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The Pandemic Economy: Exploring the change in new business license activity in Chicago, USA from March – September, 2020

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Abstract. Since its emergence in 2019, the worldwide spread of the novel coronavirus SARS-CoV-2 (COVID-19) has created a vast economic crisis as government lockdowns place considerable strain on businesses of all kinds – particularly those that rely on face-to-face contact, such as retail restaurants, and personal services. Given the importance of these businesses to local economic development and urban vitality, this paper makes use of the point-level Chicago Business License dataset to examine the impact of the COVID-19 pandemic on new business activity in the City of Chicago. The results indicate that on average, from March to September 2020, total monthly new business starts have declined by 33.4% compared to the monthly average of new starts in the City from 2016 to 2019. Food service and retail businesses have been hardest hit during this period, while chains of all types have seen larger average declines in new startup activity than independent businesses. These patterns also demonstrate interesting intra-urban spatial heterogeneity; ZIP codes with the largest resilience to pandemic-related drops in new business activity tend to have more dense, diverse, and walkable built environments, lower levels of social vulnerability, lower percentages of young residents, and higher percentages of Black and Asian (non-Hispanic) residents. These findings provide some useful evidence in support of the “15-minute city” and ethnic enclave resilience hypotheses. Interestingly, observed COVID-19 case rates also appear to have a positive relationship with new business resilience for new chain and food service establishments. This is likely due to the fact that neighborhoods with relatively high levels of new food service business activity also have relatively higher proportions of food service employees, who are more at risk for contracting COVID-19 as “essential” workers.

1 Introduction and Background

Since the emergence of the novel SARS-CoV-2 (COVID-19) virus in late 2019, its global spread has led to a variety of negative economic consequences, from restrictions on business operations and government lockdowns to reduced consumer confidence, discretionary mobility, and stock market fluctuations (McKinsey & Company 2020). According to some estimates, real global Gross Domestic Product (GDP) dropped by 10% between 2019Q4 and 2020Q2 (McKinsey & Company 2020), while US GDP experienced its largest quarterly drop in history (9.1% in Quarter 2 of 2020), far outstripping the impact of any previous recessions (measured since data collection began in 1947) (Bauer et al. 2020,

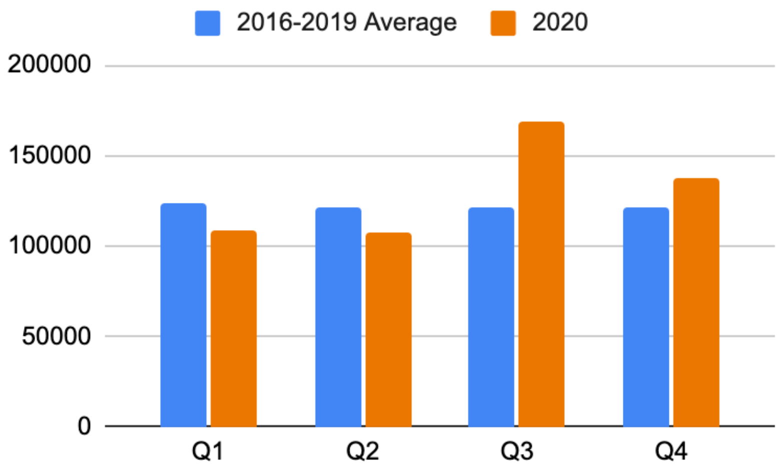


Figure 1: Applications for new businesses with planned wages, 2016 - 2019 average and 2020 (US Census Bureau 2020)

Routley 2020). Concurrently, the US unemployment rate reached its highest-ever recorded value in April 2020 at 14.7% (FRED 2020), while the S&P 500 lost 33% of its value in just one month (Capelle-Blancard, Desroziers 2020).

Accordingly, US national data show that small business revenues across all industrial sectors dropped by 40% in April and had not yet recovered to pre-pandemic (January 2020) levels by August, remaining at a 20% deficit; revenue in "leisure and hospitality" small businesses, which includes the arts, entertainment, recreation, accommodation, and food service sectors, have fared even worse, bottoming out at a roughly 70% deficit and only recovering to around 40% of pre-pandemic levels (Chetty et al. 2020, Bauer et al. 2020). At the same time, as Figure 1 shows, applications for new businesses "with planned wages" dropped significantly in 2020Q1 and 2020Q2 compared to recent years, before significantly rebounding in 2020Q3 and 202Q4 (US Census Bureau 2020). While this amounts to a higher net number of applications in the first four quarters of 2020 compared to the 2016-2019 average, it is not yet clear whether this is due primarily to an administrative backlog created by the pandemic, the entrepreneurial activity of the newly unemployed, or re-adjustments in the market due to increased demand for particular kinds of goods and services (Bauer et al. 2020).

Further understanding the specific effects of the pandemic on entrepreneurial activity is particularly important because new business creation is the primary engine for diversity, economic growth, and innovation in the economy as a whole (Frenken et al. 2007, Neumark et al. 2006, Wennekers, Thurik 1999), and declines in startup activity can have substantial negative long-term economic consequences (Sedláček 2020, Guorio et al. 2016). There is also significant spatial heterogeneity in startup activity that plays an important role in cluster formation, regional economic development, and even the development trajectory of individual neighbourhoods within regions (Mack, Credit 2016, Malmberg, Maskell 2002, Florida 2002, Klepper 2009a,b, Porter 2000, Rutten, Boekema 2007). Understanding the fine-grained spatial and industrial effects of the pandemic on new businesses in more detail can help researchers and local governments to understand how to develop more economically resilient regions, which can provide insulation from future economic shocks.

Data on new business applications are available on a weekly basis at the state level from the US Census Bureau's Business Formation Statistics (2020). However, other datasets used to evaluate new business activity at finer spatial scales are not updated quickly enough to allow researchers to examine the fine-grained spatial and industrial/sectoral effects of the pandemic on new business activity. These include public datasets like the ZIP Code Business Patterns, as well as private datasets such as InfoUSA or the National Establishment Time Series (NETS).

To overcome this problem, this paper utilizes a novel large dataset of business establishments (at the point level) derived from the open source Chicago Business License dataset, which is updated weekly and contains a comprehensive set of information on all new business license applications in the City of Chicago (2020) to assess two primary questions: first, to what extent has there been a decline in new business establishment[1] starts during the pandemic (March to September, 2020) when compared to recent pre-pandemic trends (averages from 2016 to 2019)? Specifically, we are interested in whether there are distinct temporal trends by business sector or type (e.g., retail, food service, personal care and fitness, etc.) or between multi-establishment (or "chain") (≥ 4 establishment) businesses and "independent" (< 4 establishment) businesses.

Second, given the temporal analysis, what is the spatial expression of these trends? Are there particular areas of the city that are more resilient to declines in new business startups, and, if so, what are the characteristics of these areas? To analyse this formally, we aggregate changes in pandemic-related (i.e., March to September 2020) business activity to the ZIP code level in order to explore the relationship between pandemic-related decline and characteristics of social vulnerability, the built environment, demographics, and cumulative COVID-19 activity.

The results of the analysis indicate that 1) on average, from March to September 2020 (through which complete data was available at the time of writing), total monthly new business starts have declined by 33.4% compared to the monthly average of new starts in the City from January 2016 to December 2019. 2) In general, food service and retail businesses have been hardest hit during this period (although all categories have experienced declines), while chains of all types have seen larger average declines in new startup activity (an average monthly drop of 61.9% from March to September compared to pre-pandemic averages) than independent businesses (a 29.2% drop). 3) These patterns demonstrate interesting intra-urban spatial heterogeneity; overall, a regression analysis suggests that the ZIP codes with the smallest pandemic-related declines in new business activity (i.e., those most resilient to the effects of the pandemic) tend to have more dense, diverse, and walkable built environments (defined in more detail below), lower levels of social vulnerability, lower percentages of young (age 18-39) residents, and higher percentages of Black and Asian (non-Hispanic) residents. Interestingly, observed COVID-19 case rates appear to have a positive relationship with new business resilience (after controlling for a variety of covariates), particularly for new chain and food service establishments. This could be a case of reverse causality, where areas with relatively high levels of new food service business activity also have relatively higher proportions of food service employees, who are more at risk for contracting COVID-19 as "essential" workers.

2 Theoretical Framework

2.1 Economic Benefits of New Business Creation

New business creation provides a number of benefits to both local and macro-level economies that make it particularly important in the contemporary era of "flexible specialization" (Harvey 1989, Piore, Sabel 1984). The theoretical pathways from new business creation to economic benefits are diagrammed in Figure 2. Most directly, new (generally small) businesses create jobs that contribute to local economic growth (Birch 1987, Kirchhoff, Phillips 1988, Neumark et al. 2006). While on net these jobs may not always exceed the number of jobs lost from the older businesses they replace (Mack, Credit 2017), this process of business "churn" increases the probability of creating high-growth firms (so-called "gazelles") that tend to produce the majority of new jobs (Henrekson, Johansson 2010, Nightingale, Coad 2014) and also provides for the "creative destruction" that fosters evolution and innovation in the economy[2] by replacing jobs and businesses in

[1] In this case, a new establishment is considered to be a new unique physical location of a given business; this is determined by coordinating the address and business name information for individual business licenses in the Chicago Business License dataset.

