Mapping local economic recovery paths using pedestrian counts. A City of Melbourne Case Study.

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Abstract:

National Economic indicators are important. However, they may portray an incomplete and misleading picture of localised urban economies. In this study, we explore features of the patterns and dynamics of localised economies with a particular focus on examining economic recovery paths from the Covid-19 pandemic. Exploring the definition, identity and measurement of local economies and using the City of Melbourne as a case study, we interrogate the potential use of Pedestrian Counts to indicate current and future economic activity. We illustrate how pedestrian counts are available in real-time at high frequencies and can provide an opportunity to gauge real-time and forecast patterns in local-level economic activity.

Section 1 – Introduction

Modelling current or near-recent activity on a regular (i.e., monthly) basis of local activity zones (i.e., within a suburb) is challenging. This is despite the significant economic role local centres can play in the wider economy. Consider, for example, Melbourne's central business district (CBD), a local activity zone within the City of Melbourne, Victoria's capital and the second largest city in Australia. Data on local activity, productivity and other economic factors are unavailable or infrequently updated for timely analysis and decision-making.

In this study, we examine the use of pedestrian counts in the City of Melbourne which are free to download, available at high frequencies and in near real-time to understand and predict changes in local activity patterns. Previous research has shown that quarterly pedestrian volumes of Melbourne's CBD are associated (albeit not causally) with the overall economic activity of Victoria (Navon & de Silva, 2022). This link between footfall and economic activity is not surprising given that Melbourne has a diverse range and scale of businesses located in its centre. We acknowledge the need to also measure local economic activity in economically smaller and rural areas as explained by (Compagnucci et al., 2022b)

This quest for timely economic data on local activity zones is not new. Over the last ten years, for example, the use of night light data has been employed to gauge activity in the absence of accurate and reliable economic data (Henderson, Storeygard and Weil, 2012). More recently, (Feeny et al., 2022) used luminosity to map and classify recovery paths following natural disasters demonstrating the importance of using monthly readings in contrast to yearly measures. In this paper, we follow (Feeny et al., 2022) conceptually, applying it to time-related activity type using hourly features of pedestrian data records. Rather, than considering recovery paths following natural disasters we explore the extent that pedestrian volumes as a proxy for local economic activity have returned to pre-Covid-19 trends.

In the developed economy setting, public infrastructure (i.e., street lights) is an obvious limitation of using night light data. Alternatives to night lights include transaction data as well as using the information contained within Google Trends. These alternatives also have their limitations, finding suitable localised Google trend data activity zones within suburbs can be very challenging. Transaction data (potentially better at gauging activity within small spatial zones than Google trends) is often proprietary-based and may have lagged time stamps as well as unreliable location data (i.e., when payments are processed by a parent company in a different location).

We suggest that pedestrian data is a credible measure of local (economic) activity with some inherent advantages. First, it is available in real-time at very high frequencies. Specifically, pedestrian volumes are readily available on an hourly frequency every day of the year. Further, in the case of Melbourne, it is freely accessible. This means it has the potential to be used as a nowcasting input, see for example (Eraslan & Götz, 2021). Recognising these qualities, our study uses pedestrian data to gauge to what extent which different time-associated economic activities related to pedestrian movements have changed following the impact of the pandemic and associated restriction policies.

Importantly, because it can be observed hourly and at a street level, we can explore different recovery patterns and consider how this is changing the use of the city, and the associated economy and culture. Drawing on common understandings of engagement patterns such as work commute, education, entertainment etc -- we can generalise different times of day and locations which will predominantly correspond to different activities. For example, the most recent Victorian Integrated Survey of Travel and Activity survey (2020) identified the morning peak work–related trips to be between 7.30 am and 9 am in Melbourne. Saturday evening footfall is likely to be dominated by engagement in entertainment, sporting and cultural activities and its supporting businesses rather than office traffic. Analysing footfall by day and time enables detailed insights into the long-, medium- and short-term trends of (economic) engagement with the CBD for different activity types.

Consistent with mainstream discussions on the CBD visitor traffic we find that weekend traffic has returned to pre-covid trends. This however is not the case for city office worker traffic where we estimate that pedestrian volumes and therefore associated CBD economic activity is still several years away from being close to the pre-Covid-19 trend suggesting that much of this activity may now be located in various suburbs. We discuss the implications of this in more detail in section 5.

Finally, we note that nowcasting typically takes the form of collating high-frequency variables to predict low-frequency economic aggregates such as GDP. No conventional economic aggregates are available for Melbourne's CBD. Therefore, we are unable to perform a conventional nowcasting exercise. We believe that we have captured the concept. Specifically, we show how pedestrian counts can be used to gauge current and recent activity that can be used to approximate local economic activity – albeit imperfectly.

This paper is organised as follows. Section 2 provides a context for the use of pedestrian data and the application of the City of Melbourne, including a brief literature review. Section 3 describes the data used. Section 4 presents our analytical approach. Section 5 presents our analysis results. The last section, Section 6, discusses our findings and concludes our analysis.

Section 2 – Context

The key premise of our investigation is that understanding local activity zones matter - this is supported by studies such as (Xiao et al., 2018). A second, equally important premise is that public policy as well as non-public sector initiatives can be conducted with more confidence and efficiency if knowledge of local areas is based on current and regular information suitable for nowcasting or forecasting.

Nowcasting conducted on larger spatial units is important, however, we argue that without information on local economies, the effectiveness of any place-based initiatives, interventions, or innovations (public or private) can be significantly impeded or may even mask important unintended consequences. This argument is consistent with (Compagnucci et al., 2022b) who consider that knowledge of local activity zones will likely improve efficiency thereby more effectively driving economic growth/recovery. An interesting case study of divergence of trends at spatial levels is presented by (Angelopoulos, de Silva, Navon, et al., 2022) who show that a generalised association between industry diversity and Jobkeeper applications at the national level did not hold for the state of Victoria.

An important feature of local areas is that they are diverse across multiple dimensions. as per (Angelopoulos, de Silva, Sinclair, et al., 2022), identify three broad dimensions of place -- resources, people and life -- concluding a need for both qualitative and quantitative information when assessing the condition of regions.. Given the dynamic nature of local areas, in the absence of qualitative data, we suggest that activity related data needs to be current and frequent for it to be useful. This suggestion is supported by several studies that have concluded there may be significant societal consequences if heterogeneity of local areas is not understood. These consequences include increased inequality of living standards as well as political and social unrest (Alesina & Rodrik, 1994; Compagnucci et al., 2022a; Furceri et al., 2022; Xiao et al., 2018). Lack of local knowledge may also affect a community's response to shocks and subsequent resilience and thus its ability to recover from shocks.(Alesina & Rodrik, 1994; Compagnucci et al., 2022b; Furceri et al., 2022; Xiao et al., 2018).

Having established that knowledge relating to local activity zones is essential for policy and planning reasons we now consider how localised data could be used for gauging economic activity. As stated earlier, in the developing economy setting, luminosity (nightlights) has been an important theme. (Henderson et al., 2012) used such data to measure economic activity (and progress) at sub-national levels in Africa. Since this work, there has been a number of contributions employing luminosity as a proxy for current and historical economic activity. As stated earlier, whilst insightful in a developing economy setting, luminosity is unlikely to provide meaningful economic measures in developed settings such as Melbourne given the level of public infrastructure. Alternatives to luminosity iincludetransaction data (Aladangady et al., 2019) and Yelp (restaurant reviews) (Glaeser et al., 2017). Our study extends this body of literature by considering pedestrian flow counts.

Previous studies have indicated that footfall is associated with economic activity, including (Eraslan & Götz, 2021; Navon & de Silva, 2022). Pedestrian counts have been applied as a means for revealing economic insights; for example (Panay et al., 2021) used it to predict consumer behaviour and (Mumford et al., 2021) employed it to assess characteristics of local areas. Pedestrian counts have also been used to explore social and cultural constructs (Matthews & Gadaloff, 2022). Our contribution to this literature is that pedestrian counts provide a way to gauge both the current and near-recent recovery paths with respect to the effect the Covid-19 pandemic had on cities.

Pedestrian counts are unique as they provide the means to proxy the direct and indirect effects of peer-to-peer engagement at highly localised levels.

A particularly useful aspect of pedestrian counts is that they are available hourly. This means times that are more likely to be dominated by engagement in certain (economic) activities can be modelled specifically. For example, post-Covid-19 there has been much discussion about the flexibility of working from home. Using this data, we can proxy (albeit imperfectly) the extent of this phenomenon by modelling footfall in the CBD corresponding to typical office work times. For example, early morning weekday counts will likely capture the arrival of construction workers followed by office workers and the businesses that service these sectors. In contrast, weekend traffic such as Friday and Saturday evenings more likely represents hospitality and entertainment-related activities such as theatres, sporting events, and restaurants.

Empirically we know that the pandemic resulted in serious implications to businesses located in city centres and retail districts (Florida et al., 2021). Closure of businesses, rapid digitisation and reduced demand for office space may result in a redesign and resource reallocation of the built environment, particularly if a blended work environment is maintained into the long-run for workers able to work remotely Already, studies are finding a falling demand for residential apartments in city and central regions (Kang et al., 2021), with slower internal migration flows that are favouring non-city regions at the expense of capital cities (Borsellino et al., 2022) and mobility decisions driven by lifestyle choice rather than employment choice. These findings appear to be country-specific in many instances (Perales and Bernard, 2022). Whether this is a transitory phenomenon is yet to be determined especially when coupled with soaring inflation and interest rates in many nations. Interestingly, we believe that pedestrian counts are one way we can gauge current practices and the shape of long- and short-term trends.

