Apr	2nd movement control announcement	"Circuit Breaker" (Stay-home mandate). announcement for controls which begins 7 Apr—closure of "non-essential" workplaces, schools, preschools, student care services, and no more dine-ins.
5 Apr	3rd stimulus package	"Solidarity Budget". *Jobs Support Scheme* now co-funds 75% of local wages, now without qualifiers. Additional 300 one-time cash, plus faster release of cash payouts. Additional tax rebates, rental waivers, foreign worker levy, plus other alleviating measures.
7 Apr	2nd movement control	*Stay-home Mandate*. Initially to end on 4 May.
21 Apr	Extension ↑	Stay-home mandate unexpectedly extended from 4 May to 2 June.

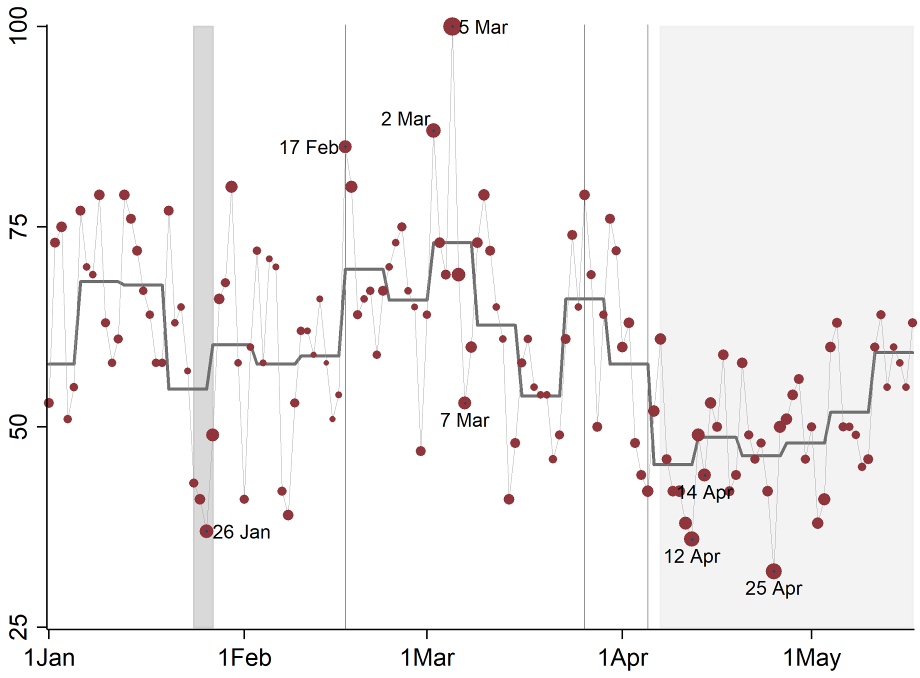
to the six categories and are anonymised.[2]

Figure I plots the summary of the changes in visit over the sample period, weighted by anomaly scores (see below). As expected, there is a drop in visits to workplaces, retail, parks, and transit stations as the movement controls set in, around 26 March and 7 April. Visits to grocery have a lower drop than the above four places, while "visits" to residential areas increased over the same time period. An anomaly that is well-known locally is on 17 March, when there was a panic buying and hence a recorded spike in grocery visits. Another anomalous behaviour in visit to grocery occurs around 3 April—the date of announcement of the stay-home mandate—suggesting that the announcement led to another wave of panic buying. I test this formally below.

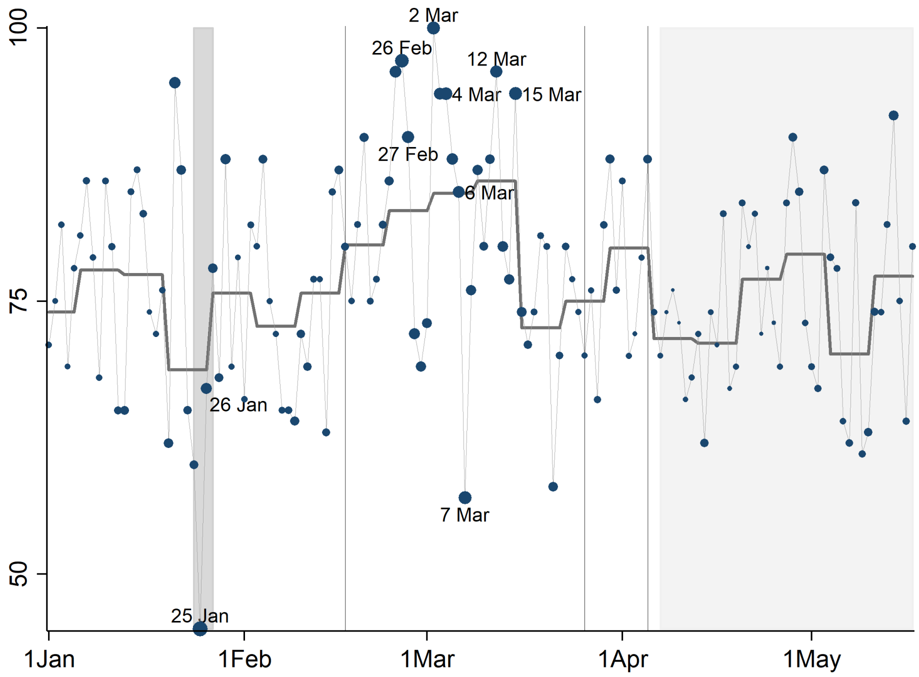
Job Search Data. Various studies find that online job search trends correlate well with unemployment claims and survey measures of job search (Choi and Varian, 2009; Baker and Fradkin, 2017).[3] For daily search of *full-time* job search

[2] Three caveats might be worth noting about the representativeness of the mobility data. First, no data is recorded for a place at a certain time when there is insufficient traffic to pass a privacy threshold. Second, artificial noise is added to the data as part of their differential privacy policy to anonymise users of Google Maps. Third, only visits of users who have opt-in to turn on their location history setting are recorded. These make the estimates less precise and allows only direct inference on a subset of the population. In addition, Google decides the categorisation of places, which should not pose a problem unless a comparison is made across regions where categorisation varies.

[3] Other studies using Google search data include how online search behaviour changed following



(a) Google Search for [jobs]



(b) Google Search for [part-time jobs]

Figure II: Summary of Job Search Trends from Google

Notes. Scatterplot of job search trends from Google for (full-time) jobs and part-time jobs, over the period of 1 Jan to 17 May, 2020. Flat lines are the weekly average. Scatter points are weighted by anomaly scores from the isolation forest, with larger markers implying greater anomaly. The first vertical grey area indicates the 4–day Chinese New Year weekend, and the second vertical grey area indicates the stay-home mandate period.

the 2013 revelations of the PRISM surveillance (Marthews and Tucker, 2017), how searches for bitcoin correlates with the bitcoin market (Kristoufek, 2013), and how intolerance-related search terms correlates with college education (Chan, 2019) and the vote share of a Black presidential candidate (Stephens-Davidowitz, 2014).

Table II—*Detected Anomalies in Job Search*

Date	Index	Date	Index	Date	Index	Date	Index	Date	Index
25-Aug-19	42	30-Jan-20	80	7-Mar-20	53	7-Apr-20	61	15-Apr-20	53
24-Oct-19	78	17-Feb-20	85	8-Mar-20	60	10-Apr-20	42	25-Apr-20	32
27-Oct-19	39	18-Feb-20	80	10-Mar-20	79	11-Apr-20	38	26-Apr-20	50
22-Dec-19	43	2-Mar-20	87	1-Apr-20	60	12-Apr-20	36	27-Apr-20	51
26-Jan-20	37	5-Mar-20	100	5-Apr-20	42	13-Apr-20	49	2-May-20	38
27-Jan-20	49	6-Mar-20	69	6-Apr-20	52	14-Apr-20	44	3-May-20	41

Notes—30 daily (full-time) job search index with the highest anomaly score over the 9–month period of 25 Aug 2019 to 20 May 2020. Index is the Google trends search index for that date for the query `[jobs - steve - covid - part - parttime]`. Anomaly scores are from the unsupervised isolation forest algorithm.

(or, just job search), I query Google Trends for `[jobs - steve - covid - part - parttime]` over the 9-month period of 25 Aug 2019–20 May 2020, with location restricted to Singapore. The "-" removes any search containing the word that comes after, removing unnecessary noise. Google trends returns the search index between 0 to 100, with 100 indicating the largest search volume in that location and period for that search term, and every other day's index is defined in relation to that, so that a measure of 50 indicates search volume half as high as the highest in that period.

Part-time job search is retrieved using `[(part + parttime) jobs - steve - covid]` for the same period. The "+" indicates an "or". To get the hourly data for jobs and part-time job search for the period 1 Jan–22 May 2020, I use the third-party *PyTrends* API.[4] [5]

Figure II plots the job search indices for the year of 2020 (1 Jan–20 May), weighted by the anomaly score. Two observations might be worth noting here. First, for both type of job searches, there is a dramatic drop during the 25–26 Jan period, which coincided with the 4-day long weekend for the 2020 Chinese New Year. This helps validate how well the google search trends capture job-seeking behaviour.[6] The second observation is the spike in both type of searches over the 26 Feb–5 Mar period, also notable because this is the largest search volume over the entire queried 9-months.[7]

[4] https://github.com/GeneralMills/pytrends.

[5] The "- covid" prevents the results from returning COVID-19 related jobs such as testers and temperature screeners. A caveat about replication that might be worth noting is that Google returns the search index by using an unbiased sample of their entire search corpus. This means that the requests for the exact same search terms in the same period and location would still exhibit sampling variation, if the request is done on a different day (daily cache). In addition, the Google query results are case-insensitive, and nuances in linguistic variations are not captured (e.g. jobs vs. job and jobs vs. work), though neither are not regarded as an issue in studies using Google search.