[2] In addition to generating 1) productivity gains, 2) new knowledge that fosters new business creation, and 3) specialized clusters and entrepreneurial ecosystems, sustained innovation over time leads to technological change. This is particularly important for economic growth at two scales: locally, individual

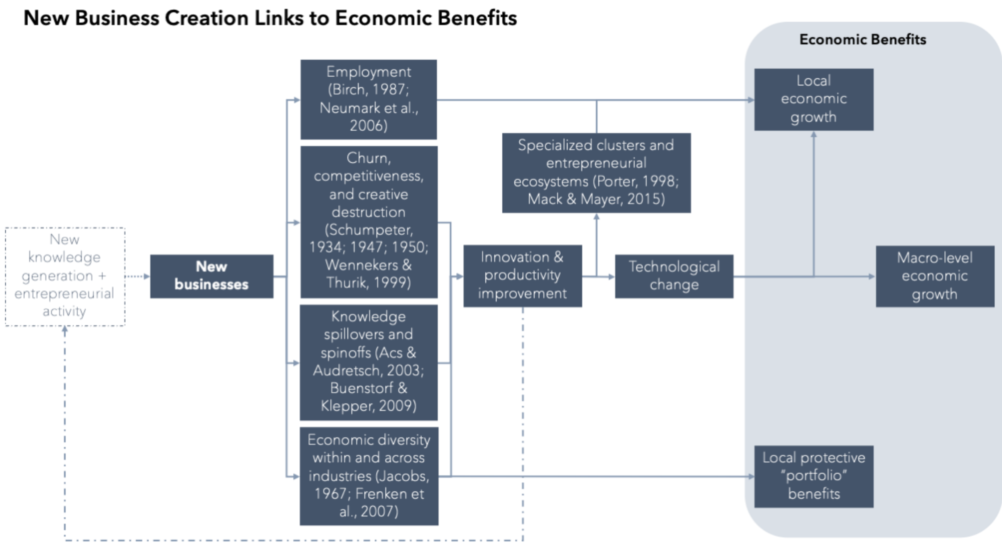


Figure 2: Diagram showing the theoretical connections between new business creation and economic benefits at both the local and macro levels

older declining industries with new jobs in more innovative industries (Schumpeter 1934, 1947, 1950, Brown et al. 2006, Fogel et al. 2008).

Another way that entrepreneurship fosters innovation and productivity improvement is through the creation of a more competitive economic environment that produces a selection process through which only the most viable and/or innovative businesses survive (Wennekers, Thurik 1999, Carree, Thurik 2003). Interestingly, this more competitive environment can drive a positive feedback loop through which increased competitiveness drives demand for better products, which creates incentives for additional innovation and new business creation (Teece 2007, Asheim 1996, Florida 1995, Porter 2000, Rutten, Boekema 2007, Malmberg, Maskell 2002). Fully fledged clusters, such as Silicon Valley, can develop a unique entrepreneurial culture of "competition and community" (Saxenian 1994) and attract additional educational, political, and financial investments that foster a holistic "entrepreneurial ecosystem" (Mack, Mayer 2015, Stam 2015) that captures the indigenous benefits of innovation, leading to economic success for individual businesses and associated local economic benefits, as well as providing a more supportive environment for further new business creation (Delgado et al. 2010). New businesses also contribute to innovation because they are often created as a direct result of knowledge spillovers, i.e., a new business is formed specifically to take advantage of some newly generated knowledge or idea (Acs, Audretsch 2003, Acs et al. 2009). These are often in the form of spinoffs from large existing companies, which some argue constitute the bulk of cluster forming activity (Buenstorf, Klepper 2009, Klepper, Sleeper 2005, Klepper 2009a,b).

Finally, new businesses directly contribute to economic diversity. Increased diversity within related industries (i.e., "related variety") provides another engine for innovation as the pool of new ideas and possible interactions and exchanges increases with the diversity of firms (Jacobs 1967, Boschma, Lambooy 1999, Boschma, Frenken 2006, Saviotti, Pyka

high technology businesses are often significant contributors to economic growth because they drive competitiveness and attract highly skilled and highly compensated workers (Malecki 1984, 1991, DeVol, Wong 1999, Chapple et al. 2004), and there are substantial local productivity benefits for regions that develop transformative technologies rather than lagging behind technological change and being forced to adapt to new structures and activities (Boschma, Lambooy 1999, Boschma, Frenken 2006, Jacobs 1967, Saviotti, Pyka 2004, Frenken et al. 2007). But perhaps more importantly, at the macro-economic level new technology restructures the basic functions, markets, products, and demands of the economy as a whole (Schumpeter 1934, 1947, 1950, Breschi et al. 2000, Wennekers, Thurik 1999), which (if these gains are distributed throughout the economy) has the potential to significantly improve overall human development outcomes and standards of living.

2004, Frenken et al. 2007). On the other hand, diversity through “unrelated variety” provides important portfolio benefits to local economies by distributing economic risk across a variety of different industries, making the economic system more resilient to unexpected shocks that may occur, no matter what sector they are concentrated in (Montgomery 1994, Frenken et al. 2007).

In this paper, we are particularly interested in new business creation for small, independently owned businesses in customer-facing sectors such as retail and food service, for several reasons. These businesses are significant contributors to land use diversity, street life, and overall urban vitality (Jacobs 1961, Gehl 2010). At the same time, small retail shops help to contribute to a unique “sense of place” in a given locality that is the direct product of local creative efforts and sensibilities (Jacobs 1961, Relph 1976, Robertson 1999, Kunstler 1994, Walljasper 2007, Alexander 1977, Montgomery 1998). The owners of these kinds of businesses themselves are also often more connected to the specific dynamics, demands, and politics of the local community, and tend to contribute to local import substitution (increasing the local multiplier effect) by spending profits to purchase requisite subsidiary goods and services locally, rather than exporting profits to another region, as is the case with larger chain businesses (Jacobs 1967, Talen, Jeong 2019a,b).

2.2 Fostering Economic Resilience

Given this paper’s interest in exploring features of economic resilience at the neighbourhood level, it is useful to lay out the theoretical justifications for a number of possible hypotheses about the characteristics that might foster increased protection to the pandemic-related shock on new business activity. First, the literature on disaster resilience has identified a range of basic sociodemographic vulnerabilities to natural and man-made disasters, as codified in measures such as the Centers for Disease Control’s (CDC) “Social Vulnerability Index” (SVI) (Flanagan et al. 2011, 2018, Cutter et al. 2003, Bolin 2006, Morrow 1999, Juntunen 2005, Gay et al. 2016, Tate 2012, Rufat et al. 2019, Cimellaro et al. 2016, Kotzee, Reyers 2016, Ramirez, Lee 2020). Importantly, these include not only the standard features of socioeconomic status such as educational attainment and income, but also demographic features such as age, disability status, and race/ethnicity, as well as housing and transportation characteristics[3] (e.g., vehicle access and crowded housing) that make it more difficult to avoid or recover from a disaster. In this case, given previous research on the impact of COVID-19 deaths on new business applications at the state level (Sedláček, Sterk 2020), we are specifically interested in the role of COVID-19 vulnerability on economic resilience, and have included observed COVID-19 case and testing rates by neighbourhood to account for this potential relationship.

In addition to sociodemographic vulnerability, scholars and practitioners in urban planning have long posited that the fundamental form of the built environment plays an important role in economic resilience. A variety of literature argues that walkable, high density, mixed use districts with short blocks and high accessibility to a range of destinations tend to foster urban vitality and economic resilience by providing the physical “habitat” for the economic engine of new business activity described above (Jacobs 1961, 1967, Talen 2006, Desouza, Flanery 2013, Talen, Jeong 2019a,b, Abstante et al. 2020).

Finally, we have included racial and ethnic neighbourhood composition variables in the analysis to account for the beneficial role that “ethnic enclaves” can play in fostering protected markets for particular racial/ethnic demographic groups located in specific neighbourhoods (Cummings 1999, Li 1998, Liu 2009, Waldinger et al. 1990). These enclaves develop initially to serve the segregated residential neighbourhoods of particular immigrant or migrant communities – in the US, often Black, Asian, or Hispanic – and provide a supportive environment for new business creation, acting as incubators in part

[3] In this paper’s analysis (as described below), some of the race/ethnicity, age, housing, and transportation characteristics have been broken out of the composite social vulnerability indicator due to specific interest in these individual relationships with new pandemic-related change in new business activity. Additional adjustments were made to the social vulnerability indicators used in this paper due to our focus on economic resilience specifically, rather than a generalized resilience to all kinds of natural and man-made disasters.

because of the pervasive shared knowledge in these areas. In addition to providing all of the benefits of community involvement, profit re-circulation, and local responsiveness provided by small, independently owned businesses in general (described above), as ethnically oriented businesses grow, they are often able to orient themselves outside of the enclave to serve larger (non-ethnic) markets, improving business performance (Waldinger et al. 1990, Li 1998).

3 Data and Methods

3.1 Chicago Business License Data

To use the Chicago Business License dataset to analyse recent spatial and temporal trends in new business activity, the data had to first be prepared and transformed rather extensively to capture the presence of individual business establishments – and estimates of their industrial sector or type – from the license data. In raw form, the dataset contains entries for individual business license filings, organized with each observation or row representing one filing (either for original issuance or renewal) of a single business license with its own license ID. Account numbers identify unique owners/applicants; thus one account number can be associated with multiple individual business establishment locations (i.e., businesses with unique addresses), and each individual establishment can have more than one license associated with it if it fulfils functions that fall under more than one of the city's license types (e.g., a restaurant may have both a "Consumption on Premises" liquor license and a "Retail Food" license)[4]. In addition to the license type, an establishment may also be associated with additional "business activities," of which there can be several or none listed for each license (these are somewhat subjectively chosen by the individual applying for a business license in their online portal). See Figure 3 for a sample of the data structure.

