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Restaurant turnover and anti-Asian behaviour

Did Asian restaurants in Gothenburg's' turnover suffer an outsized pandemic toll in 2020?

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Abstract

COVID-19 has so far been a global crisis for the restaurant industry and Swedish restaurants have struggled to avoid heavy losses. Parallel to reports throughout the pandemic on the loss of turnover for restaurants, there have also been reports on the intensification of anti-Asian behaviour targeting Asian individuals and their businesses. Since restaurants in Sweden continued to operate throughout the pandemic, we make use of the restaurant market in Gothenburg by examining if being an Asian restaurant had a negative effect on turnover in 2020 compared to previous years. We have created a dataset that includes panel data on turnover and control for restaurant characteristics from annual reports, time invariant data on restaurant characteristics and local market level panel data from the City of Gothenburg's database on its 97 primary areas to control for local market demographics and market structure. The main independent variable of interest is an interaction between 2020 and being an Asian restaurant. We identify which restaurants are Asian by using data from Google Maps. The model with the difference-in-differences estimator, time-varying controls and fixed effects indicates that there are no statistically significant results regarding being either East Asian, Southeast Asian, and Chinese restaurant in 2020 in Gothenburg. We have identified that the lack of significant results in the regression might be an effect of the model failing to control for confounds regarding adaptation to the pandemic, primary area time varying confounds such as change in tourism as well as the treatment group being small. Therefore, this thesis provides no empirical evidence of East Asian, Southeast Asian, and Chinese restaurants has an impact on turnover in 2020.

Keywords: Restaurants; Turnover; COVID-19; anti-Asian behaviour; Restaurant performance

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Introduction

In the beginning of 2020, as COVID-19 became a known hazard to society it began to cause disruptions to everyday life (WHO, 2020, March 11). The story of the first year of COVID-19 became one of social distancing, restrictions, recommendations, and adaptation to the pandemic. While some disruptions were due to voluntary (Lo Presti et al., 2022) actions, such as withdrawing from social activities, as responses to overhanging risk to one's health, some disruptions were an effect of restrictions made by governments (Folkhälsomyndigheten, 2020) which caused industries and markets to be subject to different kinds of shifts in demand due to the pandemic.

As industries and markets were impacted by the pandemic, a global economic crisis followed. The initial effects on the Swedish markets became evident early on as the virus reached the country in early 2020. The restaurant industry was especially affected by both social distancing and restrictions as demand shocks followed when individuals began to withdraw from public spaces. In June 2020 reports from the Swedish Tax Agency alarmed that in the Swedish Hotel and restaurant industry, four out of ten businesses had already lost a fourth of their turnover as an effect of the pandemic even before the Swedish government implemented restrictions specifically aiming to mitigate the spread of the pandemic connected to restaurant visits (Rudbäck, 2020).

Parallel to the restaurant industry suffering tolls to their turnover, there were reports of an increase in anti-Asian behaviour due to the pandemic. So, what is anti-Asian behaviour? and what motivates it? anti-Asian behaviour is negative behaviours that targets individuals of Asian origin, such as racial discrimination or racially motivated crimes. Reports show that these behaviours are a cause of individuals blaming individuals of Asian descent for the pandemic. Reports on outlets for anti-Asian behaviour has since the pandemic focused on attitudes towards individuals of Asian origin (Reny & Barreto, 2020), crimes, hate and discrimination (Gover et al., 2020), as well as negative impacts for Asian owned and Asian businesses (Fairlie, 2020). Observed as early as in the beginning of 2020, in multiple contexts such as in the US (Dhanani, 2021) and in Sweden (Svahn/TT, 2020; Rönnqvist, 2020). As well as in different outlets (Gover, 2020) targeting individuals with varying Chinese, Eastern and South-eastern Asian ethnicities, and backgrounds.

This raised concerns that while the pandemic itself caused the restaurant market to suffer tolls to their turnover, then there might be indications of heterogeneous impacts on turnover based on anti-Asian behaviour.

However, to examine heterogeneity in outcomes following a global health crisis and recessions is not something new. Researchers are still examining heterogeneity regarding social and economic outcomes and difference in redistributive effects of pandemics for events such as the Great influenza pandemic known as the “Spanish flu” in 1910 (Basco et al., 2021) and Economic and Social impacts of the Avian flu in 2005 (Brahmbhatt, 2005) and recurrent influenza pandemics (Osterholm, 2017).

The Swedish Public Health Agencies' strategy to mitigate the effects of the pandemic has been unique and sometimes criticized for not enforcing any type of lock-down (Pashakhanlou, 2021). In other European countries, non-essential businesses, among those restaurants, have been completely closed (ECDC, 2022). Since the Swedish restaurant market operated throughout the pandemic, we use this context to estimate the initial effect on restaurants turnover and use the context to examine anti-Asian behaviour by comparing differences in restaurant turnover.

To build on the previous research on heterogeneity in outcomes following a global health crisis, we make use of the Swedish context during the first year of the pandemic to examine short-term differences in turnover for restaurants. Restaurants make for handy entities subject to analysis due to them being comparable regarding information that is publicly available. They are with a great majority, with exceptions of concerns and franchises, small firms due to the norm being that one company owns one restaurant. Restaurants also differentiate based on services available to customers which is something they need to communicate publicly to attract customers, which makes differentiating factors available for a consumer to observe, hence the collection of data is relatively accessible. For restaurants to be able to compete, their information must be accessible online, and all restaurants communicate their services and additional information using Google Maps, a free service which provides detailed information about restaurants, what kind of food they serve, opening hours, delivery options etc. in combination with consumer applications regarding reviews and rating.

Swedish restaurants also report their financial data to The Swedish Tax Agency yearly, which makes up for valid yearly observations of restaurant performance in terms of turnover and additional information that makes it possible to examine within-firm differences yearly. In addition, the City of Gothenburg has divided the city into 97 different primary areas. These primary areas are a way to divide the city into smaller areas which the City of Gothenburg's statistical database gathers yearly data on regarding population, age, income, number of workers in the area and other demographic differences.

For the purpose of this study, we created a dataset with available data from 2016 to 2020 on all restaurants in Gothenburg. The year limitation is due to some important primary area variables not being available prior to 2016 and Retriever Business annual reports are not available after 2020. The limitations of using Gothenburg as the geographical area of analysis is that individuals living in a city might consume restaurants differently than those outside the city, but on the other hand we do not have to include as many controls for city versus countryside differences. In addition, the city of Gothenburg can differ from other cities in Sweden by changing in different ways than other cities. We hope to mitigate some of that effect by including all 97 different areas in Gothenburg and control for differences by using controls and fixed effects, which could make our results more representative, but we are aware that the results we find might be slightly skewed and specific for Gothenburg, which is something future research can address further by comparing our results to those of for example Malmö and Stockholm.

To quantify the estimated effects, we chose a model using difference-in-differences estimator. Primarily we aim to estimate if being a Chinese restaurant during 2020 has had a negative effect on turnover in 2020. We then extend this model by instead including more restaurants into the treatment group, to create a treatment group including East Asian restaurants and Southeast Asian restaurants as we acknowledge that these restaurants might be subject to spill-over effects of anti-Asian behaviour that target more restaurants than only Chinese restaurants based on previous studies on anti-Asian behaviour due to the pandemic.

The results found in the study showed statistically non-significant results on turnover of being either a Chinese, East Asian or Southeast Asian restaurant during the pandemic. For the three treatment groups compared, the results were rather similar. There were some minor differences in the coefficients and significance levels. Since the treatment groups being a lot smaller than the control group this might have been one of the reasons for the statistically non-significant results. For future research we suggest controlling for more specific factors related to change in strategy, change in primary area factors such as tourism.

