The Impact of Work-from-Home on Brick-and-Mortar Retail Establishments: Evidence from Card Transactions

James Duguid, Bryan Kim, Lindsay Relihan, and Chris Wheat*

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Abstract

We build a novel dataset tracking retail establishments based on billions of card transactions to study the impact of COVID-19 induced work-from-home (WFH) on brick-and-mortar retail locations. We find that retail establishments have paralleled the exodus of populations from large, expensive cities and city centers in preference for smaller Sun Belt cities and suburbs. In contrast to office markets, the negative behavioral impact of WFH on retail establishment growth is strongest near residential locations. The effects are also negative where nearby workers transitioned to WFH and for establishments with products tied to in-office employment.

*Corresponding author: Lindsay Relihan, Purdue University, 403 Mitch Daniels Blvd., West Lafayette, IN 47907, lrelihan@purdue.edu. Chris Wheat, James Duguid, Bryan Kim are affiliated with the JPMorgan Chase Institute (JPMCI). This research was made possible by a data-use agreement between Lindsay Relihan and the JPMorgan Chase Institute, which has created de-identified data assets that are selectively available to be used for academic research. All statistics from JPMCI data, including medians, reflect cells with multiple observations. The opinions expressed are those of the authors alone and do not represent the views of JPMorgan Chase & Co. We are thankful for the many helpful comments from Gilles Duranton, Andra Ghent, Jessie Handbury, Stijn Van Nieuwerburgh, seminar participants at Notre Dame, officials from the Census, Bureau of Labor Statistics and the Bureau of Economic Analysis, and participants at the 2023 Allied Social Science Associations meeting, Center for Regional Economic Development Workshop on Regional and Urban Economics, the Bank of Canada Access to Cash and Financial Services workshop, and European Urban Economics Association meeting.

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The modern city relies on the consumption benefits of density (Glaeser, Kalko and Saiz 2001). For the past four decades, college graduates working in skilled business services have flocked to downtowns in major cities, not only for the jobs located there, but for their vibrant retail amenities (Baum-Snow and Hartley 2020; Couture and Handbury 2020; Diamond 2016). The pandemic has upended that pattern, with work-from-home (WFH) pushing these workers from downtown to suburban neighborhoods and out of large, expensive cities (Althoff et al. 2022; Brueckner, Kahn and Lin forthcoming; Ding and Hwang 2022; Ferreira and Wong 2022; Li and Su 2021; Ramani and Bloom 2021). This movement threatens the viability of brick-and-mortar retail and the ability of cities to grow through their consumption benefits. If so, there are important implications for real estate and labor markets and for aggregate economic growth (Duranton and Handbury 2023). In this project, we document the changing locations and composition of retail establishments due to the adoption of WFH during the pandemic using a new dataset we construct to track establishments based on billions of transactions at card terminals.

For retail establishments, exposure to WFH is primarily through changes to the location and behavior of their customer base, rather than through their workforce (which remains largely in-person). Given that a substantial share of consumer shopping trips begin or end at home locations (Davis et al. 2019), WFH may drive retail firms to similarly shift to where consumers have moved. In addition, consumers tend to visit retail establishments near their jobs (Miyauchi, Nakajima and Redding 2022; Oh and Seo 2022). For example, going out to lunch or picking up coffee on the way to work. With fewer consumers commuting each day and commuting from different locations, traditional employment centers may be unable to support the same level of retail establishments. However, this retail activity may not simply move to residential locations if consumers who WFH make fewer and different trips. For example, a worker at home may prepare their own lunch rather than visit a restaurant.1

To study the impact of WFH on brick-and-mortar retail locations, we utilize the high-frequency credit and debit card transactions of 70 million Chase customers from January 2017 to June 2022. Our most novel data contribution is the development of a derivative dataset which tracks the quarterly entry and exit of 1.7 million retail establishments based on the credit and debit card activity at card terminals in 16 major American cities through Q4 2021. To our knowledge, this is the first establishment dataset built on transaction data which can be used to reliably measure the entry and exit of retail establishments at a fine spatial scale. Unlike public datasets, our measurement is also timelier, at a higher frequency, covers small, non-employer businesses that are common in retail markets, and provides a consumption-based view of the availability of retail amenities.

We then document important stylized facts about the changing location and composition of retail establishments since the start of the pandemic consistent with the effects of WFH. First, we show that retail establishments have paralleled the exodus of populations from large, expensive cities and city centers in preference for smaller Sun Belt cities and suburbs. To do this, we document the cross-city correlation between aggregate establishment and population growth and utilize locally weighted scatterplot smoothing to measure average establishment and population growth within cities from the downtown to outer suburbs. We find that cities including Atlanta, Phoenix, and Houston show net gains in both population and establishments while San Francisco, New York, and Los Angeles are net losers on both measures. Within each city, we observe that downtown establishment growth has substantially underperformed

1As documented in USDA survey results on pre-pandemic WFH food habits.
that in suburban areas. On average, establishments in city centers have declined by 3.7 percent while establishments in neighborhoods at the inner and outer suburban rings have grown by an average of 1.1 and 0.3 percent, respectively, in the most recent data.

In addition to these striking overall spatial patterns, we find differences in effects by the goods and services offered at retail establishments. For instance, grocery stores and restaurants both recovered quickly through suburban entries. This makes sense if consumers who WFH still have strong demand for food prepared in and out of the home. Furthermore, while leisure and consumer services establishments are still down overall, they are growing in suburban areas. Consumers who are working from home may still demand these products despite a change to their working habits (Aksoy et al. 2023). This contrasts with clothing and personal care services, which show no such increase, as they may no longer be similarly desired by those who WFH. We also observe persistent suburban decline for brick-and-mortar stores in general goods and home goods and services.

Given these stylized facts, we use a simple decomposition analysis to understand the importance of WFH in explaining variation in establishment growth across neighborhoods from Q4 2019 to Q4 2021. We show that the impact of WFH operates foremost through residential moves. The results show that a 1.0 percentage point increase in neighborhood population growth is associated with 0.3 percentage points more establishment growth. Then, conditional on population growth, changes in consumer habits driven by the adoption of WFH depresses the recovery of physical retail establishments. A 1.0 percentage point increase in neighborhood pre-pandemic residential or employment exposure to WFH decreases establishment growth by -0.25 and -0.12 percentage points, respectively. Thus, the WFH behavioral impact is most potent around residential locations where many residents were likely to transition to WFH, but also substantial around employment locations where many workers were likely to transition to WFH. This may be the consequence of the WFH population making fewer overall consumption trips and having lower demand for products that are less relevant for their new working environment.

Unlike most previous research, we move beyond describing the economic impact of the acute phase of the pandemic on retail markets when vaccines were unavailable and lockdowns were common (Relihan et al. 2020; Baker et al. 2020; Chetty et al. 2022; Couture et al. 2021; Fairlie 2020). A notable exception is Crane et al. (2022), who use other sources of real-time data, such as payroll and cellphone data, to measure business and establishment exit. Instead, we focus on understanding the persistent effects on both entry and exit patterns operating through the widespread adoption of WFH and do so at fine spatial scales with data particularly suited to studying retail markets.

We also relate to papers on the effects of WFH on urban real estate markets. To date, most of the literature on the responding change in firm locations has focused on the office market tied to workers making the WFH transition. They find that office-based firms are leaving downtown locations and substantially reducing their commercial office space (Dalton and Groen 2022; Gupta, Mittal and Van Nieuwerburgh 2022). Several also analyze the impact on retail markets, as reflected in commercial retail rents and valuations (Rosenthal, Strange and Urrego 2021; Van Nieuwerburgh 2022). To the best of our knowledge, we are the first to study retail establishment location decisions and find that, unlike for office markets, the effect is most pronounced for retail markets where the nearby residents have transitioned to WFH rather than the workers.