Because the City of Chicago employs a multitude of descriptors for business activity and license description that vary in their specificity and usage, an original categorization scheme was developed for the purposes of this investigation. Each "business activity" or "license description" that exists in the data is sorted into one of five super-categories that focus on distinguishing the effect of the pandemic on neighbourhood-level goods and services: Food, Retail, Personal Care and Fitness, Arts, and Other[5]. A shortened sample of the classification scheme is shown in Table 1; the full version is available by request from the authors. Though many of the labels for each business activity or license description fell intuitively into these categories, some were more ambiguous or commonly caused conflict with other categories[6]. To ensure these categorizations were internally consistent, an analysis was conducted in which business activities were compared against the license descriptions they most often appeared with in the data. Those combinations that shared the same categorization confirmed the validity of the final categorization scheme, and in the few cases where there were discrepancies, classifications of those labels were adjusted to resolve them. Finally, licenses or activity descriptions not relevant to the research objective, such as home occupations, mobile food vendors, vending machines, and parking garages, were removed from the dataset.

To begin assigning the devised categories to individual business establishments, the

[4]For a comprehensive list of all of Chicago's business license types, see: https://www.chicago.gov/city/en/depts/bacp/sbc/business_licensing.html.

[5]Due to the ambiguous nature of the widely used "Limited Business License" and "Regulated Business License" types and the lack of comprehensive entry for the business activities associated with these license types, a larger "catch-all" category of "Other" was created. While it is possible that finer distinctions could be made between, e.g., manufacturing/production, office/consulting, and accommodation businesses within this category, given the focus of this paper on neighbourhood-level goods and services, these distinctions were not made for the purposes of this analysis.

[6]Food-related services, which are of special interest to a pandemic-related analysis due to the unique set of restrictions placed on these establishments, were not easily sorted. While it was the original intent of the researchers to split restaurants from retail food operations like grocery stores, the "retail food" license does not adequately distinguish between these two types of activities, and no clarification of the meaning of the various "business activity" labels is provided to those who apply for business licenses on the city's website, which likely leads to their inconsistent appearances in the data. Therefore all food-related services are grouped together for the purposes of this analysis.

ACCOUNT NUMBER	LEGAL NAME	BUSINESS ID	ADDRESS		LICENSE #	APPLICATION	LICENSE DESCRIPTION	BUSINESS ACTIVITY	TOT VOTES	ARTS PCT	FOOD PCT	RETAIL PCT	PCF PCT	OTHER PCT	TYPE	CHAIN LOCATIONS	CHAIN	START DATE
147	WALGREEN CO.	36624	1051 W RANDOLPH ST 1				1	2	710	0	36.34	47.89	0.70	15.07	Retail	122	1	2018.05
				4 votes	2602004	ISSUE	Retail Food Establishment	Retail Sales of General Merchandise and Non-Perishable Food | Pharmacy / Photo Services | Retail Sales of Perishable Foods 4										
					2602004	RENEW	Retail Food Establishment	3 Retail Sales of Perishable Foods | Retail Sales of General Merchandise and Non-Perishable Food | Pharmacy / Photo Services										
				3 votes	2602005	ISSUE	Tobacco	Retail Sales of Tobacco and Flavored Tobacco Products | Retail Sales of Tobacco Products										
					2602005	RENEW	Tobacco	Retail Sales of Tobacco and Flavored Tobacco Products | Retail Sales of Tobacco Products										
					2602005	RENEW	Tobacco	Retail Sales of Tobacco and Flavored Tobacco Products | Retail Sales of Tobacco Products										
				2 votes	2602006	ISSUE	Package Goods	Retail Sales of Packaged Liquor										
					2602006	RENEW	Package Goods	Retail Sales of Packaged Liquor										
147	WALGREEN CO.	66744	2351 E 71ST ST 1 A						710	0	36.34	47.89	0.70	15.07	Retail	122	1	2016.05
147	WALGREEN CO.	70324	2 N STATE ST 1ST						710	0	36.34	47.89	0.70	15.07	Retail	122	1	2016.03
147	WALGREEN CO.	72497	6500 N CLARK ST 1 101						710	0	36.34	47.89	0.70	15.07	Retail	122	1	2016.05
147	WALGREEN CO.	76845	218 S WABASH AVE 400RX						710	0	36.34	47.89	0.70	15.07	Retail	122	1	2019.05

Total votes across all instances of this account #

% of total votes in this category

"Winning" category

Chain =1 if >= 4 Chain locations

Figure 3: Data sample showing how licenses aggregate to business establishments, and categories are assigned by voting across all rows of a given account number

Table 1: Sample of classification scheme for assigning license types and business activities to business super-categories

Category: ***Retail***

License Type

Electronic Equipment Repair; Package Goods; Pawnbroker; Public Place of Amusement-TCC; Retail Computing Center; Secondhand Dealer; Secondhand Dealer - Children's Products; Secondhand Dealer (No Valuable Objects); Sports Facilities Authority License

Business Activity

Retail Sales of Animal Treats and Animal Food; Retail Sales of Carpet and/or Furniture; Retail Sales of New Electronics and Accessories; Retail Sales of Outdoor Equipment and Supplies; Retail Sales of Used Electronics; Sale of Furniture; Retail Sales of General Merchandise; Retail Sales of Clothing / Accessories / Shoes; Retail Sales of Jewelry and Jewelry Repair; Retail Sales of Appliances; Buying and Reselling of Used Cell Phones; Retail Sale of Musical Instruments; Retail Sale of Tobacco; Retail Sales of Laundry Cleaning Products; Retail Sales of Tobacco Products; Retail Sales of Tobacco Accessories; Retail Sales of Tobacco and Flavored Tobacco Products; Retail Sales of Packaged Liquor; Retail Sales of Flowers; Pharmacy / Photo Services; Shipping / Printing Services; Sales / Rental / Lease of Motorized Vehicles

Category: ***Food***

License Type

Caterer's Liquor License; Caterer's Registration (Liquor); Consumption on Premises - Incidental Activity; Outdoor Patio; Produce Merchant; Retail Food Establishment; Special Event Food; Special Event Liquor; Tavern; Wholesale Food Establishment

Business Activity

Wholesale Food Sales; Retail Sale of Food for Offsite Consumption; Retail Sales of Fresh Fruits and Vegetables; Retail Sales of Perishable Foods; Retail and Wholesale of Perishable Foods; Retail Sales of General Merchandise and Non-Perishable Food; Deli, Butcher or Bakery; Sale of Food Prepared Onsite With Dining Area; Preparation and Sale of Coffee and/or Drinks; Consumption of Liquor on Premises; Preparation of Food and Dining on Premise With Seating

Category: ***Other***

License Type

Affiliation; Animal Care Facility; Animal Care License; Animal Exhibition; Assisted Living/Shared Housing Establishment; Automatic Amusement Device Operator; Bed-And-Breakfast Establishment; Bicycle Messenger Service; Board-Up Work; Children's Services Facility License; Commercial Passenger Vessel; Explosives; Filling Station; Grooming Facility; Guard Dog Service; Hazardous Materials; Home Repair; Hospital; Hotel; Laboratories; Late Hour; Laundry, Late Hour; License Manager; Long-Term Care Facility; Manufacturing Establishments; Motor Vehicle Repair: Engine Only (Class II); Motor Vehicle Repair: Specialty(Class I); Motor Vehicle Repair: Engine/Body(Class III); Motor Vehicle Services License; Night Care Privilege; Pet Shop; Public Place of Amusement; Veterinary Hospital

Business Activity

Administrative Commercial Office; Commercial Landscaping Services; Commissioned Staffing of Professional, Secretarial and Clerical Work; Advertising / Marketing / Sales Office; Computer Design/Development Consulting; Cable or Satellite Installation - Commercial Properties; Computer and Electronic Products Manufacturing; Drug, Chemical, Paint Factory; Food Manufacturing; Machinery Manufacturing; Plastics, Foams, Construction Materials, Glass, Rubber; Printing Activities, Metal Processing; Production; Textile Mills, Leather, Paper Products, Rubber, Petroleum, Coal; Toy, Furniture, Household Goods Factory; Miscellaneous Manufacturing; Machine Shop, Foundry, Roof / Paving Materials; Business and Management Consulting; Business Consulting; Financial and Accounting Services; Hotel - 7 or More Sleeping Rooms; Provides Onsite Amusement or Entertainment; Provides Onsite Entertainment or Rentals; Self Storage Facility; Smoking of Tobacco on Premises; Clothing Alterations; Dry Cleaning - Drop Off Location; Laundromat - Self Service; Laundry Service; Commercial Construction; Demolition / Wrecking; Home Repair Services; Residential Construction number of rows associated with each license number is reduced to one, to eliminate the effect of differential renewal frequencies for different types of licenses. Then, after removing those rows with duplicate information, the amount of activity information (either business activities or license types) falling into each of the five categories is counted and aggregated to each account number ("TOT VOTES"). This enables a calculation of the proportion of associated rows that falls into each of the five categories and ensures that different business establishments with the same account number (i.e., chain locations) retain the same classification as other chain locations. The "winning" category is determined by the category (across account numbers) that demonstrates the highest percentage; if tied, a random selection among tied categories is made. The start date is determined by the earliest license term start date associated with a given business ID.