[6] A similar drop is seen at 1 Jan. Table A1 shows the top 10 related search terms for [jobs] and [part-time jobs], ensuring that the measures capture what they should be capturing.

[7] I conjecture that these spike in searches are capturing an early wave of retrenchments and withdrawn job offers.

Detecting Anomalies. To detect anomalies in the movement and job search, I use the isolation forest algorithm—an ensemble of randomly constructed decision trees (over features and split values) that progressively isolates each observation (Liu et al., 2012). The anomaly score for an observation is $2^{-\frac{E[h(x)]}{c(n)}}$, where $E[h(x)]$ is the average number of edges the observation passes through from the ensemble of trees, and $c(n)$ is the normalising constant as a function of the sample size so that the anomaly score is [0, 1]. As the average number of edges approaches 0, the anomaly score approaches 1, indicating higher probability of an anomaly. The intuition is that anomalies are easier to classify, and thus take less partitions to isolate.[8]

Table II lists the 30 days in the 9-period sample of job search with the highest anomaly scores, in chronological order. An immediate observation that can be made is that other than the four dates in 2019 and the 26–30 Jan 2020 period coinciding with the 2020 Chinese New Year, the most probable anomalies over the entire 9-month period all occur between 17 Feb to the end of April. Relative to the mean search index of 58 in the first week of 2020, the upward anomalies in 17–18 Feb coincide with the first GDP forecast downgrade and the first COVID-19 stimulus package announcements, and the downward anomalies from 5–27 April coincide with the stay-home mandate announced on 3 April and implemented on 7 April. I test this more formally below.

III Method and Expected Results

To track weekly changes in movement and job searches, I estimate:

$$y_t = \alpha + \beta_t \omega_t + \delta_t + \varepsilon_t, \tag{1}$$

where y_t is the percent change in visits to the six categories of places; and the daily Google job search indices. β_t is the coefficient capturing weekly changes, with the first week of year 2020 in the sample period as the baseline week of comparison. δ_t is the day-of-week fixed effects. This allows for say, job searches to be lower on Sundays (which is indeed implied by the search data). α is the constant shock over the 2020 sample period.

[8] I primarily use the soft classifier approach in this paper—using the anomaly probability score instead of a hard binary classification. In practice, I implement the isolation forest algorithm using the *scikit-learn* (Pedregosa et al., 2011) library, with a 1,000 trees. Additional features for each observation are the weekly mean, monthly mean, moving averages (for 3, 5, and 7 days, backfilled for the first of those $(n-1)$ days), and exponentially smoothed values (with decay of 0.5, 0.3, and 0.1), and day-of-week fixed effects.

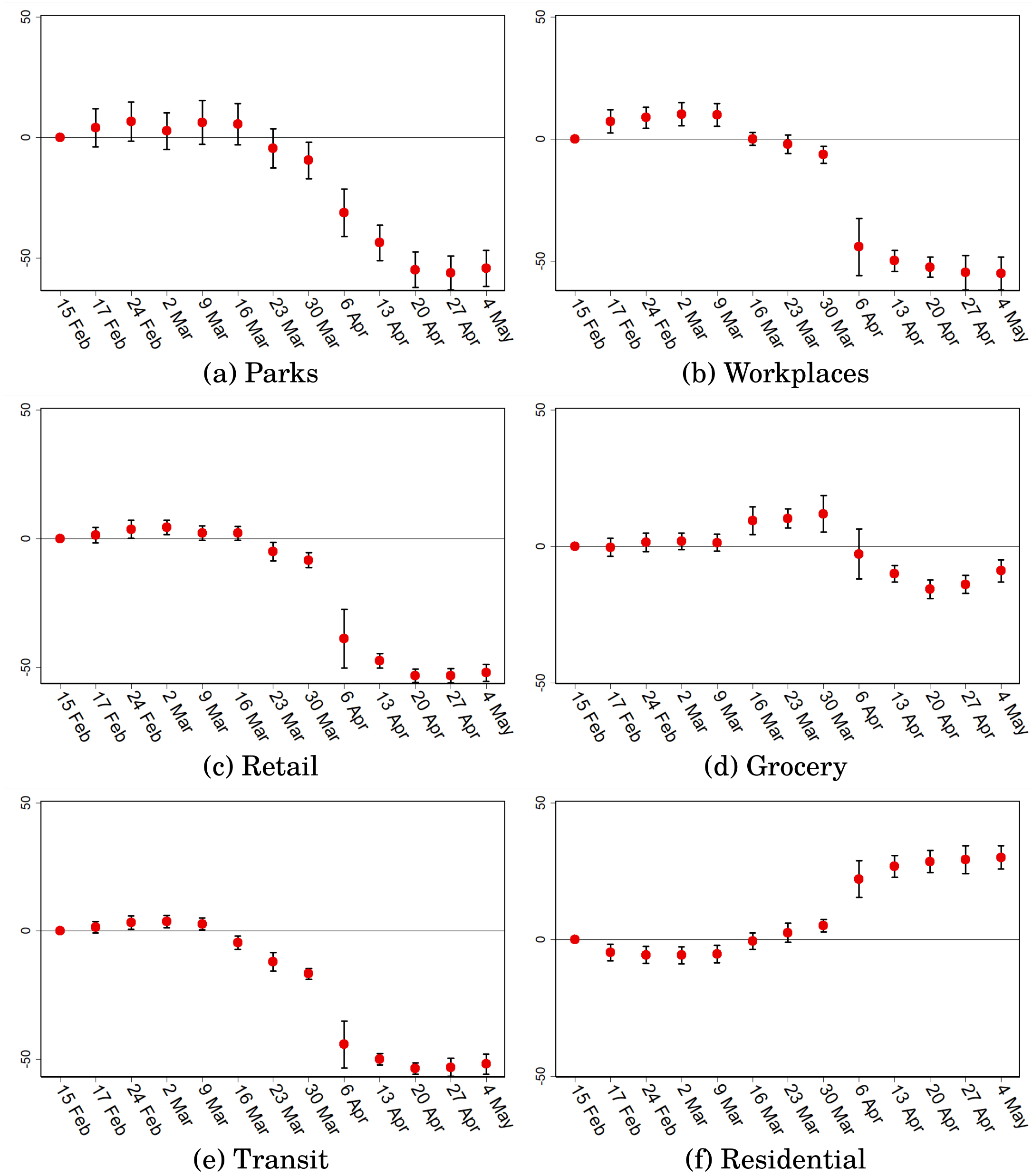
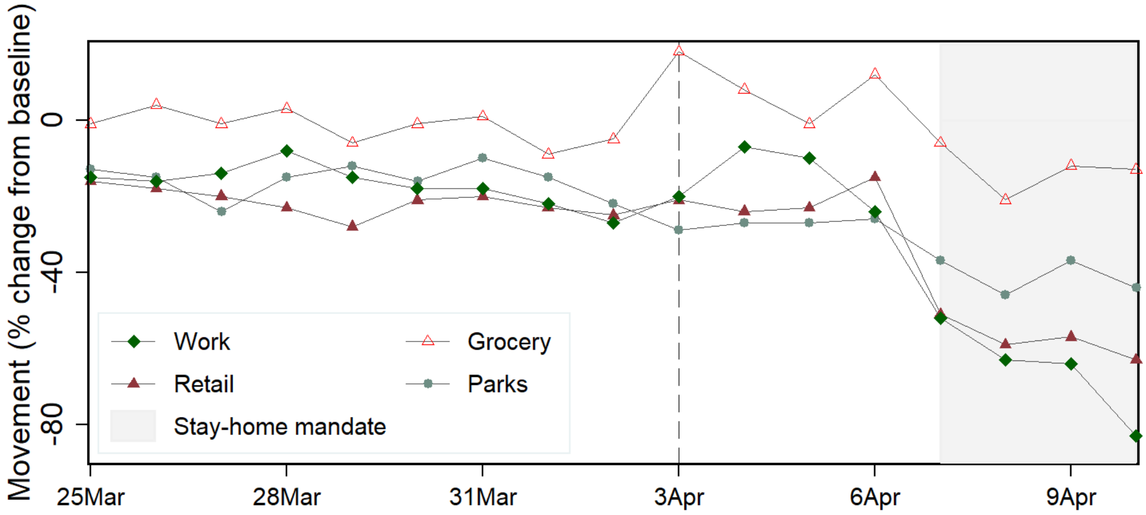


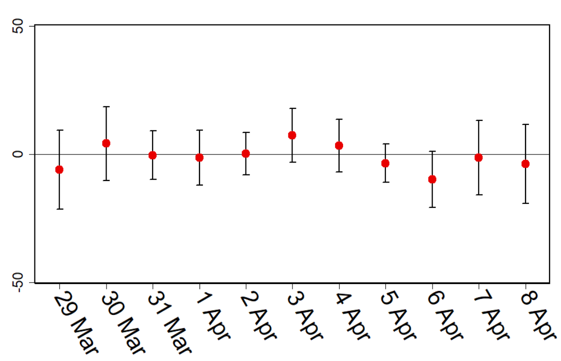
Figure III: Weekly Changes in Visit

Notes. Figure shows weekly changes in visits. A negative coefficient implies a the drop in visits relative to the baseline week of 15 Feb. Each subfigure is a linear regression of 85 observations from 15 Feb to 9 May of 2020. All regressions include day-of-week fixed effects. Capped vertical lines are the 95% confidence interval constructed from the robust standard errors.

