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ABSTRACT

We document that, after remaining almost constant for almost 30 years, real labor productivity at U.S. restaurants surged over 15% during the COVID pandemic. This surge has persisted even as many conditions have returned to pre-pandemic levels. Using mobile phone data tracking visits and spending at more than 100,000 individual limited service restaurants across the country, we explore the potential sources of the surge. It cannot be explained by economies of scale, expanding market power, or a direct result of COVID-sourced demand fluctuations. The restaurants' productivity growth rates are strongly correlated, however, with reductions in the amount of time their customers spend in the establishments, particularly with a rising share of customers spending 10 minutes or less. The frequency of such 'take-out' customers rose considerably during COVID, even at fast food restaurants, and never went back down. The magnitude of the restaurant-level relationship between productivity and customer dwell time, if applied to the aggregate decrease in dwell time, can explain almost all of the aggregate productivity increase in our sample.

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Restaurants (NAICS 722: Food Services and Drinking Places) employ about 7 percent of private nonfarm workers in the U.S., the second-largest among all 3-digit NAICS industries.

Though it is massive, the industry is not known for rapid technological change. Indeed, real labor productivity had been flat for decades in restaurants even as it steadily grew for the rest of the economy.

Yet in 2020, after a brief, utilization-related productivity dip during the initial COVID shock, the industry experienced a startling surge in productivity to a level some 15% higher than the pre-COVID steady state that had prevailed for decades. This surge has persisted even as overall economic conditions seemed to return to normal.

In this paper we document this productivity surge and examine it using micro-level data on mobile phone visits for over 100,000 restaurants across the U.S. While not without noise, the private sector microdata generally exhibit output and employment patterns broadly consistent with industrywide numbers from the official government statistics. Importantly, though, these microdata allow us to go beyond the industry aggregate to better understand the potential mechanisms driving the surge. To this end, we focus in particular on the limited service (i.e., fast food) segment of the restaurant industry, where our microdata have fairly comprehensive information on not just visits but customer spending as well.

The microdata reveal significant productivity growth among individual restaurants whether measured in sales per employee or even in a more basic/physical measure of total consumer visits per employee.

We show that in our micro data, the productivity surge cannot be explained by economies of scale, rising restaurant market power, or as the direct result of COVID demand shifts.

However, we do find evidence in the microdata tying productivity growth to significant drops in the amount of time customers spend in restaurants, especially to increases in the fraction of customers visiting for 10 minutes or less. The observed decrease in customer dwell times fell during COVID and did not go back up to pre-pandemic levels even when other economic conditions re-normalized. We believe this growth in short-visit customers represents rising demand for take-out/delivery and additional outside data documents the rise of such demand.

This relationship between shorter dwell times and productivity growth is present in both industry-wide trends and in restaurant-level patterns. Across the 100,000+ individual restaurants in our data, measured productivity growth rates are strongly correlated with the reductions in customer dwell times they experience. In fact, the magnitude of the cross-sectional relationship, if applied to aggregate changes in dwell times, is large enough to explain virtually the entire surge in restaurant productivity.

This paper has some antecedents in a small restaurant economics literature that has studied aspects of productivity—e.g., Reynolds and Thompson (2007); Reynolds and Biel (2007); and Shimmura, Ichikari, Okuma, Ito, Okada, and Nonaka (2020). It is also related to work exploring various productivity patterns during and after the COVID pandemic, like Bloom, Bunn, Mizen, Smietanka, and Thwaites (2023); Dao and Platzer (2024); Igan, Rosewall, and Rungcharoenkitkul (2024); and Lalinsky, Meriküll, and Lopez-Garcia (2024).