Finally, a "chain" label is assigned to any business whose account number is associated with four or more unique locations in the data. Though four locations is not a rigid cut-off at which all businesses should be considered chains[7], the limit is not arbitrary, but rather a balance between conceptual matching (i.e., a large enough number of establishments per account to constitute a truly non-independent business) and sample size (i.e., a small enough number of establishments per account to produce a useful sample size for regression analysis). As Figure A.1 in the Appendix shows, the density of account numbers with different numbers of associated establishments decreases systematically as the number of establishments increases. While the largest difference is between accounts with 1 and 2 associated establishments (a drop of 85.8%), and the second largest difference is between accounts with 2 and 3 associated establishments (a drop of 76.3%), we feel that accounts with these numbers of establishments are fundamentally too small to embody the concept of non-independent chains. At the same time, using 5 or more as the cut-off reduces the sample size of chain establishments significantly. Fortunately, sensitivity analyses of the regression results (shown in Tables A.2, A.3, and A.4 in the Appendix) do not show large differences in the results when using alternate numbers of establishments to define chains. Additionally, studying random samples of business names at or above the 4 establishment cut-off suggests that the majority could plausibly be considered chain businesses. The end result of this categorization scheme is shown in Figure 3.

3.2 Exploratory Covariates

In addition to the individual business points by category and start date, this paper also utilizes data from the American Community Survey (ACS) to explore the neighbourhood characteristics that are associated with resilience to the pandemic-related shock to new business activity. Two indices are created to capture effects related to the built environment and social vulnerability. The built environment index (*JACOBS*) is based primarily on Jacobs' (1961) principles of vibrant, diverse neighborhoods, which have been generalized and expanded on over time to include various "D" variables: density, diversity, design, and distance to transit (Cervero, Kockelman 1997, Ewing, Cervero 2010). To compute the JACOBS index for this paper, data from the 2014-2018 ACS on the average Census block perimeter, housing unit density, building age diversity[8], and

[7] "Chainness" as a concept for customer-facing businesses exists across multiple dimensions, including national orientation/distribution, corporate ownership, standardized design/place qualities, and the existence of multiple establishments under one unified brand. Of course, these features are not so straightforward to categorize – for example, despite having unified branding, McDonald's restaurants operate through a franchise system, so individual McDonald's establishments are independently owned (although some franchisees own multiple, regional groupings of McDonald's, which complicates the matter even further, creating a kind of "chain-within-a-chain"). But by the conceptual definition we are interested in here vis-a-vis small, independently owned businesses, McDonald's restaurants should certainly constitute a "chain." Unfortunately, in large open source datasets such as the one that we employ in this analysis, information on most of the complicated dimensions of chainness is limited. Generally the only available information is the number of occurrences/establishments under one account name or number, which can be counted, as is the case in this paper. Thus we follow an empirical approach in operationalizing the "chain" concept by selecting a cut-off of establishments under one corporate account based on the distribution of the data – in this case, 4 was chosen; similar analyses have used other cut-offs based on their specific research questions, e.g., a recent analysis of chain restaurants in the US used 5 establishments as the cut-off for classification as a "chain" (Liang, Andris 2021).

[8] Computed by calculating a Herfindahl Index using the share of units built in the following decade ranges: 2010-current, 2000-2010, 1990-2000, 1980-1990, 1970-1980, 1960-1970, 1950-1960, 1940-1950, and

percent of workers 25 and older commuting to work by public transit at the ZIP Code Tabulation Area (ZCTA) are used. To create the index, we add (+) together the z-scored variables that positively contribute to built environment diversity, i.e., density and transit commuting, and subtract (-) the variables that negatively contribute to built environment diversity, i.e., block length (because shorter blocks are seen as encouraging more activity) and building age diversity (because the Herfindahl Index used to create the building age diversity measures ranges from 0 to 1, with larger values indicating lower diversity).

An index of social vulnerability (*SOLCVULN*), based generally on the CDC's SVI index, is calculated in a similar way using z-scores for a range of 2014-2018 ACS variables that capture increased vulnerability to environmental and economic shocks (Flanagan et al. 2018): median household income (-), percent population that are not citizens (+), percent families with public assistance income (+), percent population 25 years and older with a Bachelor's degree or higher (-), percent of the civilian noninstitutionalized population without health insurance coverage (+), and percent of the population 65 years or older (+).

Beyond the *JACOBS* and *SOLCVULN* indices, 2014-2018 ACS data on the percent of Black non-Hispanic population (*BLACKPER*), Hispanic population (*HISPER*), and Asian non-Hispanic population (*ASNPER*) – as an operationalization of the presence of ethnic enclaves – and the percent of the population aged 18-39 (P1339) – as an indicator of neighbourhood "hipness" and pre-pandemic demand for customer-facing businesses such as bars and restaurants – by ZCTA are also collected for use in the regression models. In addition, the cumulative number of confirmed COVID-19 cases and tests[9] by ZIP code as of November 10, 2020, are obtained from the website of the Illinois Department of Public Health (IDPH 2020) and divided by ZCTA population to create a COVID-19 case rate (*COVIDR*) and test rate (*TESTR*).

3.3 Analysis Methods

To visually assess temporal trends during the pandemic timeframe for the entire city, the number of monthly new starts by category from January 2016 to September 2020 is plotted on a line graph; graphs of the % difference in new starts (by category) for each month in 2020 compared to the monthly average from January 2016 to December 2019 for both chains and independent businesses are also created.

For visual analysis of spatial trends, Kernel Density Estimate (KDE) maps for all new business starts for each business type for the period March to September for each year from 2016 to 2020 are created using the same set of specifications in the "kernelUD" function in R[10] (Yin 2020). Then, using the raster calculator, a KDE showing the average density of new starts from 2016 to 2019 (*KDEAVE*) is calculated for each business type (t), as shown in Equation (1):

$$KDEAVE_t = \frac{KDE2016_t + KDE2017_t + KDE2018_t + KDE2019_t}{4} \tag{1}$$

This provides a 4-year average of the fine-grained spatial pattern of new starts for each business type and allows us to subtract these values from the 2020 KDE to find the pandemic-related difference in new starts ($KDEDIF_t$) in order to observe the areas in which the density of 2020 pandemic-era (March to September) new starts significantly under- or over-perform the previous 4-year average, according to Equation (2):

$$KDEDIF_t = KDE2020_t - KDEAVE_t \tag{2}$$

While the use of KDE allows for a finer-grained examination of the spatial pattern of the individual business points that is not obscured by the specific boundaries of the

pre-1940.

[9]To control for the fact that there were structural heterogeneities in testing rates by racial/ethnic neighbourhood type in the city (in particular, lower testing in Hispanic neighbourhoods), testing rate is included as a variable in the analysis (Credit 2021).

[10]The kernel function ("bivnorm"), bandwidth ($h = .005$), and cell size (grid = 5000) are maintained for each SpatialPointsDataFrame (sp) for a given business type/year. No projection is used – spatial points are instantiated directly from latitude and longitude coordinates provided in the Chicago Business License dataset.

ZIP codes (or other areal zones), aggregating the individual counts of new starts in each period to ZIP code boundaries allows us to bring additional sociodemographic and built environment covariates into the analysis. To control for the size of the average baseline new business activity in a given ZIP code from 2016 - 2019 (March to September), we calculate the percent difference ($PERDIF_t$) in the number of new business starts (N) by type (t) between 2020 and the 2016-2019 average ($N_{(2016-2019)}$) for each ZIP code, as shown in Equation (3):

$$PERDIF_t = \frac{N_{2020} - N_{2016-2019}}{N_{2016-2019}} \tag{3}$$

Finally, a set of regression models are estimated at the ZIP code level according to the specification shown in Equation (4):

$$\begin{aligned} PERDIF_t \quad = \quad & \beta_1 JACOBS + \beta_2 SOLCVULN + \beta_3 P1839 + \beta_4 COVIDR + \beta_5 TESTR + \\ & \beta_6 HISPER + \beta_7 ASNPER + \beta_8 BLACKPER + \epsilon \end{aligned} \tag{4}$$

The covariates (described in the section above) are included to explore the features of neighbourhoods that are associated with pandemic-related declines in new business activity. All models are estimated using Ordinary Least Squares (OLS) in R v.4.0.4. Robust Lagrange multiplier (LM) tests for spatial dependence were conducted for the pooled model; while the Robust LM Lag test was significant for the pooled model at $p < .05$, this was matched only in the Independent and Other subset models, so to maintain consistency, standard OLS model specifications were used throughout[11]. The studentized Breusch-Pagan test of heteroskedasticity and the adjusted Jarque-Bara test for normality were also applied to the pooled model, but were both non-significant at $p < .05$, so the unadjusted standard error estimates were also used throughout.