We also believe the study would benefit from extending to for example Stockholm, to create a treatment group that is a lot larger than the one we could identify in Gothenburg. We still believe there is more to the subject than what we were able to capture with our model, we hope future research acknowledges the flaws we identified in the thesis and hopefully can find better models, better measurements, and significant results.

Research question

Did Asian restaurants in Gothenburg' turnover suffer an outsized pandemic toll in 2020 due to anti-Asian behaviour?

The aim of this thesis is to quantify differences in turnover for 3 subgroups of Asian restaurants, which is captured by the three following hypotheses:

(1) H1: *Does being a Chinese restaurant have a negative effect on annual turnover in 2020?*

And to extend that analysis:

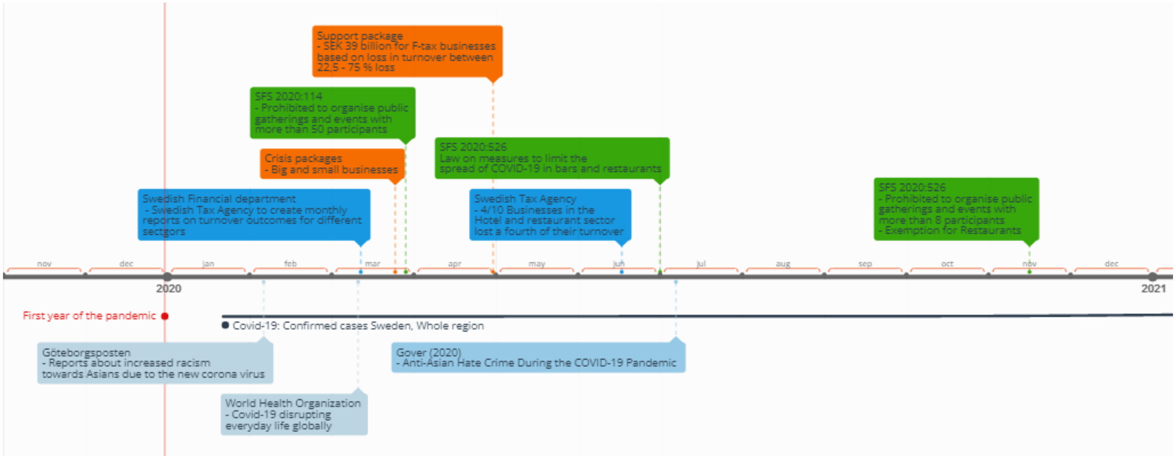
(2) H2: *Does being an East Asian restaurant have a negative effect on annual turnover in 2020?*

(3) H3: Does being a Southeast Asian restaurant have a negative effect on annual turnover in 2020?

Background

In the background section we present a brief overview of the COVID-19 timeline regarding early reports of the pandemic, anti-Asian behaviour, the impact on the restaurant sector and implementation of laws with various implications for restaurants.

Figure 1: Timeline of reports on anti-Asian behaviour, reports on restaurant turnover in Sweden and restrictions targeting the restaurant industry



In the beginning of 2020, the corona virus became widely known to society. Göteborgs-Posten, which primarily focuses on news regarding Gothenburg, reports increased racism towards individuals with Asian descent, dating February of 2020.

The economic consequences of the pandemic have been closely documented by the Swedish Tax Agency (2020, May 19). The Swedish Tax Agency followed the pandemics' early effects on market turnover and released in May of 2020 a thorough picture of the first months of the pandemic. Almost half of all 26000 companies that applied for suspension, regarding the period of January to March 2020, to declare and pay their taxes belonged to the Trade, Hotel and restaurant industry. In the same report, Restaurants that make up 25 percent of the monthly declarations, turnover had decreased 38 percent. Following report, from June 2020 declared that the largest number of companies within the industry, had a negative change in turnover compared to the same period in 2019 of at least 10 and 25 percent (Skatteverket, 2020).

In March, the Swedish government in agreement with other political parties, launched crisis packages for both large and small companies, many of them restaurants (Swedish Government, 2020, 25 March).

On the 30th of April in 2020, the government and the Centre party and the Liberal party launched a support package totalling SEK 39 billion for businesses with F-tax which is Swedish corporate taxation, including all restaurants that have business activities in Sweden. The size of the support was based on loss in turnover between 22,5 and 75 percent of the business fixed costs, excluding wage in March and April 2020 (Swedish Government, 2020, 30 April).

As the crisis packages were based on loss in turnover, the results of this study can contribute to further studies regarding future crisis packages during similar events. If the result in this study implies that some types of restaurants were more impacted short-term during the first year of the pandemic and if there are systematic differences between which groups that accessed these government aid in terms of crisis funds, due to information barriers such as language, then there is a problem with the government's strategy. This might even be amplified if Asian businesses do not have the same access to, for example, banking relationships. We argue that these aspects are of the kind that contribute to COVID-19 being a magnifier of inequality.

Theory and literature review

This section outlines the literature on why the restaurant market suffered tolls during the pandemic, restaurant market structure, factors that affect restaurant performance, restaurant performance during the pandemic followed by how we relate the study to theory and literature.

Why the restaurant industry has been especially affected (World Bank Group, 2020, June 8) during the pandemic can in theory be explained by several factors regarding restaurant supply, demand and type of market and market structure. In general, the restaurant market is a service market, a type of market that is especially affected by recommendations and rules targeting social distancing as they are reliant on socio-physical interaction and physical presence in society. In addition, restaurants supply perishable goods, which causes restaurants to be reliant on continuous transactions and constant flow of customers (Lang, 2021). As a result, social distancing restrictions that affect the necessity of physical presence in society as well as the severity of businesses' shutdown shocked the restaurant market relying on this kind of presence (Moradi, 2022).

Along these predictions, early restaurant industry reports in the US (Alan J. Liddle, 2020, April 21 ; Haas et al., 2020) began to map out just why restaurants sales and turnover have been affected by the pandemic due to factors connected to social distancing.

However, some restaurants manage to outperform the market and since these reports on a global decline in sales and turnover for the restaurant industry, the heterogeneous short-term impact of the pandemic on restaurant demand and activity has been estimated including explanatory variables as to why there's heterogeneous effects across restaurants. The section that follows will address restaurant market structure, competition, cost, turnover as measurement of performance and other factors that are relevant when comparing outcomes for restaurants.

Restaurant market structure

What makes the restaurants comparable is their similarities in how they operate, differentiate, and compete in the same product market. Cosman and Schiff (2019) states that what signifies the restaurant market are low entry barriers and many firms competing with differentiated but similar goods, where the differentiation lies in the characteristics of the product. Using panel data in their research and investigating menu options and prices, the results implies that restaurants do not change their prices or menus due to new competition. It is stated that the restaurant market has the attributes of a market in monopolistic competition, as change in competition rarely results in change of prices due to price being set based on costs in terms of wages and cost of production rather than competition.

Further the authors mention the difficulty of changing established characteristics of a restaurant after entering. This highlights that restaurants, while subject to change in competition, do not change their goods or raise prices as a response. The main findings in this study supports the assumption that restaurants, while similar, compete with differentiated goods based on the correspondent variable type. It also supports the assumption that restaurants rarely lower their prices as a response to exit or entry on the market. In addition, the notion of similarity in goods supports those costs are similar which indicates that turnover is a valid representation of performance when we account for differences in supply.

In a study on supply by Mun and Jang (2017) they focus on restaurant cost and how restaurants adapt their supply accordingly. On the cost side of restaurants, the main expenses are found in the commodities for producing meals and the wage of the employees, these kinds of cost factors could make restaurants adjust their supply. For the purpose of this study, we will account for cost adjustments to the pandemic by estimating the effects of change in the number of employees.