1. The Aggregate Surge in Restaurant Productivity

Figure 1 shows the remarkable shift in restaurant productivity after years of stagnation. It plots monthly real sales per employee in the industry from the beginning of 1992 to the present (in annualized terms).[2] The numerator of this labor productivity measure divides the NAICS 722's seasonally-adjusted nominal sales from the monthly U.S. Census Monthly Retail Trade Survey report, by the seasonally adjusted CPI for food and drink away from home in 2024 dollars (and then multiplies by 12 to annualize it). The denominator is seasonally adjusted total industry employment from the

[2] Electronic retail sales data begin in 1992.

monthly Current Employment Survey data from the U.S. Bureau of Labor Statistics.[3]

From 1992 to 2019, industry labor productivity had no real trend. (For simplicity, we normalize real annualized sales per employee to 100 for its average value in the sample's first year, which was about $80,000 in 2024 dollars.) The arrival of the COVID pandemic saw a brief but large productivity drop—more than 20 percent below the previous level. Very quickly, though, the first wave of the pandemic subsided and productivity surged. It did not return to the previous level, however, but ended up 15 percent higher and has remained there since. This 15 percent growth in real sales per employee splits roughly into about 20 percent higher real sales and 5 percent more employees than their 2015-19 averages.

The growth in sales per employee did not come from employees working longer hours. Average weekly hours in the industry in the 24 months from July 2022 through June 2024 were 25.1, the same as in the first 24 months from March 2006 through February 2008 (when the CES series began reporting weekly average hours per employee). In fact, current hours per worker are actually a bit below the 2018-19 pre-COVID average of 25.6 hours per week.

To better understand the nature of this productivity surge, we need microdata on restaurants. For that, we turn to mobile phone records.

2. Microdata on Restaurants

Our primary microdata come from two datasets compiled by SafeGraph's *Monthly Patterns* and *Spend* data products.[4] Both of these datasets contain

[3] The nominal sales data can be found at https://www.census.gov/retail/sales.html. The industry CPI is at https://www.bls.gov/cpi/data.htm (series CUSR0000SEFV), and industry employment is at https://www.bls.gov/ces/ (series CES7072200001).

[4] These data were made available by Advan Research (https://advanresearch.com/) and SafeGraph (https://www.safegraph.com/) via the Dewey Data platform (https://www.deweydata.io/).

monthly data for specific points of interest (POIs) in the United States, including restaurants and other food service establishments.[5]

The *Monthly Patterns* dataset contains foot traffic data derived from a panel of opted-in mobile devices extending from January 2019 to December 2022. Over this time period the panel had a daily average of nearly 17 million devices recording at least one restaurant visit. (See the appendix for "visit" definitions.) The data aggregate the phone-specific visit patterns to the restaurant-month level. This restaurant panel contains information on the total number of visits to that restaurant in that month, a categorical distribution of customer visit times, and the times of day when these visits occur.

SafeGraph's *Spend* dataset contains debit and credit card transaction data from a panel of monthly active bank and credit cards in the United States ranging from January 2019 to the present. From 2019 through 2022, the *Spend* data record an average of 180 million transactions per month from over 10 million customers at various restaurants. Because the *Spend* data uses the same POI identifiers as the *Monthly Patterns* data, we can merge the two datasets into a restaurant-month panel dataset of foot traffic and spending.

The *Spend* data covers major national brands disproportionately, making it much more representative for limited-service/fast-food restaurants than full-service restaurants. We therefore restrict the sample to POIs reporting NAICS codes corresponding to limited-service eating places (NAICS 722513, 722514, and 722515) and associated with a brand for which there is non-missing visit and spend data. This encompasses three subcategories: limited-service restaurants (e.g., Taco Bell, McDonalds); cafeterias, grill buffets, and buffets (e.g., Hartz Chicken Buffet); and snack and nonalcoholic beverage bars (e.g., Starbucks). Our final sample contains over 100,000 unique restaurants from over 600 distinct brands. From January 2019 to December 2022, our sample captures a total of about $24 billion in nominal sales.

[5] These are the same data used in research studies like Alcott et al. (2020), Cronin and Evans (2021), Goolsbee and Syverson (2021), Alexander and Karger (2023), and Zheng et al. (2024).

Neither the *Monthly Patterns* nor *Spend* data include a direct measure of restaurant employment. However, we do know visit lengths, and the longest visit length category in the data counts those over four hours long. We take visits over four hours in length during the month as a measure of the number of employee-shifts at the restaurant.[6]

For consumer visits, we have data on visit length for four categories of dwell times under four hours: 0-10 minutes, 11-20 minutes, 21-60 minutes, and 61-240 minutes (we combined less than 5 minute and 5-10 minute visits for the shortest category and the 61-120 minute and 121-240 minute categories for the longest).