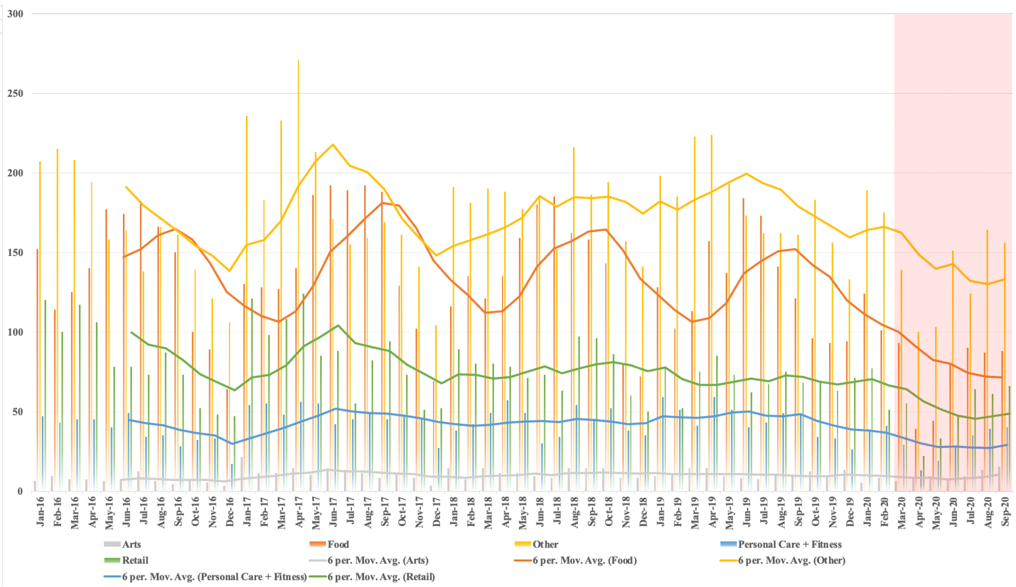
4 Results and Discussion

Figure 4 shows the monthly trend in new starts by business type from January 2016 to September 2020. The lines on the bar graph display a 6-month rolling average to smooth the month-to-month (and seasonal) oscillations, and the pandemic era is marked in red. This graph shows the relative size of each category (with Other, Food, and Retail as the largest categories in terms of number of new starts), as well as the fact that each of the five categories has clearly declined in the pandemic era compared to its recent trend (with the exception of Arts, whose trend is generally very flat).

To see these trends in more detail, and to compare chains and independent businesses, Figures 5 and 6 show the percent difference in new starts between each month in 2020 and the average number of monthly new starts for each category from January 2016 to December 2019 for independent and chain establishments, respectively. This clarifies the general patterns observed in Figure 4: all categories decline significantly in April and May, with some recovery towards recent averages in July, although all categories for both chains and independents demonstrated declines relative to recent averages in nearly every month since the pandemic began. However, it does appear that new business starts in particular industries, such as chain Retail and Personal Care and Fitness, as well as independent Arts, have come close to matching or exceeding pre-pandemic levels by September. This finding is supported by the national data showing a significant rebound in new businesses "with planned wages" in 2020Q3 and Q4 shown in Figure 1 and perhaps reflects business planning in anticipation of an easing of lockdown restrictions sometime in 2021.

Overall, chain new starts declined on average 61.9% per month from March to September 2020 (compared to 2016-2019 averages), while independents declined only 29.2%. In some ways this may reflect the difference in the average number of new starts in each category. From January 2016 to December 2019, the city averaged around 58 new

[11] As shown in Table A.5 in the Appendix, coefficient signs and significances were robust to the choice of spatial or non-spatial specification in each case, so the use of a non-spatial specification is empirically justified.



Notes: Red shading denotes pandemic time period

Figure 4: Monthly new starts by business type from January 2016 – September 2020

chain and 387 new independent establishments per month; from March to September 2020, the city averaged only 22 new chain and 274 new independent establishments per month, so a relatively smaller drop in the number of chains generates a much sharper drop in terms of percentage due to the smaller denominator. The issue of small denominators may also help to explain the fact that some of the smaller categories, e.g., chain Personal Care and Fitness and independent Arts, show relatively "spiky" temporal patterns.

However, Figure 7 shows that these aggregate declines are not homogenous across space. For independent establishments, the biggest declines are in gentrifying north- and northwest-side neighbourhoods like Albany Park, Bucktown, Roscoe Village, Lakeview, and the West Loop – high growth areas with active commercial districts. The biggest increases are in River North and Lincoln Park, long-gentrified neighbourhood centres that attract a large amount of export retail, dining, and entertainment activity. Interestingly, the spatial pattern for chain establishments is somewhat different. Roscoe Village, Albany Park, and Lakeview all show up as hotspots of pandemic-related decline for chains, along with the rapidly growing, younger-population neighbourhoods of Pilsen and South Loop. On the other hand, Bucktown, Hyde Park, and the West Loop join River North and Lincoln Park as neighbourhoods with relatively high levels of pandemic-era chain business activity.

When new business points are aggregated to ZIP codes and the percent change between pandemic and pre-pandemic trends ($PERDIF_t$) are calculated, we can see (in Figure 8) that these patterns intersect in interesting ways with the spatial patterns of the paper's primary covariates of interest. The aggregate pattern of new business change shows significant declines across the majority of the city, with pockets of resilience in the near north (Lakeview/Lincoln Park) and south sides, including the Hyde Park, Beverly/Mount Greenwood, and South Shore neighbourhoods[12]. There is some overlap here with the spatial pattern of the city's Black population, which is primarily focused on the south and southwest sides of the city. However, there is less visible overlap with the city's Hispanic population, which tends to be concentrated in the west and northwest sides, or Asian population, which is most concentrated in the near south side, around the Chinatown neighbourhood. On the other hand, there appears to be some spatial association between

[12]It is worth noting that the two positive outliers on the map – Hyde Park and Beverly/Mount Greenwood – have very small denominators for the percent change calculation (average new business counts of 3.12 and 1.42, respectively, per year between March-September 2016-2019), so it only takes a small increase in 2020 to create a positive percent change.

Figure 5: Percent difference in new starts between each month in 2020 and the average number of monthly new starts from January 2016 - December 2019 for independent establishments

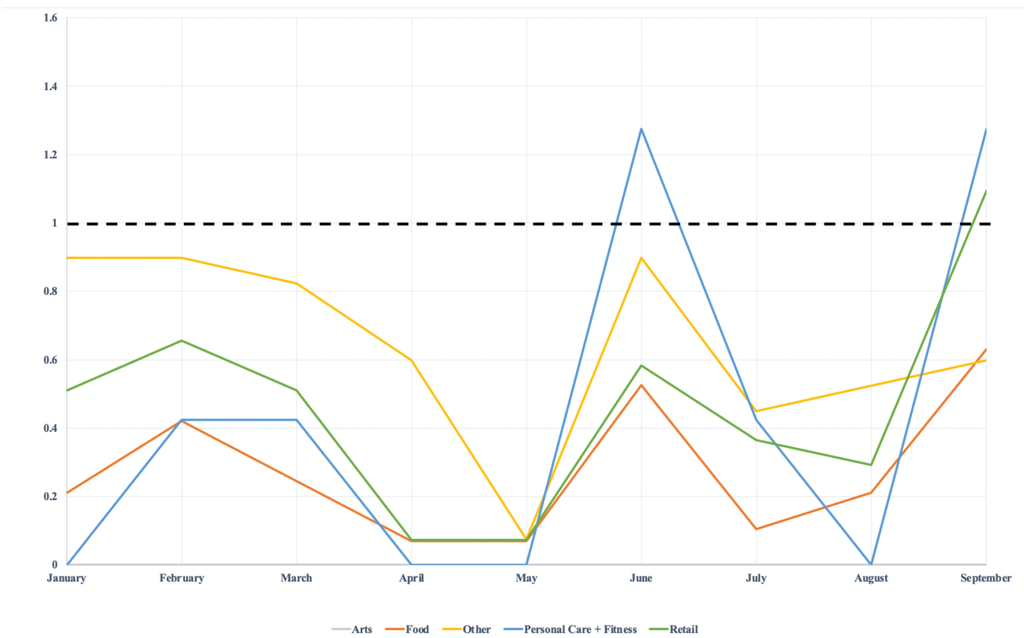


Figure 6: Percent difference in new starts between each month in 2020 and the average number of monthly new starts from January 2016 - December 2019 for chain establishments

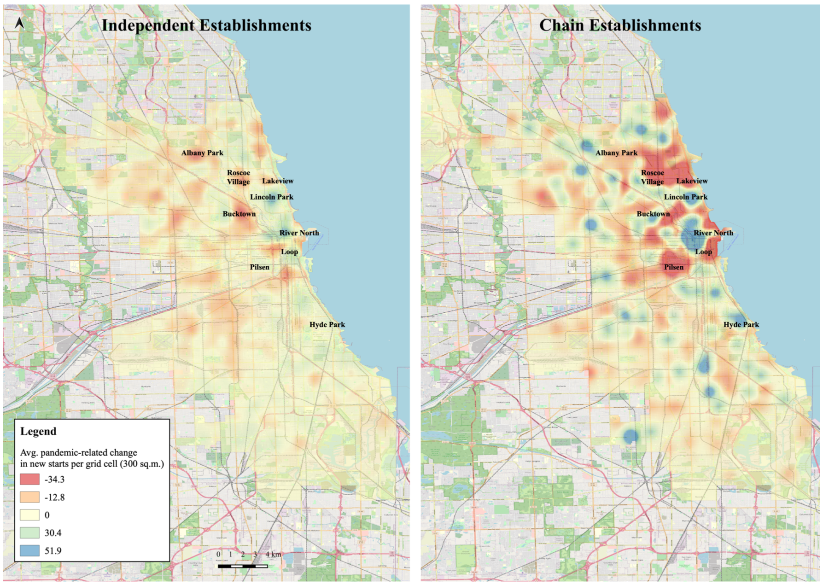


Figure 7: Difference in new start density between 2020 (March - Sept.) and average new start density from 2016 - 2019 (March - Sept.) for independent and chain establishments

ZIP codes with relatively high levels of resilience and high JACOBS index values, which are most concentrated on the historic, high density north and northwest sides. Interestingly, the patterns of the *SOLCVULN* index and COVID-19 case rates reflect a nearly inverse image, demonstrating significant overlaps with the pattern of Hispanic population[13] (in particular) (Credit 2021). Finally, we see the highest concentration of young population in the rapidly gentrifying, "hip" West Loop, Lincoln Park, and Bucktown neighbourhoods, many of which have been particularly hard hit by the pandemic-related decline in new business activity.