What affects restaurant performance

Literature on restaurant performance that focuses on restaurant firm characteristics and geographical market characteristics has been broadly divided into two categories, micro-level and macro-level factors. Micro-level characteristics are those directly affecting the performance of a restaurant and macro-level factors are the external conditions that affect business performance (Kim & Lee, 2020) The micro- level factors include factors such as quality (Namkung & Jang, 2007), perceived value (Kwun & Oh, 2004), rating and reviews (Luca, 2011), location (Yang et al., 2017), physical environment (Duarte Alonso et al., 2013). Macro-level factors are population and disposable income (Reynolds et al., 2013 ; Lasek et al., 2016; Koh et al., 2013), government policies and financial and health crises. Relating this literature on restaurant performance to the thesis, we will use a similar structure to examine restaurant turnover. We will both use controls for time-varying factors and fixed effects estimation on time invariant micro-level factors as well as macro-level factors.

What has become especially important during the pandemic is factors related to financial and health crises. This branch of literature includes more factors that affect restaurant performance during a pandemic, more connected to restrictions and perception of risk. Theory regarding perception of risk and economic behaviour during a pandemic is discussed in the health belief model addressing that age and income determine market behaviour for individuals as a response to risk of one's health and behaviour as an response to economic uncertainty due to the recession (Champion and Skinner, 2008).

Reports on restaurant performance have put emphasis on additional factors such as off-premises versus on-premises sales, reliance on day-part occasions, location and demographics, digital maturity and its effects on mitigating the effects of the new market environment (Lee & Ha, 2012). These factors become more important as individuals seek ways to avoid health risk and as availability during lockdowns and stay-at-home orders (Kim & Lee, 2020). Especially off-premises service options, as dining-out habits change (Ferrante et al., 2021), including an increased demand for takeout and delivery (Yang et al., 2020).

The thesis contribution to previous literature

There are few studies that make use of differences in turnover regarding if Asian restaurants have had an outsized pandemic toll in 2020 compared to other restaurants. Therefore, we have chosen to add to previous literature by including Asian types of restaurants as the main independent variable. In doing so, we focus on Chinese, East Asian and Southeast Asian restaurant subgroups. We examine if there has been any difference in turnover regarding these three groups compared to all other restaurants. We also add a control for daytime reliance by including opening hours and closing hours in interaction with economically active day-time population (daily workforce) in the area, something that is not brought up in previous literature on measuring differences in turnover during the pandemic, something that intuitively should determine turnover. In addition, we make use of Gothenburg's primary areas as a local market with demographic differences regarding age and income as well as other time-varying factors that affect the market such as population per firm, aforementioned interaction term between lunch and workforce in combination with restaurant and area fixed effects.

Variables

According to previous literature, restaurant performance is an effect of both time-varying and time-invariant factors connected to different levels such as firm and area level. In the section following, we will introduce the dependent variable, independent variable as well as the time-varying control variables. Some being interaction terms between time invariant factors and panel data.

Dependent variable

To use turnover as a measure for restaurant performance has been used in previous studies (Heo, 2017). In Sweden, turnover is calculated as sales minus tax related to the goods and services which include sales done to staff, or any cause of sales done with a discount will affect turnover (SFS 1995:1554). Previous literature supports the usage of restaurant turnover as restaurants operate similarly which makes turnover a suitable measurement of restaurant performance. We acknowledge due to the definition of turnover in Sweden, it might not perfectly be comparable since some restaurants might have systematic differences in ”sales done to staff” and “sales done with a discount”. In addition, turnover is used in most hospitality literature when comparing restaurant performance and demand.

If there are systematic differences in which restaurants have, for example, large sales to their own employees, then turnover might not reflect customer demand and performance. This might, for example, be occurring when some restaurants import goods which are not available in a normal convenience store which might make restaurants more reliant on import of goods prone to have this measurement error.

Independent variable

The objective is to include East Asian, Southeast Asian, and Chinese restaurants in the model to estimate if these groups had a negative estimated effect on turnover in 2020. We want to be clear that the independent variable aims to measure heterogeneity in turnover over time but in terms of terminology, we use terminology such as discrimination with cation. This is due to literature using terminology such as discrimination towards Asians as their independent variable, these articles use methods and models that controls for all possible variation, which generate an unexplained term which can be said to be discrimination. Although we can not do that (due to unexplained confounds) we can estimate indications of heterogeneity based on the restaurant being East Asian, Southeast Asian and Chinese, which in turn might be caused by discrimination.

The use of the three subgroups, East Asian, Southeast Asian, and Chinese restaurants, is motivated by previous studies examining these three groups. Similarly, to our study, studies that used COVID-19 pandemic as an exogenous shock and by using panel data examine the difference in outcomes before and after the shock use these classifications. In this study by Huang et al., (2022) show that attitudes towards Chinese and other East and Southeast Asian cuisines changed during the first year of the pandemic, which could be linked to the spread of the virus. The results indicate there are potential spill-over effects as attitudes towards Chinese restaurants got negatively shifted and influenced its surrounding countries' cuisines. This not only motivates the use in our study of three subgroups to measure spill-over effects, but our data allows us to do the same classifications regarding the restaurants.

Control variables

Age and income

Theory regarding perception of risk and economic behaviour during a pandemic is discussed in the health belief model addressing that age and income. These are included in the model as they divide responses to the pandemic into two main factors of response, those of response to risk of infection and that of response to the economic recession due to the pandemic. These are especially relevant in the context of Sweden and the pandemic, since self-imposed social distancing becomes more reliant on the individual's decisions which are linked to age and income. We have chosen to include average income, as it can affect restaurant consumption by causing individuals with less income to consume less goods that are non-essential (such as restaurant visits) due to uncertainty of future income. As well as changing consumption regarding basket of goods, income is also connected with uncertainty of future income and employment which can cause poorer individuals to save more, relative to their income. It is an important control since we want to control so the change in turnover for restaurants is not an effect of the average income changing.

To extend on the risk response controls we also use dispersion of population among age groups 65-74 and 75+. Recommendations, especially targeting people that are elderly will cause restaurants in areas with a relatively large group of individuals 65+ and above to perform worse.

Consumers per firm

As stay-at-home orders and social distancing became prevalent practices during 2020, we believe that some restaurants had a large decrease in customers. According to industrial organization theory, firms will increase as population increases (Stennek, 2020). This could indicate that, with control for restaurant size and type of establishment, the number of firms per population is an important measure. If there are many restaurants per population, we assume there's less turnover before the market adjusts. We therefore include control for population per restaurant in each primary area as a control. This could indicate that restaurants under a new type of local competition will change their performance outcome in terms of turnover.

Reliance on daytime occasion

As individuals were recommended to work from home, offices and physical attendance at the workspace decreased. We believe that restaurants that primarily open for lunch had a larger decrease than other restaurants when society transitioned towards remote work. We therefore have chosen to include an interaction term as a control for primary areas *economically active day-time population* and a dummy that states that a restaurant only is open during lunch to account for transition to a decrease of workers-effects. *Economically active day-time population* and the interaction with restaurant opening hours affect restaurant turnover negatively if opening hours indicates it is a lunch restaurant. Restaurant opening and closing hours are also included separately to control for effects that determine how restaurant restrictions regarding operating hours affected turnover. This captures the effects of opening hours restrictions.

Restrictions - Opening hours and Size

The 20th of November in 2020, the Swedish government implemented restrictions targeting restaurant opening hours (2020:526). Although implemented in the last period of 2020, restaurants that normally close after 22:30 should be more negatively affected during the pandemic due to restrictions targeting opening hours. We therefore include a control for if the restaurant closes after 22:30 in the model by using fixed effects.

The same logic is applied to restrictions targeting restaurant size. We have included the number of employees as an approximation of restaurant size. When restaurants are subject to restrictions regarding restaurant size, such as limits of seats, distance between seats, mandatory table orders and serving, restaurant size could affect general restaurant activity and therefore turnover. Although the number of employees is by any means a perfect proxy for restaurant size, it is interpreted as an indication with caution.