3. Comparing Industry Aggregates and SafeGraph Data

The SafeGraph data cover a large number of establishments in many different geographic markets and subsectors within the restaurant industry, allowing us a more granular view than available in the official government aggregate statistics. However, they were not designed to be a representative sample of U.S. restaurants. To get a sense of how similar the Safegraph sample might be relative to the sector at large, we create aggregates from our sample and compare them to is to the industry's broader trends as reported in the official government statistics.

First note that limited service eating places, which comprise about 45 percent of industry employment and sales, saw very similar productivity movements to the overall restaurant industry over the past several decades, as shown in Appendix Figure A1 for annualized real sales per employee (both

[6] The four-hour cutoff to measure employees is, of course, arbitrary. However, our results are not sensitive to using a two-hour cutoff instead. Furthermore, we checked shift length data from Homebase spanning January 2018 to the end of the Safegraph sample period. Homebase provides employee scheduling and time tracking software and is used most frequently by owner-managed restaurant, retail, and service businesses. Restaurants in the Homebase sample indicate only about 10 percent of employee shifts in restaurants are less than four hours long, and these shifts in aggregate account for less than 5 percent of total reported employee-hours in the industry. The Homebase data also indicate virtually no change in average shift length over the sample, remaining near 6.8 hours throughout.

series indexed to their 1992 averages).[7] The correlation coefficient between the two series' year-over-year growth rates is 0.83.

Figure 2 plots the aggregated sum of monthly visitors, spending, and employees from SafeGraph. These SafeGraph aggregates track the official Census and BLS aggregates. The correlation between the monthly growth rates of Census real sales and our visits and spending data are respectively 0.88 and 0.72. The correlation between monthly growth rates of BLS employment and implied employees in SafeGraph is 0.63.

Figure 2 shows one complication with the SafeGraph sample. In May of 2022, following some media scrutiny of the cell phone tracking industry overall, one of the providers of mobile data to SafeGraph introduced a processing change to improve privacy protection. In our SafeGraph aggregates, this seems to have generated a discrete drop in the overall number of reported customer visits and an increase in the share of visits lasting more than four hours (which we are counting as employees). This caused an abrupt shift in the levels of our productivity measures starting that month. We have demarcated the time of this shift in our figures for reference. Nevertheless, despite this anomaly, the correlations reported above indicate that the SafeGraph data still capture a notable share of movement in the Census/BLS-based series.

One other caveat is that the SafeGraph-tracked restaurants have less entry and exit than the official statistics imply for the overall industry. The Census Business Dynamic Statistics (BDS) average annual establishment entry and exit rates for Restaurant and Other Eating Places (NAICS 7225) from 2020-22 are 10.3% and 9.4%. The average annual entry and exit rates for the SafeGraph microdata for the same period are 6.1% and 2.0%. That may reflect lower turnover and higher survival rates for national brands, but regardless, it

[7] Both series here use non-seasonally adjusted sales and employment data, because seasonally adjusted sales are not separately reported for limited service establishments. The series are deflated using the seasonally unadjusted CPI for food away from home. The BLS does issue a CPI series separately for limited service food, but it did not begin until 1998. Using that in the shorter sample also indicates the two series are quite similar.

means our sample includes more continuing/surviving restaurants than is true for the industry as a whole.

As an independent check on the SafeGraph data, we also obtained the Restaurant Performance Index data from the National Restaurant Association (NRA). These include a series of diffusion indexes reflecting surveyed restaurants' growth of same-store sales, customer traffic, and labor. We constructed analogous diffusion indexes of restaurant-monthly changes in our limited-service establishment sample for these three indexes. The correlations between the growth of the SafeGraph and NRA same-store sales, customer traffic, and labor diffusion indexes were respectively 0.47, 0.78, and 0.69.

The SafeGraph aggregates therefore give us some comfort that the microdata are worth exploring more deeply.

4. Explaining the Surge in Productivity

Some potential explanations for the productivity surge fall apart almost as soon as we look at the data.