More broadly, this research relates to literature studying how persistent technology shocks reshape
cities. Recent work specific to retail markets focuses on online retail, large discount retail firms, and ride-sharing services (Atkin, Faber and Gonzalez-Navarro 2018; Dolfen et al. 2023; Gorback 2022; Relihan 2022; Sinai and Waldfogel 2004). Longer-term analysis of technology focuses on a broader class of information technologies, including first-generation communication technologies and the personal computer (Gaspar and Glaeser 1998; Beaudry, Doms and Lewis 2010), and transportation, such as the impact of railroad, highway, and subway systems on city structure and trade (Baum-Snow 2007; Duranton, Morrow and Turner 2014; Heblich, Redding and Sturm 2020; Tsivanidis 2022). Notably, Baum-Snow (2020) finds that employment in wholesale and retail trade was among the most likely to relocate in response to highway expansion.

1 Data

Our primary data source is the billions of credit and debit card transactions made by 70 million Chase customers from Q1 2017 to Q2 2022 accessed through the JPMorgan Chase Institute (JPMCI). In addition to the date and dollar amount of each transaction, we observe whether the card was physically present at the terminal, the location of the terminal (including the ZIP code, city, and country), and the merchant category code (MCC) for the good or service associated with the terminal. We also observe a description of the name under which business is conducted at the terminal.

We limit our study of brick-and-mortar establishments to 16 major cities in which Chase has a significant customer footprint. In these cities the customer base closely resembles the wider population and includes many customers who use one or both of debit and credit card products. As we show in Figure A.1, the unweighted Chase customer base is representative enough to match aggregate population flows from the Census during the pandemic in these cities. In addition, the size of the customer population in these cities increases the probability of observing many transactions at both large and small establishments across every neighborhood on the condition that they accept card payments.

Our study is also limited to everyday retail goods and services that are well-captured by card transactions. The following is a non-exhaustive list of the examples of retailers included in each product. Our general goods product type includes department stores, discount stores, internet retailers selling miscellaneous goods, and other retailers that sell non-food everyday goods (e.g. florists or book stores). The home goods and services product type includes goods retailers like hardware stores and furniture stores and general and specialist contracting services likely employed for home maintenance. Our professional consumer services product type includes self-storage, veterinarians, tax preparation, and childcare. Personal care services includes salons, barbershops, and dry cleaners. Grocery includes grocery stores, supermarkets, liquor stores and specialty food retailers. Restaurants includes full-service and fast-food restaurants and bars that sell food to be consumed on premises. Clothing includes clothing, shoe, and accessory stores. Leisure goods and services includes video game stores and venues like movie theaters, bowling alleys, and gyms. Pharmacy is strictly pharmacy.

Subject to these restrictions, we develop an algorithm that identifies a quarterly panel of 1.7 million unique establishments. In our data an establishment is a unique combination of merchant name, estab-

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2 Core Based Statistical Areas (CBSAs) delineate cities.
3 Ganong and Noel (2019) and Relihan (2022) are examples showing the representativeness of the Chase customer base.
4 Product categorization details in the Data Appendix.
lishment number, ZIP code, and product corresponding to a point of sale where in-person transactions take place (algorithm details in the Data Appendix). Our transaction data are available with a short lag and after running our algorithm we exclude the first and last two quarters to improve identification of true entries and exits. This provides an establishment panel that is less than one-year from the current quarter. Thus, the first two advantages of our measure over current sources is its frequency and timeliness.

Figure 1: Benchmarking in levels and growth

Notes: In the left column, this figure shows establishment counts by ZIP code for selected products in the JPMCI sample in Q1 2019 as compared to the CBP in 2019. The right column shows the difference in log growth rates from Q1 2018 to Q1 2019 for JPMCI and 2018 to 2019 for CBP.

Sources: JPMorgan Chase, Census.

We benchmark our measure to the Census County Business Patterns (CBP) for validation and to further illustrate its advantages. To our knowledge, CBP is the only publicly available dataset with establishment counts down to the ZIP code. These data are based on surveys and administrative records, such as payroll, collected in March of each year and are available at a two-year lag. In Figure 1 we compare the count and growth of establishments by ZIP code for selected products based on the Q1 2018 and Q1 2019 measure from JPMCI and the 2018 and 2019 data from CBP. We focus on three products with clear alignment with the North American Industry Classification System (NAICS) used by CBP: grocery, restaurants, and personal care services. As is clear, the JPMCI measure shows close agreement with the CBP on where these establishments tend to locate. However, the comparison of log growth rates in the right column, which would be more sensitive to small differences in coverage, shows

\[ y = 0.74x + 1.616, \quad R^2 = 0.7038 \]

\[ y = 0.928x + 0.599, \quad R^2 = 0.9024 \]

\[ y = 0.826x + 1.368, \quad R^2 = 0.6088 \]

\[ y = -0.033x + 0.071, \quad R^2 = 0.0013 \]

\[ y = -0.033x + 0.088, \quad R^2 = 0.0007 \]

We exclude the nearly identical 2018 comparison for brevity.
no agreement in which ZIP codes are increasing or decreasing in each product over a one-year horizon.

In a series of exercises we detail in the Data Appendix, we show that disagreement with CBP in short-term growth rates is likely due to sample coverage and construction that advantage our measure for retail markets. For instance, we show that our measure is likely capturing very small non-employer retail establishments that may not report payroll but still accept card payments. These could include small corner bodegas, family-run restaurants, and sole-proprietor hair salons. Capturing them is important for retail markets as they are plausibly more common than other industries, like manufacturing. Furthermore, differences in coverage can arise because our measure is a consumption-based, rather than production-based, view of where retail establishments are located. This manifests, for example, in the farmers market stands we observe that generate many card payments but may not be recorded as an employment location. Other establishments, such as bakeries and general merchandisers, can generate sales for grocery and other products that give a fuller view of where grocery items are available, but also generates more establishments in our measure than would be counted based on employees at stores singly classified under NAICS.

The CBP is also not designed for careful tracking of the same establishments over time. It is constructed as a repeated cross-section using a comprehensive 5-year Economic Census that is updated between with an annual Report of Organization survey. The latter survey targets all large multi-establishment companies with at least 500 employees and then surveys small single- and multi-establishment companies for which administrative data indicate a probable organizational change. This survey construction may be particularly prone to miscounting the entry and exit of establishments for small companies over short horizons. Reassuringly, however, we show that the aggregate establishment growth we capture is consistent with Census measures designed for that purpose, such as the Business Dynamics Statistics (Crane et al. 2022). Thus, our transactions-based measure likely provides significant advantage in tracking establishment dynamics at fine spatial and temporal scale.

One caveat to our measure during the pandemic is that more establishments are likely to have adopted card payment terminals for the first time early in the pandemic than in a typical quarter. This could create a surge in false entries. While we are not aware of data that tracks payments accepted by merchants in the U.S., the Merchant Acceptance Survey of small and medium retail businesses (50 or fewer employees) from the Bank of Canada shows that since the pandemic, acceptance of credit and debit cards among those merchants increased from approximately 67 to 88 percent. Virtually all larger merchants would already accept card payments. In the Data Appendix Figure A.2, we observe that the entry rate of establishments between Q2 2020 and to Q3 2020 increased by 2 percentage points before moderating again in Q4 2020. That increase may reflect such card payment adoption and, therefore, we may somewhat overestimate growth in establishments since the pandemic.

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6Barnatchez, Crane and Decker (2017) review research documenting a similar phenomenon when comparing Census to the National Establishment Time Series based on the privately collected Dunn & Bradstreet data.

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2 Stylized facts

2.1 Population and establishment growth across cities

We first compare aggregate city establishment growth against population growth, where population growth is measured with changes in reported addresses of Chase customers.\(^7\) The results in the left panel of Figure 2 show that in the year before the pandemic, all cities increased their establishments despite already declining populations in many high-cost coastal cities. The relationship between the two measures is also weak. However, since the pandemic, there is wide variation across cities in establishment recovery that closely reflects population changes during the pandemic. Cities such as San Francisco, Los Angeles, San Diego, and New York City experienced some of the largest declines in establishments in addition to large population declines.\(^8\) The stronger correlation with population declines during the pandemic is likely the result of the changing demographics of movers toward the high end of the socioeconomic spectrum (Li and Su 2021). These movers would comprise the core of many retail establishments’ customer base.

Figure 2: Population and establishment growth across cities

Sources: JPMorgan Chase.