Strategy

To estimate the effects of different strategies to the pandemic use two different types of variables. One proxy for strategy is change in the number of employees. The change in employees can be an indicator of strategy since while some restaurants chose to dismiss many employees, some restaurants chose not to and focus on other strategies to mitigate the effects of the pandemic.

Data

In this section we will present the data compiled from three main sources, method of merging and sample. We address limitations and advantages with panel data, and we present a variable operationalization.

Sources

Retriever Business

The first sub-data set includes panel data over the years 2016 and 2020 regarding turnover, number of employees, and the last annual report is from Retriever Business, a Swedish database that supplies information on all Swedish companies. From this dataset we sourced all annual reports from companies with restaurant activity in Gothenburg. The data from Retriever Business is from the Swedish Tax Agency, we can therefore assume the reports are verified and are consistent between years and companies.

The City of Gothenburg statistical database

The second sub-data set consists of demographic data panel data between the years 2016 and 2020 on the City of Gothenburg's primary areas from the City of Gothenburg statistical database. The primary areas are official zones used by the City of Gothenburg. The primary areas consist of 97 different zones and the area these zones include has not changed over since 2012. The primary area variables in the sample are income, age, daily population, nightly population. In one case, regarding the primary area Högsbo, the population of 75+ year olds are so small that they cannot present income information due to it then becoming “individual level data” which is something they cannot disclose. This is the only data point missing in this data set.

Google Maps

The third sub-dataset is restaurant data from Google Maps on time invariant restaurant characteristics. Google Maps is used for restaurants to supply information to customers what kind of service they supply as well as a way for consumers to rate and review each restaurant. Most importantly, all restaurants use Google Maps since it supplies a market dominating service.

All information displayed on Google Maps is determined by the restaurants themselves, except the reviews and ratings that are from consumers' contributions. Google Maps is used by all restaurants in the sample. We used Google's own API to retrieve the relevant information by scraping data by generating a code in Python that applied loops to extract data from Google Maps coordinates. This method had to be complimented by adding some restaurants manually by using the companies from Retriever Business to guarantee that we had all matches possible from Retriever Business and Google maps. This was a way to avoid not only getting results on the firms paying Google for exposure and guaranteeing we had all restaurants possible.

The data includes the restaurant's name, type of restaurant, rating, number of reviews, visiting address, estimated opening and closing hour, price point and dummy variables regarding dine-in, delivery, take-away and curb side pickup options. All the data is sourced post the COVID-19 restrictions on restaurants were lifted on the 9th of February 2022. The importance of this is that we know that the opening hours are accurate and not a result of restrictions. The information on opening and closing hours is confirmed on Google Maps due to Google Maps supplying information regarding when the restaurant last made changes to the information available. The same method is used to verify the Service option-dummies as we can see when changes last were made to the information.

Method of merging

To merge the data, we have used two common denominators in the sub-data sets. Starting with the first one, the fiscal data has the *company name* as the entity. The company name has then been linked to the Google Maps dataset by identifying which restaurant is linked to which company. This is primarily done by using an official registry supplied by the City of Gothenburg statistical database on which restaurant belongs to which company. In the cases it was not possible to identify using the official registry, we used Eniro as well as Foodora, both sites make it possible to confirm which restaurant is owned by which company. These data were also double checked to the Allabolag.se registry (Which is just a more convenient way to access information from Business Retriever as they use the same source), to guarantee to as great extent as possible that it is in fact one restaurant - one company to verify that turnover actually belongs to the restaurant we aim to examine. To merge this data set with the primary area data set we used the restaurants visiting addresses on Google Maps to an address registry supplied by the City of Gothenburg statistical database connecting each restaurant's visiting address to each primary area.

Sample

The final sample consists of data of 4825 observations (965 over 5 years) of restaurants. The panel data includes the years 2016 to 2020. The timeframe of choice is determined by limiting factors such as missing data prior to 2016 on primary area characteristics as well as there not being public records of annual reports after 2020.

Creating the sample, we started by including all 2500 companies' annual reports registered as restaurants in Gothenburg. To avoid selection bias, this data is from Retriever Business which in turn sources their data from Skatteverket which makes it possible to verify we have all available data. How we got from 2500 yearly to 965 is due to reasons such as inactivity, companies registered in Gothenburg but does not operate their restaurant from Gothenburg, not all companies actually having restaurant activities even if they are registered as such etc. Therefore, inactive companies have been excluded and these correspond to the largest portion of the restaurants excluded, approximately 1000 restaurants are registered but have no record of either turnover or any employees. If the restaurant is inactive it is based on a combination of criteria. The restaurants must have no record of turnover in 2020 and 2019 in Retriever Business and there must be no historical record of them being active in the same time period when searching for the company on a Google Search.

To control for selection bias regarding that some restaurants might have gone out of business due to the pandemic, we have systematically searched for all restaurants in the sample on a regular Google Search to conclude when they went out of business, and if they did during 2020, if there's systematic differences in which restaurants that seem to go out of business or stopped business activities due to other reasons. We have concluded that there are very few, just a handful, companies that have applied for bankruptcy during 2020 and that there seems to be no systematic difference in which restaurants have gone out of business and not regarding them being Asian versus other restaurants. Secondly, Retriever Business and the City of Gothenburg's statistical data base’s method of defining the addresses included in the region of Gothenburg is not a perfect overlap. Therefore, some companies have been excluded due to the restaurant not being in Gothenburg's primary areas.

An additional factor of exclusion is that even though the norm is one restaurant per company, some restaurants are excluded due to being a part of a chain or company concern.

The reason for this is if a company holds many restaurants, it's impossible to verify which company's fiscal information and turnover regards which restaurant. By dropping all restaurants that are a part of the same company while being different restaurants, we solved this problem of verifications. As another problem then arises, if there's systematic differences in which restaurants are a part of a chain or restaurant concern, we could not identify any systematic differences in if Asian restaurants versus other restaurants were excluded due to being a part of a restaurant concern or chain.

Another reason for exclusion is that while some companies are registered in Gothenburg, they do not operate in Gothenburg. If the company is registered in Gothenburg but the restaurant is not, the restaurant has been excluded. Similar exclusion occurs when the visiting address of a restaurant is in Gothenburg's' primary areas, but the company is not, which makes it impossible to verify which company it regards due to it being in some other region that we cannot verify. Although a small portion of "disjointment" of visiting address and company address we found that a predominant majority of companies and restaurants share the same address, and if they do not, then the norm is that the company is in Gothenburg as well as the visiting address of the restaurant. This has resulted in a very small exclusion of restaurants due to the disjointment. Lastly, we excluded companies that are not mainly restaurant businesses. These are typically occurring as other types of businesses on Google Maps, for example car mechanics and car dealers but occur in Retriever Business as restaurants. Again, there seem to be no systematic differences between which companies are excluded due to aforementioned criteria.

Advantages and limitations

The panel data are available for 97 different primary areas which makes it possible to have a nuanced analysis of primary area differences. In that way, we don't have to be as concerned about *within*-primary area heterogeneity which would be the case with larger geographical areas. Although we mitigate within-primary area differences by using many small areas, average income might be a bad representation of the primary area in the cases where rich and poor neighbourhoods are geographically close.