First, any explanation mechanically tying productivity to the collapse of demand during COVID would not explain the sustained rise in productivity because that collapse was temporary. Indeed, as mentioned above, real consumption in the industry is currently about 20 percent above its level in the years prior to the pandemic.

Second, scale economies within restaurants cannot explain the productivity change. If COVID-related failures meant that resurgent demand led surviving restaurants to become larger and benefit from increasing returns to scale in their production processes, it would raise output per unit labor (though would not correspond to TFP growth). This didn't happen. Figure 3 shows the average employment of the restaurants in the SafeGraph sample. Average employment per restaurant dipped at the onset of the pandemic and recovered after but did not return to its pre-pandemic average until early 2022, well after the productivity surge in early 2021. This is further confirmed in Census County Business Patterns data, where the overall restaurant industry averaged 17.9 employees per establishment in 2022 (the latest data available), smaller than the 2019 average of 19.0 employees per establishment.[8]

Nor does a shift in market power seem to be at work. We deflate the *Spend* data by the CPI series for Limited Service Meals and Snacks. If the price index accurately reflects any change in prices separate from changes in real quantity or quality, the observed growth in spend-based productivity reflects growth in real output per unit labor. But even if CPI does not perfectly capture market-power-based markup changes (thereby allowing some price increases to "leak" into implied real spending), we have the advantage here of observing raw customer visits in the *Monthly Patterns* data. This is a proxy for real output that does not depend on the accuracy of the price series. As we describe below, we observe similar patterns in both the spending- and visits-based productivity measures.

Role of Short Dwell Time Customers

Having dismissed these candidate explanations, we note a persistent change to the restaurant business during this time that is readily apparent in the SafeGraph microdata: consumers are spending less time in restaurants when they visit.

Figure 4 shows this evolution by plotting the shares of visits in each of the reported categories (except the over 4-hour category we impute to be employees). Average customer dwell times fell, and most of the reduction came from the rise in the share of the visits lasting less than 10 minutes. This share had been steady before the pandemic at about half (recall that our sample is limited-service restaurants, where sit-down meals are not the modal customer experience). The share jumped substantially as the pandemic began and rose

[8] We don't have a measure of total hours in our SafeGraph data, as employee-shifts are measured by their (common) categorical dwell time. However, the fact that industry-wide productivity measured as real sales per hour exhibited the same patterns as real sales per employee (due to steady hours per worker) means we are not missing an hours-based change in operating scale.

steadily thereafter, ending the sample at over 60 percent. Most of this initial jump in short-visit share came at the expense of visits lasting 21-60 minutes, but all three categories of over-10-minute visits saw declines over the course of the sample.[9]

This pattern is consistent with faster service times for customers or an increase in take-out meals and delivery service at sample restaurants. If the increase in under-10 minute visits reflects decreased service times among all customers, however, one might expect at least some of the growth would come out of 11-20 minute visits. This is not what happened in the data, however. The 11-20 minute visit share did not fall at all when the share of under-10-minute visits jumped. In fact, it increased slightly.

As a result, we think the growth in take-out or delivery is the primary driver of the jump in short visits. With take-out, the customer orders on their phone and then comes into the restaurant to pick it up without eating there. With delivery, the customer orders food to be delivered to their home either from a food app like Grubhub or directly from the restaurant itself as with a Domino's Pizza. It is important to recognize that either of these things connotes a substitution of home production for restaurant labor. The customer cleans up after themselves and washes their own dishes, for example. And delivery services substitute for the customer traveling themselves. But they are still, from the restaurant's perspective, just a new stream of demand. If the restaurant can satisfy such quick-turn customers in addition to their regular customers with the same labor force, that would show up in the data as a clear, legitimate increase in their productivity.[10]

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[9] If we impute customers' visit lengths as the median value of their categorical endpoints and average these across all observations, this average time per visit fell about 16 percent between the pre-COVID period and the end of our sample.

[10] A useful feature of having a sample here exclusively of limited service restaurants is that there is less of any such potentially confounding substitution to home production, as the scope of normally provided in-restaurant services is narrower (e.g., no table service by definition, less dishwashing, etc.). In any case, the total welfare implications of the shift toward home production would be more complex than just the cost effects of productivity improvement.