In order to statistically characterize these spatial patterns in pandemic-related resilience in new business starts, a number of regression models (one for each business type) at the ZIP code level are run to associate these changes with various measures of the built environment, social vulnerability, age, and the existing baseline new start activity (2016-2019 average). Results of the regression analysis are shown in Table 2[14]. Several interesting findings stand out. First, in the pooled model for all businesses, the JACOBS built environment index is significantly positively related to pandemic-related change in new business density, while the social vulnerability index, *SOLCVULN*, is significantly negatively related to the dependent variable. This suggests that the *JACOBS* factors are associated with some resiliency to the economic effects of the pandemic, even after controlling for the other covariates of interest. The percent of population aged 18-39 is also negatively related to resilience in new business activity, which suggests that some of the economically hardest-hit neighbourhoods are those that had a high level of pre-pandemic investment, particularly in the Retail and Personal Care and Fitness categories. We also see some evidence of enclave effects in Black and Asian neighbourhoods, which both display significant positive relationships with the dependent variable. Finally, we see a surprising significant positive relationship between pandemic-related change in new business starts and observed COVID-19 rates (after controlling for the full suite of other covariates). There are a couple of possible explanations for this result: 1) reverse causality (assessed in Table A.1 in the Appendix) in that neighbourhoods with high levels of new business resilience (particularly in the Food category, which, based on the individual

[13]The significant spatial overlaps between Hispanic population, COVID-19 rates, social vulnerability index values, and some of the constituent factors in the *JACOBS* index may provide another explanation for the somewhat surprising positive significance of the *COVIDR* variable in the final regression model.

[14]Table A.1 in the Appendix presents the regression results without the COVID-19 case and testing rate variables, and shows the robustness of the primary findings of the analysis.

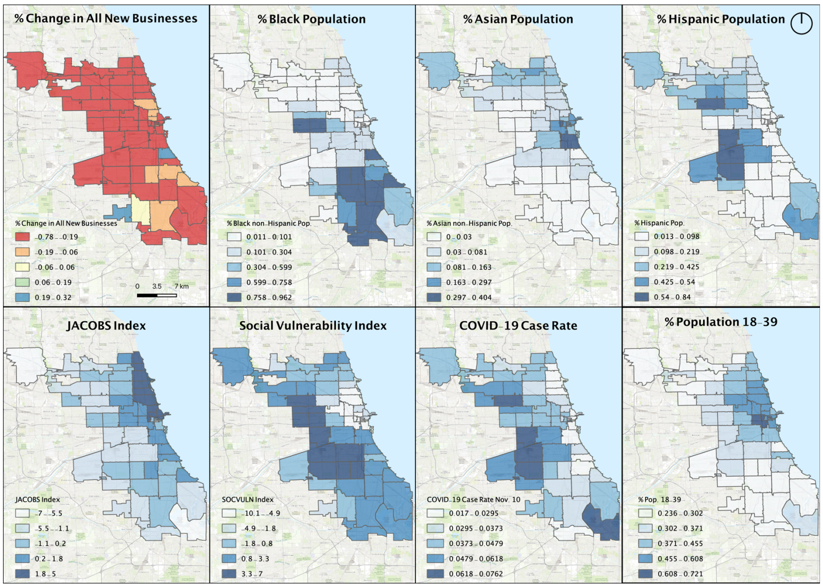


Figure 8: Panel map showing spatial distribution of the primary dependent variable and covariates used in the regression analysis

regression results, appears to be driving the relationship) also have high proportions of essential workers who are more at risk for contracting COVID-19; 2) collinearity and spatial overlap in the pattern of Hispanic population, $SOLCVULN$, and COVID-19 rates (e.g., the raw relationship between $PERDIF_t$ and $COVIDR$ is negative). However, the inclusion of each of these covariates is central to this paper's exploratory research objective and cannot be omitted without changing the nature of the results and risking omitted variable bias. We are interested in the partial effect of each variable on the dependent variable while controlling for the presence of the other covariates, so it is essential to control for baseline social vulnerability before assessing the relationship between the other factors and economic resilience.

These relationships generally also hold for the individual regressions of various subsets of the business data, with some interesting differences. Asian enclave effects are particularly pronounced for chain, Other, and Personal Care and Fitness businesses, while Black enclave effects are significant for independent and Other businesses. Food businesses demonstrate negative enclave effects for the Hispanic and Asian groups, which perhaps is a result of the fact that pre-pandemic activity in these neighbourhoods was particularly strong. Given the fact that our measure of resilience is a percent change from average pre-pandemic new start activity, this penalizes neighbourhoods with particularly strong pre-pandemic levels of activity as much as it rewards neighbourhoods with particularly strong pandemic-related levels of new start activity.

5 Conclusion

Given the widespread national and international economic impacts of the COVID-19 pandemic, the purpose of this paper is to assess the fine-grained spatial and temporal impacts of the pandemic on new business starts. This is accomplished using a novel dataset on all business establishments in the city compiled from the frequently updated City of Chicago Business License dataset. The results of the temporal analysis for the City of Chicago through the end of September 2020 closely mirror the national data on small business revenue, with significant declines in April that have somewhat (although not fully) recovered through September, with food service and retail businesses hardest hit. In April, the total number of food service and retail new starts had dropped 71.6% and 72% compared to the 2016-2019 monthly average, respectively; in September, they were still 35.9% and 16% below monthly averages, respectively. While the national data

Table 2: OLS regression results for dependent variable $PERDIF_t$ – Percent Change in New Establishments: 2020 (March to September) vs. Average 2016-2019 (March to September) by ZIP Code

	All (Pooled)	All Chains	All Independents	Other	Food	Retail	Personal Care and Fitness	Arts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JACOBS	0.040***	0.056**	0.034**	0.081***	0.013	0.061	0.046	-0.132
	(0.014)	(0.027)	(0.015)	(0.030)	(0.021)	(0.038)	(0.041)	(0.196)
SOLCVULN	-0.057***	-0.019	-0.064***	-0.107***	0.030	-0.102**	-0.052	0.178
	(0.017)	(0.031)	(0.018)	(0.034)	(0.024)	(0.044)	(0.041)	(0.206)
%Aged 18-39	-1.727***	-1.550*	-1.657***	-2.926***	0.183	-3.248**	-1.585	4.550
	(0.462)	(0.878)	(0.494)	(0.955)	(0.680)	(1.225)	(1.124)	(5.388)
COVID-19 Case Rate	5.137	11.228*	3.193	6.826	10.125**	4.136	-2.235	-5.751
(Nov. 10)	(3.092)	(5.881)	(3.306)	(6.397)	(4.554)	(8.208)	(7.493)	(32.373)
COVID-19 Testing Rate	0.238	-0.208	0.298	0.434	-0.017	-0.896*	0.406	2.110
(Nov. 10)	(0.186)	(0.354)	(0.199)	(0.385)	(0.274)	(0.494)	(0.438)	(1.967)
% Hispanic Population	0.132	-0.394	0.236	0.601	-1.184**	-0.190	0.781	-1.126
	(0.303)	(0.577)	(0.324)	(0.628)	(0.447)	(0.805)	(0.716)	(3.734)
% Black Population	0.429***	0.261	0.476***	0.886***	-0.302	0.036	0.130	0.284
	(0.149)	(0.284)	(0.160)	(0.309)	(0.220)	(0.396)	(0.369)	(1.911)
% Asian Population	0.741*	2.297***	0.539	1.633*	-1.053*	0.752	0.969	-4.622
	(0.415)	(0.790)	(0.444)	(0.859)	(0.611)	(1.102)	(0.993)	(4.857)
Constant	-0.257	-0.544*	-0.209	-0.181	-0.552**	1.317***	-0.208	-2.174
	(0.168)	(0.319)	(0.179)	(0.347)	(0.247)	(0.446)	(0.395)	(1.741)
Observations	59	59	59	59	59	59	57	53
R^2	0.452	0.288	0.459	0.355	0.229	0.32	0.113	0.134
F Statistic	5.161***	2.530**	5.300***	3.441***	1.852*	2.941***	0.762	0.853
	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 48)	(df=8; 44)

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

on applications for new businesses with planned wages show a significant uptick in 2020Q3 and 2020Q4 (Figure 1) that is not reflected in the Chicago data, given the significant heterogeneity in the progression of the pandemic and various government restrictions across the country, it remains to be seen whether Chicago is a unique case in this regard among large urban areas (US Census Bureau 2020).