The panel data consists of a few years but many entities. One positive aspect is that we avoid unobserved effects that might occur due to the data being inconsistent over a long period of time such as other economic shocks with heterogeneous effects. A downside of this is that since the data only include a few years, and only one year of the pandemic, we can only observe short term effects and never conclude that any results are nothing else than short term effects. Possible other measurement errors we want to address are that the restaurants themselves chose what kind of information they want to communicate on Google Maps. One factor is that restaurants might have more types than one, which could potentially make identical restaurants pick different types because they are forced to only choose one. This might be especially relevant for the Buffet type restaurants, which might serve a specific type of cuisine, but it's not displayed on Google Maps. These kinds of differences can make it hard to interpret the results later, since we try to capture an effect of being Asian rather than, let's say, a buffet restaurant. The issue occurs since buffet restaurants might be particularly subject to the effects of the pandemic by not being able to serve the same number of customers or simply had to change their restaurant model. We will interpret the results acknowledging this fact, that there might be a high correlation between buffet restaurants and Asian restaurants in the sample.

Variable operationalization

TABLE 1 – VARIABLES, MEASURES, EXPLANATION AND SOURCE

Variables	Measures	Explanation	Source
Log(turnover)	Demand	Restaurant performance	Retriever business
Change in number of employees	Strategy	Change in number of employees	
Number of employees	Restaurant size	Number of employees	
Average Income	Average income	Average income conducted from Primary areas	Statistikdatabasen Göteborgs stad
Population 65-74 years	Age group 65-74	Number of individuals in the age group 65-74	
Population 75+ years	Age group 75+	Number of individuals in the age group 75+	
Daytime population	Economically active day-time population	Daily population	
CHINESE	Chinese type of restaurant	Chinese restaurants	Google Maps
EAST	East Asian type of restaurants	Chinese, Japanese, Korean, Taiwanese restaurants	
SEAST	Southeast Asian type of restaurants	Chinese, Japanese, Korean, Taiwanese, Thai, Vietnamese, Indonesian and Filipino restaurants	
Treatment x 2020	Difference-in-differences estimator	Interaction between being either EAST, SEAST, CHINESE restaurant in 2020	Interaction between sources
Daytime population x Lunchonly	Business reliance on on-premises work	Interaction term between lunch restaurants and daily population	
Population per restaurant	Competition	Population/No.Firms in primary area	

Empirical strategy

In the following section we will present the econometric model, the difference-in-differences framework and assumptions and econometric considerations. We also include descriptive statistics and a robustness check for outliers regarding years and entities.

Econometric models

The connection between the model and variables and method is motivated by previous literature, which in turn caused us to identify a gap in previous literature on what effects turnover during the pandemic short term. The literature, while using a range of models and methods, have pointed towards either using excessive controls or using fixed effects to control for time-invariant factors affecting both firms and areas. We have chosen to use fixed effects since we are aware that the controls, we can access do not capture all time-invariant controls. The estimator of choice, difference-in-differences, the model can be used both with controls and fixed effects. This is based on literature by Wooldridge (2013) on panel data analysis which step by step explains how analysing interaction between time periods and factors can be analysed using difference-in-differences using controls for time invariant factors or fixed effects to account for all.

To estimate the effects of being an Asian restaurant in 2020 we have constructed three treatment groups of interest. These are EAST, SEAST and CHINESE which will be our main classifications of Asian restaurants. As we want to estimate the effect of being either of these groups on turnover in 2020, we have constructed a difference-in-differences estimator. In the section below, we have constructed a generalized model in which either of the sub-groups EAST, SEAST and CHINESE is replaced with TREATED.

By implementing this estimator, we can compare the estimated effect of being an Asian restaurant in 2020, the difference-in-differences estimator can be expressed as:

(1) $\delta_1 = (\text{turnover}_{\text{after, TREATED}} - \text{turnover}_{\text{after,other}}) - (\text{turnover}_{\text{before,TREATED}} - \text{turnover}_{\text{before,other}})$

where after is 2020 and before is previous years. TREATED is either of the three types of restaurant-classifications. δ_1 is the estimated average difference over time on the turnover for the different types of restaurants.

To test if there is a significant difference in the parameter δ_1, we run a regression to determine if there are any significant differences between the two groups.

(2) $\text{turnover}_{it} = \beta_0 + \delta_0 \text{*after} + \beta_1 \text{*TREATED} + \delta_1 \text{*after*TREATED} + u_{it}$,

As we know turnover is an effect of both firm level and area level factors, we have chosen to include panel data on various controls. The model with time varying control looks as follows:

(3) $turnover_{it} = \beta_0 + \delta_0{*}after + \beta_1{*}TREATED + \delta_1{*}after{*}TREATED + \beta_2{*}C_{it} + u_{it}$,

Where C_{it} represents the different time varying control variables on both firm and area level and β_2 is the coefficient. Including time-varying control variables acknowledges that change in both firm and primary area characteristics can affect turnover. In addition it would make sense to measure the change in percent rather than in real turnover. Therefore we have chosen to create a log(turnover) to get a percentage effect. To interpret the log-transformed dependent variable Benoit (2011) explains that $\beta_i * 100$ gives the percentage change in the dependent variable. The model therefore becomes:

(4) $\log(turnover)_{it} = \beta_0 + \delta_0{*}after + \beta_1{*}TREATED + \delta_1{*}after{*}TREATED + \beta_2{*}C_{it} + u_{it}$,

where $100{*}\delta_1$ is the approximate percentage change in turnover due to being TREATED. The coefficient therefore implies that because of being TREATED, restaurants lost a percent in value in 2020.

In the next model we decided to separate firm and area levels control, where i represent the entity, restaurant and t represent time, in this case yearly observation, φ_{it} represents time varying restaurant control variables, and ζ_{it} primary time varying area control variables. u_{it} is the time varying error and represents unobserved factors that might vary with time and between entities.

(5) $\log(turnover)_{it} = \beta_0 + \delta_0{*}after_t + \beta_1{*}TREATED + \delta_1{*}after{*}TREATED + \beta_2{*}\varphi_{it} + \beta_3{*}\zeta_{it} + u_{it}$

To build on this model, we conduct a model using fixed effects. We have identified from previous literature that time-invariant factors affect turnover such as factors related to restaurant differentiation that are kept constant such as the restaurant's own price-level, location, physical environment, service options etc.

The purpose of conducting the fixed effects model instead of a model with excessive control is because we are aware that we cannot control for all time-invariant confounds. The downside of conducting such a model is that we cannot examine time-invariant effects.

To determine whether to use fixed effects or random effects models, we conducted a Hausman test to examine which one was more suitable. It's an additional control for which model to apply, even though intuitively, since our main variable of outcome is time varying and not experimental, fixed effects is the commonly used estimate (Wooldridge, 2013)

(6) $\log(\text{turnover})_{it} = \beta_0 + \delta_0{*}\text{after}_t + \beta_1{*}\text{TREATED} + \delta_1{*}\text{after}{*}\text{TREATED} + \beta_2{*}\varphi_{it} + \beta_3{*}\zeta_{it} + \alpha_i + f_i + \varepsilon_{it}$

Where i is the restaurant and t is the year. $\log(\text{turnover})_{it}$ is the dependent variable. φ_{it} represents time varying restaurant control variables, and ζ_{it} time varying primary area control variables. To adjust for unobserved unit-specific and time-specific confounders at the same time, we include time fixed effects and unit-specific fixed effects. The α_i allows for the primary area fixed effects and f_i adjusts for the restaurant (firm) fixed effects. Standard errors, adjusted for clustering at the primary area level to adjust for that the error term might be correlated across time within primary areas to avoid biased estimators.

Econometric considerations

Omitted Variable Bias

To avoid issues of omitted variable bias, one possibility of panel data regression is to use a fixed effects model to adjust for unobserved unit-specific and time-specific confounders. Opposed to a regular OLS model with control variables, a fixed effects model with control variables includes both a vector of unknown or immeasurable variables that vary between entities but are kept constant between different years within the entity. So, to avoid these OVB, we use fixed effects in the extended model.

Additionally, the model with panel data does not include a vector that varies between years but not between entities (Wooldridge, 2013). As we use a short panel (2016-2020), it is not as likely to violate the assumption of omitting the vector that varies between years but not between entities since there will be less of a time-effect due to the observations only being 5 years.