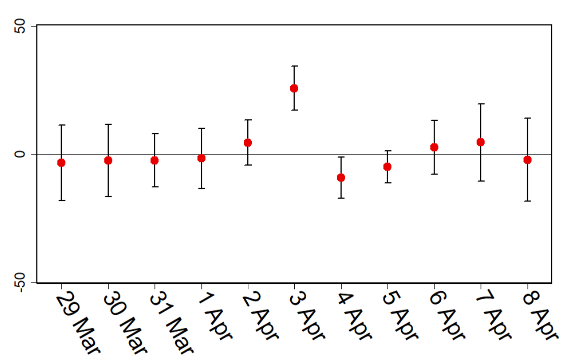
Figure III plots the estimated β_t coefficients for the six places. Controlling for day-of-week fixed effects, visits to the six places all move in the expected manner, with visits falling over time except for residential areas, which naturally saw an increase in "visits" as more people stayed home. Visits to parks, retail, and transit (left column) fall from the week of 16 March, before the first movement control of a 10–people gathering limit on 26 March, indicating that drops in visits to these places are more voluntary. Grocery and workplace visits drop sharply only from the



(a) Movement Trends Around 3 April



(b) Workplace Relative Change



(c) Grocery Relative Change

Figure IV: Short-run Movement Changes (Stay-home Mandate Announcement)

Notes. Panel (a) shows the trends in movement around 3 April, annoucement date for the stay-home mandate. Residential movement trends omitted. Markers unweighted. Panels (b) and (c) show the estimated coefficients for the 5-days lags and 5-days lead around 3 April for workplace and grocery visits, respectively. Estimated coefficients are difference-in-differences regression with workplace and grocery visits as the "treatment" group, and with retail and park visits as the "control". All regressions control for day-of-week fixed effects, week fixed effects, and the treatment-specific day-of-week fixed effects. Capped vertical lines are the 95% confidence interval constructed from the robust standard errors.

week of 6 April, after the stay-home mandate with mandatory closure of schools and non-essential businesses from April 7.

IV Unexpected Changes

IV.A Visits

Panic Buying on 3 April. Based on Figure I (and Figure III), there was a surge in visits to grocery on 3 April, the date when the stricter stay-home mandate was announced. Figure I also show a sudden increase in workplace visits (blue square markers) immediately on 4–5 April. To formally test if the 3 April announcement caused these transient increases, I estimate a difference-in-differences-type regression with a 7–day lead and lag:

$$y_{it} = \alpha + D_i + \sum_{\tau=-7}^{7} \beta_\tau d_\tau D_i + \sum_{\tau=-7}^{7} d_\tau + \omega_t + \boldsymbol{\delta}_{it} + \varepsilon_{it}, \tag{2}$$

where $\tau = 0$ on 3 April. D_i is the dummy for the "treated" place of visit, which is alternatively workplace and grocery visits. As the "control" places of visits I use retail and park visits. The usual assumption on parallel pre-trends apply, and panel (a) of Figure IV supports this. ω_t is the week fixed effects and $\boldsymbol{\delta}_{it}$ now includes the treatment-specific day-of-week fixed effects.

Panels (b) and (c) of Figure IV plot the estimated coefficients of β_τ from equation (2) for workplace and grocery visits. On the exact day of 3 April, there is indeed a surge in grocery visits (panel (c)), relative to retail and park visits which have virtually the same trends in the previous days.

For workplace visits however in panel (b), the change is no different than the change in retail and park visits, which is likely driven by how the timing of the 3 April announcement on a Friday coincides with the periodic pattern of increased weekend workplace visits.[9]

I perform a similar analysis with $\tau = 0$ for 24 March when the first movement control order—10-people gathering limit and closure of entertainment venues—was announced, with park visits and grocery visits as the alternate treatments. Relative to the controls of workplace and retail visits, there is an unexpected increase in park, but not grocery, visits (Figure A2).[10]

Weekday vs. Weekend Visits. Figure V shows that the drop in visits is not the same for weekends (Sat and Sun) and weekdays. I estimate:

$$y_t = \alpha + \beta_t(\omega_t \times \text{weekday}_t) + (\text{weekday})_t + \omega_t + \varepsilon_t, \tag{3}$$

where $(\text{weekday})_t$ is the dummy for Mondays–Fridays. Figure V plots the estimated β_t coefficients for each of the six places, with a positive coefficient implying that the drop in weekday visits is smaller than on weekends. Although the estimates are noisy on certain weeks, this is the case for parks and retail visits, suggesting that there is substitution of foot traffic either across places or across days of the week.

[9] A pattern I do not fully understand. Figure A1 highlights this periodic weekend increase in workplace visits (and also weekend decrease in "residential" visits).

[10] The analogous movement data for 2019 is not available for comparison.

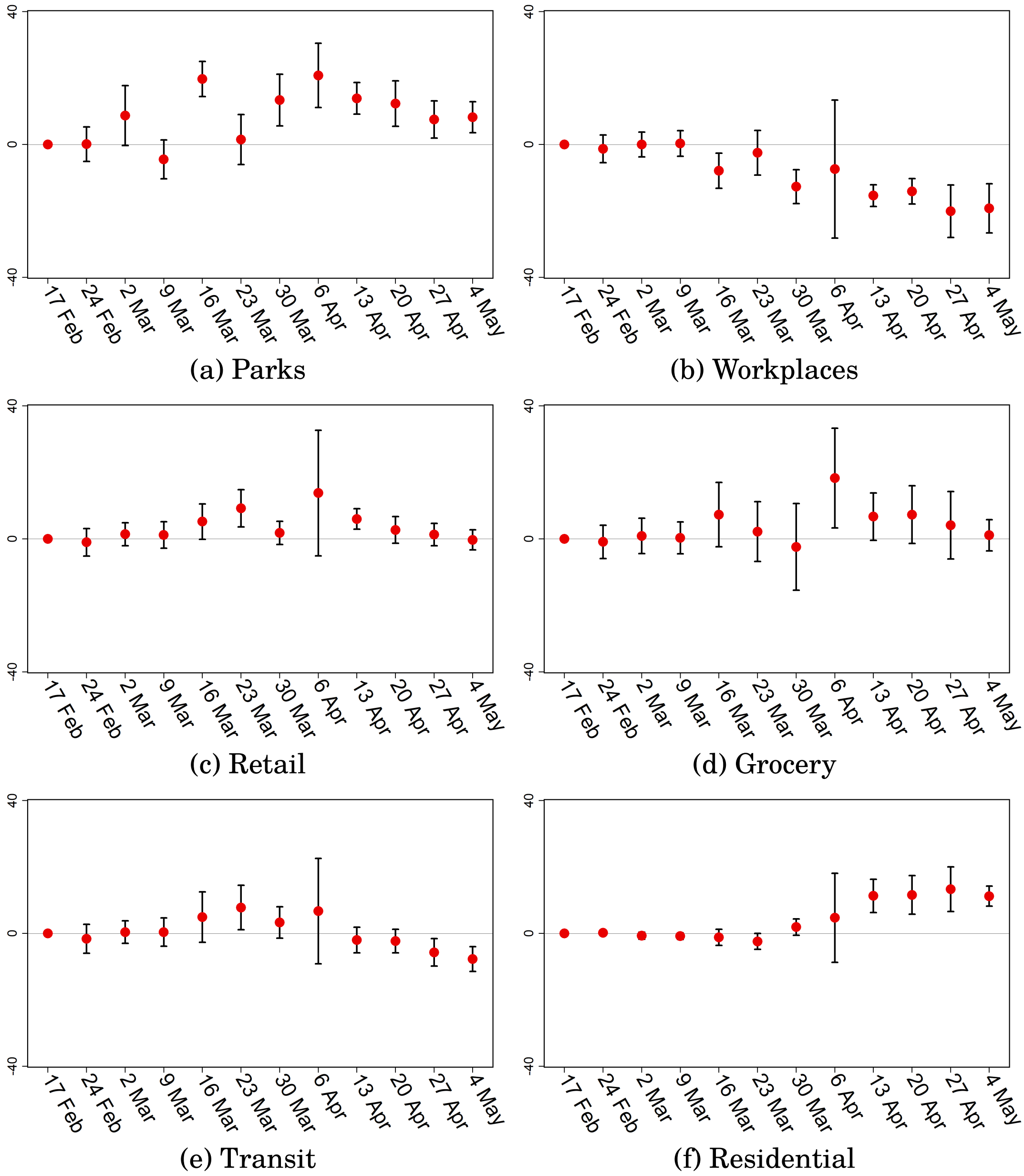
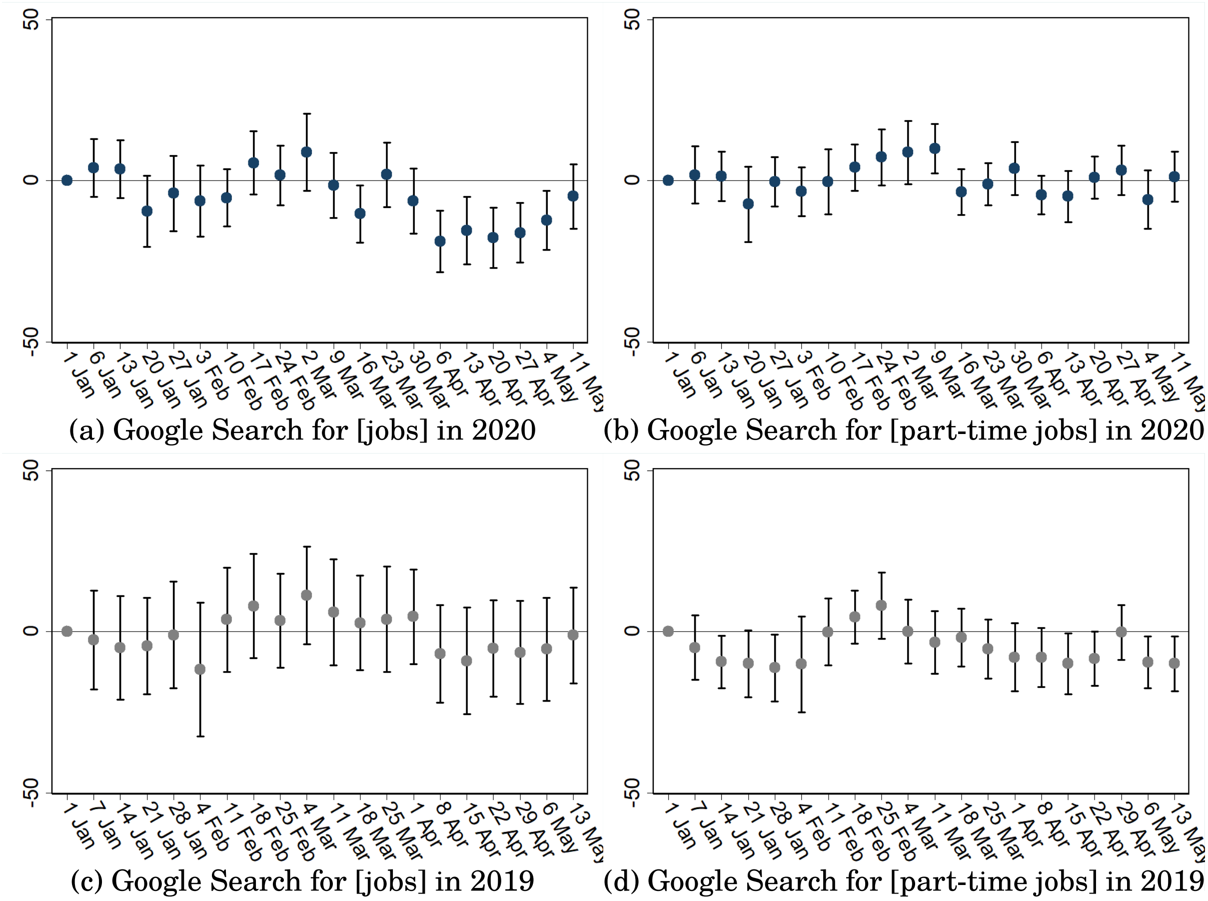