Given the emerging understanding of the costs and benefits of working from home, a hybrid work model may be the outcome of the natural experiment that Covid-19 forced into the labour market landscape (Florida et al., 2021). Yet even a hybrid work model, where some sort of balance is struck between working from home and commuting to the 'office' will likely have significant implications for the economics of the spatial environment. Hybrid work can result in a structural change to the way that large cities CBD's , and surrounding suburbs are used especially given the 'live-work neighbourhood' focus of many urban planners (Florida et al., 2021). A sustainable hybrid model may affect residential location decisions of people who previously chose to live 'closer to work' to minimise commute time (Kang et al., 2020; Perales & Bernard, 2022), changing not only major city residential areas but the surrounding and outer regions as well. These structural changes in city traffic can have profound effects on local economies and thereby the national economy.

In the wake of this behavioural change, cities are having to adapt and compete with these different engagement patterns. Rapid digitisation during Covid-19 has added a new dimension to the nature of cities, creating innovative and potentially disruptive means of engaging with place, both physically and digitally. Understanding the dynamics of these new patterns of engagement in real time will be a vital part of ensuring cities can remain innovative and creative centres of employment, creativity and entertainment, responding quickly to changing-use patterns.

Melbourne has long been Australia's cultural and sporting city known for its entertainment and retail opportunities. It is also Australia's second largest city, and hosts some of the largest organisations in key sectors such as higher education, retail, finance and health. Further, it is an international cultural icon drawing visitors from all over the world. Therefore, changes in its usage have the potential to have nationwide impacts. Melbourne has also seen the longest and stricter restrictions during Covid-19 lockdowns in Australia.

We posit that given that pedestrian counts in Melbourne CBD are available almost in real time on an hourly basis spread across several zones, they can be useful to predict short, medium and long-term changes in localised economic activity proxied by footfall traffic, with implications to the larger economy.

Section 3 – Data Description

Like many cities around the world, the City of Melbourne has sensors located throughout the central business district (CBD) which count, in real-time, the volume of pedestrians. The City of Melbourne is different however from many other cities - it is one of a few cities around the world with a well-developed automated pedestrian counting system established as early as 2009 (Sydney for example only started trailing pedestrian sensors in 2020) that can be freely accessed. [1]

The pedestrian system comprises pedestrian counting sensors in various locations across the city based on three criteria – retail and event activity, regular pedestrian use, and the egress and entry flow to these areas. The system consists of counting sensors that are installed under awnings or on light poles in various locations throughout Melbourne's CBD. Each sensor forms a "counting zone" on the footpath below it and records pedestrian movement[2] passing through the zone area, 24 hours, 365 days per year. The data is first saved on a computer on-site and then transferred to the City of Melbourne's server every 10-15 minutes.

We downloaded all available pedestrian counts data for the period 1 January 2010 to 31 January 2023 for the top 10 sensors with the most pedestrian counts volume based on whether they had been in place during that entire sample period.[3]

In Table 1 the locations for which data is available for this period along with the descriptive statistics for the pedestrian counts are provided. The busiest location is Melbourne Central which is near one of the busiest train stations and in close proximity to the centre of Melbourne's CBD with an average pedestrian volume of 1,087 per hour. Conversely, Waterfront City at the edge of the CBD has the smallest average volume per hour (92). As expected, higher pedestrian counts are observed in the more popular and central locations around the CBD, e.g., train stations and tourist attractions.

Table 1

Sensors - descriptive statistics

Sensor Location	Mean	Median	Min	Max	Std Dev	Obs.
Bourke Street Mall (South)	935	373	0	6942	1119	114451
Collins Place (North)	301	119	0	3759	415	109839
Flinders Street Station Underpass	1078	890	0	6568	996	114257
Melbourne Central	1087	839	0	5890	951	109666
New Quay	197	147	0	11284	269	111181
Princes Bridge	1005	846	0	7391	909	111332
Southern Cross Station	459	111	0	5873	752	114425

[1] http://www.pedestrian.melbourne.vic.gov.au.

[2] The system records movements, not images, so no individual information is collected.

[3] Note we excluded counts from sensors that had been either added or eliminated during this period.

Victoria Point	147	73	0	3113	191	114129
Waterfront City	92	50	0	9805	193	113172
Webb Bridge	153	115	0	4320	159	113233

Table 1 presents descriptive statistics for the 10 sensors with data available for the full sample period between 1 January 2010 and 31 January. Mean, median, Min, Max, and standard deviation are for the hourly volume of pedestrians identified by each sensor across our sample. Obs is the number of hours for which data is available across the sample period.

Pedestrian Counts – Preliminary Insights

We begin our analysis by examining average hourly pedestrian counts per day of the week for each calendar year spanning 2010 to 2022. Table 2 presents information on the average pedestrian count for every day of the week in every year across our sample. The data illustrates changing patterns of footfall from pre covid norms with a shift from Friday being on average the busiest day pre covid to Saturday in 20 / 21. We also observe a change in the least busy day from Sunday to Monday (post-Covid)- indicatively illustrating a change in working week-related engagement patterns. We note that there is a positive trend with an increase in the number of pedestrians from 2010 to 2019 across all days of the week except Sundays, with a drop in 2020 and 2021. This reflects the effect of lockdowns and restrictions imposed during Covid-19 in Victoria which resulted in limited pedestrian movement in Melbourne's CBD during large parts of 2020 and 2021. Comparing the last full year prior to Covid-19's restrictions (2019) to the first year clear of major restrictions (2022), we observe that, on average, pedestrian counts on weekdays (Monday-Friday) in 2022 are back to only about 59% of the 2019 figures. Conversely, weekend pedestrian counts (Saturday-Sunday) in 2022 are back to about 92% of the 2019 figures.

Table 2

Average Pedestrian Counts by Day of the Week

	Year													
Day	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average**
Monday	535	568	569	557	558	635	635	647	689	669	251	221	374	**531**
Tuesday	554	572	582	585	566	640	655	684	703	704	263	236	402	**550**
Wednesday	577	596	605	597	599	670	674	706	734	713	278	250	424	**571**
Thursday	596	623	614	606	603	681	697	717	743	740	280	257	441	**585**
Friday	669	698	686	691	691	759	768	787	799	783	295	275	493	**646**
Saturday	469	505	504	533	538	598	602	584	593	577	257	290	546	**508**
Sunday	427	423	441	455	461	504	495	497	500	480	221	245	425	**429**
Average	**547**	**569**	**572**	**575**	**574**	**641**	**647**	**660**	**680**	**667**	**264**	**253**	**443**	

Table 2 presents average hourly pedestrian counts for each day of the week across all sensors in our sample period for the years 2010-2022.

We now turn to examining the intra-day change in pedestrian counts. Specifically, Table 3 presents the average pedestrian count for every hour of the day per year from 2010 to 2022. As expected, the busiest times of the day on average are 8-9am, 12-2pm, and 4-6pm, which roughly correspond to before work, lunchtime, and after work times on weekdays, respectively. There is a clear decline in pedestrian movement across all hours of the day in 2020 and 2021, again, due to the effect of lockdowns and restrictions imposed during Covid-19 in Victoria. Comparing the last full year prior to Covid-19 (2019) to the first year clear of major restrictions (2022), we observe that pedestrian counts in 2022 are back to only about 70% of the 2019 figures, on average. The busiest times of 8-

9am, 12-2pm, and 4-6pm in 2022 are back to only about 45%, 65%, and 62%, respectively, of the numbers in 2019, indicating a very low (high) return to work (work from home) figures. In comparison, the evening (8pm to midnight) and early hours after midnight (until 4am) which are generally associated with nightlife and entertainment times, are back to about 89% and 95% respectively. In addition, further examination separately for each day of the week (see tables A1-A7 in Appendix A), reveals different intra-day patterns during a typical week. Specifically, while the 8-9am, 12-2pm, and 4-6pm periods are busiest during Monday-Friday, 12-9pm is the busiest time of the day on Saturdays, and 11am-6pm on Sunday.

Table 3

Average Pedestrian Counts by Time of the Day

	Year													
Hour	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average**
0	402	120	130	133	117	151	149	149	149	139	59	62	131	**145**
1	62	63	67	71	63	75	84	87	86	75	34	36	74	**68**
2	45	41	43	44	41	42	52	51	55	46	21	24	44	**42**
3	33	33	33	32	29	32	41	40	44	36	17	19	34	**32**
4	22	21	22	20	22	25	31	31	32	28	15	15	24	**24**
5	40	37	37	36	50	48	56	58	63	61	32	26	37	**45**
6	134	134	143	136	178	164	180	184	209	202	86	73	100	**148**
7	385	384	387	388	491	460	479	509	538	537	185	157	224	**394**
8	815	876	866	815	818	948	984	1030	1058	1054	321	273	469	**794**
9	578	595	599	586	549	661	673	715	754	764	269	235	399	**567**
10	557	562	557	580	601	629	625	634	660	641	275	273	442	**541**
11	708	718	700	732	804	789	784	788	808	786	348	348	575	**684**
12	1108	1151	1134	1178	1202	1208	1191	1205	1235	1187	480	457	777	**1039**
13	1207	1254	1226	1251	1167	1280	1256	1253	1267	1218	503	481	809	**1090**
14	1000	1034	1021	1047	1017	1106	1090	1082	1105	1062	476	465	771	**944**
15	994	1027	1021	1042	1047	1125	1117	1122	1159	1118	497	471	794	**964**
16	1115	1149	1148	1150	1195	1270	1296	1334	1387	1382	550	494	867	**1103**
17	1339	1426	1420	1364	1304	1572	1614	1661	1720	1725	617	552	984	**1330**
18	905	963	986	962	890	1129	1146	1179	1213	1208	454	446	790	**944**
19	603	626	647	658	639	784	783	804	825	815	330	341	625	**652**
20	459	477	496	506	524	621	623	641	652	655	267	285	535	**519**
21	388	401	425	435	446	538	532	547	565	559	221	238	493	**445**
22	323	338	356	378	355	440	440	448	456	438	170	192	405	**365**
23	227	229	247	249	216	294	278	284	285	265	103	117	248	**234**
Average	**560**	**569**	**571**	**575**	**574**	**641**	**646**	**660**	**680**	**667**	**264**	**253**	**444**	

Table 3 presents average pedestrian counts for every hour of the day across all sensors in our sample period for the years 2010-2022.