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\(^7\)Customer address ZIP codes are tracked on a monthly basis. When a customer reports multiple ZIP codes within a quarter, we use the modal ZIP for the quarter. To be included in the cohort for the population growth calculation between two quarters, customers must have 10 transactions in each month of both quarters. This limits error from inactivate customers who are less likely to report changes in address and the effects from entry and exit from the Chase customer base.

\(^8\)Consistent with data from Bureau of Labor Statistics Business Employment Dynamics and Business Formation Statistics showing strong establishment growth in the Sun Belt and weak or negative growth in urban areas on the coasts (Decker and Haltiwanger 2022a).
2.2 Population and establishment growth within cities

To facilitate within-city comparisons, we normalize distance between each ZIP and the center of its corresponding city along a 0 to 1 distance scale. We follow Holian (2019) and Couture and Handbury (2020) in defining the city center based on the location of the dominant city’s city hall. Each scaled distance is then the ZIP centroid distance from city center divided by the distance of the farthest ZIP centroid in the city. For exposition, we define neighborhoods in the downtown core as those ZIPS from a distance of 0.0 to 0.1, the outer core neighborhoods as those from a distance of 0.1 to 0.4, the inner suburbs as neighborhoods from a distance of 0.4 to 0.8, and the outer suburbs as those from 0.8 to 1.0.

We then estimate average establishment and population growth within cities at each distance using locally weighted scatterplot smoothing (Cleveland 1979). For these regressions, our dependent variables, \( \Delta Est_{z,q} \) and \( \Delta Pop_{z,q} \), are the growth rate in establishments or population, respectively, in ZIP \( z \) between quarter \( q \) and the same quarter in 2019. Our independent variable, \( dist_z \), is the scaled distance from city center. Smoothed values of the dependent variables in each quarter are estimated by taking a subset of the points closest to \( dist_z \) in distance (those within the span), and using a kernel function to specify weights for those points in a weighted linear regression. A span of one-third of the data and the standard tricube weighting function are used in our estimation.

We find that early pandemic conditions created different growth curves for populations and establishments within cities. This can be seen in the orange lines in the top panel of Figure 3. At the start of the pandemic in Q2 2020, population declines in the downtown and outer core areas were modest and similar to previous quarters (see Figure A.10 for pre-pandemic population growth). We observe little immediate effect for population because initially temporary customer moves out of the city would not yet be reflected in permanent address changes. However, our transactions-based measure of establishment activity shows immediate permanent closures of retail establishments across the city, with greater declines toward the city center. For neighborhoods at the center, there is an average effect of 12.9 percent fewer establishments relative to Q2 2019. Moving marginally out of the city center to neighborhoods at a distance of just 0.1 dramatically reduces the negative effect to just 6.0 percent. From there, the gradient toward the outer areas of the city is much less steep. Neighborhoods farthest away from the center experienced just a 1.1 percent drop in establishments at the start of the pandemic.

There are important differences in these growth curves as of Q4 2021. The first noticeable feature is the dramatic rotation of the population curve. Neighborhoods at the city center and the start of the outer core show declines of 8.9 percent and 3.4 percent, respectively. Population growth at the starting points for the inner and outer suburbs, however, is robust at 1.0 percent and 4.9 percent, respectively, in the most recent data. The time series in the bottom panel of Figure 3 shows that this pattern is the result of a continuous population shift from downtown to suburban areas over the previous two years. This shift is decelerating but continuing to grow through the most recent quarters.

In contrast, the time series for establishments is one of recovery after the initial shock, with a return to growth only in suburban areas as of the most recent data. Establishments at the city center still show substantial losses of 3.8 percent. Unlike for population, recent growth is most robust in the inner suburbs, though no higher than a 1.7 percent growth rate. This is a reversal from pre-pandemic trends.

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9We take the pre-1954 city hall location in the central business district for Miami.
10Figure A.9 shows city maps with these neighborhood regions.
Figure 3: Population and establishment growth within cities

(a) Growth by distance from city center curves

(b) Growth by distance from city center time series

Notes: Scaled distance is calculated as the distance between the centroid of each ZIP and the city hall of the principal city of its CBSA, then dividing this distance by the greatest ZIP to city hall distance in the CBSA. Growth in each quarter is relative to the same quarter in 2019. Bootstrapped 95% confidence interval bands are shown as shaded areas in the top panel.

Sources: JPMorgan Chase.

in which downtown areas of cities had the highest growth in establishments and growth everywhere was positive (see appendix Figure A.10). The time series in the bottom panel of Figure 3 shows downtown cores still quickly recovering establishments through 2021, while other areas of the city have maintained steady growth rates since early 2021.

11However, new entry is not smooth across space. In fact, in Figure A.11, recent entry is more spatially concentrated than the exit of establishments early in the pandemic. This likely reflects the agglomeration forces that drive retail to co-locate, as with malls and other retail districts, zoning, and limited availability of existing retail space.
2.3 Establishment growth for different goods and services

The observed establishment growth within and across cities is clearly correlated with the movement of people to new residential locations in response to the pandemic-induced adoption of WFH (Althoff et al. 2022; Brueckner, Kahn and Lin forthcoming; Ding and Hwang 2022; Ferreira and Wong 2022; Li and Su 2021; Ramani and Bloom 2021). However, WFH adoption is likely to affect more than residential location choice – it is also likely to affect the everyday consumption behavior of individual consumers. For instance, consumers who now WFH may switch from purchasing lunch from a restaurant near their job to purchasing lunch from a restaurant near their home or switch to utilizing more grocery stores to prepare lunch at home. They may also purchase less work-related clothing or personal care services used to maintain a professional appearance.

Figure 4: Establishment growth within cities by product

Notes: Growth is for Q4 2019 to Q4 2021. Scaled distance is calculated as the distance between the centroid of each ZIP and the city hall of the principal city of its CBSA, then dividing this distance by the greatest ZIP to city hall distance in the CBSA. For pharmacies, there is no statistically significant difference in growth within cities. 
Sources: JPMorgan Chase.

We look for evidence of differential growth consistent with WFH by replicating our distance from city center growth rate analysis by product using half the data in the span and the same tricube weighting function. Figure 4 shows the result. Here, we find that restaurant growth is positive outside the downtown core, with the strongest growth in the inner suburbs. In contrast, grocery growth is stronger in the outer suburbs. This may reflect stronger shifts in demand from restaurants to grocery stores farther into the suburbs if the WFH adoption also increases with distance. Zoning restrictions or higher minimum customer density requirements may also prevent restaurants from equally following residents into the outer suburbs. We also find that leisure (e.g. gyms and theatres) and consumer services (e.g. vets and daycares) establishments are also growing farther into the suburbs. Demand for these products is likely
more independent of where and how residents work and can increase as WFH residents spend more time at home (Aksoy et al. 2023).

In contrast, clothing and personal care services (e.g., salons and dry cleaners) show no establishment growth anywhere in the city. In fact, the growth rates for these products are convex, with a negative correlation between population and establishment growth in suburban areas. This again would be consistent with stronger WFH effects farther out into the suburbs. Such residents would no longer need to maintain the same professional appearance standards that clothing and personal care establishments facilitate. For general and home goods, residents working from home in the suburbs might go on fewer trips than required to support the entry of a wide class of merchandisers – creating the convex shape for those product types. Pharmacies show no differential growth rate within cities so far, possibly a reflection of binding licensing requirements.

3 Decomposition analysis

We now use a simple OLS regression to understand the relative importance of the pandemic-induced WFH adoption on brick-and-mortar establishment growth within cities.

To measure the impact of WFH, we would ideally measure which customers are engaged in remote work and then directly study their residential moves and spending changes near their residential and employment locations. However, there is no direct WFH or employment location indicator in our data. Outside data for this purpose is also limited. Instead, we measure the impact of WFH with a combination of our measure of population growth with a measure of pre-pandemic neighborhood exposure to WFH shocks with 2019 Longitudinal Employer-Household Dynamics Local Origin-Destination Employment Statistics (LODES) data. We measure this exposure at the ZIP level in two ways — residential exposure as measured by the percent of residents in industries that had a high likelihood of transition to fully remote or hybrid working schedules and employment exposure as measured by the percent of jobs in a neighborhood in those industries. These industries are the two-digit NAICS industries corresponding to Information (51), Finance and Insurance (52), Professional Services (54), and Management of Companies (55) and are closely correlated with the adoption of remote work during the pandemic (Althoff et al. 2022; Dingel and Neiman 2020). In this way, we measure the direct association between residential pandemic moves likely induced by WFH and then, conditional on those moves, how neighborhoods that are more likely to have residents and jobs who transition to WFH are differentially impacted.