The industry data we could find backs up the idea that take-out grew significantly. Appendix Figure A3 shows usage of food delivery apps in the Global Wireless Solutions' Magnify data, an app usage dataset derived from an opt-in consumer panel of U.S. Android smartphone users. Delivery app use surged at exactly the same time as the surge in short visits in the SafeGraph data, and it has not fallen since. We can also see in Appendix Figure A3 that usage of the apps by drivers (i.e., the delivery people themselves) also surged and has remained elevated.

Next, we examine the SafeGraph microdata to see if these aggregate relationships between the rise of take-out and the growth of productivity hold at the restaurant level. We regress restaurants' logged productivity (measured as real spending per employee, though we obtain similar results of we use customer visits per employee) in a month on restaurant fixed effects, indicators for each sample month, and the shares of a restaurant's customers staying various amounts of time (the excluded category is the share spending 61-120 minutes).

Table 1 reports the results. Column 1 shows the estimates for our entire sample. We see that within restaurants, a greater share of customers spending any amount of time less than 61 minutes in the restaurant corresponds to significantly higher productivity, but this is most so for the share spending 10 minutes or less. In fact, holding constant the 61-120 minute share but reallocating share from either 11-20 minutes or 21-60 minutes into 0-10 minutes also correlates with increased productivity.

The lower panel of Table 1 shows the observed change in dwell time shares (and the implied change in average dwell time as calculated above) over the sample. To obtain a sense of the magnitude of the relationship between productivity and customer dwell time, we calculate the total implied productivity change based on the regression coefficients and the observed

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Examining this quantitatively would require measures of consumers' disutility from home production, which is beyond the scope of our study.

change in shares. This is shown in the bottom row of the table. We calculate total implied productivity growth of 11.3 percent, similar in magnitude to the observed change in industry aggregates. Interestingly, this quantitative similarity holds even though the estimated relationship here relies only on variation in productivity growth and changes in dwell time across restaurants, not any average changes over time. Therefore this mechanism, if causal and operating in the same magnitude across time when aggregated as it does across the restaurant panel, explains much of the observed aggregate increase in productivity.

To obtain a sense as to the generality of this result across the industry, we repeat the regressions separately for each of the top five quick-service chains in the SafeGraph data: McDonald's, Chick-fil-A, Taco Bell, Wendy's, and Burger King. The results are reported in columns 2-6 of Table 1. The same patterns hold in each case. Within McDonald's restaurants, for example, the locations with the largest increase in short-stay customers saw the most productivity growth. The implied total productivity change from this shift, 22.5 percent, is about twice as large as for the overall sample. In fact, each of the top five chains saw implied productivity growth that was larger than for the overall sample.

We include additional analyses in the Appendix to accompany these main results. Figure A4 shows more temporal detail in the estimated average productivity effect by calculating for each restaurant-month the difference between a restaurant's observed productivity level and its counterfactual productivity level had its customer visit length shares remained at pre-COVID values. We then aggregate this difference to obtain the plotted time path of the implied productivity level due to dwell time changes for the entire sample.

Table A1 extends the chain-specific analysis to the next six largest chains, which includes a variety of formats: Starbucks, Dunkin', Subway, Chipotle, Domino's, and Pizza Hut. All chains' estimates and observed dwell time share changes imply productivity growth, though with considerable variation. The implied changes for coffee shops are larger than for the overall sample, they are somewhat smaller for the sandwich/burrito chains, and rather modest for the pizza chains. Figure A5 is the same plot as Figure A4, but constructed for these additional chains.

Finally, Figure A6 plots the analogous results to Figure A4, except measuring restaurants' productivity levels as customer visits per employee rather than real spending per employee. While the implied changes in aggregate productivity measured this way are somewhat smaller than for spending-based productivity, overall patterns are similar along multiple dimensions, including the notable variation in implied changes across restaurant chains.

5. Conclusion

Restaurants experienced a persistent surge in productivity coming out of COVID that contrasted strongly to the multi-decade productivity stagnation that preceded it. Micro data on consumers suggests that this surge was strongly correlated with the rise in take-out and delivery customers staying only a short time in the restaurant.