Taken together, results in tables 2 and 3 indicate that there are different intra-day patterns in the number of pedestrian counts across the day, and that the number of pedestrian counts in 2022 compared to 2019 is different for weekdays and weekends. We therefore choose to focus our analysis on the number of pedestrian counts in Melbourne's CBD during the periods 6-9am on weekdays, 6-9pm on Saturdays, and 1-4pm on Sundays. This is because our objective is to distinguish between recovery paths related to two different domains: 1) the number of people travelling to the city for work, which is captured in the 6-9am period on weekdays periods, and 2) the number of people travelling to the city for various entertainment activities such as dining and shopping which is captured in the 6-9pm on Saturdays, and 1-4pm on Sundays periods.

Section 4- Analysis

Having established that pedestrian counts in 2022 differ from previous years we now turn our attention to recovery paths. Figure 1 presents four types of recovery that are likely to correspond to the preliminary data analysis performed in the previous section. The four recovery paths are depicted as follows:

1. Scenario 1: Snap-back – a return of pedestrian traffic to pre-Covid-19 levels and trends.
2. Scenario 2: Gradual Return – a steady return to the historical trend
3. Scenario 3: Permanent decrease – pedestrian traffic grows at the same rate but the level at any given point in time is lower than the historical trend
4. Scenario 4: Permanent departure – A shift in volume as well as a lower growth culminating in increasing divergence from the historical trend

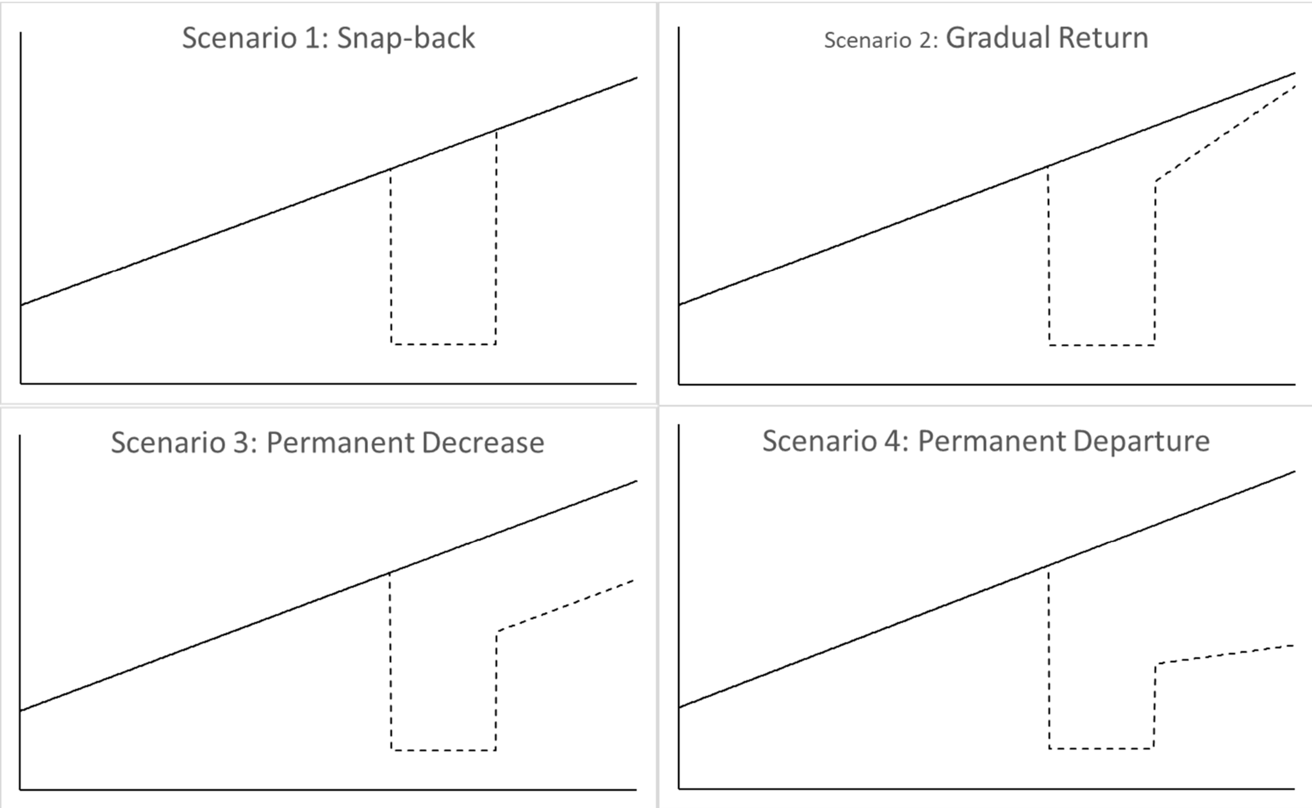

Figure 1 Types of Recovery Paths. Dashed Lines represent smoothed pedestrian counts during and after covid. The solid line represents long-term trend. X- axis is time, and Y-axis is pedestrian volumes (proxy for economic activity)

Each of these recovery paths has different implications for the city and provide an opportunity to nowcast its (changing) economic profile. The first type depicts the instance where there is the least impact on the local economy - specifically it is when consumers returned to the city after restrictions eased. This means those activities that are distinctly 'city' such as premier shopping opportunities, hospitality and business activity essentially return to pre-pandemic levels and profile.[4]

In the second scenario, a gradual return is pictured. Under this scenario the city does not return immediately to its historical path. Similar to the first scenario, changes to the city's profile are likely

[4] Note, we are distinguishing between level and profile, where profile refers to the composition of the level.

to be minimal. However, the longer it takes to return to the historical trend it is likely that any interim changes will become more entrenched.

A permanent decrease is our third scenario. In this scenario, although city activity continues to grow at the same rate as in the pre–Covid-19 period, it is always lower that what it would have been without the shock of Covid-19, as depicted, by extrapolating the historical trend. In this scenario the level of activity changes more than the profile with structural change occurring in the region and its role as an employment, shopping and entertainment hub.

In the final scenario, a significant structural (levels and profile) change to the city occurs. Under this scenario, there is a permanent divergence from pre-Covid-19 settings. Under this scenario the impact on the city and its dynamics is significant, city engagement permanently changes altering the way the city is used.

The return path will also provide insight into the resilience of the city. Will the region return to its pre-Covid-19 state, demonstrating its ability to ride-out temporary shocks, readjust or reposition itself and continue its growth path; will it return with a new and higher growth trajectory, demonstrating its ability to adapt and even take advantage of shocks (to re-invent itself); or will it be forced on a new lower route as a result of permanent changes to its original role as an employment, commerce and entertainment hub.

Technical approach

Having mapped change scenarios, we now outline how we will model them. Broadly, the four models contain a mixture of trend and level breaks. All scenarios contain two level breaks, the first coinciding with the beginning of the pandemic[5] and the second with the end of the pandemic[6]. Trend breaks are also present in each scenario, common to all scenarios is the upward trend prior to the pandemic and the period of no growth during the pandemic. Scenarios 1 and 2 depict a return to pre-pandemic trends, while scenarios 3 and 4 do not.

In the first instance we apply the following baseline model letting y_t denote pedestrian counts:

$$y_t = \alpha_0 + \alpha_1 D_1 + \alpha_2 D_2 + \beta_0 t + \beta_1 D_1 t + \beta_2 D_2 t + \gamma PH_t + e_t, \quad t = 1,2, \dots T \quad e_t \sim N(0, \sigma^2)$$

Where

- α_i represent (shifts in) the conditional mean
- β_i represent (shifts in) growth rates
- D_1 and D_2 are indicator variables defined as:
    - $D_1 = \begin{cases} 1 \text{ during pandemic restrictions} \\ 0 \text{ Otherwise} \end{cases}$
    - $D_2 = \begin{cases} 1 \text{ Post pandemic restrictions} \\ 0 \text{ Otherwise} \end{cases}$
- t denotes a time trend

[5] A state of emergency was declared on March 16th 2020, and the first of six lockdowns were enacted on 30 March 11:59pm. We have nominated March 17th 2020 as the start date, noting that pedestrian volumes noticeably decreased after the March 16th announcement.

[6] Whilst the last lockdown ended on 21st October 2021, restrictions remained in place throughout the summer, this included density limits and vaccine requirements. Nominally, we set the pandemic end date to March 31st 2022.

- PH_t represents relevant a set of pulse dummies corresponding to public holidays and events

Under scenario 1: $\alpha_1 < 0, \alpha_2 = \alpha_0 + \beta_0 \, t_{|restriction\ end\ date}$, $\beta_0 = \beta_2, \beta_1 = 0$
Under scenario 2: $\alpha_1 < 0, \alpha_2 < \alpha_0 + \beta_0 \, t_{|restriction\ end\ date}$, $\beta_0 < \beta_2, \beta_1 = 0$
Under scenario 3: $\alpha_1 < 0, \alpha_2 < \alpha_0 + \beta_0 \, t_{|restriction\ end\ date}$, $\beta_0 = \beta_2, \beta_1 = 0$
Under scenario 4: $\alpha_1 < 0, \alpha_2 < \alpha_0 + \beta_0 \, t_{|restriction\ end\ date}$, $\beta_0 > \beta_2, \beta_1 = 0$

Section 5 – Analysis

As stated earlier we focussed on three sets of times:
1. Monday, Tuesday, Wednesday, Thursday, Friday 6am – 9am
2. Saturday 6pm-9pm
3. Sunday 1pm -4pm

We believe, that each of these sets corresponds predominately to a particular form of economic activity. The first to office workers looking to spend the day onsite, the second to those engaging in cultural activities as well as hospitality and the last to retail and hospitability. These activities may be thought of as direct forms of economic activity. In reality, each of these activities will include an array of purposes to visit the city.