It is also unclear whether this paper's finding that chain establishments have experienced larger pandemic-era drops in new starts (on a percentage basis) than independent establishments is representative of the larger national trend or unique to Chicago (or unique to the empirical definition used in this paper, i.e., individual business accounts with 4 or more associated establishments). It is possible that, given larger financial resources and planning capabilities, multi-establishment firms are better able to defer new establishment openings in this pandemic period to avoid immediate losses, while smaller firms must go ahead with planned openings despite low-revenue conditions. Smaller firms may also be more flexible and able to adapt their business concept to access new market opportunities generated by the pandemic (e.g., a restaurant modifying its operations to become a take-out grocery-style service).

Given these temporal trends, this paper also provides useful insight on the fine-grained spatial patterns of pandemic-related changes in new business density using kernel density estimates and OLS regression at the ZIP code scale. In general, the results confirm the hypothesis that areas of the city with a higher proportion of goods and services provided at the neighbourhood scale, in more diverse, walkable built environments have been more resilient to the effects of the pandemic on new starts across all business types. However, younger (population) neighbourhoods, including gentrifying residential neighbourhoods like Albany Park, Roscoe Village, Bucktown, and the West Loop appear to be hardest hit in terms of new independent business creation in the pandemic era. At the same time, the results support the hypothesis that ethnic enclaves – in particular, Asian and Black neighbourhoods – provide additional resilience from the economic shock of the pandemic. Interestingly, COVID-19 infection rates appear to play a significant role in predicting positive change in new business activity in the pandemic era, particularly for food service businesses, which could be a result of the fact that employees in these businesses were classified as "essential" workers and thus places at higher risk of COVID-19 infection.

While additional research is needed to confirm whether these patterns hold as the pandemic progresses – and whether there are long term economic consequences for particular neighbourhoods that have seen decreased new business activity as a result of the pandemic – these results provide some useful information to city planners and researchers looking to foster economic resilience for this (or future) large-scale economic shocks that significantly restrict mobility. Another pandemic of this magnitude may or may not arise in the near- or medium-term future, but reducing the volume of travel – and providing services closer to residents – remains a fundamental goal for sustainable urban planning practice. This paper's results provide some evidence that the built environment conditions commonly thought to enhance economic vitality at the fine-grained neighbourhood scale, do, in fact, work.

This is particularly important to consider as regions plan for changes in urban development and mobility patterns in the wake of the pandemic. Suburban, auto-oriented areas enjoy some advantages in the strict lockdown conditions of the pandemic (e.g., larger homes with interior and exterior private space, widespread design for enclosed private automobiles, etc.) (Florida 2020). Increased rates (and acceptance) of remote working may also reduce some of the of the intense agglomeration benefits that large, expensive cities currently enjoy, as well as demand for the full range of diverse amenities and business types currently provided in those cities (Wolff-Mann 2020, Lister 2020, Florida et al. 2021).

However, this paper's results provide evidence in favour of the view that more suburban environments may not, in fact, be as economically resilient to large-scale shocks as those with an inherently urban, diverse, and walkable character. Thus, it would seem to be a mistake, from an economic perspective, to abandon dense, diverse urban environments in post-pandemic regional planning processes, even if the pandemic conditions have temporarily made dense, urban living less appealing to some residents. Similarly, the demonstrated resilience of specific ethnic enclaves supports continued investment in these neighbourhoods and the adoption of more explicit economic development strategies that focus on upgrading these enclaves and connecting them to the larger economic networks of the city and globe.

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A Appendix

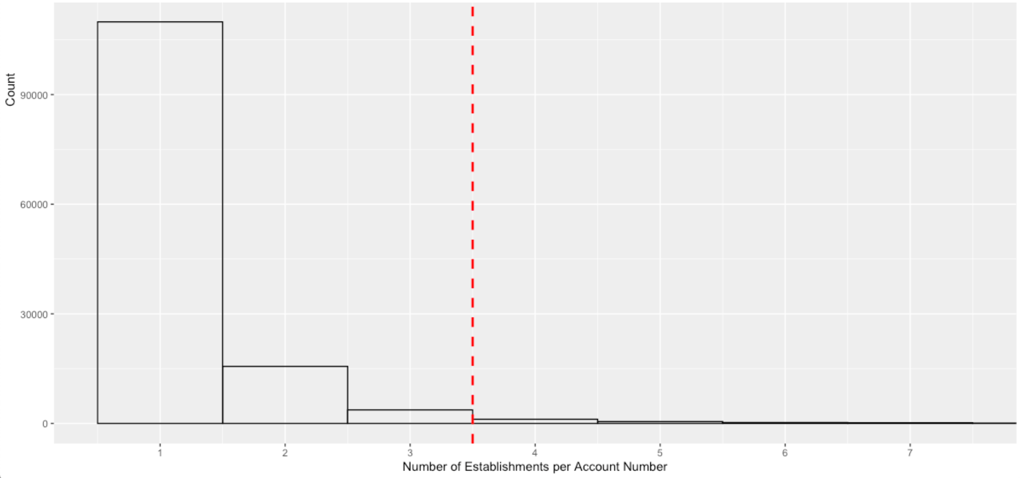

Figure A.1: Histogram showing the distribution of the number of establishments associated with a unique account number. 97.9% of establishments in the dataset are in accounts with fewer than 4 associated establishments

Table A.1: Regression results without the COVID-19 case and testing rate variables (to avoid possible reverse causality) – Percent Change in New Establishments: 2020 (March to September) vs. Average 2016-2019 (March to September) by ZIP Code

	All (Pooled)	All Chains	All Independents	Other	Food	Retail	Personal Care and Fitness	Arts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JACOBS	0.025*	0.037	0.021	0.058**	-0.007	0.071**	0.042	-0.183
	(0.013)	(0.025)	(0.014)	(0.027)	(0.020)	(0.035)	(0.034)	(0.172)
SOLCVULN	-0.057***	-0.020	-0.064***	-0.107***	0.030	-0.103**	-0.052	0.206
	(0.017)	(0.032)	(0.018)	(0.035)	(0.025)	(0.044)	(0.040)	(0.203)
%Aged 18-39	-1.489***	-1.603*	-1.391***	-2.518***	0.268	-3.913***	-1.295	6.627
	(0.457)	(0.849)	(0.481)	(0.921)	(0.668)	(1.181)	(1.050)	(4.968)
% Hispanic Population	0.294	0.168	0.293	0.782	-0.726*	0.253	0.570	-2.452
	(0.266)	(0.496)	(0.280)	(0.538)	(0.390)	(0.689)	(0.630)	(3.245)
% Black Population	0.419***	0.319	0.453***	0.860***	-0.268	0.148	0.090	-0.144
	(0.153)	(0.284)	(0.161)	(0.308)	(0.224)	(0.396)	(0.363)	(1.851)
% Asian Population	0.618	2.235***	0.421	1.437	-1.157*	0.961	0.884	-5.661
	(0.428)	(0.795)	(0.450)	(0.863)	(0.625)	(1.106)	(0.965)	(4.698)
Constant	-0.008	-0.316	0.011	0.201	-0.272	1.044***	-0.095	-1.386
	(0.139)	(0.259)	(0.147)	(0.281)	(0.204)	(0.360)	(0.304)	(1.328)
Observations	59	59	59	59	59	59	57	53
R^2	0.386	0.236	0.412	0.312	0.147	0.275	0.097	0.112
F Statistic	5.437***	2.681**	6.067***	3.925***	1.492	3.291***	0.891	0.963
	(df=6; 52)	(df=6; 52)	(df=6; 52)	(df=6; 52)	(df=6; 52)	(df=6; 52)	(df=6; 50)	(df=6; 46)

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table A.2: Regression results for account numbers with 2 establishments – Percent Change in New Establishments: 2020 (March to September) vs. Average 2016-2019 (March to September) by ZIP Code

	All (Pooled)	All Chains	All Independents	Other	Food	Retail	Personal Care and Fitness	Arts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JACOBS	0.040***	0.069***	0.034**	0.081***	0.013	0.061	0.046	-0.132
	(0.014)	(0.021)	(0.015)	(0.030)	(0.021)	(0.038)	(0.041)	(0.196)
SOLCVULN	-0.057***	-0.037	-0.064***	-0.107***	0.030	-0.102**	-0.052	0.178
	(0.017)	(0.024)	(0.018)	(0.034)	(0.024)	(0.044)	(0.041)	(0.206)
%Aged 18-39	-1.727***	-1.420**	-1.657***	-2.926***	0.183	-3.248**	-1.585	4.550
	(0.462)	(0.681)	(0.494)	(0.955)	(0.680)	(1.225)	(1.124)	(5.388)
COVID-19 Case Rate	5.137	13.299***	3.193	6.826	10.125**	4.136	-2.235	-5.751
(Nov. 10)	(3.092)	(4.561)	(3.306)	(6.397)	(4.554)	(8.208)	(7.493)	(32.373)
COVID-19 Testing Rate	0.238	-0.227	0.298	0.434	-0.017	-0.896*	0.406	2.110
(Nov. 10)	(0.186)	(0.274)	(0.199)	(0.385)	(0.274)	(0.494)	(0.438)	(1.967)
% Hispanic Population	0.132	-0.377	0.236	0.601	-1.184**	-0.190	0.781	-1.126
	(0.303)	(0.448)	(0.324)	(0.628)	(0.447)	(0.805)	(0.716)	(3.734)
% Black Population	0.429***	0.222	0.476***	0.886***	-0.302	0.036	0.130	0.284
	(0.149)	(0.220)	(0.160)	(0.309)	(0.220)	(0.396)	(0.369)	(1.911)
% Asian Population	0.741*	1.098*	0.539	1.633*	-1.053*	0.752	0.969	-4.622
	(0.415)	(0.612)	(0.444)	(0.859)	(0.611)	(1.102)	(0.993)	(4.857)
Constant	-0.257	-0.488*	-0.209	-0.181	-0.552**	1.317***	-0.208	-2.174
	(0.168)	(0.248)	(0.179)	(0.347)	(0.247)	(0.446)	(0.395)	(1.741)
Observations	59	59	59	59	59	59	57	53
R^2	0.452	0.294	0.459	0.355	0.229	0.32	0.113	0.134
F Statistic	5.161***	2.608**	5.300***	3.441***	1.852*	2.941***	0.762	0.853
	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 48)	(df=8; 44)