This striking result of a one-time surge in the level of productivity where the "technology" of customer demand may have changed during COVID calls for future research into other industries that may have experienced similar bursts of service-sector productivity.

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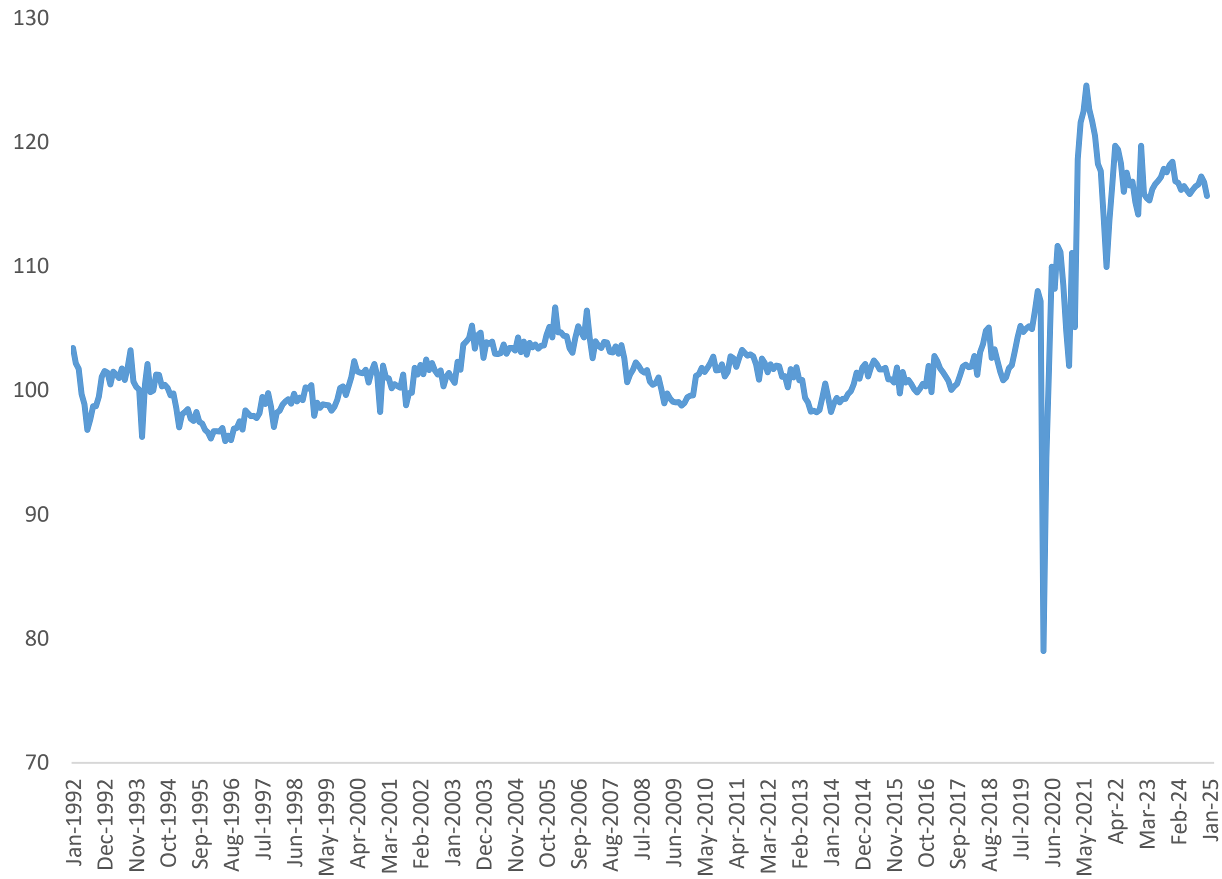
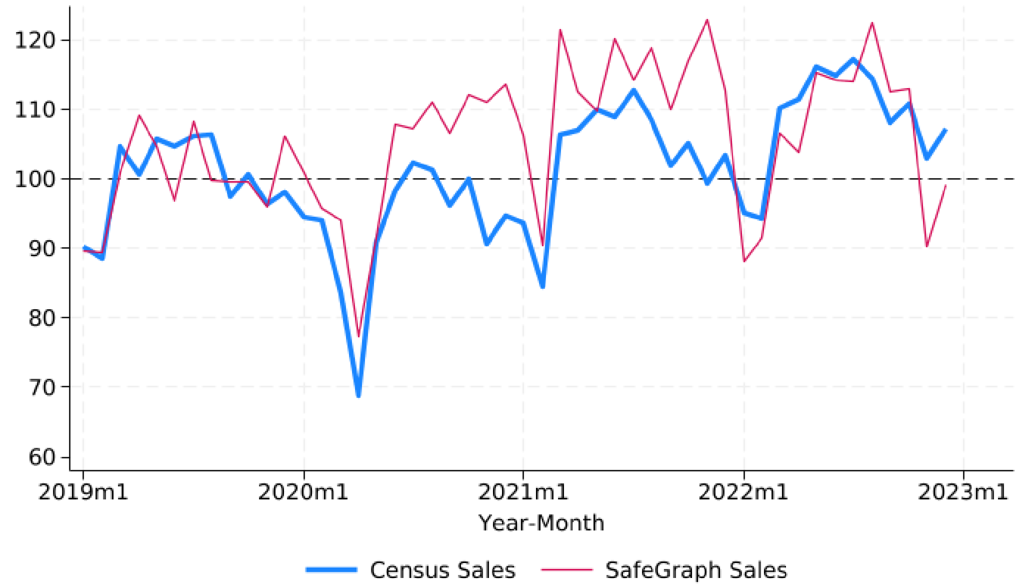
Figure 1. Annualized Real Sales per Employee (1992=100), Food Services and Drinking Places, Seasonally Adjusted