Our specification is

$$\Delta \text{Est}_{zc} = \beta_1 \Delta \text{Pop}_{zc} + \beta_2 \text{WFH Resi}_{zc} + \beta_3 \text{WFH Emp}_{zc} + X_{zc} + \gamma_c + \epsilon_{zc}, \quad (1)$$

where $\Delta \text{Est}_{zc}$ is the percent growth in establishments in neighborhood $z$ in city $c$, $\Delta \text{Pop}_{zc}$ is the percent growth in customer population, and $\text{WFH Resi}_{zc}$ and $\text{WFH Emp}_{zc}$ measures pre-pandemic residential and employment exposure to WFH, respectively. We also include a vector of neighborhood characteristics, $X_{zc}$, which includes measures of pre-pandemic neighborhood non-white residential share and median income from the 2015-2019 5-year American Community Survey (ACS) data, a Downtown$_{zc}$ dummy.

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12 Figure A.12 shows how these exposure measures map to ZIPs along our 0 to 1 scaled distance within cities.
to control for remaining differences in pandemic effects in downtown cores that are not captured by our other controls, and the growth in online and offline residential spending among Chase customers in each neighborhood.\(^{13}\) In all specifications we include city fixed effects, \(\gamma_c\), and cluster standard errors at the city level.

Identifying the effects of WFH on establishment growth presents many challenges. We argue that COVID-19 induced adoption of WFH in this short two-year window had a largely exogenous impact on customer locations and spending behaviors that then fundamentally altered the viability of retail establishments in different locations. The clear break in both mean population and establishment growth within cities outside of a narrow range in the year prior to the pandemic, even absent controls, supports this interpretation (see Figure A.10). However, the inclusion of neighborhood characteristics and spending growth by channel recognizes that the pandemic differentially affected the economic performance of low- and high-socioeconomic status neighborhoods and online shopping behavior, which plausibly correlates with both WFH and establishment growth. These effects could operate through the direct impact of the disease and other indirect economic effects, such as through the labor market or stimulus payments (Chetty et al. 2022). These characteristics also control for correlated merchant card payment adoption during the pandemic that could create more false entries in some neighborhoods. City fixed effects control for the common effects of the pandemic across each city. After controlling for these factors, we believe that reverse causality is not a significant concern in this context.

Our results are found in Table 1. Echoing our earlier results, we first show in Model 1 that being in a downtown area is associated with an average 3.6 percentage point lower rate of growth in establishments, absent other controls. Model 2 adds our estimate of population growth for the same period and again we find that changes in population have a strong correlation with establishment growth during this period, enough so that the downtown dummy variable becomes insignificant. Adding instead our exposure measures in Model 3, only employment exposure has a statistically significant impact on establishment growth conditional on the downtown dummy. This points to the downtown dummy primarily capturing the effect of population loss at the core, but not the employment effects. Once population loss is included in Model 4, the downtown dummy once again becomes insignificant. The stability of the coefficients across Models 2-4 suggests that the effects of WFH through population versus employment effects are relatively independent sources of variation in the data.

In our final specification in Model 5, we include spending by channel and other controls for neighborhood demographics. These controls quadruple the size of the negative coefficient for WFH residential exposure to -0.25 percentage points and make it strongly statistically significant. This makes sense given that we observe strong positive correlation among neighborhoods with more WFH residential exposure, higher income, and fewer non-white residents. With these correlations partialled out, the impact of the WFH residential exposure measure becomes the most important driver of retail establishment growth next to population growth. The meaning of this effect is that, conditional on a positive population shock to a neighborhood who receives many new residents due to WFH, a likely transition of residents in

\(^{13}\)For each quarter \(q\) and the same quarter in 2019, we filter to customers (regardless of location) who make at least 10 transactions in each month of both quarters to focus on active customers. We aggregate the spending of these customers for each ZIP and quarter for the growth calculation. In this way, an active customer who moves from San Francisco to Atlanta in November of 2019 would have their October 2019 spending allocated to their San Francisco ZIP and their November and December 2019 spending to their Atlanta ZIP for Q4 2019.
Table 1: Decomposition analysis of Q4 2019 - Q4 2021 establishment growth (%)

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<td>Downtown core</td>
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<td>-1.095</td>
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<td>WFH residential exposure (%)</td>
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<td>Offline spending growth (%)</td>
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<td>Non-white residents (%)</td>
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<td>Median income ($1000s)</td>
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Observations 3,651 3,651 3,651 3,651 3,651
R² 0.039 0.059 0.049 0.066 0.072
Adjusted R² 0.035 0.054 0.045 0.061 0.066

Notes: All models include CBSA fixed effects. Standard errors in parentheses and clustered at the city level. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level. Mean establishment growth rate is 1.94 percent.

those locations to WFH reduces establishment growth. This matches our intuition that if consumers who WFH go on fewer trips overall, the impact of that daily WFH behavior change will be large near their residential locations where most shopping trips originate. Beyond that, the impact of employment exposure is also substantial with a coefficient of -0.12. This points to the critical reliance of some retail on the commuters in employment locations. Finally, the impact of online retail growth, while small and marginally significant, is overall positive. This is suggestive that the growth in online retail for more non-tradable products during the pandemic, like groceries and restaurant meals, has supported brick-and-mortar establishments during the pandemic, rather than replaced them.14

In the Data Appendix Tables A.1 and A.2, we show how our estimates vary using data from earlier in the pandemic and by establishment growth for specific product types. The impact of WFH through population change and neighborhood exposure is highly stable from early- to late- pandemic quarters. For other covariates, we see some time variation; neighborhoods with more non-white residents experienced lower growth early in the pandemic and the positive effect of online retail growth is specific to later quarters once the rate of new entries increases. Matching our earlier intuition on product-specific effects, we find significant variation in the impact of WFH across product types. For the three largest categories of establishments: grocery establishment growth is strongly associated with population growth but shows no significant correlation with WFH exposure, restaurant establishment growth is more affected by employment than residential WFH exposure, and general goods are strongly affected by resi-

14In the Data Appendix, we show that changes in consumer spending online since the pandemic supports this interpretation.
dential exposure but show no association with employment exposure. For clothing and personal care, we again find significant and negative associations with more residential WFH exposure, while for leisure and professional consumer services there is a positive association with population but no effect through exposure to WFH.

4 Final Remarks

Over the short-run, the relocation of retail establishments can primarily operate through sorting among existing retail properties with higher vacancy rates in downtowns and lower vacancy rates in suburbs. The least capital intensive will be the most mobile. Over time, the movement of people and establishments could encourage new developments that durably alter the location of retail. The consequent increase in amenities could further attract new residents, reinforcing the initial migration wave due to WFH. These dynamics have until recently been largely excluded from urban and trade models of city structure, but are clearly crucial for modeling the persistent effects of WFH. Almagro and Domínguez-Iino (2022) is a new and important example of how to successfully incorporate such endogenous amenities.

The greater suburbanization of retail establishments will have ripple effects outside the retail market. Most immediately, retail employment is likely to strengthen in suburban areas. However, such gains may exacerbate existing inequities. For example, Black households are more likely to reside and work in downtown areas and are underrepresented in remote work-exposed industries. Therefore, the relocation of retail to the suburbs could increase the spatial mismatch between Black residents and jobs (Miller 2023). Similarly, these patterns imply less access to retail amenities for Black households.