To each set of these times, we fitted the model described in the section above. Initial estimates of these models revealed that for the period of restrictions (March 2020 to March 2022) the coefficients corresponding to D_1-- during the Covid-19 pandemic -- were insignificant. Closer inspection of the data as well as review of pandemic policies revealed various grades of lockdown during the two-year period causing the model to be respecified to:

$$y_t = \alpha_0 + \alpha_1 D + \beta_0 t + \beta_1 Dt + \gamma PH_t + e_t, \quad t = 1,2, \dots T \quad e_t \sim N(0, \sigma^2)$$

Where

- α_i represent (shift in) the conditional mean
- β_i represent (shift in) growth rates
- D is an indicator variable defined as:
  - $D = \begin{cases} 17th\ March\ 2020\ Onwards \\ 0\ Otherwise \end{cases}$
- t denotes a time trend
- PH_t represents relevant a set of pulse dummies corresponding to public holidays and events

Algorithmically, this changes the scenarios such that we are primarily interested in whether there is a downward shift at the commencement of Covid-19 (noting March 16th 2020 corresponds to when the state government first made a definitive statement about impending measures) and whether there is statistical evidence that the trend since that date has been slower, the same or faster than the pre-Covid-19 Trend.

Table 4 Coefficient Estimates corresponding to model 2 -

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Intercept	15243.97	15745.70	15623.03	15171.28	15027.72	21778.91	34315.50
Covid Shift in Intercept	-43506.60	-56183.53	-51801.10	-50535.58	-36136.55	-100300.35	-102879.80
Trend	12.45	14.85	13.50	13.68	11.03	12.30	-1.61**
Medium Term Trend following Covid (β_1)	43.68	62.74	55.75	53.60	31.78	147.03	149.91

*** Not Statistically Different from Zero at 10% level (fuller set of results available in appendix)*

Whilst there are some differences in scaling when comparing across weekdays and weekends, it is interesting to note the medium-term trend following Covid-19 (β_1) for Saturday and Sunday are at least twice as large as those observed the Weekdays. Using each of the coefficient estimates permits inference on the level of activity now relative to the pre-Covid-19 historical trend thus providing policymakers and other stakeholders the ability to gauge different forms of current economic activity (Figures 2 – 8). From these charts we can conclude that:

- Weekend traffic has returned to trend and may even exceed trend values on current estimates.
- Weekday traffic in general is still significantly down compared to what it would have been if the pandemic (and its policies) had not occurred.
    - Friday and Monday, unsurprisingly, are the furthest away from being 'normal', unlikely to return to pre-Covid-19 levels for another six years.
    - Tuesday in contrast to Monday and Friday could be back on trend within four years.

Figures 2 – 8 show there are stark differences in the pedestrian flows which can be measured in current times as well as over short and medium terms which is important for understanding local economic activity. In the next section we briefly discuss possible implications of these findings.

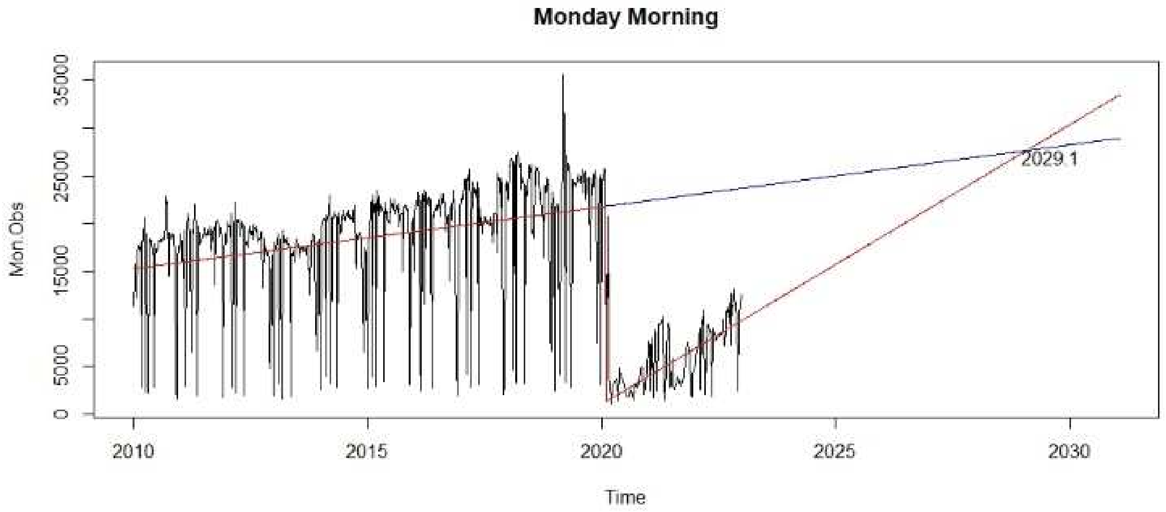

Figure 3: Monday Work Traffic. Authors Calculations (Blue – Pre-Covid19 Historical Trend fit and extrapolation, Red – Trend with Covid-19 breaks fitted, Black – Actual data)

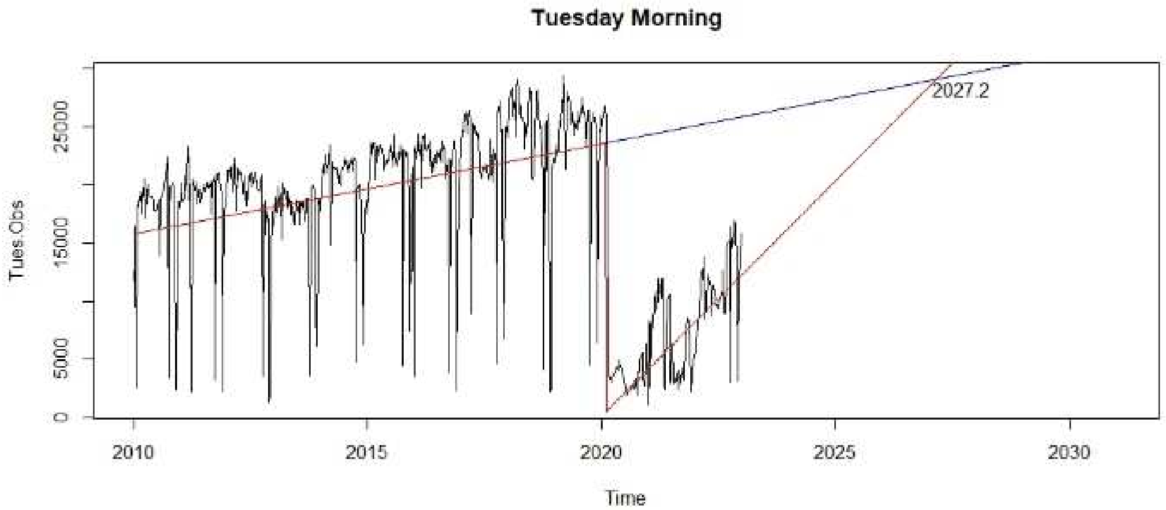

Figure 3: Tuesday Work Traffic. Authors Calculations. (Blue – Pre-Covid19 Historical Trend fit and extrapolation, Red – Trend with Covid-19 breaks fitted, Black – Actual data)

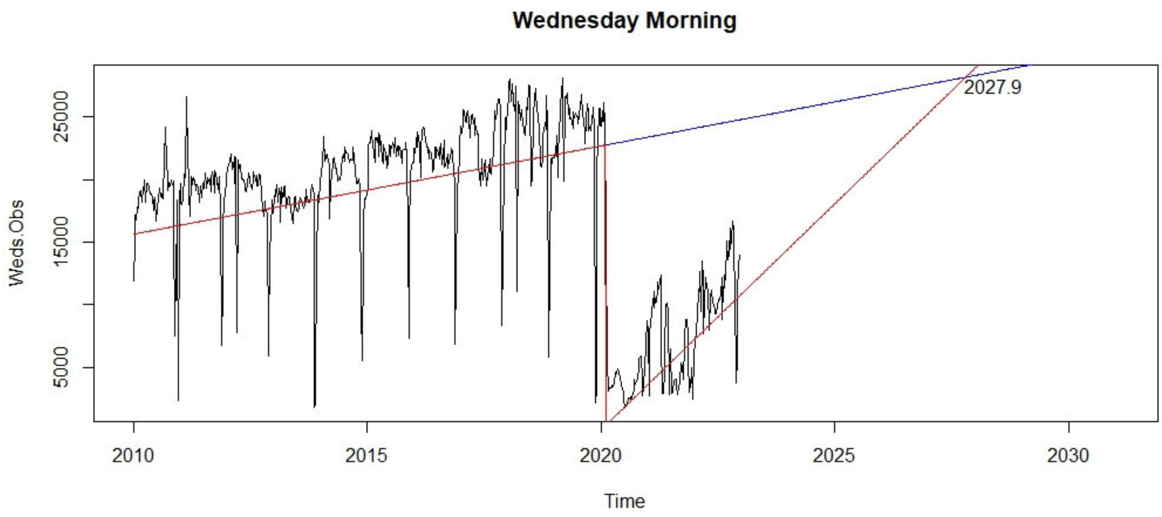

Figure 4: Wednesday Work Traffic. Authors Calculations (Blue – Pre-Covid19 Historical Trend fit and extrapolation, Red – Trend with Covid-19 breaks fitted, Black – Actual data)