Figure V: WEEKDAY VS. WEEKEND CHANGES IN VISIT

Notes. Figure shows the difference-in-differences coefficients for weekly differences in weekday to weekend (Fri to Sun) changes in movement, relative to the baseline week of 17 Feb. A positive coefficient implies that the drop in weekday visits is *smaller* than on weekends. Each subfigure is a linear regression of 83 observations from 17 Feb to 9 May of 2020. Capped vertical lines are the 95% confidence interval constructed from the robust standard errors.

IV.B Job Searches

Decrease in Job Search. First, I use the subset of 2020 job search data, and estimate weekly changes in the job search indices as in equation (1). Figure VI plots the estimated β_t s, with job search taking a month-long dip starting the week of 6 April. This drop in job search is consistent with the detected anomalies in job search



(a) Google Search for [jobs] in 2020

(b) Google Search for [part-time jobs] in 2020

(c) Google Search for [jobs] in 2019

(d) Google Search for [part-time jobs] in 2019

Figure VI: Weekly Changes in Job Search Trends from Google

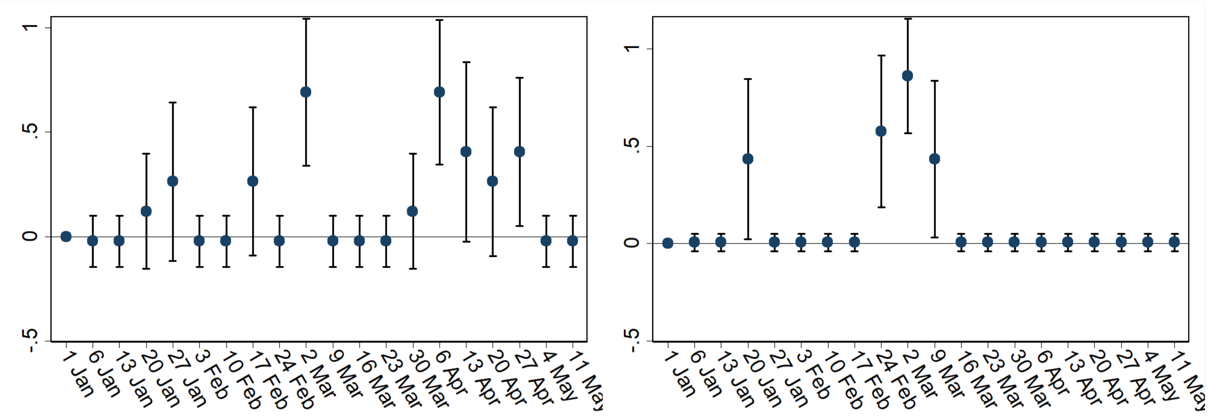
Notes. Figure plots the weekly ceofficients in Google search for (full-time) jobs and part-time jobs for 2020 and 2019. All regressions include day-of-week fixed effects. Capped vertical lines are the 95% confidence interval constructed from the robust standard errors.

(Table II), where a substantial number of dates in April are downward anomalies in search volume. Part-time job search on the other hand, does not exhibit a similar trend. I also repeat the estimation for job searches in the same period of 2019, providing evidence against the concern annual seasonal trends are driving the changes.

I also estimate a difference-in-differences specification with job search as the "treatment" and part-time job search as the "control". The results are consistent with the above—starting on the week of 30 March, job search fall by more than the fall in part-time job search until the last week of 11 May in the sample (Figure A3).[11]

Since there must have been an increase in unemployed workers (Tang, 2020;

[11] Specifically, I estimate $y_{it} = \alpha + \beta_t(\text{FT Jobs}_i \times \omega_t) + (\text{FT Jobs})_i + \omega_t + \boldsymbol{\delta}_{it} + \varepsilon_{it}$, where FT Jobs$_i$ is the dummy for (full-time) job searches, with part-time job searches as the omitted category. $\boldsymbol{\delta}$ includes the full-time job search-specific day-of-week fixed effects. Figure II shows fairly similar weekly trends (grey horizontal lines) for jobs and part-time job search up until the middle of March.



(a) Anomalies in Job Search (b) Anomalies in Part-time Job Search

Figure VII: PROBABILITY OF OBSERVING ANOMALIES

Notes. Figure shows the estimated weekly coefficients from regressing the probability of getting classified as an anomaly by the isolation forest algorithm (analogous to equation (1)). 10% of the 267 observations in the training sample are classified as anomalies using the observations with the 27 highest anomaly score. The regression uses only the 138 observations in the 2020 sample. Panel (a) is for job searches; panel (b) is for part-time job searches. Both are linear regressions. Capped vertical lines are the 95% confidence interval constructed from the robust standard errors.

Kahn et al., 2020; Hensvik et al., 2020), I interpret the above results as one where the average daily job search rate per worker has decreased since the onset of COVID-19 impact on the labour market. This finding is consistent with the procyclical job search behaviour of workers, where workers search less during recessions (Krueger et al., 2011; Hensvik et al., 2020).

Figure VII plots the estimated coefficients of β_t from equation (1), where the dependent variable is an indicator for whether the day's search index is an anomaly. The estimates imply two main anomalies in job search— the week of 2 March, with a sudden increase in job searches, and in the week of 6 April, with a sudden and month-long decrease in job searches. The latter provides another evidence that the anomalous fall in job search coincide with the start of the stay-home mandate.[12]

Is Drop in Job Search a Response to Fiscal Stimulus? The data points to job search falling because of movement restriction. As is standard with event studies, a major concern is that the estimates are capturing other events occurring at the same time. The drop might be a short-run response to the fiscal stimulus announced on 5 April, as a case of moral hazard in the job market. The one-time cash payout of 600 dollars[13] however, is unlikely to generate a drastic decrease in job search activity. As supporting evidence, the largest estimate from Baker and

[12] The coefficients for the weeks after the week of 6 April are no longer "anomalous", since a persistent change is not an anomaly.

[13] Approximately 420 USD.

Fradkin (2017) suggest that a ten-week increase in unemployment benefits duration led to only a 3.3% decrease in aggregate job search. Moreover, the timing of the decrease in job search does not fit the timing of the COVID-19 specific *Self-Employed Person Income Relief Scheme* which grants freelancers $9000 over the course of 9 months. The announcement for this came earlier on 26 March, and the first payout in this scheme occurs in May, when job search already returned to its baseline level. The timeline of the cashflow for a relief fund of $3,000 to low-wage workers, (to be) disbursed in July and October does not match the timing of the job search decrease as well. The decrease may also in principle be a consequence of other demand-side stimulus policies targeted directly at employers, such as wage co-funds, levy waivers, and tax rebates. These however, are merely augmentations to the previous fiscal packages (18 Feb and 26 Mar). So neither the timing of employer nor employee-targeted stimulus fit the timing of the decrease in job search in April.