The relocation of retail establishments also has implications for aggregate economic growth by potentially reducing agglomeration benefits. With less consumption amenity advantage in large coastal cities and downtowns, there may be less reason for knowledge-intensive workers to jointly locate in specific neighborhoods. Furthermore, as discussed in Atkin, Chen and Popov (2022), retail like coffee shops can provide valuable locations for meetings of workers in knowledge-intensive industries where face-to-face interactions are central to innovation. Such meetings may be less likely to take place if fewer retail establishments near employment centers can be sustained with only a partial return to office. Whether these harms are enough to outweigh the possible gains to productivity at the individual level from WFH is unclear (Delventhal, Kwon and Parkhomenko 2022; Davis, Ghent and Gregory 2021; Monte, Porcher and Rossi-Hansberg 2023).

To counteract negative impacts, officials may be tempted toward policies that mandate a return to the office. However, mandates ignore the productivity and income gains of WFH that may prove substantial for some firms and workers. More promising are redevelopment policies that put land toward more productive use and others that reduce frictions preventing lower socioeconomic households from accessing economic gains. For instance, more flexible zoning, redevelopment grants, and taxes on extended vacancies could help move downtowns toward more residential use and use by firms that value and provide

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15Decker and Haltiwanger (2022b) also document stronger business formation in suburban areas since the pandemic.
16The Census Current Population Survey for 2019 shows only 8.8 percent of employees in the 2-digits NAICS industries (51, 52, 54, and 55) most exposed to WFH where Black, while 78 percent were White.

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in-person interactions. This new residential and commercial activity could then support an appropriate mix of retail establishments for that customer base. In the suburbs, a reduction in single-family zoning and more multifamily housing units would lower barriers to moving to the suburbs and accessing the new jobs and amenities available there.

References


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17Moszkowski and Stackman (2023) show some vacancy is desirable with frictions in matching between landlords and tenants in retail markets. Vacancy taxes are more effective where negative externalities of vacancy are substantial.


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5 Data Appendix

5.1 Measuring population

We measure the location and activity of an individual person using their accounts with the bank across potentially multiple products, including deposit, credit, and mortgage products. The bank-provided identifiers that attempt to link product accounts together when they appear to belong to the same person are a sometimes imperfect proxy for a single individual, as with shared accounts. Where credit and debit card accounts are associated with multiple people, we assign all transactions to the primary account holder and use the location information associated with the primary account holder. We would then count the change in location for the primary account holder as a residential move of one person, even though an entire household may move. Other entirely unobserved members of a household, such as children, are not measured in our data.

Figure A.1 shows how the JPMCI cohort for population change estimates from Q3 2019 to Q3 2020 by city compares against the latest Census estimates, as calculated by Frey (2022). The one-year changes in population at the city level closely match the Census estimates without any sample weighting of the JPMCI cohort. This is by design, as we focus on cities where the bank has the largest footprint and serves a broad cross-section of the population as customers. Of course, there is generally less representation at the lower end of the socioeconomic spectrum where the population is more likely to be underbanked. To the extent that the coverage of different populations vary across space, that can contribute to some error. Finally, note that, on average, the JPMCI cohort suggests slightly less population growth than the Census. Besides differences in population coverage, this could also reflect delays in updating addresses reported to the bank over the one-year horizon.

Figure A.1: Population growth benchmarking

Notes: This figure shows population growth in the JPMCI cohort from Q3 2019 to Q3 2020 relative to the 2019 - 2020 Census estimates for each city.
Sources: JPMorgan Chase, Census estimates from Table B of Frey (2022).
5.2 Measuring establishments with card terminals

There are several challenges in accurately measuring establishments using transaction data within major cities and products. One major issue is that, to the best of our knowledge, card terminals do not have an establishment identifier that links all transactions made at multiple terminals within a single establishment. As a result, we have focused on using the location and merchant identifying information available to create our own common identifier. However, there are additional complications with this observed information. For instance, different card terminals at the same establishment may contain variations of the same information, possibly due to being programmed by different people or at different times. Additionally, terminal information may be processed differently depending on the method of payment (e.g., chip vs. swipe) or may be reported differently by different card payment processors. For example, the text description of the merchant may vary in the number of characters allowed, depending on the payment processor. Therefore, we develop an algorithm that joins transactions describing the same establishment, such as “Joe’s Famous Pizza” and “Joes Famous Pizz”, in the same ZIP code and product:

1. Exclude all online transactions to focus on brick-and-mortar locations where in-person transactions take place.\(^{18}\)

2. Create clean merchant name and establishment identifiers. Specifically, use regular expressions to distinguish merchant names from establishment numbers in transaction descriptions (if present, such as in “Big Box Store #1234”), remove all remaining non-alphanumeric characters, convert all alphanumeric characters to uppercase, and extend merchant names and numbers to the longest merchant name and number for which it is a shortened version within the same product and ZIP code.\(^{19}\) Thus both “Joe’s Famous Pizza” and “Joes Famous Pizz” observed in the same ZIP for restaurants become “JOES FAMOUS PIZZA”.

3. Define an establishment as a unique combination of merchant name, establishment number, postal code, and product corresponding to a point of sale where in-person transactions take place.

4. Measure transaction volume for each establishment at a quarterly frequency to improve observation of small establishments at which transactions are sparse.

5. Measure the first and last quarter each establishment is observed with at least one transaction and assign those as the entry and exit date, respectively.\(^{20}\)

6. Exclude establishments that are likely to be noise. This includes those establishments observed for only one quarter and those which are observed to be active for less than half of the quarters between their entry and exit dates.

We then exclude the first and last two quarters for which we have data from our analysis. By construction, all establishments that exist prior to Q1 2017 or after Q2 2022 have these end dates defined

\(^{18}\)We classify a transaction as online if that card is not physically present at the point of sale or if the card terminal location information is not a physical location (phone numbers or website addresses recorded as the terminal’s city).

\(^{19}\)Different card payment processors allow for different character lengths in the merchant text description, such that cut-off descriptions are a major source of variation.

\(^{20}\)Thus, seasonal establishments like ice cream parlors are inactive in winter rather than non-existent for quarters between their entry and exit dates.
as their entry or exit dates, respectively. We also exclude an additional quarter at the beginning and end of the panel because some establishments have too little activity in the first or last quarter to be detected by terminals, either through the size of the establishment or the seasonal nature of its product. This substantially artificially inflates the entry and exit rates for Q2 2017 and Q1 2022, respectively. Similar effects in subsequent quarters are likely to show similar effects, but to a decreasing extent away from panel end dates. As new quarters are added to the transactions data and we extend the panel past Q4 2021, some establishments that appeared to have exited in the most recent quarters we report may reappear if they were only temporarily inactive for more than Q1 and Q2 2022. As such, subsequent updates may show a level shift in growth rates for the quarters we report here. To the extent that temporary inactivity varies across different classes of establishments (e.g. across space or products), that may also shift the cross-sectional patterns we document.

Figure A.2: Aggregate changes in establishments

Notes: The top panel shows growth in all establishments versus active establishments relative to the same quarter in 2019. Active establishments are those at which customers make transactions in the quarter. The bottom panel shows the entry and exit rate relative to the stock of establishments in the previous quarter. Sources: JPMorgan Chase.

With this resulting dataset, we can trace out the overall entry and exit rate of retail establishments across the pandemic in Figure A.2. The quarterly rate of establishment entry and exit we observe in our data prior to the pandemic is an average of 4.5 percent. This is above the 2.5 quarterly rate in the Business Employment Dynamics (Crane et al. 2022). The higher rate may be related to the differences in geographic and industry coverage as well as more representation of small establishments who enter and exit at higher rates. Consistent with Crane et al. (2022) and Fairlie (2020), we find that establishment exit was much more muted than was feared given the declines in consumption in the early pandemic. Our measure shows that even though 15.2% of establishments were completely inactive in Q2 2020, only one-third of that decline was due to permanent closures. The surge in the exit rate was limited to Q2 2020 and dropped below the 2019 average in Q3 2020, suggesting that the pandemic partly accelerated
closures that were already likely to have taken place. By Q4 2020, exit rates of retail establishments had returned to their 2019 rate. The entry rate of new establishments in the second half of 2020 and 2021 was somewhat muted, but total establishments slowly converged to their pre-pandemic level. As of Q4 2021, there were only 1.0% fewer establishments relative to Q4 2019.