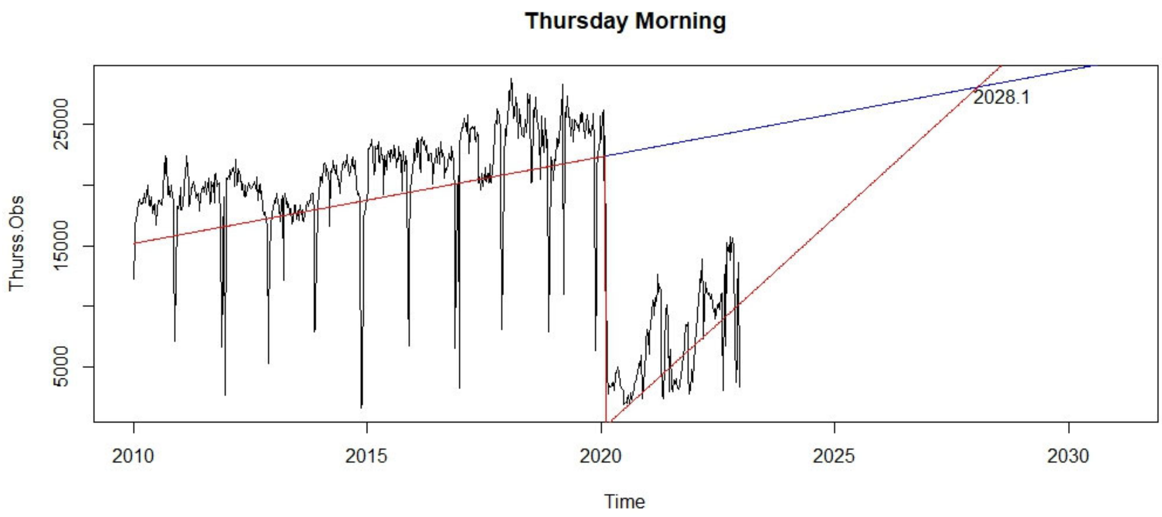

Figure 5: Thursday Work Traffic. Authors Calculations (Blue – Pre-Covid19 Historical Trend fit and extrapolation, Red – Trend with Covid-19 breaks fitted, Black – Actual data)

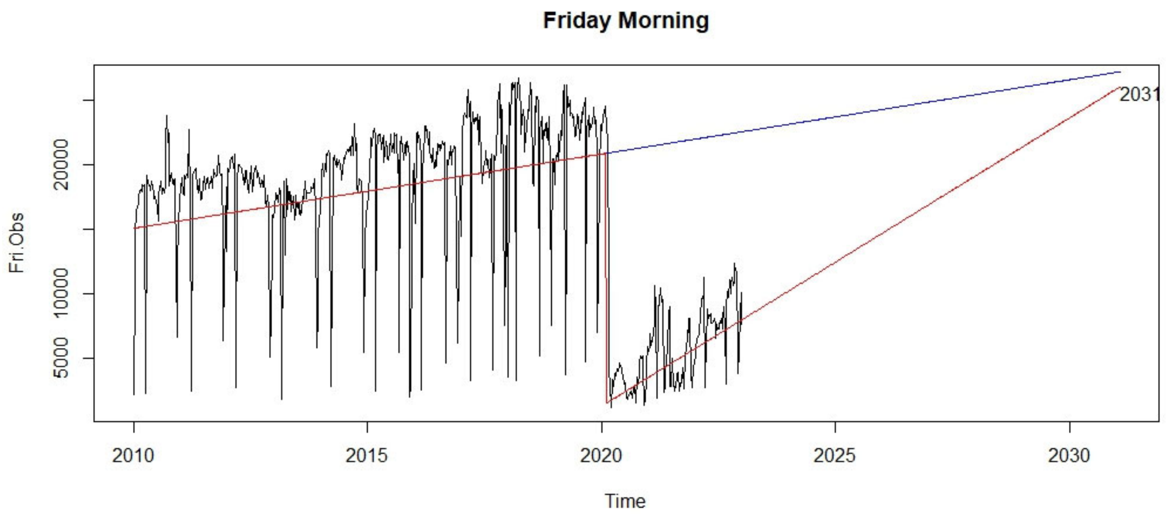

Figure 6: Friday Work Traffic. Authors Calculations (Blue – Pre-Covid19 Historical Trend fit and extrapolation, Red – Trend with Covid-19 breaks fitted, Black – Actual data)

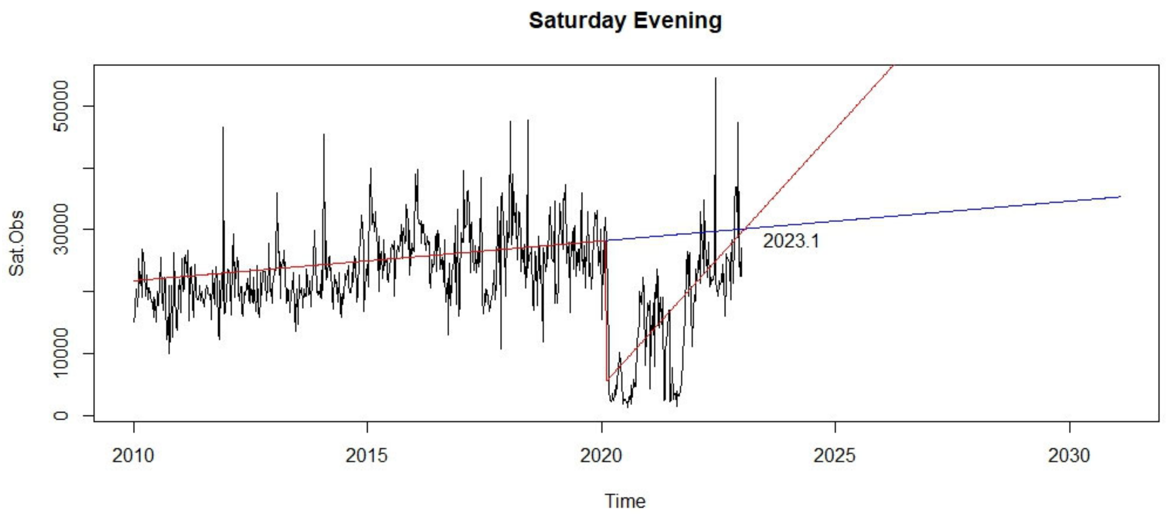

Figure 7: Saturday Cultural Authors. Calculations (Blue – Pre-Covid19 Historical Trend fit and extrapolation, Red – Trend with Covid-19 breaks fitted, Black – Actual data)

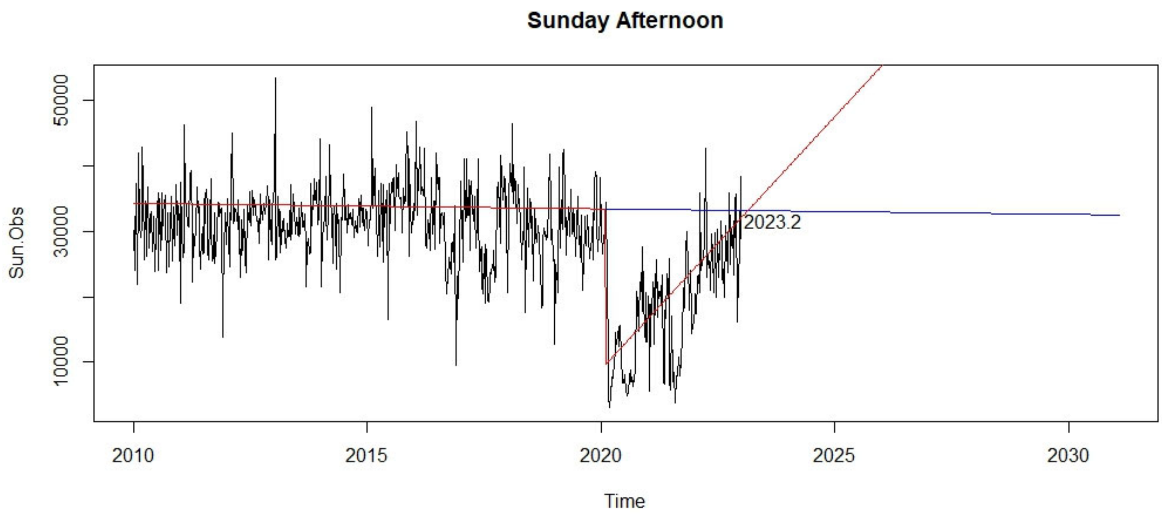

Figure 8: Sunday Retail. Authors Calculations (Blue – Pre-Covid19 Historical Trend fit and extrapolation, Red – Trend with Covid-19 breaks fitted, Black – Actual data)

Section 6 - Discussion

Rich pedestrian data, combined with regional spatial data provide an opportunity to quantify the various elements of place and explore whether local activity can be extrapolated from this information, providing valuable insight to local councils and urban planning (Lai & Kontokosta, 2018). Crowd behaviour and importantly, the ability to predict behaviour is becoming increasingly important, particularly for smart cities (Cecaj et al., 2021)to organise and manage events, respond effectively to emergencies, manage the provision of public transport and a myriad of planning decisions by local and government agencies. Recovery for cities and regions may be a long and difficult process (Kang et al., 2020), and detailed micro data, such as pedestrian data, will provide timely information to enable more effective interventions to support regions' residents and businesses in their recovery.

Results from our investigation show that recovery paths for different sorts of economic activities vary. This variation is significant and provides nuanced insight into the current and near-recent economic activity of the city of Melbourne. We suggest that it can be argued that this captures a conceptual aspect of nowcasting. In particular, using this information permits stakeholders to gauge the type and level (albeit imperfectly) of economic activity before official data is available noting that such data corresponds to higher levels of aggregation. We also note that Melbourne's CBD is the largest local economy in Victoria and is likely to be a barometer of state-level economic activity as shown by (Navon & de Silva, 2022).

Importantly, our results show that (assuming the same level of employment exists), there has been a significant embrace of hybrid working behaviours. Further, on both Mondays and Fridays, workers that were typically located in the city work offsite (most likely from their primary place of residence). Even for Tuesdays and Wednesdays, where the return to the city becomes more apparent, these levels are still significantly below *a* Covid-19 trend extrapolation. We suggest that this has significant implications for the city and even the national economy.