Multicollinearity and Serial Autocorrelation

Multicollinearity arises when two or more of the independent variables are highly correlated with each other due to its ability to increase standard errors and therefore affect the real scope of the coefficients. We address this further in the results section by conducting post-estimate controls for multicollinearity to control for correlation in a correlation matrix. Although, we do not suspect that any of the control variables are highly correlated and should not explain the same variation to a great extent. We also do not believe we compromise the R^2 by using too many controls as we highly rely on fixed effects rather than excessive controls which could inflate the R^2 . Serial autocorrelation can become an issue where the entities are few and there is a long panel of years used in the regression. In this case, we use many entities over 5 years' time, and should not violate the serial autocorrelation assumption. Serial autocorrelation can occur when using long time series for panel data (Drukker, 2003) but as we have short period of time series data it should not be of concern. We deal with this by clustering standard errors at primary area level.

Heteroskedasticity

Since we are estimating a linear effect one assumption of the linear regression is constant variance in the error term (Wooldridge, 2013). By clustering at primary area level, we can mitigate the effect of potential heteroskedasticity caused by outliers by using robust standard errors to not violate the assumptions of the linear model. By doing so, we assume that the inference is unbiased. The purpose of clustering at primary area level is that we suspect restaurants in area to be clustered at primary area level, something that could make the standard errors of the regression's coefficients decrease in relation to its real value, which in turn cause t-statistics to be enlarged or p-values to be too small hence the confidence intervals too small.

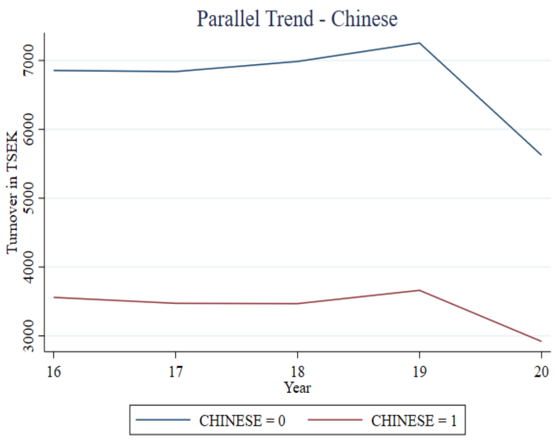
Unbalanced Panel

We have unbalanced data on turnover since some restaurants have not operated throughout 2016-2020. Although, all restaurants have at least one post and two years prior to 2020. For the purpose of the study, it should not create any problems for the estimation since we essentially estimate the effect in 2020. All previous years are therefore considered as we only have one year post treatment; it should not affect the estimation (Wooldridge, 2013).

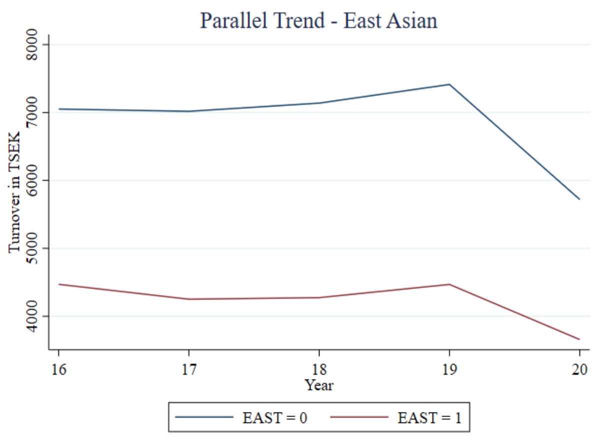
Difference-in-differences assumptions

Parallel trend assumption

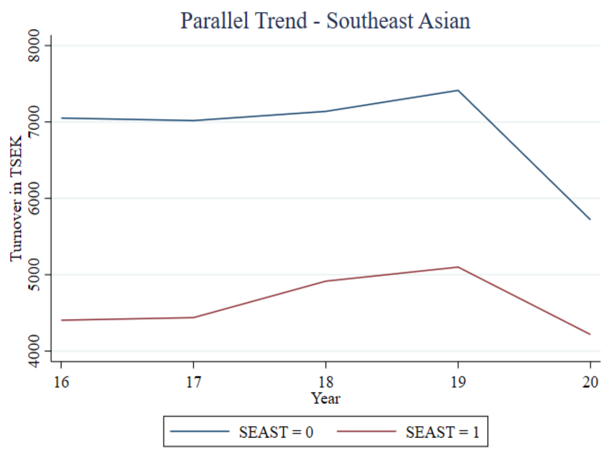
Graph 1. Parallel trend - Chinese



Graph 2. Parallel trend - East Asian



Graph 3. Parallel trend - Southeast Asian



The difference-in-differences estimator relies on the parallel trend assumption. This is due to the model estimating the counter factual results, assuming that if no shock or treatment occurs, then the restaurants would develop parallel. That is that the control develops over time, and the treatment group develops over the two time periods, we must assume that the treatment group would have developed similarly to the control group in the two time periods, in the absence of treatment.

The parallel trends assumption must hold for the estimates to be consistent and for the causal inference to be valid. If the parallel trend does not hold, we can no longer assume the counterfactual effect, and estimate the effect of being treated. As we have graphically shown in Graph 1 for , we examined how the two groups developed before the treatment, which appears to be parallel before 2020. Since there are parallel trends between treatment and control group before 2020 the assumption holds (Pischke, 2005).

Random assignment to treatment

As difference-in-differences requires random assignment to treatment we will treat the transition from 2019 to 2020 as an exogenous shock. In this case, we assume all restaurants are subject to the same amount of COVID-19, especially on an annual level as we cannot determine if some restaurants have been more or less impacted short term by COVID-19 by using annual data.

Summary statistics

TABLE 2 – DESCRIPTIVE STATISTICS

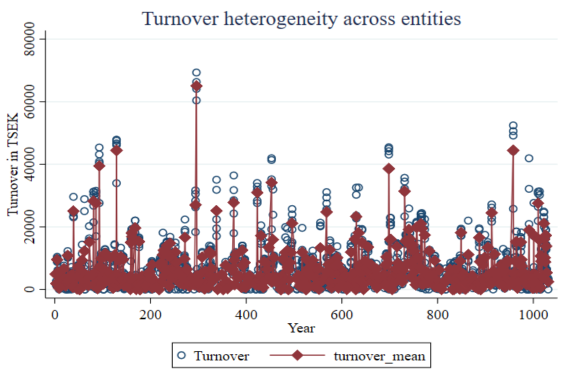
Variable lables	Observations	Mean	Median	Min	Max
Log turnover	2228,00	8,37	8,45	0,00	11,15
Chinese restaurants	4825,00	0,02	0,00	0,00	1,00
East Asian restaurants	4825,00	0,05	0,00	0,00	1,00
East Asian & South-East Asian restaurants	4825,00	0,09	0,00	0,00	1,00
Average income in Primary area	4825,00	330182,09	341620,14	92998,43	516802,71
Population 65-74 years	4825,00	692,01	653,00	5,00	1352,00
Population 75+ years	4825,00	474,43	469,00	1,00	1166,00
Change in Employees	4825,00	−0,09	0,00	−16,00	11,00
Number of Employees	2362,00	6,51	4,00	0,00	66,00
Population per restaurant	4825,00	541,59	227,21	8,67	9509,00
Interaction between lunch restaurant-dummy and economically active day-time population	4645,00	2837,02	0,00	0,00	39521,00
Economically active day-time population	4825,00	12274,38	5685,00	243,00	39521,00

What we can conclude from the descriptive statistics is that we do not have perfectly balanced panel data. Although we have a max amount of observation which is 4825 (965 over 5 years) some restaurants have not been active throughout the whole time period. Other than that, by looking at Log turnover and Number of Employees, we note that the min value of both variables is above 0. This is an additional check to conclude that there are no restaurants that potentially register as restaurants but are inactive before they open, which could be the case if both Log turnover and Number of Employees are 0.