5.3 Product mapping

The basis for our product categorization are Merchant Category Codes (MCCs) defined by the International Organization for Standards. The codes’ purpose is to define the primary good or service the firm is engaged in and are used to detect fraud, allocate reward points, and determine tax and interchange rates for different purchases. They are typically assigned at firm birth by a credit card network (or when card terminals are first adopted by the firm). Multiple codes may be assigned to different lines of business at the same firm and different credit card networks may assign different MCCs to the same firm. MCCs are fairly static over time so that even if a firm’s primary good or service changes, the MCC would not. For example, a firm that starts by selling books but goes on to sell a wide-variety of general merchandise may continue to be classified as a book store. Some firms, like airlines, are assigned their own MCC.

We map MCCs to a broader product type based on our analysis of the merchants that commonly appear in each MCC in our data. We believe our custom mapping to be more appropriate than other mappings for data categorized by MCC, which first map between MCCs and 6-digit North American Industry Classification System (NAICS) codes based only on similar code descriptions and then aggregates to 3-digit or 2-digit NAICS. Issues arise with the latter in this context because even though it is intuitive that the vast majority of our card transactions reflect retail spending on goods and services, relying only on similar descriptions of 6-digit NAICS codes would lead many of our transactions to be categorized as manufacturing, wholesale trade, and construction when this is clearly not reflective of the actual spending. For example, one may find it natural to map MCC 5462: Bakeries to the 6-digit NAICS code 311811: Retail Bakeries. However, this is part of the 2-digit NAICS code: Manufacturing. We find this inappropriate as the typical bakery we observe in our data is a small retail outlet rather than a large manufacturing operation. It would be more appropriate to map to the 6-digit NAICS 445291: Baked Goods Retailers.

We do not, however, strictly map MCCs to particular 2-, 3-, 4-, or 6- digit NAICS codes for two reasons. First, NAICS codes are better optimized to classify manufacturing-related industries rather than retail-related goods and services. We find it more natural to group some goods and services together in the same product category because of their closely related consumption. For example, video game rentals, online streaming services, books and golf courses are a selection of goods and services related to leisure activities that are well-represented by card spending. These would map to different 2-digits NAICS including 44-45: Retail Trade, 51: Information, and 71: Arts, Entertainment, and Recreation, which would obscure patterns in everyday leisure-related consumption if aggregated separately. Furthermore, broad-swaths of the latter 2-digit NAICS are not well-represented by card spending.

Second, in observing the firms that appear in particular MCC or NAICS codes, there is often no clear one-to-one correspondence. For example, home internet providers and video streaming services appear in the same 6-digit NAICS 516210, but separate MCC codes which then themselves include firms in other 6-digit NAICS. These issues particularly relate to our leisure goods and services, professional
consumer services, home goods and services, and general goods product categories. However, for the remaining products, there is a more clear (though not strict) cross-walk. Clothing maps to 4-digit NAICS 4481 and 4482; Restaurant to 3-digit NAICS 722; Grocery to 3-digit NAICS 445; Personal Care Goods and Services to 4-digit NAICS 8121, 8123, and 7298; and Pharmacy to 6-digit NAICS 456110.

Finally, we complement our MCC mapping with custom mapping for large online-only retailers in grocery, restaurant, and general goods that tend to fall into residual MCC codes that capture miscellaneous spending not elsewhere categorized. To do this, we use regular expressions to find merchant transaction descriptions which include the names of these retailers.

Figure A.3: Aggregate changes in establishments by product

![Figure A.3: Aggregate changes in establishments by product](image)

Notes: The top panel shows growth in all establishments versus active establishments relative to the same quarter in 2019. Active establishments are those at which customers makes transactions in the quarter. The bottom panel shows the entry and exit rate relative to the stock of establishments in the previous quarter.
Sources: JPMorgan Chase.

The aggregate patterns in establishment growth that we observe by product are in Figure A.3. Groceries and restaurants are the only establishments that show aggregate growth relative to the pre-pandemic baseline by the end of our sample. Clothing, personal care, and leisure show some of the strongest and persistent declines. Crane et al. (2022) also break out establishment closure statistics by several subsectors and provide a useful reference. Like our results, they show that permanent restaurant closures were far smaller than initial spending declines suggested. They also show that leisure-related firms and establishments were some of the most severely impacted.

5.4 Benchmarking establishments to the CBP

In this section, we discuss the results of additional exercises to illuminate differences between the JPMCI measure of establishments and the CBP. First, looking more closely at the count comparison in the left column of Figure 1, a salient difference is that our measure systematically identifies more establishments relative to the CBP for every product – the fitted regression lines each have an intercept above one. One factor that can drive this is that our establishment identification algorithm can overcount establishments when it fails to consolidate transactions appropriately. For example, a restaurant with two terminals in which one reports “Joe’s Famous Pizza” and the other “Joe’s Famous Piza” will count two restaurants in
a location. This weakens the dataset’s ability to give an accurate picture of the count of establishments, but would have a smaller impact on making comparisons across locations or over time so long as the rate of false overcounts from transaction description variation is relatively constant.

Another large factor likely to drive overcounting is coverage by JPMCI of small locations that are sole proprietorships or where few people work. This would reflect the same source of discrepancy that is well-documented between Census’ payroll-based datasets and alternate private sources of establishment information, as surveyed in Barnatchez, Crane and Decker (2017). While we cannot test this directly in our data because we lack a view on establishment employment, this issue is less likely to affect restaurants, as most have employees; indeed, this is where we overcount the least.

Figure A.4: Comparison excluding small and large restaurants

Notes: The left panel of this figure shows the correspondence in establishment counts by ZIP code for restaurants in the JPMCI measure for Q1 2019 with the CBP as collected in March 2019. The middle and right panel show the correspondence when establishments above and below the tenth and ninetieth percentile of transaction volume, respectively, are removed from the JPMCI measure. Percentiles are calculated using only restaurants and are specific to each city.

Sources: JPMorgan Chase, Census.

We can, however, test whether these differences are due to coverage at the bottom of the establishment distribution. In Figure A.4 we show how our match in counts to the CBP for restaurants in 2019 changes when we remove the bottom ten and top ten percent of restaurants ranked by their transaction activity. The results show that removing the bottom 10 percent of restaurants reduces our count of restaurants in ZIP codes where the CBP measures few restaurants, pushing the intercept toward zero. Removing these restaurants also pushes the slope toward one and slightly improves the linear fit. In contrast, removing the top ten percent of restaurants creates the opposite effect by removing restaurants in zips where both our measure and the CBP agree that there are many restaurants. Thus, we are not simply overcounting everywhere at the same rate relative to the CBP, but particularly where our measure

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21 Improvements in string cleaning based on fuzzy matching and machine learning could by applied in future versions to reduce this type of mismeasurement.

22 Transaction ranking is within product and city to account for different baseline transaction activity across products and Chase customer coverage across cities, respectively. For example, the bottom ten percent of restaurants in New York City have fewer than 16 card transactions in Q1 2019.
detects more very small establishments.

There are other features of our measure that can compound the overcounting relative to the CBP for grocery and personal care services that we observe in Figure 1. For grocery, we observe what are likely many temporary establishments, like farmers markets, that may not report as employment locations. We also find that there are many more establishments that sell groceries, and therefore create transactions with a grocery MCC, than what may be otherwise categorized as grocery establishments in other datasets. For example, delis, bakeries, and gas station convenience stores can sell a subset of items classified as groceries and such examples would create additional grocery establishments in our data. In personal care services, what may be elsewhere categorized as a single salon can appear to us as a collection of individual personal care service providers if the stylists rent and operate their chairs independently. We view these differences as salient for interpretation, but not necessarily mismeasurement, and valuable in trying to understand consumption, rather than production, locations.

Figure A.5: Difference with CBP by count of retail establishments

Notes: This figure shows differences in establishment counts by ZIP code between the JPMCI and CBP measures by the count of the establishments measured by JPMCI.
Sources: JPMorgan Chase, Census.