One implication of hybrid working relates to informal knowledge exchange that occurs with workers located within spatial proximity to some extent a micro form of agglomeration, with tacit knowledge spillovers. We posit that digital interactions are an imperfect substitute to person to person interaction ,and the degree of substitution is dependent on the types of agglomeration economies in play, such as knowledge spillovers, labour market pooling, and input sharing, and the variation in spatial reach of these dimension across industry, location, and size of firms. As discussed by Rosenthal & strange 2020) Technological advancements and changes in communication technology may be changing the spatial reach of agglomeration economies over time and knowledge transfer will continue to be dampened for some time based . This of course may be offset by productivity gains from other avenues (Productivity Commission (Australia), 2021) including happier workers (DiMaria et al., 2020; Oswald et al., 2015).

A direct consequence of less pedestrian activity that cannot be digitised however, is the cultural landscape of the CBD which has an economic dividend. This includes a vibrant café and retail presence, something that Melbourne is well known for. Importantly, whilst Saturdays and Sunday traffic appears to have recovered – we expect that they are insufficient to compensate for the decrease in worker traffic during week days.

We suggest that if this recovery path continues, that is workers continue to work less in the city, then a structural change will likely take place. Importantly, this structural change will not be limited to the CBD. This structural change has the potential to change built environments and infrastructure requirements beyond the CBD.

We note that studies that assess region recovery after natural disasters (given the lack of research on pandemic recovery), suggest that large multinational firms did not relocate after a disaster, instead re-establish operations in their existing sites (Kang et al., 2020), as such, we suggest that changes may be centred around a redesign of space to accommodate greater flexibility in the use of office and retail space to incorporate virtual work, retail, and entertainment.

Overall, we concur with (Florida et al., 2021) that the pandemic has caused 'microgeographic' changes in the nature of work, retail and leisure, and expect a significant restructure of space and place to facilitate distancing in many regions around the world. The degree to which these changes becomes permanent remains to be seen, regardless we believe that footfall can be used to gauge current changes in activity. Shortages created by distribution problems experienced during (and post) pandemic, coupled with political rhetoric of the need to manufacture particular goods within national borders (Florida et al., 2021), may see growth in manufacturing regions – but this outcome will be dependent on whether active policy is implemented to promote growth in the sector or whether it remains as simply political rhetoric.

Conclusion

We began this study wanting to explore how pedestrian counts may illuminate types and volumes of economic behaviour. Our use of pedestrian counts is partly founded on its statistical association (Navon & de Silva, 2022) with Victoria's State Final Demand (a state-wide measure of economic activity equivalent to Country level GDP). We noted also that pedestrian counts have been employed elsewhere to gauge economic activity including a weekly index (Eraslan & Götz, 2021).

An important intent of our investigation is to measure the activity of a local area, i.e., a zone within a suburb. Given no conventional economic variable exists, we have not been able to perform a conventional nowcasting exercise. We have however, we believe, captured the concept. Specifically, we have shown how pedestrians counts may be used to gauge different types of current economic engagement.

There are several limitations of our study that need to be acknowledged. First, we have used the Melbourne's CBD as a case study. We believe that using Pedestrian Counts in this way is not limited to major city centres although we note it may not be suitable to some business districts such as an industrial hub featuring warehouse and or manufacturing plants. We do believe however it can be applied to activity centres spread across Australia's landscape. Econometrically, we believe our models to be robust. However, we acknowledge that a more sophisticated approach can and should be explored. This may include endogenous break models.

Looking ahead, in the absence of an alternative, we suggest that Pedestrian Counts can be used to gauge economic performance of local areas. We also believe it provides valuable insights (albeit imperfect ones) into different types of behaviour which is important to all community stakeholders.

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Appendix A

Tables A1-A7 present average pedestrian counts for every hour of the day across all sensors in our sample period between 2010 and 2022, for every day of the week from Monday (A1) to Sunday (A7).

Table A1

	Year													
Hour	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average**
0	368	54	62	67	63	85	84	83	118	81	41	40	90	**95**
1	31	26	27	31	29	37	41	40	69	39	22	20	45	**35**
2	24	16	16	16	17	19	20	20	38	23	12	14	26	**20**
3	15	12	13	13	14	15	17	16	30	19	10	13	19	**16**
4	16	15	16	12	16	19	20	19	26	20	13	12	19	**17**
5	42	38	36	35	52	48	56	57	65	63	32	27	38	**45**
6	159	154	160	153	206	182	201	202	231	231	93	80	110	**166**
7	469	472	469	472	602	554	592	613	655	666	216	179	241	**477**
8	1008	1115	1082	1023	1018	1180	1253	1301	1345	1359	381	305	507	**990**
9	647	693	687	657	608	749	779	823	871	900	289	229	399	**641**
10	563	588	566	587	607	657	661	651	688	668	271	249	420	**552**
11	707	718	687	714	801	784	778	757	795	763	330	303	521	**666**
12	1153	1223	1199	1229	1286	1288	1264	1247	1312	1248	475	413	709	**1081**
13	1249	1320	1283	1272	1185	1341	1296	1269	1316	1249	490	436	725	**1110**
14	955	999	978	990	972	1084	1041	1018	1072	1015	451	401	662	**895**
15	925	983	966	974	980	1081	1038	1056	1119	1073	465	401	673	**903**
16	1113	1149	1134	1129	1194	1269	1275	1340	1421	1429	541	440	740	**1090**
17	1434	1581	1559	1462	1374	1714	1749	1833	1914	1934	635	523	864	**1429**
18	859	946	968	908	806	1092	1088	1145	1202	1185	432	396	642	**898**
19	483	513	544	527	510	659	645	673	716	696	284	274	462	**537**
20	362	381	414	399	412	518	498	517	551	532	216	215	393	**416**
21	284	304	354	328	322	425	399	410	447	427	165	166	329	**335**
22	197	211	271	239	214	290	271	289	333	281	109	113	218	**234**
23	119	120	169	130	109	157	159	156	200	149	61	58	121	**131**
Average	**549**	**568**	**569**	**557**	**558**	**635**	**634**	**647**	**689**	**669**	**251**	**221**	**374**	

Table A2

	Year													
Hour	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average**
0	388	48	55	92	46	63	64	66	70	93	30	28	56	**84**
1	21	21	22	47	21	26	28	28	33	50	17	15	27	**27**
2	14	12	13	26	13	14	16	16	19	29	10	11	17	**16**
3	11	12	13	19	11	12	13	12	16	23	9	10	14	**13**
4	13	12	14	14	14	16	18	18	20	21	12	11	15	**15**
5	42	39	40	39	58	51	59	65	69	70	37	29	37	**49**
6	174	176	192	178	238	219	235	243	277	267	112	91	130	**195**
7	516	513	530	522	673	623	645	699	741	734	253	205	306	**535**
8	1077	1185	1182	1089	1091	1293	1326	1409	1458	1441	436	359	677	**1079**
9	677	698	726	680	609	770	800	859	915	927	318	255	456	**668**
10	554	551	552	565	572	615	628	654	664	645	274	253	397	**533**
11	669	665	656	686	758	738	741	779	772	750	328	310	492	**642**
12	1149	1173	1194	1226	1228	1233	1224	1291	1299	1244	481	437	727	**1070**
13	1251	1281	1277	1286	1150	1285	1268	1315	1304	1262	493	451	728	**1104**
14	940	957	944	986	920	1022	1013	1039	1044	1024	436	409	638	**875**
15	932	940	939	970	955	1028	1037	1081	1119	1104	466	415	660	**896**
16	1108	1142	1145	1139	1207	1263	1314	1404	1464	1481	559	474	808	**1116**
17	1515	1613	1621	1514	1431	1756	1826	1916	1994	2022	686	578	1030	**1500**
18	938	1002	1042	999	877	1152	1196	1242	1270	1282	463	429	732	**971**
19	541	563	587	592	546	692	715	743	756	766	302	292	501	**584**
20	401	417	445	466	445	540	559	571	576	599	230	234	426	**455**
21	333	335	372	404	357	445	452	461	478	491	178	181	375	**374**
22	225	235	256	314	242	319	340	322	337	360	124	128	266	**267**
23	130	137	162	192	125	181	178	180	185	206	68	67	142	**150**
Average	**567**	**572**	**582**	**585**	**566**	**640**	**654**	**684**	**703**	**704**	**263**	**236**	**402**	

Table A3

	Year													
Hour	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average**
0	424	53	64	63	94	72	70	75	77	74	63	30	62	**94**
1	22	22	25	27	45	30	30	33	35	34	42	16	30	**30**
2	14	13	14	14	26	15	16	16	20	19	25	11	18	**17**
3	10	14	14	12	19	12	12	13	17	15	18	10	14	**14**
4	13	13	15	12	17	18	17	18	19	18	16	12	15	**16**
5	43	40	41	38	60	53	59	64	74	70	40	30	38	**50**
6	182	180	195	183	239	221	240	249	281	270	114	95	132	**199**
7	532	529	535	536	663	634	657	706	734	730	244	212	309	**540**
8	1142	1190	1186	1110	1080	1293	1360	1426	1437	1434	419	370	663	**1085**
9	712	720	730	701	626	795	825	890	925	938	311	270	463	**685**
10	579	584	582	589	606	650	651	674	716	670	276	270	420	**559**
11	723	735	706	728	817	798	793	810	857	797	342	332	525	**689**
12	1215	1259	1243	1290	1308	1308	1294	1328	1378	1293	500	452	772	**1126**
13	1305	1346	1321	1333	1216	1353	1325	1350	1374	1285	511	467	765	**1150**
14	980	1008	1007	1005	988	1072	1046	1072	1117	1038	466	423	680	**916**
15	974	993	997	1007	1022	1094	1077	1110	1185	1124	501	435	730	**942**
16	1183	1182	1199	1169	1248	1317	1341	1422	1498	1498	577	482	844	**1151**
17	1548	1639	1653	1548	1461	1805	1859	1949	2021	2054	696	602	1067	**1531**
18	949	1030	1075	1011	908	1189	1206	1285	1329	1327	489	463	768	**1002**
19	562	584	622	616	587	736	732	784	806	788	333	313	539	**616**
20	403	414	452	450	470	560	553	602	614	605	256	257	451	**468**
21	326	346	377	381	390	479	464	498	517	489	204	203	408	**391**
22	236	263	297	319	302	372	343	377	386	358	152	157	304	**298**
23	156	151	169	182	176	213	193	203	197	189	80	81	158	**165**
Average	**593**	**596**	**605**	**597**	**599**	**670**	**673**	**706**	**734**	**713**	**278**	**250**	**424**	