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$

Table A.3: Regression results for account numbers with 3 establishments – Percent Change in New Establishments: 2020 (March to September) vs. Average 2016-2019 (March to September) by ZIP Code

	All (Pooled)	All Chains	All Independents	Other	Food	Retail	Personal Care and Fitness	Arts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JACOBS	0.040***	0.062***	0.034**	0.081***	0.013	0.061	0.046	-0.132
	(0.014)	(0.024)	(0.015)	(0.030)	(0.021)	(0.038)	(0.041)	(0.196)
SOLCVULN	-0.057***	-0.0558	-0.064***	-0.107***	0.030	-0.102**	-0.052	0.178
	(0.017)	(0.028)	(0.018)	(0.034)	(0.024)	(0.044)	(0.041)	(0.206)
%Aged 18-39	-1.727***	-1.795**	-1.657***	-2.926***	0.183	-3.248**	-1.585	4.550
	(0.462)	(0.773)	(0.494)	(0.955)	(0.680)	(1.225)	(1.124)	(5.388)
COVID-19 Case Rate	5.137	10.511**	3.193	6.826	10.125**	4.136	-2.235	-5.751
(Nov. 10)	(3.092)	(5.179)	(3.306)	(6.397)	(4.554)	(8.208)	(7.493)	(32.373)
COVID-19 Testing Rate	0.238	-0.055	0.298	0.434	-0.017	-0.896*	0.406	2.110
(Nov. 10)	(0.186)	(0.312)	(0.199)	(0.385)	(0.274)	(0.494)	(0.438)	(1.967)
% Hispanic Population	0.132	0.087	0.236	0.601	-1.184**	-0.190	0.781	-1.126
	(0.303)	(0.508)	(0.324)	(0.628)	(0.447)	(0.805)	(0.716)	(3.734)
% Black Population	0.429***	0.504**	0.476***	0.886***	-0.302	0.036	0.130	0.284
	(0.149)	(0.250)	(0.160)	(0.309)	(0.220)	(0.396)	(0.369)	(1.911)
% Asian Population	0.741*	2.121***	0.539	1.633*	-1.053*	0.752	0.969	-4.622
	(0.415)	(0.695)	(0.444)	(0.859)	(0.611)	(1.102)	(0.993)	(4.857)
Constant	-0.257	-0.654**	-0.209	-0.181	-0.552**	1.317***	-0.208	-2.174
	(0.168)	(0.281)	(0.179)	(0.347)	(0.247)	(0.446)	(0.395)	(1.741)
Observations	59	59	59	59	59	59	57	53
R^2	0.452	0.279	0.459	0.355	0.229	0.32	0.113	0.134
F Statistic	5.161***	2.414**	5.300***	3.441***	1.852*	2.941***	0.762	0.853
	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 48)	(df=8; 44)

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table A.4: Regression results for account numbers with 5 or more establishments – Percent Change in New Establishments: 2020 (March to September) vs. Average 2016-2019 (March to September) by ZIP Code

	All (Pooled)	All Chains	All Independents	Other	Food	Retail	Personal Care and Fitness	Arts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JACOBS	0.040***	0.050	0.034**	0.081***	0.013	0.061	0.046	-0.132
	(0.014)	(0.031)	(0.015)	(0.030)	(0.021)	(0.038)	(0.041)	(0.196)
SOLCVULN	-0.057***	-0.044	-0.064***	-0.107***	0.030	-0.102**	-0.052	0.178
	(0.017)	(0.036)	(0.018)	(0.034)	(0.024)	(0.044)	(0.041)	(0.206)
%Aged 18-39	-1.727***	-2.009**	-1.657***	-2.926***	0.183	-3.248**	-1.585	4.550
	(0.462)	(0.996)	(0.494)	(0.955)	(0.680)	(1.225)	(1.124)	(5.388)
COVID-19 Case Rate	5.137	8.579	3.193	6.826	10.125**	4.136	-2.235	-5.751
(Nov. 10)	(3.092)	(6.673)	(3.306)	(6.397)	(4.554)	(8.208)	(7.493)	(32.373)
COVID-19 Testing Rate	0.238	-0.305	0.298	0.434	-0.017	-0.896*	0.406	2.110
(Nov. 10)	(0.186)	(0.401)	(0.199)	(0.385)	(0.274)	(0.494)	(0.438)	(1.967)
% Hispanic Population	0.132	-0.003	0.236	0.601	-1.184**	-0.190	0.781	-1.126
	(0.303)	(0.655)	(0.324)	(0.628)	(0.447)	(0.805)	(0.716)	(3.734)
% Black Population	0.429***	0.309	0.476***	0.886***	-0.302	0.036	0.130	0.284
	(0.149)	(0.322)	(0.160)	(0.309)	(0.220)	(0.396)	(0.369)	(1.911)
% Asian Population	0.741*	2.556***	0.539	1.633*	-1.053*	0.752	0.969	-4.622
	(0.415)	(0.896)	(0.444)	(0.859)	(0.611)	(1.102)	(0.993)	(4.857)
Constant	-0.257	-0.362	-0.209	-0.181	-0.552**	1.317***	-0.208	-2.174
	(0.168)	(0.362)	(0.179)	(0.347)	(0.247)	(0.446)	(0.395)	(1.741)
Observations	59	59	59	59	59	59	57	53
R^2	0.452	0.222	0.459	0.355	0.229	0.32	0.113	0.134
F Statistic	5.161***	1.788	5.300***	3.441***	1.852*	2.941***	0.762	0.853
	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 50)	(df=8; 48)	(df=8; 44)

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table A.5: Regression results for the spatial lag specification, estimated using a first-order queen spatial weights matrix – Percent Change in New Establishments: 2020 (March to September) vs. Average 2016-2019 (March to September) by ZIP Code

	All (Pooled)	All Chains	All Independents	Other	Food	Retail	Personal Care and Fitness	Arts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
JACOBS	0.040***	0.056**	0.034**	0.077***	0.012	0.061*	0.041	-0.146
	(0.013)	(0.025)	(0.014)	(0.027)	(0.019)	(0.035)	(0.036)	(0.160)
SOLCVULN	-0.052***	-0.017	-0.058***	-0.098***	0.031	-0.102**	-0.042	0.182
	(0.015)	(0.029)	(0.016)	(0.031)	(0.022)	(0.040)	(0.037)	(0.169)
%Aged 18-39	-1.635***	-1.510*	-1.578***	-2.779***	0.194	-3.235***	-1.498	5.713
	(0.411)	(0.808)	(0.446)	(0.865)	(0.622)	(1.135)	(1.003)	(4.413)
COVID-19 Case Rate	5.913**	10.884**	3.706	7.337	9.783**	4.164	-2.202	-10.157
(Nov. 10)	(2.728)	(5.390)	(2.974)	(5.769)	(4.172)	(7.556)	(6.690)	(26.469)
COVID-19 Testing Rate	0.218	-0.153	0.290	0.391	-0.032	-0.901**	0.369	1.932
(Nov. 10)	(0.164)	(0.325)	(0.179)	(0.347)	(0.251)	(0.455)	(0.391)	(1.609)
% Hispanic Population	0.083	-0.382	0.192	0.479	-1.213***	-0.189	0.581	-0.304
	(0.268)	(0.529)	(0.292)	(0.567)	(0.410)	(0.745)	(0.640)	(3.053)
% Black Population	0.353***	0.279	0.411***	0.740***	-0.306	0.036	-0.041	1.234
	(0.135)	(0.261)	(0.148)	(0.285)	(0.201)	(0.369)	(0.332)	(1.571)
% Asian Population	0.658*	2.303***	0.448	1.393*	-1.152**	0.741	0.944	-3.288
	(0.368)	(0.728)	(0.400)	(0.778)	(0.563)	(1.016)	(0.886)	(3.970)
Constant	-0.164	-0.666**	-0.153	-0.084	-0.585**	1.319***	-0.244	-2.844**
	(0.153)	(0.313)	(0.166)	(0.316)	(0.235)	(0.412)	(0.357)	(1.425)
Observations	59	59	59	59	59	59	57	53

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$