We next focus on understanding the variation in differences between the JPMCI and CBP counts observed around the trend line. To do this, we first plot the difference in counts by the JPMCI count of establishments in 2019. This is shown in Figure A.5. The first feature to call attention to with this view is that the JPMCI and CBP measures more closely agree on where there are few or many of each establishment type. Where they primarily differ is in locations where the CBP measures a moderate number of each establishment and JPMCI measures many more, like with very small restaurants. Secondly, this view makes clearer that while the JPMCI measure generally overcounts relative to CBP, JPMCI undercounts relative to CBP for some zip codes. These would be all the points that lie below the horizontal bar in each panel. Undercounting is more likely for restaurants and personal care services, products that likely include more unobserved all-cash establishments than groceries.

In Figure A.6 we plot these difference across ZIP code features, including distance to center, share
non-white residents, and median income. The latter two features are pulled from the same ACS data used in our main results. For context, we also show the two-way scatter plots of each pair of ZIP codes features in Figure A.7. There are a number of notable patterns that emerge:

1. The ZIP codes with the most extreme negative differences tend to occur in the middle of the scaled distance of cities. Inspection of the small number of these specific zip codes reveals that they tend to occur in the suburban areas of a few CBSAs where there is significant presence of non-Chase bank branches and, thus, likely weaker coverage of local residents. While this is a minor issue in this analysis in cities where Chase is a dominant presence, this highlights the necessity of good resident coverage for measurement of retail establishments with card transactions.

2. For restaurants and personal care services there are also a cluster of ZIP codes with extreme positive differences in the suburbs. Inspection of these specific ZIP codes reveals that they tend to occur in locations with unusual features. For example some are specialty leisure offerings, such as ski resorts, beach towns, and casinos. We measure them as collections of different establishments via their different transaction descriptions, but which may be considered as one establishment when measured from an employment-based view. These types of locations tend to also attract many temporary establishments, like refreshment stands or vending machines, which may similarly be reflected in transactions data, but not other sources. We also frequently observe colleges and universities with dining halls and gyms in these ZIP codes, while education establishments are specifically excluded from the CBP.

Notes: This figure shows differences in establishment counts by ZIP code between the JPMCI and CBP measures across ZIP characteristics from Census data of distance to center, non-white residents, and median income.
Sources: JPMorgan Chase, Census.
3. The JPMCI measure overcounts relative to CBP in more low-income neighborhoods for restaurants and personal care services. This makes sense if low-income neighborhoods have higher concentrations of small or non-employer establishments for these product types.

4. In contrast, the observed pattern for grocery stores strongly suggests a “farmers market effect”. For grocery stores we observe more overcounting relative to CBP where there are more white residents and higher median income, a pattern which is not present for the other products. Inspection of specific ZIP codes is consistent with the interpretation that we pick up many temporary and small establishments that sell food that may not be recorded as employment locations by firms.

5.5 The growth of online retail

The proliferation of online retail in the three decades prior to the pandemic forced the closure of many traditional brick-and-mortar establishments and the adoption of omnichannel strategies by other retailers (Bell, Gallino and Moreno 2017; Brynjolfsson, Hu and Rahman 2009). This growth was concentrated in highly tradable products, like books and clothing. However, the growth of online retail during the pandemic was concentrated in a less tradable product set, particularly newer products like online groceries and restaurants (Relihan et al. 2020).\footnote{Online retail sales currently account for 14.1 percent of retail sales, an increase in share of 3.9 percentage points from 2019 (Q3 2022 Census Quarterly E-Commerce Sales Report).} Given that these newer online products still strongly rely on brick-and-mortar stores for local production and distribution, it is not ex-ante clear that their growth...
will have the same negative impact. Beyond these direct effects, the restructuring of shopping trips and changes in consumer time use resulting from the shift to online markets may have both negative and positive spillover effects on non-competing establishments. For instance, Relihan (2022) finds that consumers of online groceries tend to use their time savings to increase in-person trips to non-tradable services like coffee shops. Therefore, while the persistence of the shift towards online markets brought about by the pandemic may further disrupt the locations of traditional brick-and-mortar stores, the extent and direction of this disruption will depend on the products adopted and their indirect effects on consumer behaviors.

To investigate the persistence and scale of online retail growth across products during the pandemic, we construct a panel comprising 10.6 million individuals in any location who made at least 10 transactions per month from July 2018 to June 2022. We focus on the five largest product categories (as measured by total spending across channel), analyzing both the percentage of people using online products each month and the total spending on each product online. This is itself an important data contribution, as tracking online growth by product is not currently possible with public data sources and these differences across product are distinct during the pandemic.

Figure A.8: Online spending growth

Notes: The top panel shows the percentage point change in the share of customers shopping online for products relative the share in the same month in 2019. For context, in February 2020 the share of customers shopping online for each product was 21 percent for clothing, 19 percent for grocery, 68 percent for general goods, 23 percent for home goods, and 49 percent for restaurants. The bottom panel shows the growth in spending relative to the same month in 2019. Winter declines in grocery and restaurant are because these products were already used more in winter months prior to the pandemic.

Sources: JPMorgan Chase.

\(^{24}\)For example, many online grocery orders are filled at nearby grocery stores. Similarly, online restaurant meals still require nearby restaurant kitchens.
We find that the COVID-19 pandemic led to the largest and persistent increase in the adoption of newer online products, groceries and restaurants, as depicted in Figure A.8. The percentage of consumers using online channels for purchases of these products each month rose from 19 to 30 percent and 50 to 61 percent, respectively, between February and May 2020. Usage continues to widen to almost 15 percentage points for both products in the most recent data. In the case of groceries, this represents almost twice as much market penetration due to the pandemic. In contrast, fewer individuals increased their monthly use of more established online products – clothing, general goods, and home goods. This smaller increase is also declining over time. These results suggest that the fixed costs of adoption may play a role in the differential impact on new versus established online products, particularly for those products that are still in their introductory phase.

While grocery and restaurants also experience the strongest overall spending growth, our analysis shows that the overall increase in spending on established online products is also sustained and reflects a more frequent use of this channel by consumers who previously only made occasional online purchases. As of June 2022, spending on general goods, home goods, and clothing was 53, 42, and 52 percent higher, respectively, compared to February 2020. These patterns may be influenced by factors such as inflation and an increase in overall spending due to saved income, but the recent online spending growth still significantly exceeds offline spending for these products. So much so, for instance, that more clothing is now purchased online than offline in our data as a result of the pandemic.

Given this increase, online retail is another technological shift driven by the pandemic that can affect the growth of establishments across space that we document. As with the earlier growth of online retail in the more tradable products, additional increases in spending online for general goods, home goods, and clothing could contribute to the continued depression in establishment growth in these products. But online groceries and restaurants, the products with the most growth during the pandemic, still have a large non-tradable component – in most cases fulfilling those online orders relies on local grocery stores and local restaurants. Thus, this type of online retail growth may actually be supportive of the local establishments growth we observe in suburban locations. Complementary effects across products through channels like time use, may also play a role (Relihan 2022).
5.6  Additional supporting figures and tables

Figure A.9: Example city maps with region classification

**Notes:** This figure shows ZIP codes in each region of example cities defined with our scaled distance from 0 to 1, where ZIPs at the center have a distance of 0 and the furthest ZIPs have a distance of 1. As shown in these examples, the first three inner regions consistently create well-populated rings of ZIP codes. The outer suburbs are then comprised of a more sparse set of ZIP codes which are the farther from the city center but often disconnected from each other due to the shape of the CBSA boundary.

**Sources:** JPMorgan Chase, Census.

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Figure A.10: Extended time series for population and establishment growth within cities

Notes: This figure shows an extended time series for Figure 3. Growth is relative the same quarter in 2018. Sources: JPMorgan Chase, Census.

Figure A.11: Growth in concentration of entries and exits

Notes: This figures shows the average growth in the HHI for entry (exit) of establishments across cities based on the share of entry (exit) for each zip code out of all entry (exit) in its respective city. Growth is relative to the same quarter in 2019. Sources: JPMorgan Chase.
Figure A.12: WFH employment and residential exposure by distance

Notes: This figure shows a smoothed scatterplot of the percent of jobs and workers likely to transition to remote work in ZIP codes by scaled distance from city center. Remote work-exposed industries are in NAICS codes 51, 52, 54, and 55 as in Althoff et al. (2022). Bootstrapped 95% confidence intervals are shown in the shaded region. Along both margins, downtown cores were more than twice as exposed as areas at the city edge. Furthermore, in this sample of large cities, it was generally the case that more of the workers than the jobs in each location were exposed to WFH.