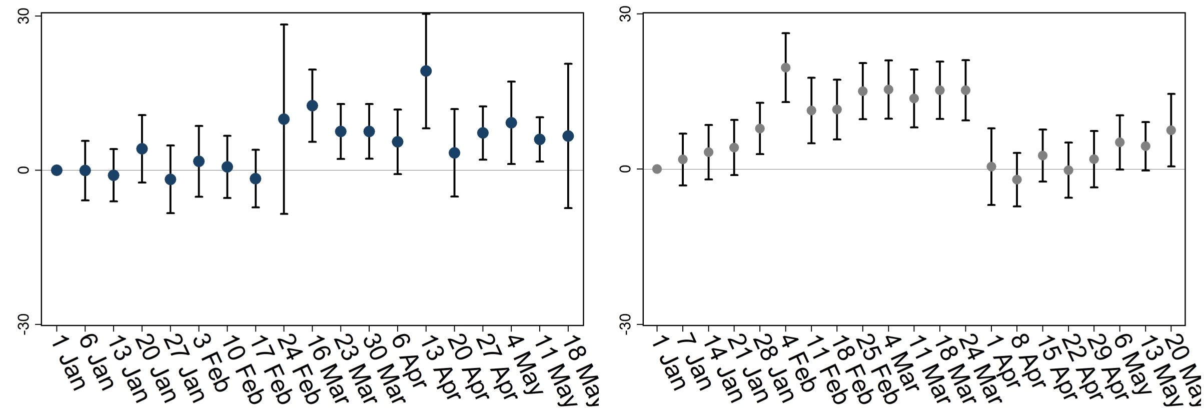
A suggestive evidence that the decrease in job search is not a response to the stimulus packages comes from hourly job search data. If job search fall because of alleviating concerns about the labour market, one would expect night-time specific job search to also fall, at least at the same rate as rest-of-day search. This is not the case. To test this formally, I define night-time job search as those that take place in the 4-hour period between 1am–5am local time, and estimate:

$$y_{it} = \alpha + \beta_t(\text{night-time search}_i \times \omega_t) + (\text{night-time search})_i + \omega_t + \boldsymbol{\delta}_{it} + \varepsilon_{it}, \tag{4}$$

where y_{it} is hourly job search for night or day time searches. $\boldsymbol{\delta}_{it}$ now includes the full interaction of night-time job search and the day-of-week fixed effects. Figure VIII plots the β_t estimates, and it turns that there is a relative increase in night-time job search (or at least, a smaller decrease in night-time job search relative to day-time search). This does not square with job search decreasing because of a more positive outlook from the supply side. Using 2019 data in the same period as a placebo reveals an opposite pattern, where night-time search is initially higher than day-time search before falling off.[14]

Is Drop in Job Search Capturing Changes in Sentiment? Another possible explanation is that job search fell because of because economic anxiety and sentiment. To help rule out this explanation, I turn to Google search data again. First, I query

[14] Another potential explanation for the drop in job searches is that search got redirected to COVID-19 specific jobs such as temperature screeners, COVID-19 testers, and other healthcare and administrative related jobs. Querying for both [jobs] and [covid jobs] however shows that the search for the latter is one to two orders of magnitude smaller than the former, indicating that redirection of jobs search to the health-sector does not substitute regular searches for non-COVID-19 related full-time jobs.



(a) Night-time Job Search (2020)

(b) Night-time Job Search (2019)

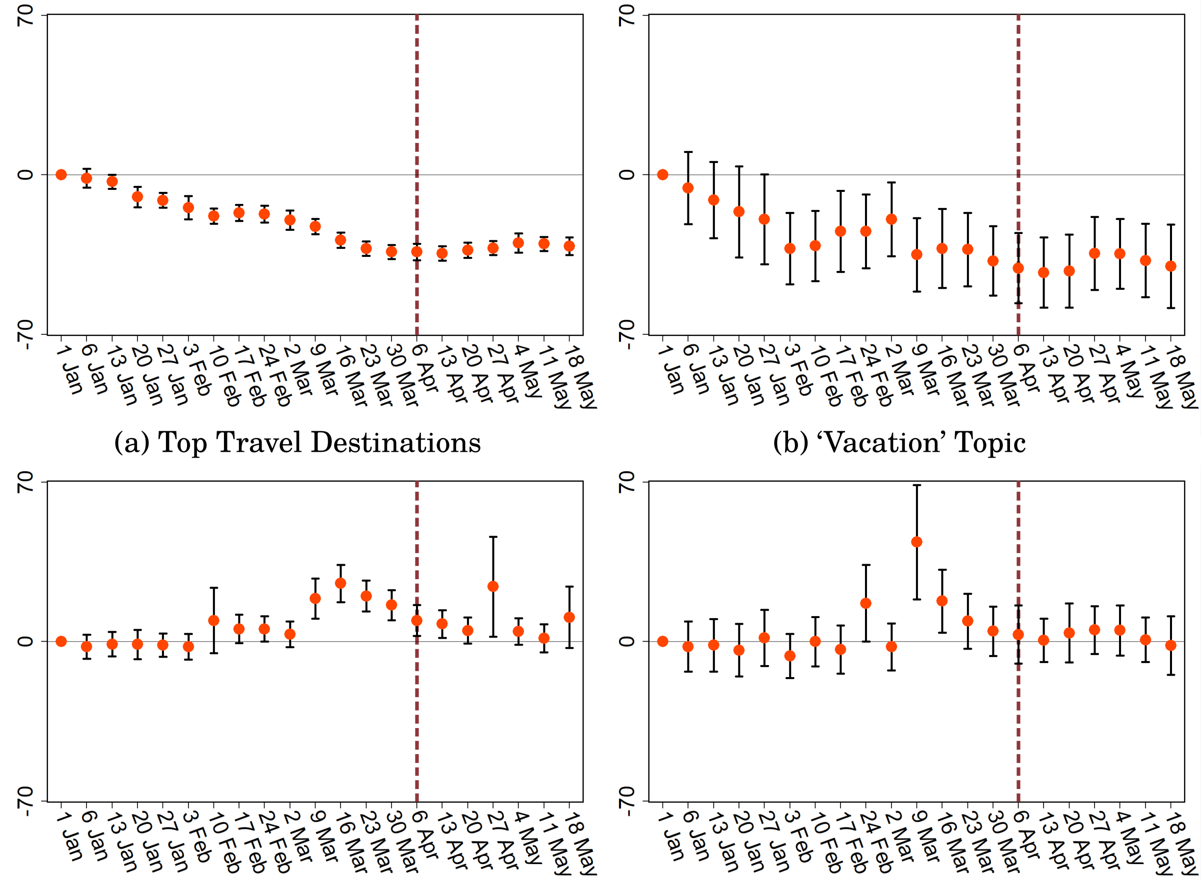
Figure VIII: Relative Increase in Night-time Job Search

Notes. Figure shows the estimated weekly difference-in-difference coefficients with night-time search (1am–4am) as the treatment" and rest of day search as the "control". The regressions control for day-of-week fixed effects, week fixed effects, and the night-specific day-of-week fixed effects (night-time search $\times$ day-of-week). Panel (a) is for the 2,717 hourly job search observations over the period 1 Jan 2020 to 22 May 2020. 2020 data for week of 2 March and 9 March is missing. Panel (b) is data for 2019 over the same period. Capped vertical lines are the 95% confidence interval constructed from the robust standard errors.

Google Trends for some of the most popular overseas vacation spots that Singaporeans go to, according to Expedia. Second, I use Google's own topic of 'Vacation'. Following Fetzer et al. (2020), I also use two additional Google topics of 'Recession' and 'Stock Market Crash' as leading indicators of aggregate demand and economic downturn.

Figure IX shows the trend of these four indicators. As anticipated, searches that include popular travel destinations, and more broadly, searches that fall into the 'Vacation' topic drop gradually through the year. These drop however, preceded the sharp fall in job search (timing indicated by the vertical dashed line). Searches relating to 'Recession' and 'Stock Market Crash' had transient increases in the March, and the timing of the changes again do not coincide with the drop in job search in April. Moreover, none of the four search behaviours display a sharp change during the week of 6 April, mitigating concerns that the week had salient economic event(s) not identified in Table I.

Finally, if movement controls indeed led to a decrease in job search intensity, the decrease should persist through May until the stay-home madnate is lifted in June. This requires some explanation. A potential insight comes from Briscese et al. (2020), who use survey responses in Italy and find that the timing of policy announcements matter in managing public expectations and behaviour. They find that a hypothetical unexpected extension to movement controls lowers the public's



(a) Top Travel Destinations

(b) 'Vacation' Topic

(c) 'Recession' Topic

(d) 'Stock Market Crash' Topic

Figure IX: Search Intensities as Economic Indicators

Notes. Figure shows the estimated weekly coefficients from estimating equation 1. In panel (a) the search is for `[(kuala lumpur) + bangkok + (hong kong) + denpasar + taipei + tokyo + penang + seoul]`—8 of the most visited destinations by Singaporeans (https://www.businessinsider.sg/the-10-most-visited-destinations-by-singaporeans-in-2018-were-all-in-asia-expedia-data-shows). As with the job search data, these are queried for the 9-month period of 25 Aug 2019–20 May 2020, with the regressions including only the 2020 observations. All regressions include day-of-week fixed effects. Capped vertical lines are the 95% confidence interval constructed from the robust standard errors. The vertical line indicates the week of 6 April when job search dropped/stay-home mandate began.

willingness to increase self-isolation effort (something which is difficult to monitor).

An unexpected extension to movement controls is exactly what happened on 21 April in Singapore, when the government announced a month-long extension of the stay-home mandate until the start of June. From Figure VI, 21 April is right about the time when the drop in job searches start reversing. To a modest extent, the Google mobility data corroborates this reversal in movement behaviour following the unexpected extension—imposing discontinuities at key dates, Figures A4 and A5 indicate that the decrease in visits to non-residential places also reverse after 21 April, though the change is not large.[15]

[15] Another potential explanation which is more pessimistic is that the return to baseline levels

V Implications

Using the context of Singapore and data from Google, this paper offers a number of insights into the impact of COVID-19 and related policies on local movement and job search. First, while movement controls are indeed effective in reducing foot traffic, visits to grocery and workplaces drop sharply only after a stricter control was put in place. Second, the movement control announcements unexpectedly led to same-day increases in foot traffic.