Table A4

	Year													
Hour	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average**
0	436	60	70	69	58	119	77	82	84	81	39	34	70	**98**
1	26	25	30	30	25	54	32	38	41	38	20	18	36	**32**
2	16	14	17	16	15	33	18	20	24	22	12	13	20	**18**
3	11	12	15	13	12	21	14	15	19	17	11	12	15	**14**
4	14	13	14	12	14	20	18	18	20	19	12	12	18	**16**
5	44	38	40	41	58	51	59	63	71	72	37	30	38	**49**
6	181	181	193	180	239	216	245	246	282	270	112	95	126	**197**
7	541	530	526	532	666	613	663	690	745	733	241	211	289	**537**
8	1112	1206	1178	1104	1092	1259	1360	1398	1457	1426	412	366	650	**1079**
9	724	744	744	717	636	797	836	887	951	970	325	274	469	**698**
10	574	584	577	605	591	642	654	671	702	702	290	273	420	**561**
11	702	713	692	722	786	761	780	796	816	817	346	330	529	**676**
12	1218	1260	1231	1252	1276	1260	1285	1302	1323	1313	498	453	757	**1110**
13	1323	1373	1316	1292	1207	1327	1338	1337	1340	1328	510	464	771	**1148**
14	1010	1043	1009	1006	977	1068	1067	1088	1094	1089	455	419	713	**926**
15	989	1014	1000	991	1021	1087	1103	1134	1172	1155	483	433	736	**948**
16	1180	1220	1196	1166	1269	1297	1373	1445	1511	1528	568	489	861	**1162**
17	1596	1692	1660	1552	1487	1778	1902	1965	2053	2061	697	613	1081	**1549**
18	1063	1142	1129	1078	961	1230	1286	1330	1368	1381	503	479	843	**1061**
19	648	685	683	681	640	797	808	826	842	843	343	343	602	**673**
20	467	491	496	506	519	631	627	641	664	666	278	282	497	**520**
21	377	399	409	425	425	554	523	547	571	573	230	230	466	**441**
22	286	314	316	346	317	447	407	424	444	433	181	184	371	**344**
23	182	194	203	206	178	293	236	245	239	234	106	100	202	**202**
Average	**613**	**623**	**614**	**606**	**603**	**681**	**696**	**717**	**743**	**740**	**280**	**257**	**441**	

Table A5

	Year													
Hour	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average**
0	486	84	89	94	83	112	143	108	113	110	46	61	94	**125**
1	55	41	43	47	42	54	76	58	59	54	24	33	50	**49**
2	34	23	25	29	29	34	49	34	37	34	17	23	31	**31**
3	24	19	20	21	22	30	41	32	31	29	15	18	24	**25**
4	25	18	19	17	19	24	29	24	27	25	14	16	21	**22**
5	46	40	41	38	58	51	61	63	71	68	37	30	38	**49**
6	167	171	181	173	229	203	220	228	254	244	107	83	114	**183**
7	489	497	497	492	617	567	587	642	657	652	227	173	235	**487**
8	1058	1144	1125	1046	1040	1192	1218	1319	1315	1316	402	299	487	**997**
9	686	733	731	714	649	778	795	860	903	920	309	244	421	**672**
10	592	614	591	626	652	675	676	693	721	692	284	268	452	**580**
11	737	772	737	785	872	819	829	847	852	826	353	328	575	**718**
12	1239	1337	1265	1351	1366	1347	1330	1376	1383	1321	507	431	778	**1156**
13	1341	1424	1356	1411	1283	1408	1389	1412	1398	1344	516	438	794	**1193**
14	1078	1122	1078	1103	1065	1157	1161	1165	1171	1127	467	423	763	**991**
15	1063	1108	1093	1113	1132	1189	1204	1226	1255	1201	502	443	795	**1025**
16	1278	1332	1317	1306	1370	1430	1467	1530	1581	1579	589	486	876	**1242**
17	1585	1741	1710	1650	1580	1864	1883	1941	1983	1989	682	580	1047	**1557**
18	1196	1284	1287	1262	1200	1430	1430	1458	1482	1464	528	514	951	**1191**
19	899	933	926	946	914	1093	1078	1072	1068	1042	403	436	821	**895**
20	691	709	700	716	737	843	855	853	844	851	334	383	700	**709**
21	615	609	616	622	657	756	754	775	790	782	301	352	694	**640**
22	587	579	572	587	574	661	670	682	700	670	254	311	645	**576**
23	450	427	440	427	380	488	464	484	481	457	163	221	419	**408**
Average	**684**	**698**	**686**	**691**	**691**	**759**	**767**	**787**	**799**	**783**	**295**	**275**	**493**	

Table A6

	Year													
Hour	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average**
0	361	280	255	252	215	278	270	275	265	257	93	115	264	**245**
1	123	152	135	133	116	138	163	176	162	144	56	67	156	**132**
2	81	93	81	77	74	74	100	103	107	87	33	43	90	**80**
3	57	66	55	53	48	55	79	78	80	63	24	30	62	**58**
4	32	35	32	30	29	35	49	47	45	41	16	18	33	**34**
5	31	34	32	28	30	42	40	41	43	43	22	19	31	**34**
6	43	46	51	45	51	60	61	64	73	70	37	34	48	**53**
7	82	84	89	88	111	136	115	121	123	127	62	62	85	**99**
8	161	162	166	172	205	219	198	206	210	210	103	106	158	**175**
9	297	305	306	326	372	382	356	363	374	362	175	190	303	**316**
10	479	488	500	529	572	584	561	564	580	560	268	299	497	**499**
11	660	700	706	742	791	815	793	779	806	777	375	423	712	**698**
12	839	895	901	951	984	1017	989	967	993	952	452	517	883	**872**
13	947	1029	1011	1095	1075	1132	1120	1088	1101	1050	512	577	1015	**981**
14	989	1064	1049	1124	1114	1175	1177	1126	1136	1093	542	611	1039	**1018**
15	1024	1106	1098	1157	1150	1226	1226	1172	1174	1148	547	616	1050	**1053**
16	986	1065	1088	1139	1113	1222	1248	1173	1183	1170	536	577	1067	**1044**
17	916	957	957	993	990	1158	1177	1120	1137	1119	494	523	1024	**966**
18	775	796	819	874	868	1056	1075	1018	1039	1037	426	471	939	**861**
19	634	662	691	746	750	901	901	894	933	925	373	428	884	**748**
20	530	579	574	608	648	750	767	767	773	790	326	380	778	**636**
21	497	533	532	568	609	689	716	690	715	723	287	338	755	**589**
22	519	557	546	607	584	684	740	691	684	664	243	308	723	**581**
23	416	443	436	455	410	529	525	500	508	446	170	213	503	**427**
Average	**478**	**505**	**504**	**533**	**538**	**598**	**602**	**584**	**593**	**577**	**257**	**290**	**546**	

Table A7

	Year													
Hour	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Average**
0	338	256	314	292	263	329	328	350	313	275	103	129	278	**275**
1	152	156	186	182	166	185	218	234	204	168	60	84	170	**166**
2	129	118	137	130	114	111	142	150	143	106	38	52	105	**114**
3	99	92	101	95	75	80	108	115	113	84	29	41	88	**86**
4	43	41	47	46	44	46	67	68	66	53	19	23	46	**47**
5	30	28	31	33	34	39	56	52	51	44	19	21	39	**37**
6	36	34	32	36	43	44	62	60	65	63	28	33	45	**45**
7	74	68	71	72	98	91	104	104	112	116	47	59	105	**86**
8	159	146	149	155	193	191	188	169	186	185	88	102	150	**159**
9	303	276	276	307	341	351	323	331	341	328	154	182	284	**292**
10	555	526	532	562	610	576	543	534	550	551	259	299	483	**506**
11	756	725	719	745	801	808	773	746	759	773	360	414	671	**696**
12	941	919	906	944	965	1001	954	928	954	941	447	496	807	**862**
13	1033	1008	1025	1065	1055	1109	1060	1008	1034	1007	490	536	861	**945**
14	1047	1046	1081	1116	1083	1165	1125	1066	1101	1049	518	574	899	**990**
15	1046	1045	1055	1083	1070	1171	1129	1076	1091	1025	515	558	913	**983**
16	959	957	962	1000	961	1092	1053	1030	1049	986	476	507	867	**915**
17	780	770	792	824	799	924	905	920	935	891	424	442	773	**783**
18	552	545	590	601	612	751	741	783	802	782	339	368	655	**625**
19	446	438	478	500	527	610	598	640	654	643	273	297	564	**513**
20	353	346	394	400	441	502	497	540	540	542	233	244	493	**425**
21	277	281	318	321	362	415	410	444	438	430	186	196	417	**346**
22	201	205	240	240	253	306	302	348	310	302	129	140	304	**252**
23	126	128	150	155	139	200	183	220	186	173	75	78	184	**154**
Average	**435**	**423**	**441**	**454**	**460**	**504**	**494**	**496**	**500**	**480**	**221**	**245**	**425**	