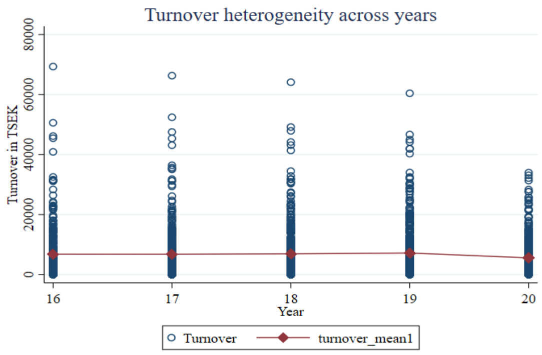
This could potentially compromise the results as inactive companies from the sample to not risk skewing our results if there's systematic differences between which companies have this practice. Examining these two observations, it seems to be 0's in Employees which can be explained by the fact that the owner is the only worker and that the one observation with 0 in Log turnover has negative turnover in 2020 which is registered as 0 in annual reports. Other than that, we have noteworthy less observations on the interaction term between lunch restaurants and economically active day-time population. This can be explained by some areas that might not have a lunch-only restaurant or 0 economically active day-time population, this should not cause any problem to the results.

Robustness checks - Turnover heterogeneity across entities and years

Graph 4. Turnover heterogeneity across entities



Graph 5. Turnover heterogeneity across years



As we plot the heterogeneity across entities and years, we can conclude that there are a few restaurants that are slightly outliers regarding turnover. As the study largely relies on the restaurants being comparable across entities, and on that we can validate that is one firm per restaurant, this is an additional control for both that and potential extreme values that can either skew the results or be indications of that we made a mistake including some restaurant concern or chain which could correlate with extreme values of turnover. What we can conclude examining heterogeneity across years is that there is a negative slope regarding average turnover looking at the difference between 2019 and 2020. This trend follows the overall reports on restaurant turnover during the pandemic. Other than that, as of these graphs, nothing stands out as abnormal.

Results

Main Results

As for the main results, we have included a table with three regressions which make a side-by-side comparison easier. To interpret the estimate effect on the log-transformed dependent variable turnover, any coefficient, $\beta_i * 100$ gives the percentage change in the dependent variable.

TABLE 3 – EFFECT OF BEING IN TREATMENT GROUP ON TURNOVER, 2020

	DD: Being a Chinese type of Restaurant	DD: Being an East Asian type of Restaurant	DD: Being a South East Asian type of Restaurant
Year of 2020	-.163*	-.164*	-.164*
	(.067)	(.067)	(.0.67)
Treatment x 2020	.053	-.087	-.086
	(.138)	(.059)	(.1)
Change in number of employees	.051*	.052*	.051*
	(.024)	(.025)	(.028)
Number of employees	.076***	.075***	.075***
	(.014)	(.014)	(.014)
Population of age 65-74	.001	.001	0
	(0)	(.0006)	(0.35)
Population of age 75+	.003***	.003***	.003***
	(.059)	(.001)	(.001)
Population per restaurant	-.001***	-.001**	-.001**
	(0)	(0)	(0)
Daytime population x Lunchonly	0	0	0
	(0)	(0)	(0)
Daytime population	.0001***	.0001***	.0001***
	(0)	(0)	(0)
Average Income	0	0	0
	(0)	(0)	(0)
Fixed Effects for primary area and firm	X	X	X
Constant	6.02***	6***	6.01***
	(.102)	(.096)	(.102)
Number of obs.	2,142	2,142	2,142
Groups of obs.	522	522	522
R^2	0.296	0.296	0.296

Notes: Table 3 outlines the results from restaurant-panel and area -panel regressions of restaurants' turnover which is log-transformed. Results are displayed using three different regressions of comparison Difference-in-differences estimator Treatment x 2020, using Chinese restaurants (Chinese), East Asian restaurants (EAST) and Southeast and East Asian restaurants (SEAST). Controls are accounted for as interactions between population and number of restaurants in the primary area and lunch-restaurants and economically active day-time population. Standard Errors in parentheses are clustered at primary area-level.

****p<.01, **p<.05, p*<.1*

In Table 3 the results of the DiD-regressions with controls are reported. The R^2 is consistent for all three research questions and takes on a value 0.296 which reports an explanation of the dependent variable with 29.6 percent from the model constructed. The time variable *Year of 2020* is significant at the five percent level, indicating a decreasing effect on the turnover for all treatment groups in the year of 2020. What we can interpret from the results is that over-all, there is on average a 16,3 percent respectively 16,4 and 16,4 percent decrease in all restaurants turnover in 2020.

Computing the confidence interval by multiplying the standard error with 1.96 we obtain a CI of 13,132. Using the significance level at five percent it allows us to interpret the results such as with 95% certainty all restaurants had an estimated negative impact on their turnover in 2020. This as the confidence interval is smaller than the negative coefficient.

The coefficient of *Treatment x 2020* is the answer to the research question in this paper. This difference-in-differences estimator is statistically non-significant for all three different treatments. As we failed to reject the null hypothesis that being an Asian restaurant in 2020 it can either be to the null hypothesis being true, that we have insufficient data or that the model does not capture change in turnover during the pandemic. As for now, we will declare the results as we failed to reject the null hypothesis. We will also declare why we want to interpret all results with caution in the following discussion section where we more specifically will address this further.

Examining the control variables and interaction variables, we note that there's statistically significant coefficients. Firstly, *change in the number of employees* is significant. As a proxy for strategy, it indicates that there is an effect of 5.1-5.2 percent on average in the turnover for every unit change in the number of employees. To interpret the effect of the change, one firm might have a negative change in the number of employees which will lead to a decrease in the turnover on average. One additional employee has a positive change in the variable, this will lead to a 5.1 percent respectively 5.2 percent and 5.1 percent increase in the turnover on average for every additional employee. Although this variable can be subject to reverse causality due to it might be that when turnover increases, the restaurant can employ additional workforce. To interpret the effect of the change, one firm might have a negative change in the number of employees which will lead to a decrease in the turnover on average. If a restaurant employs more staff in 2020 and has a positive change in the variable, this will lead to a 5.1 percent increase in the turnover on average for every additional employee.

Second, *Number of employees,* the coefficient indicates that with one additional employee there is an average increase with 7.6 percent in the turnover for a restaurant, this means that the more employees a restaurant has, there is a positive change in turnover. The variable in question is included as a possible control for the size of the restaurant and is statistically significant at the one percent level.

Regarding the primary area control variables, we note that there are both significant and non-significant results. The estimated coefficients for the variables *Population 65-74 years* are non-significant. The coefficients for the variables *Population over 75 years* and *Population during daytime* are statistically significant at a one percent level. *Population per restaurant* is statistically significant at the one percent level for the Chinese treatment group and at a five percent level for the Southeast -and East Asian treatment group. Although the coefficients seem small, the key to interpret them is in the nature of the dependent variable being log-transformed, which gives a percentage change in turnover by multiplying the coefficient by 100, as well as the interpretation of the coefficient. Referring to the descriptive statistics in Table 2 of these variables the population count takes on large values, which leads to a sensible interpretation of these relatively small coefficients. The coefficients are consistent for all treatment groups and for every extra person above the age of 75 the turnover will increase with 0.3 percent on average for a restaurant belonging to one of the treatment groups. In addition, these restaurants will have an average decrease of -0.1 percent for every extra person in the population per restaurant which could indicate a competition effect where restaurants compete more with the local restaurant market rather than a larger geographical market. The variable *Population during daytime* reports that the more crowded a primary area is during daytime, the larger increase in turnover a restaurant in this area will have. For every extra person in the daytime population, the turnover will increase by 0.01 percent on average. During the pandemic the society implemented several restrictions, and a large part of the workforce were stationed at their homes to prevent spreading of the virus. This might have led to a transfer of the daytime population between some primary areas in the city. If the daytime population for a primary area shrank in 2020 compared to previous years in the sample, then this would imply that it had an effect on the turnover for the restaurants in this primary area.