For job search, I first find a conspicuous lack of increase during the early weeks of the COVID-19 fallout. With early waves in layoffs, this implies a decrease in average search per worker, consistent with the procyclical model of job search. Job search then decrease in April, coinciding with the timing of the stay-home mandate, and constitutes a further drop in average search per worker.

There are two broad implications. First, the decrease in job search implies that the unemployment rate may understate the extent of job losses and overstate the eventual recovery of the economy, if less of the working-aged population are actively seeking jobs. Older workers who retire earlier than planned because of the unfortunate timing compounds the above issue.[16] Second, while not conclusive, a month-long decrease in total daily job search coincides with the stay-home mandate, suggesting that movement restrictions affected job search. I argue that the timing of this drop does not coincide with the timing of a series of fiscal stimulus. I also use four online searches as leading indicators of economic anxiety, noting that the timing of their changes do not coincide with the drop in job search. This also helps rule out undetected economic phenomena that coincides with the drop in job search.

To the extent that movement restrictions indeed led to reduced job search, COVID-19 induced not just a well-documented shock in labour demand, but also an additional shock to the supply side, which would amplify the labour market contraction. More conclusive evidence would come from observing similar patterns in job search at the individual-level, so that job search decrease can be pinned down to individual-level changes before and after movement restrictions. At the very least, labour force surveys might want to start including mobility as a reason for job search.

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of total daily job search in May is capturing another wave of layoffs. In this sense, the increase in search intensity is driven by the extensive rather intensive margin of job search.

[16] Coibion et al. (2020) find early evidence of this problem in the U.S. using the Nielsen Homescan survey.

References

Baker, S. R. and A. Fradkin (2017, apr). The Impact of Unemployment Insurance on Job Search: Evidence from Google Search Data. *The Review of Economics and Statistics 99*(5), 756–768.

Bartik, A. W., M. Bertrand, Z. B. Cullen, E. L. Glaeser, M. Luca, and C. T. Stanton (2020). How Are Small Businesses Adjusting to COVID-19? Early Evidence from a Survey. *NBER Working Paper No. 26989*.

Briscese, G., N. Lacetera, M. Macis, and M. Tonin (2020). COMPLIANCE WITH COVID-19 SOCIAL-DISTANCING MEASURES IN ITALY: THE ROLE OF EXPECTATIONS AND DURATION. *NBER Working Paper No. 26916*.

Chan, J. (2019, jan). The effect of college education on intolerance: evidence from Google search data. *Applied Economics Letters 26*(2), 83–86.

Choi, H. and H. Varian (2009). Predicting Initial Claims for Unemployment Benefits. *Google Inc.*.

Coibion, O., Y. Gorodnichenko, and M. Weber (2020). LABOR MARKETS DURING THE COVID-19 CRISIS: A PRELIMINARY VIEW. *NBER Working Paper No. 27017*.

Fetzer, T., L. Hensel, J. Hermle, and C. Roth (2020). Coronavirus Perceptions And Economic Anxiety.

Google LLC (2020). Google COVID-19 Community Mobility Reports. *https://www.google.com/covid19/mobility/ Accessed: <18 May 2020>*.

Hensvik, L., T. L. Barbanchon, and R. Rathelot (2020). Job Search during the COVID-19 Crisis. *SSRN* (May).

Kahn, L. B., F. Lange, and D. G. Wiczer (2020). Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims. *NBER Working Paper No. 27061*.

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific Reports 3*(1), 3415.

Krueger, A. B., A. Mueller, S. J. Davis, and A. Sahin (2011, may). Job Search, Emotional Well-Being, and Job Finding in a Period of Mass Unemployment: Evidence from High Frequency Longitudinal Data. *Brookings Papers on Economic Activity*, 1–81.

Liu, F. T., K. M. Ting, and Z.-H. Zhou (2012). Isolation-Based Anomaly Detection. *ACM Transactions on Knowledge Discovery from Data 6*(1).

Marthews, A. and C. E. Tucker (2017). Government Surveillance and Internet Search Behavior. *SSRN Electronic Journal*.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay (2011). Scikit-learn: Machine Learning in {P}ython. *Journal of Machine Learning Research 12*, 2825–2830.

Stephens-Davidowitz, S. (2014). The cost of racial animus on a black candidate: Evidence using Google search data. *Journal of Public Economics 118*, 26–40.

Tang, S. K. (2020). MAS expects more job losses, wage cuts as economy deals with 'large, abrupt shock' from COVID-19. *Channel News Asia*.

Yilmazkuday, H. (2020). Stay-at-Home Works to Fight Against COVID-19 : International Evidence from Google Mobility Data. *SSRN*.

A Appendix

Extra Tables and Figures

Table A1—*Related Searches for [jobs] and [part-time jobs]*

	Jobs `[jobs - steve - covid - part - parttime]`	Part-time Jobs `[(part + parttime) jobs - steve - covid]`
1	jobs singapore	part time
2	jobs in singapore	part time singapore
3	job	part time jobs
4	sg jobs	part time jobs singapore
5	online jobs	part time job
6	linkedin jobs	part time job singapore
7	jobs bank	best part
8	google jobs	body part
9	gumtree jobs	part time degree
10	gumtree	jobs in singapore

Notes—Top 10 related searches from the third-party API *pytrends* available at `https://github.com/GeneralMills/pytrends`. Query is done over the period 25 Aug 2019 to 20 May 2020 with geography restricted to Singapore ('SG').

Table A2—*Google Place Categories*

Place	Description
Grocery (& pharmacy)	Gorcery markets, food warehouses, farmers markets, speciality food shops, drug stores, and pharmacies.
Workplaces	Places of work.
Parks	Local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.
Retail (& recreation)	Restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.
Transit (stations)	Public transport hubs such as subway, bus, and train stations.
Residential	Places of residence.

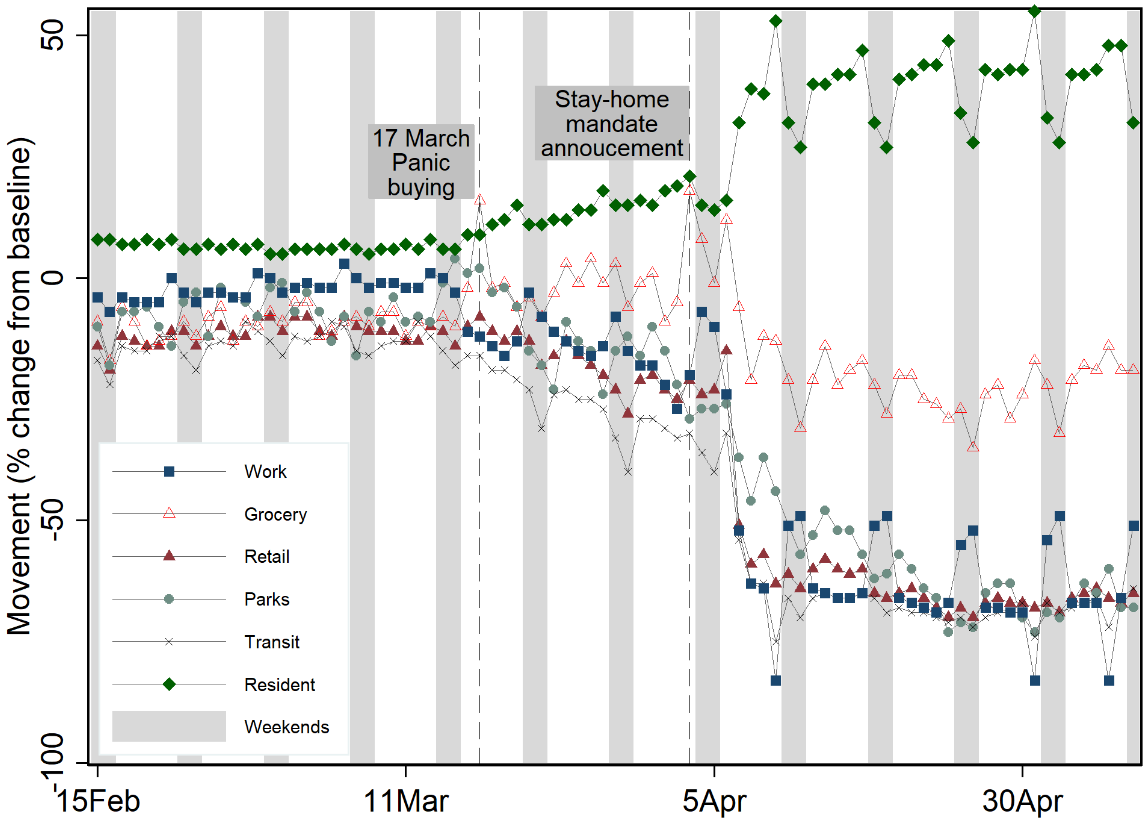
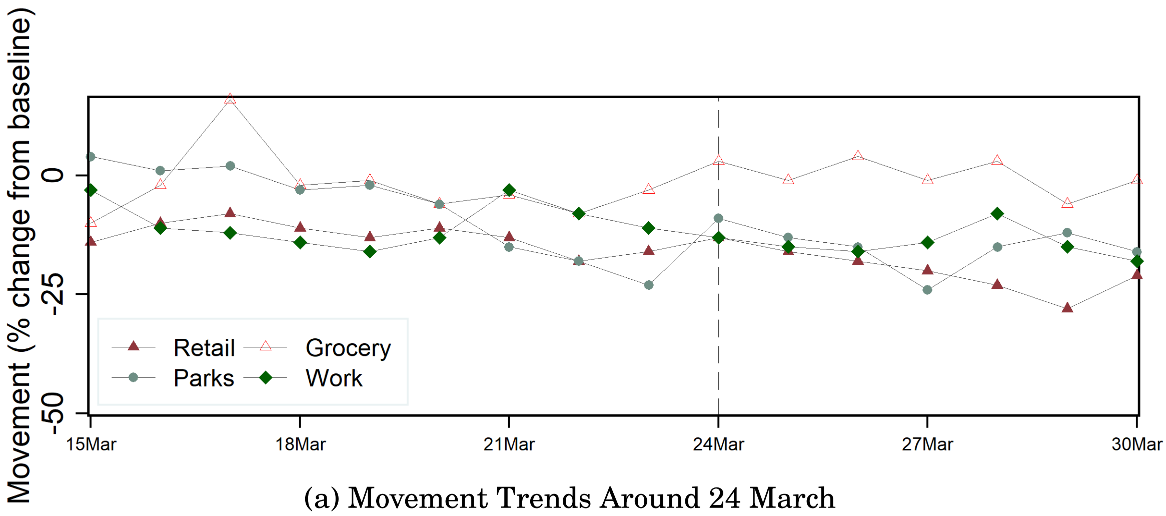
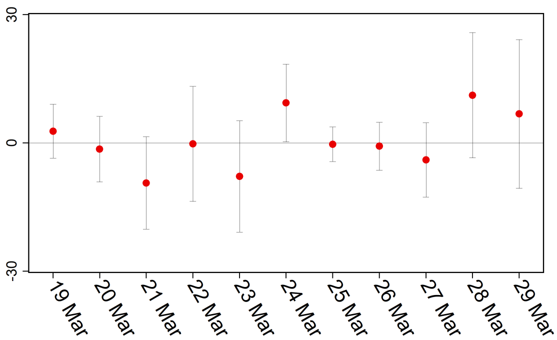