Table A8 – Pedestrian Counts in 2022 as a Percentage of 2019

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
0	103%	54%	79%	80%	79%	100%	97%
1	108%	48%	87%	87%	88%	107%	100%
2	116%	53%	91%	88%	87%	104%	100%
3	107%	56%	92%	89%	85%	99%	107%
4	94%	73%	85%	81%	82%	82%	87%
5	57%	52%	52%	52%	55%	72%	81%
6	46%	48%	47%	45%	45%	65%	67%
7	35%	41%	41%	38%	35%	65%	92%
8	35%	45%	44%	43%	35%	73%	77%
9	42%	47%	47%	46%	44%	82%	85%
10	61%	59%	60%	57%	62%	87%	87%
11	66%	63%	62%	61%	65%	89%	86%
12	55%	56%	56%	54%	55%	91%	85%
13	56%	56%	56%	55%	56%	95%	85%
14	63%	60%	62%	62%	63%	93%	85%
15	60%	57%	61%	59%	61%	89%	88%
16	49%	52%	53%	53%	52%	88%	87%
17	42%	49%	49%	50%	50%	88%	86%
18	52%	55%	55%	58%	61%	87%	83%
19	63%	61%	64%	68%	75%	91%	86%
20	69%	66%	70%	69%	76%	92%	87%
21	72%	70%	78%	76%	81%	95%	91%
22	72%	66%	78%	79%	90%	98%	93%
23	75%	64%	78%	78%	86%	97%	96%
Average	**66%**	**56%**	**64%**	**64%**	**65%**	**89%**	**88%**

Table 4

Average Hourly Pedestrian Counts by Day of the Week – 2019 vs 2022

	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
Hour	**2019**	**2022**	**2019**	**2022**	**2019**	**2022**	**2019**	**2022**	**2019**	**2022**	**2019**	**2022**	**2019**	**2022**
0	81	83	93	50	74	58	81	65	110	86	257	256	275	267
1	39	43	50	24	34	29	38	33	54	47	144	155	168	168
2	23	27	29	16	19	18	22	19	34	30	87	91	106	106
3	19	20	23	13	15	14	17	15	29	24	63	63	84	90
4	20	19	21	15	18	15	19	15	25	21	41	34	53	46
5	63	36	70	36	70	36	72	37	68	37	43	31	44	36
6	231	107	267	127	270	128	270	123	244	111	70	45	63	42
7	666	231	734	299	730	296	733	279	652	226	127	83	116	107
8	1359	477	1441	652	1434	624	1426	615	1316	466	210	154	185	143
9	900	381	927	438	938	439	970	447	920	403	362	295	328	279
10	668	406	645	382	670	399	702	400	692	430	560	486	551	477
11	763	502	750	472	797	494	817	499	826	538	777	695	773	661
12	1248	686	1244	700	1293	726	1313	709	1321	729	952	865	941	799
13	1249	701	1262	706	1285	725	1328	729	1344	750	1050	997	1007	857
14	1015	636	1024	616	1038	642	1089	673	1127	713	1093	1019	1049	893
15	1073	644	1104	634	1124	688	1155	687	1201	738	1148	1026	1025	897
16	1429	705	1481	777	1498	799	1528	807	1579	816	1170	1033	986	858
17	1934	822	2022	993	2054	1008	2061	1026	1989	988	1119	987	891	765
18	1185	613	1282	701	1327	726	1381	803	1464	898	1037	903	782	651
19	696	436	766	471	788	505	843	570	1042	779	925	845	643	552
20	532	366	599	393	605	422	666	462	851	645	790	726	542	472
21	427	306	491	345	489	382	573	434	782	637	723	688	430	392
22	281	201	360	237	358	280	433	343	670	602	664	651	302	279
23	149	111	206	131	189	147	234	183	457	391	446	434	173	166
Average	669	357	704	384	713	400	740	416	783	463	577	523	480	417

Table 4 presents average hourly pedestrian counts by day of the week for 2019 and 2022.

Appendix B: Regression Results

Sunday

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	34315.50	832.97	41.20	0.00
Dummy	-102879.80	6089.34	-16.90	0.00
Trend	-1.61	1.50	-1.07	0.29
Trend x Dummy	149.91	10.13	14.80	0.00
January	-3640.86	961.61	-3.79	0.00
February	-2724.40	1019.48	-2.67	0.01
March	822.67	994.27	0.83	0.41
April	1002.59	1000.47	1.00	0.32
May	-3010.06	990.83	-3.04	0.00
June	-2372.84	1006.04	-2.36	0.02
July	-2964.51	992.17	-2.99	0.00
August	-3401.92	997.01	-3.41	0.00
September	-4303.81	1019.00	-4.22	0.00
October	-5727.23	991.60	-5.78	0.00
November	-1775.91	1004.49	-1.77	0.08
PH	-3312.40	1283.18	-2.58	0.01

Adj R2 = 0.5959

Monday

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	15243.97	460.96	33.07	0.00
Dummy	-43506.60	3371.66	-12.90	0.00
Trend	12.45	0.83	14.93	0.00
Trend x Dummy	43.68	5.61	7.79	0.00
January	-17.23	535.02	-0.03	0.97
February	2084.40	561.25	3.71	0.00
March	2652.99	547.89	4.84	0.00
April	3331.90	554.36	6.01	0.00
May	2864.26	549.65	5.21	0.00
June	1480.20	552.61	2.68	0.01
July	1604.81	551.10	2.91	0.00
August	1163.21	546.60	2.13	0.03
September	1402.85	566.36	2.48	0.01
October	970.45	548.18	1.77	0.08
November	1039.86	553.06	1.88	0.06
PH	-13875.70	411.53	-33.72	0.00
Protest	11026.98	2948.72	3.74	0.00

Note, we fitted an additional dummy variable to capture a protest which spiked numbers Adj R2 = 0.8537

Tuesday

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	15745.70	419.76	37.51	0.00
Dummy	-56183.53	2999.38	-18.73	0.00
Trend	14.85	0.75	19.80	0.00
Trend x Dummy	62.74	4.99	12.57	0.00
January	-682.34	482.81	-1.41	0.16
February	2070.26	511.41	4.05	0.00
March	3497.61	496.49	7.04	0.00
April	2708.68	503.47	5.38	0.00
May	3129.49	498.14	6.28	0.00
June	1665.58	502.71	3.31	0.00
July	1466.56	499.81	2.93	0.00
August	1049.80	497.55	2.11	0.04
September	1404.53	513.54	2.73	0.01
October	1403.41	499.38	2.81	0.01
November	1594.74	491.60	3.24	0.00
PH	-14134.26	527.40	-26.80	0.00

Adj R2 = 0.8719

Wednesday

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	15623.03	375.54	41.60	0.00
Dummy	-51801.10	2755.26	-18.80	0.00
Trend	13.50	0.69	19.67	0.00
Trend x Dummy	55.75	4.60	12.13	0.00
January	-735.11	438.89	-1.67	0.09
February	2309.03	460.04	5.02	0.00
March	3825.14	449.82	8.50	0.00
April	3292.40	453.78	7.26	0.00
May	3418.15	451.92	7.56	0.00
June	2058.57	451.43	4.56	0.00
July	1785.95	451.51	3.96	0.00
August	1443.40	448.95	3.22	0.00
September	1724.25	463.88	3.72	0.00
October	1960.44	450.81	4.35	0.00
November	1987.36	454.70	4.37	0.00
PH	-14213.28	748.13	-19.00	0.00

Adj R2 = 0.8788

Thursday

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	15171.28	379.13	40.02	0.00
Dummy	-50535.58	2814.82	-17.95	0.00
Trend	13.68	0.70	19.53	0.00
Trend x Dummy	53.60	4.70	11.42	0.00
January	-1068.60	445.93	-2.40	0.02
February	2734.44	469.05	5.83	0.00
March	3991.65	456.30	8.75	0.00
April	3771.62	458.96	8.22	0.00
May	3605.10	458.53	7.86	0.00
June	2495.05	460.03	5.42	0.00
July	2192.18	458.22	4.78	0.00
August	1807.01	457.76	3.95	0.00
September	2054.37	466.70	4.40	0.00
October	2098.56	457.53	4.59	0.00
November	2503.72	461.57	5.42	0.00
PH	-11477.39	729.02	-15.74	0.00

Adj R2 = 0.8745

Friday

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	15027.72	421.32	35.67	0.00
Dummy	-36136.55	3133.92	-11.53	0.00
Trend	11.03	0.77	14.26	0.00
Trend x Dummy	31.78	5.21	6.10	0.00
January	-1248.81	495.20	-2.52	0.01
February	2426.75	520.45	4.66	0.00
March	3279.61	507.21	6.47	0.00
April	3042.17	510.52	5.96	0.00
May	3062.40	509.64	6.01	0.00
June	2153.95	513.32	4.20	0.00
July	1719.88	504.23	3.41	0.00
August	1607.16	508.03	3.16	0.00
September	1914.63	517.88	3.70	0.00
October	2168.75	506.40	4.28	0.00
November	2217.37	509.70	4.35	0.00
PH	-12429.62	519.38	-23.93	0.00

Adj R2 = 0.8518

Saturday

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	21778.91	653.61	33.32	0.00
Dummy	-100300.35	4849.52	-20.68	0.00
Trend	12.30	1.24	9.94	0.00
Trend x Dummy	147.03	8.05	18.27	0.00
January	-3314.86	776.09	-4.27	0.00
February	-288.56	795.76	-0.36	0.72
March	272.79	781.60	0.35	0.73
April	-752.19	786.26	-0.96	0.34
May	-2245.15	797.20	-2.82	0.01
June	-2553.17	797.93	-3.20	0.00
July	-3317.69	788.64	-4.21	0.00
August	-4043.61	794.29	-5.09	0.00
September	-5037.33	819.57	-6.15	0.00
October	-4631.61	785.23	-5.90	0.00
November	-1842.78	795.55	-2.32	0.02
Festival/Event	9367.02	600.52	15.60	0.00

Adj R2 = 0.704