Sources: JPMorgan Chase, American Community Survey.

Electronic copy available at: https://ssrn.com/abstract=4466607
Table A.1: Decomposition analysis of establishment growth over time

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<td>Population growth (%)</td>
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<td>0.353**</td>
<td>0.333***</td>
<td>0.419***</td>
<td>0.303**</td>
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<td>(0.153)</td>
<td>(0.120)</td>
<td>(0.134)</td>
<td>(0.123)</td>
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<tr>
<td>WFH residential exposure (%)</td>
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<tr>
<td></td>
<td>-0.222*</td>
<td>-0.318***</td>
<td>-0.305**</td>
<td>-0.251**</td>
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<td>(0.118)</td>
<td>(0.117)</td>
<td>(0.119)</td>
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<td>WFH employment exposure (%)</td>
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<td>-0.104**</td>
<td>-0.107***</td>
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<td>(0.046)</td>
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<td>Online spending growth (%)</td>
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<td></td>
<td>0.030</td>
<td>-0.008</td>
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<td>(0.024)</td>
<td>(0.034)</td>
<td>(0.033)</td>
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<tr>
<td>Offline spending growth (%)</td>
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<td>0.087</td>
<td>0.034</td>
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<td>(0.078)</td>
<td>(0.090)</td>
<td>(0.105)</td>
<td>(0.119)</td>
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<td>Non-white residents (%)</td>
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<td></td>
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<td>-0.040***</td>
<td>-0.009</td>
<td>-0.001</td>
<td>-0.028</td>
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<td>(0.015)</td>
<td>(0.024)</td>
<td>(0.030)</td>
<td>(0.021)</td>
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<tr>
<td>Median income ($1000s)</td>
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<tr>
<td></td>
<td>0.041***</td>
<td>0.037**</td>
<td>0.069***</td>
<td>0.048**</td>
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<td>(0.010)</td>
<td>(0.018)</td>
<td>(0.026)</td>
<td>(0.023)</td>
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<td>Mean</td>
<td>-4.03</td>
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<td>3,649</td>
<td>3,651</td>
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<tr>
<td>$R^2$</td>
<td>0.125</td>
<td>0.113</td>
<td>0.114</td>
<td>0.072</td>
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<tr>
<td>Adjusted $R^2$</td>
<td>0.120</td>
<td>0.107</td>
<td>0.108</td>
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</table>

Notes: Growth is relative to the same quarter in 2019. All models include CBSA fixed effects. Standard errors in parentheses and clustered at the city level. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level.

### Table A.2: Decomposition analysis of Q4 2019 - Q4 2021 establishment growth by product

<table>
<thead>
<tr>
<th></th>
<th>Grocery</th>
<th>General</th>
<th>Clothing</th>
<th>Rest.</th>
<th>Home</th>
<th>Personal</th>
<th>Leisure</th>
<th>Prof.</th>
<th>Pharmacy</th>
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<td>Downtown core</td>
<td>2.491</td>
<td>4.383*</td>
<td>13.055*</td>
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<td>0.683</td>
<td>2.929**</td>
<td>5.273</td>
<td>1.293</td>
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<td>(1.708)</td>
<td>(2.442)</td>
<td>(7.128)</td>
<td>(1.513)</td>
<td>(1.974)</td>
<td>(1.462)</td>
<td>(3.877)</td>
<td>(2.369)</td>
<td>(1.861)</td>
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<td>Population growth (%)</td>
<td>0.350*</td>
<td>-0.012</td>
<td>0.623**</td>
<td>0.257*</td>
<td>0.224***</td>
<td>0.123</td>
<td>0.539***</td>
<td>0.230*</td>
<td>-0.336*</td>
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<tr>
<td>(0.191)</td>
<td>(0.145)</td>
<td>(0.263)</td>
<td>(0.134)</td>
<td>(0.084)</td>
<td>(0.133)</td>
<td>(0.171)</td>
<td>(0.132)</td>
<td>(0.182)</td>
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<td>WFH residential exposure (%)</td>
<td>-0.235</td>
<td>-0.569***</td>
<td>-0.643**</td>
<td>-0.263*</td>
<td>-0.069</td>
<td>-0.293***</td>
<td>-0.329</td>
<td>0.089</td>
<td>-0.019</td>
</tr>
<tr>
<td>(0.211)</td>
<td>(0.215)</td>
<td>(0.275)</td>
<td>(0.142)</td>
<td>(0.079)</td>
<td>(0.095)</td>
<td>(0.282)</td>
<td>(0.090)</td>
<td>(0.123)</td>
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<tr>
<td>WFH employment exposure (%)</td>
<td>-0.011</td>
<td>0.138</td>
<td>0.133</td>
<td>-0.334***</td>
<td>0.018</td>
<td>-0.022</td>
<td>-0.053</td>
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<tr>
<td>(0.072)</td>
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<td>(0.253)</td>
<td>(0.066)</td>
<td>(0.075)</td>
<td>(0.071)</td>
<td>(0.134)</td>
<td>(0.082)</td>
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<tr>
<td>Online spending growth (%)</td>
<td>0.0002</td>
<td>-0.025</td>
<td>0.002</td>
<td>-0.014</td>
<td>-0.008</td>
<td>-0.012</td>
<td>0.050</td>
<td>0.016</td>
<td>0.002</td>
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<td>(0.011)</td>
<td>(0.038)</td>
<td>(0.045)</td>
<td>(0.014)</td>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.067)</td>
<td>(0.013)</td>
<td>(0.006)</td>
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<tr>
<td>Offline spending growth (%)</td>
<td>0.050</td>
<td>0.085</td>
<td>0.189**</td>
<td>0.020</td>
<td>0.072*</td>
<td>0.187*</td>
<td>-0.003</td>
<td>0.022</td>
<td>0.195***</td>
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<tr>
<td>(0.136)</td>
<td>(0.090)</td>
<td>(0.081)</td>
<td>(0.090)</td>
<td>(0.039)</td>
<td>(0.098)</td>
<td>(0.017)</td>
<td>(0.027)</td>
<td>(0.063)</td>
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<tr>
<td>Non-white residents (%)</td>
<td>0.038</td>
<td>-0.028</td>
<td>0.064</td>
<td>0.002</td>
<td>0.077</td>
<td>-0.141***</td>
<td>0.149***</td>
<td>-0.098**</td>
<td>-0.026</td>
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<tr>
<td>(0.032)</td>
<td>(0.031)</td>
<td>(0.070)</td>
<td>(0.024)</td>
<td>(0.059)</td>
<td>(0.031)</td>
<td>(0.047)</td>
<td>(0.040)</td>
<td>(0.023)</td>
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<tr>
<td>Median income ($1000s)</td>
<td>0.183***</td>
<td>0.173***</td>
<td>0.035</td>
<td>0.092**</td>
<td>0.032</td>
<td>0.032</td>
<td>0.101**</td>
<td>-0.067***</td>
<td>-0.009</td>
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<tr>
<td>(0.063)</td>
<td>(0.030)</td>
<td>(0.067)</td>
<td>(0.038)</td>
<td>(0.020)</td>
<td>(0.025)</td>
<td>(0.044)</td>
<td>(0.023)</td>
<td>(0.017)</td>
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</table>

<table>
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<tr>
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<th>Observations</th>
<th>R²</th>
<th>Adjusted R²</th>
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<td>0.045</td>
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<td>0.81</td>
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<td>0.026</td>
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<td>1.85</td>
<td>2,888</td>
<td>0.026</td>
<td>0.006</td>
</tr>
</tbody>
</table>

**Notes:** All models include CBSA fixed effects. Standard errors in parentheses and clustered at the city level. *** significant at the 1 percent level, ** significant at the 5 percent level, and * significant at the 10 percent level. Online and offline spending growth is with regard to the same product type of the dependent variable, rather than overall spending by channel. Sources: JPMorgan Chase, American Community Survey, and Longitudinal Employer-Household Dynamics Local Origin-Destination Employment Statistics.

Electronic copy available at: https://ssrn.com/abstract=4466607
References