Figure A1: Changes in Movement (Weekdays vs. Weekends)

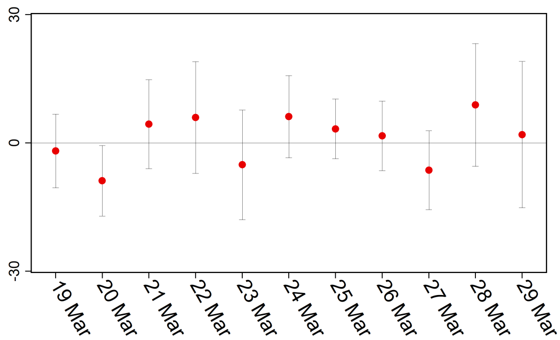
Notes. Scatterplot of the Google Community Mobility data for Singapore, 15 Feb to 9 May, 2020, analogous to Figure I. Grey vertical bars indicate weekends. Unweighted.



(a) Movement Trends Around 24 March



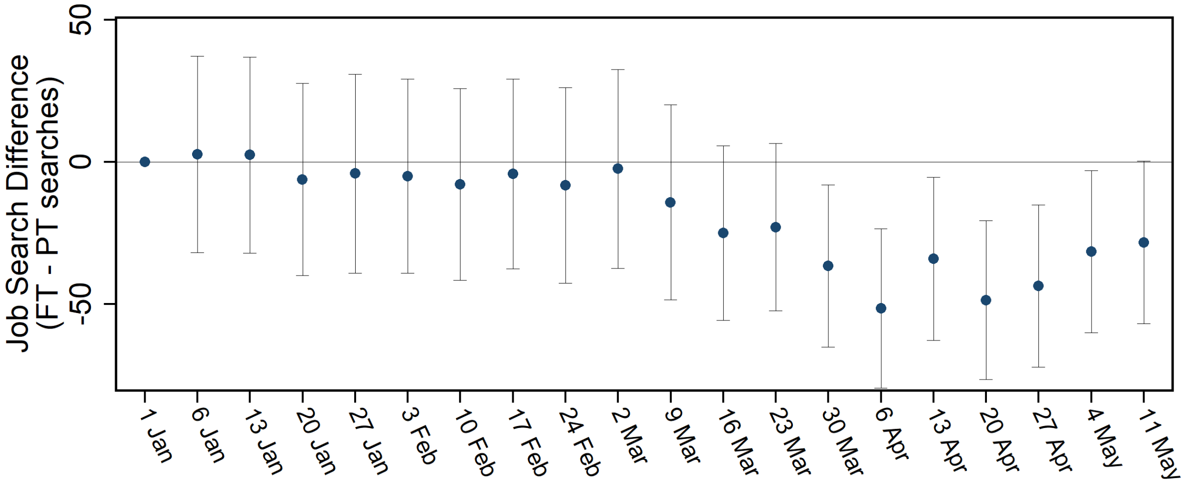
(b) Parks Relative Change



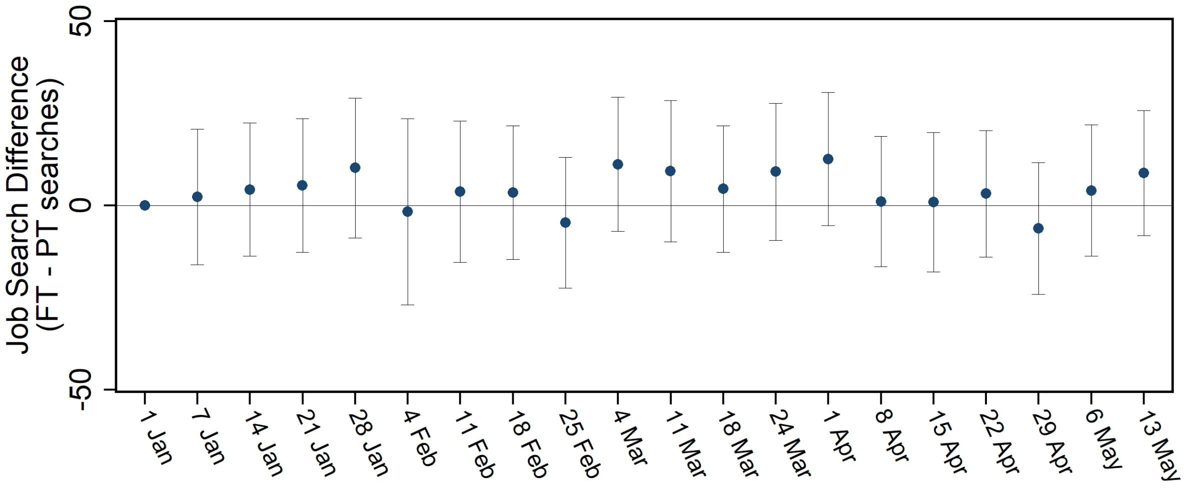
(c) Grocery Relative Change

Figure A2: Short-run Movement Changes (10 People Limit)

Notes. Panel (a) shows the trends in movement around 24 March, annoucement date for the 10 people limit in gatherings and closure of entertainment venues. Residential movement trends omitted. Panels (b) and (c) show the estimated coefficients for the 5-days lags and 5-days lead around 3 April for parks and grocery visits, respectively. Estimated coefficients are difference-in-differences regression with parks and grocery movement as the "treatment" group, and with retail and workplace visits as the "control". All regressions control for day-of-week fixed effects, week fixed effects, month fixed effects, and the parks and grocery-specific day-of-week fixed effects. Capped vertical lines are the 95% confidence interval constructed from the robust standard errors.



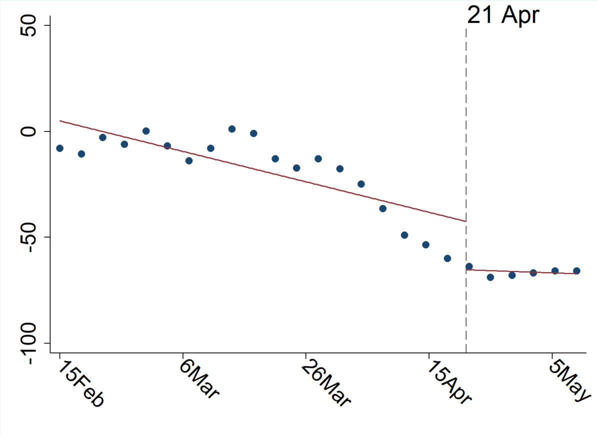
(a) Week, 2020



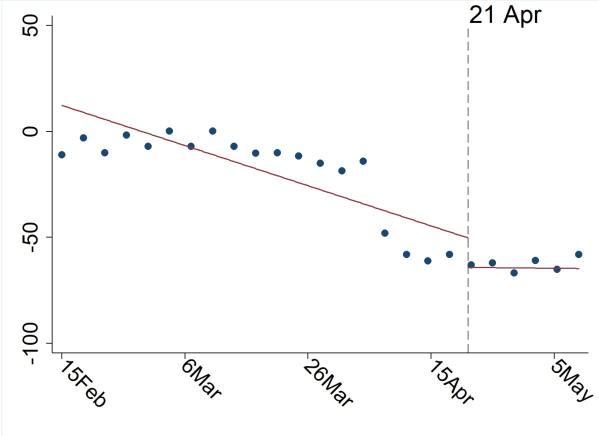
(b) Week, 2019

Figure A3: Relative Drop in FT Job Search

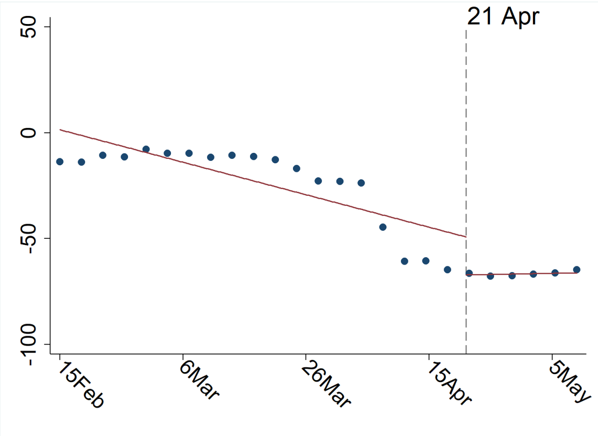
Notes. Figure shows the estimated weekly difference-in-difference coefficients with FT (full-time) job search as the "treatment" and PT (part-time) job search as the "control". The regressions control for day-of-week fixed effects, week fixed effects, month fixed effects, and the job search-specific day-of-week fixed effects (FT job search $\times$ day-of-week). Panel (a) is for the 414 daily job search observations over the period 1 Jan 2020 to 17 May 2020. Panel (b) is data for 2019 over the same period. Capped vertical lines are the 95% confidence interval constructed from the robust standard errors.