The interaction variable for *daytime population* and the binary variable *lunchonly* is statistically non-significant and takes on a value which is insignificantly small despite interpreting in percentage form. This is furthermore the case for the variable for average income.

Post estimations

Table 4. See Appendix

In the matrix of correlations, we observe mainly weak correlations between the variables in our model, see Table 4 in Appendix. One of the strongest measurements of positive correlation is found between the variables for *Population of 65-74 years* and *Population of 75 + years* where the value takes on 0.833. This could be due to using panel data over 5 years, and if individuals do not move during that period, then some individuals will be found in the age of 65-74 as in the 75+ age group. As we believe including these two groups bring two different effects, the one being elderly (65-74) and the one being specifically targeted with stay-at-home recommendations, we believe it is still purposeful to include them both. As we can see in the results, they also yield different coefficients and significance which even more strengthen that they measure different effects. The correlation between the year of 2020 and change in number of employees is negative and takes on a value of -0.249, which indicates that there is a weak relationship between these two variables. Between the three treatment groups there is a moderate to strong positive correlation. Since the treatment groups of EAST and SEAST are conducted in steps that are based on the Chinese, we can expect a high correlation here. Despite this, there are overall not any concerning correlations found in our model indicating any high relationships between the variables.

Discussion

We were not able to find significant results regarding our research questions regarding negative effects on turnover by being any sub-group of Asian restaurants in 2020. Although, a non-significant result is a result as well, we want to open for a discussion regarding the validity of the thesis before we talk about definite results. As we failed to reject the null hypothesis, that being an Asian restaurant in 2020 it can either be to the null hypothesis being true, that we have insufficient data or that the model does not capture change in turnover during the pandemic. We have identified that there are several possibilities as to why the results might be compromised. One possible explanation is that the model failed to capture differences in how restaurants adapted to the pandemic, that we could not control for confounds regarding time-varying change within restaurants and potentially that we have measurement errors.

Regarding confounds, it could be that while restaurants are the same type, they might operate differently within each type as a response to the pandemic. We suggest future research should control for more within-restaurant differences that vary over time, with a more elaborated analysis of how these restaurants made changes to mitigate the effects of the pandemic.

This would also strengthen any analysis regarding Asian restaurants, since in this model, we cannot conclude if Asian restaurants have systematically adapted a differing strategy than other restaurants or not, which would, even if we had significant results, make it hard to conclude if the results are due to the systematic differences in strategy or discrimination.

We believe that further control for area heterogeneity is needed. If ever made available, either include controls for change in tourism or exclude areas where restaurants depend on workforce and residents only if that variable is not available. Also using primary areas neglects that consumers are unevenly dispersed in that area, it would be even better if we had more control of actual distances from individuals to restaurants.

Other than that, we believe it can be hard or impossible to assess the causal effect of the pandemic without a variable measuring the levels of COVID-19. In this case, not only did we have to rely on annual reports which made it hard to measure more frequent shifts in turnover caused by the pandemic, we also had no measurement of differences in COVID-19. Even if we had more frequent data on levels of cases or deaths in the primary areas it would be hard to know if individuals responded to risk behaviours regarding information about their closest surroundings or if they were responding to national levels of cases, deaths, or hospitalizations rather than those in the primary area.

Regarding measurement errors, while using Google Maps as an accessible source of data on all restaurants and their characteristics, we also open up for measurement errors when restaurants themselves define what type of restaurant they are. This can cause similar restaurants to differentiate differently regarding the information on Google Maps, while they are actually very similar. Similar goes for the contrary, that restaurants that are not similar are assumed to be similar in the model. This can for example, make it hard to conclude if we have treated restaurants in the control group, which can make our results insignificant.

The size of the three different treatment groups had substantially fewer observations than the control group that consisted of all other restaurants. This might have contributed to the statistical non-significance of the difference-in-difference estimator. The treatment groups had minor differences in the coefficients for the variables, which might have a source in that they are based on the Chinese treatment group and are relatively similar in their content of restaurants.

Conclusion

The aim of this study was to investigate if the turnover for East Asian, Southeast Asian and Chinese restaurants was more affected by the COVID-19 pandemic compared to all other types of restaurants in Gothenburg. We sourced all companies registered as restaurants in Gothenburg and identified in which primary area they are located in. We constructed a dataset using panel data on primary areas, on time-varying and time-invariant restaurant characteristics. Most importantly we could examine if restaurants are East Asian, Southeast Asian, and Chinese restaurants, between the years of 2016 to 2020, by using Google Maps data on "Type of Restaurant". We used accessible information on restaurants from Google Maps and area statistics from the City of Gothenburg's statistical database in combination with annual reports from Retriever Business. We estimated a model using a difference-in-differences estimator and fixed effects and found no significant results regarding being East Asian, Southeast Asian and Chinese restaurants in 2020.

We believe our model fails to control for time-varying confounds regarding change in restaurant operations and strategy during the pandemic and that we may have some measurement errors regarding the independent variable. For future research we suggest controlling for more specific factors related to change in strategy, change in primary area factors such as tourism. We also believe the study would benefit from extending to for example Stockholm and Malmö, to create a larger sample which could open ways for additional ways of analysis. For example, we believe one of the limitations to the thesis is that we have a small control group, which make it hard to for example zoom in on restaurant types without losing too much statistical power by having too small of a sample. With a larger sample, we would for example be able to use a matching analysis examining for example buffet restaurants, which could open for an analysis regarding if restaurants that operate very similarly, yet one is Asian and one is not, then it would open for a discussion and results that would be able to touch upon conclusions regarding anti-Asian behaviour. We still believe there is more to the subject than what we were able to capture with our model, we hope future research acknowledges the flaws we identified in the thesis and hopefully can find better models, more precise measurements, and reliable, significant results.

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Appendix

TABLE 4 - MATRIX OF CORRELATIONS

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) after	1.000													
(2) avginc	0.043	1.000												
(3) pop6574year	0.006	0.071	1.000											
(4) pop75year	0.103	-0.058	0.833	1.000										
(5) changeEmp	-0.270	-0.094	0.057	0.045	1.000									
(6) emp	-0.075	0.172	-0.096	-0.139	-0.067	1.000								
(7) popperrest	-0.001	-0.305	0.029	0.226	0.065	-0.153	1.000							
(8) lunchonly	-0.006	-0.043	-0.158	-0.130	0.015	-0.092	-0.029	1.000						
(9) DTP	0.014	0.311	-0.405	-0.471	-0.073	0.174	-0.372	0.060	1.000					
(10) primaryareacode	0.022	-0.331	-0.212	0.067	0.067	-0.101	0.451	0.115	-0.182	1.000				
(11) year	0.718	0.130	0.027	0.153	-0.194	-0.067	0.005	-0.012	0.014	0.040	1.000			
(12) CHINESE	-0.009	-0.024	-0.075	-0.067	0.012	-0.028	-0.034	-0.073	0.034	0.032	-0.013	1.000		
(13) EAST	-0.017	-0.048	0.016	0.032	0.036	-0.049	-0.017	-0.102	0.027	0.036	-0.028	0.575	1.000	
(14) SEAST	-0.010	-0.051	0.038	0.086	0.029	-0.049	0.032	-0.147	-0.013	0.064	-0.011	0.406	0.705	1.000