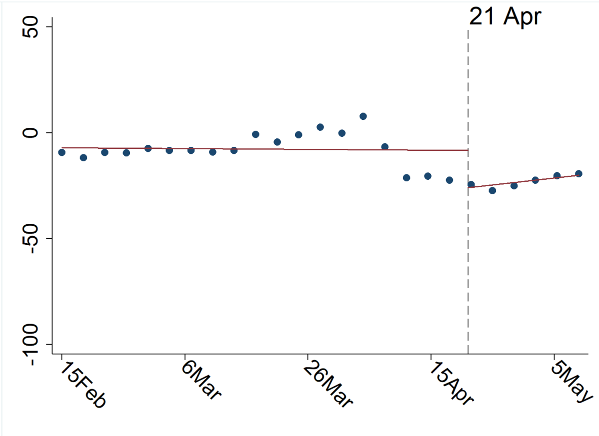
(a) Parks



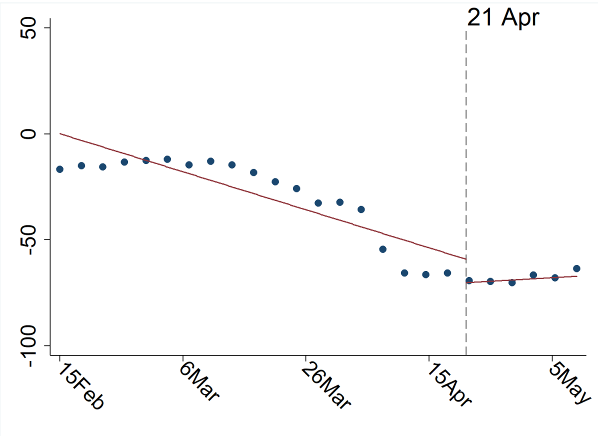
(b) Workplaces



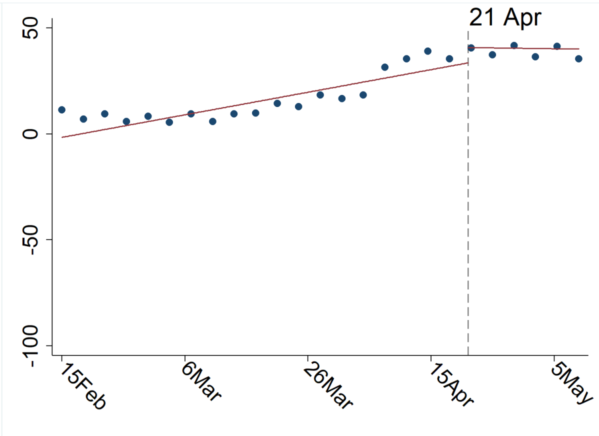
(c) Retail



(d) Grocery



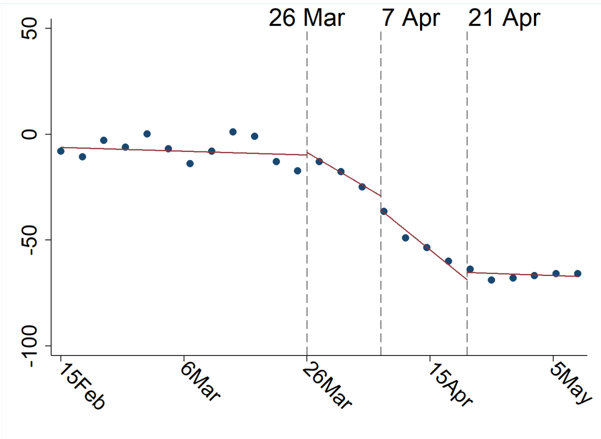
(e) Transit



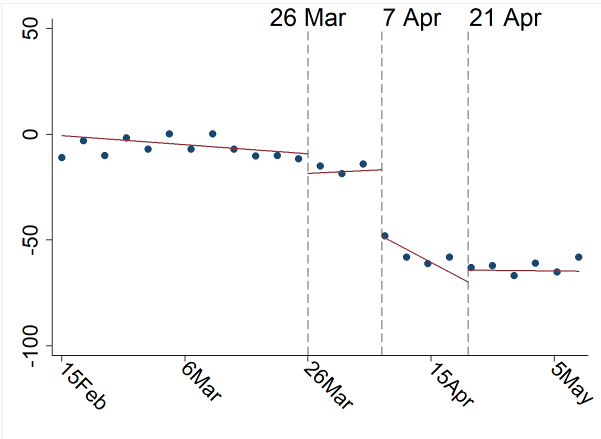
(f) Residential

Figure A4: Binned Scatterplot of Change in Visits (21 Apr)

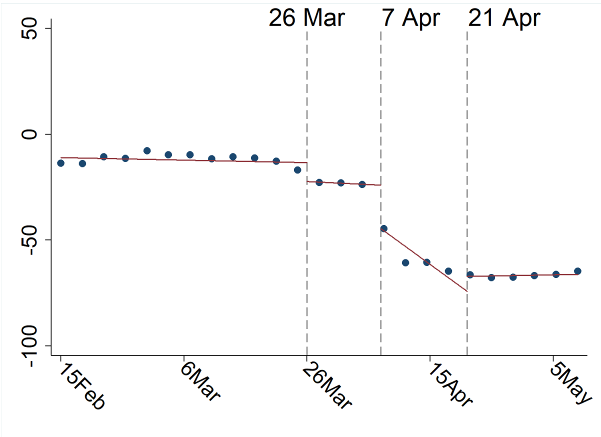
Notes. Each subfigure shows the binned scatterplot of visits to each of the 6 categories of places, with discontinuity imposed on 21 April when an unexpected extension to movement controls was announced. Each bin contains approximately 2.5% of the 85 observations in each category. Day-of-week fixed effects have been removed from the trends.



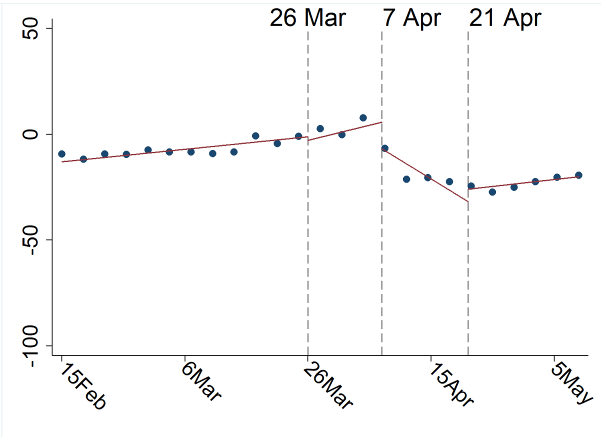
(a) Parks



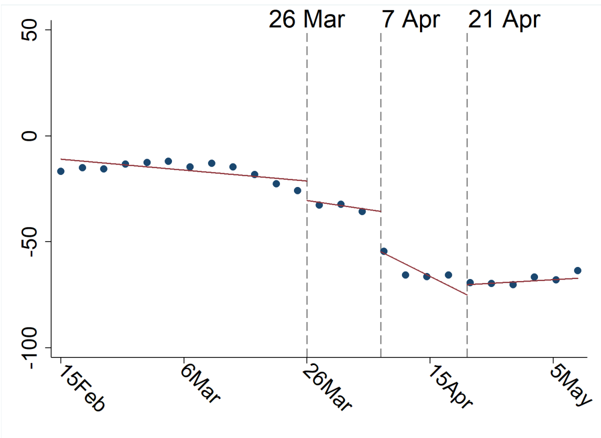
(b) Workplaces



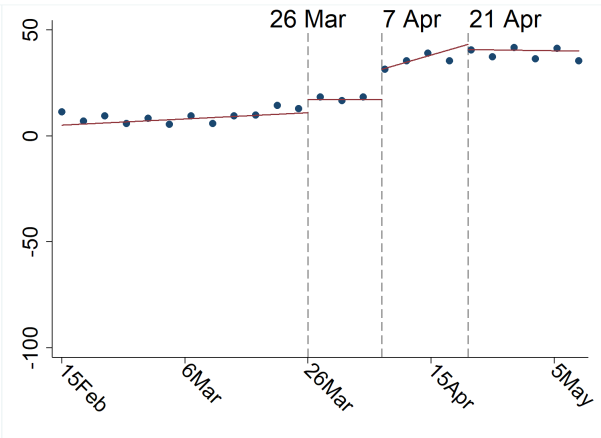
(c) Retail



(d) Grocery



(e) Transit



(f) Residential

Figure A5: Binned Scatterplot of Change in Visits (26 Mar, 7 Apr, 21 Apr)

Notes. Each subfigure shows the binned scatterplot of visits to each of the 6 categories of places, with three discontinuities imposed at (i) 26 March—beginning of 10–people gathering limit and closure of entertainment venues; (ii) 7 April—start of stay-home mandate; and (iii) 21 April when an unexpected extension to movement controls was announced. Each bin contains approximately 2.5% of the 85 observations in each category. Day-of-week fixed effects have been removed from the trends.