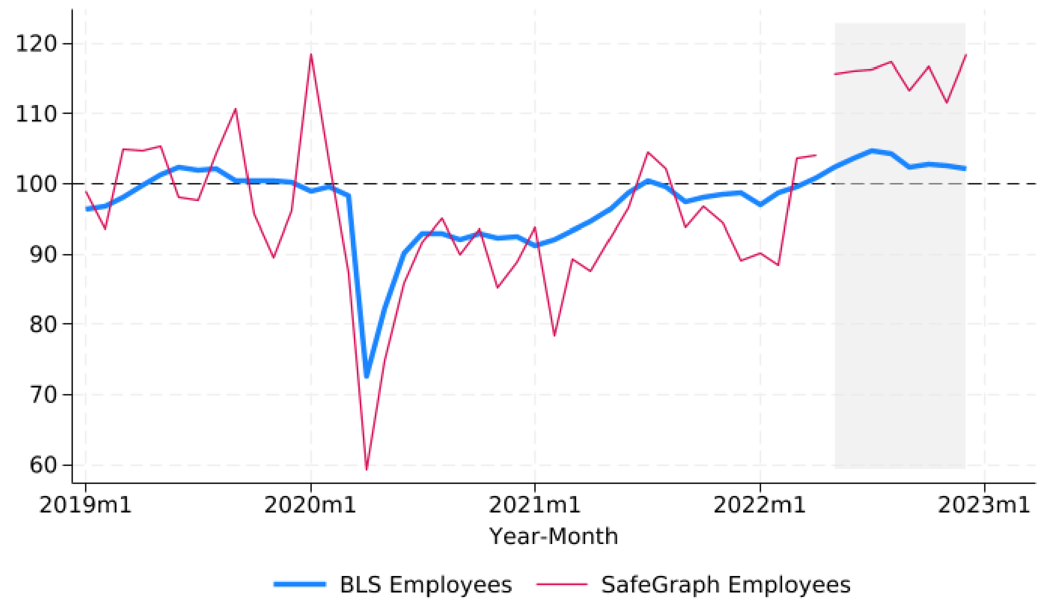
Notes: Figure shows an index (1992 = 100) of annualized monthly real sales per employee for the Food Services and Drinking Places industry. Nominal seasonally adjusted sales are from the Census Monthly Retail Trade Survey report. Real sales obtained by deflating by CPI series for food away from home. Seasonally adjusted employment from the Bureau of Labor Statistics.

Figure 2. SafeGraph and Census/BLS Aggregates (2019 Averages = 100)

Panel A. Aggregate Sales

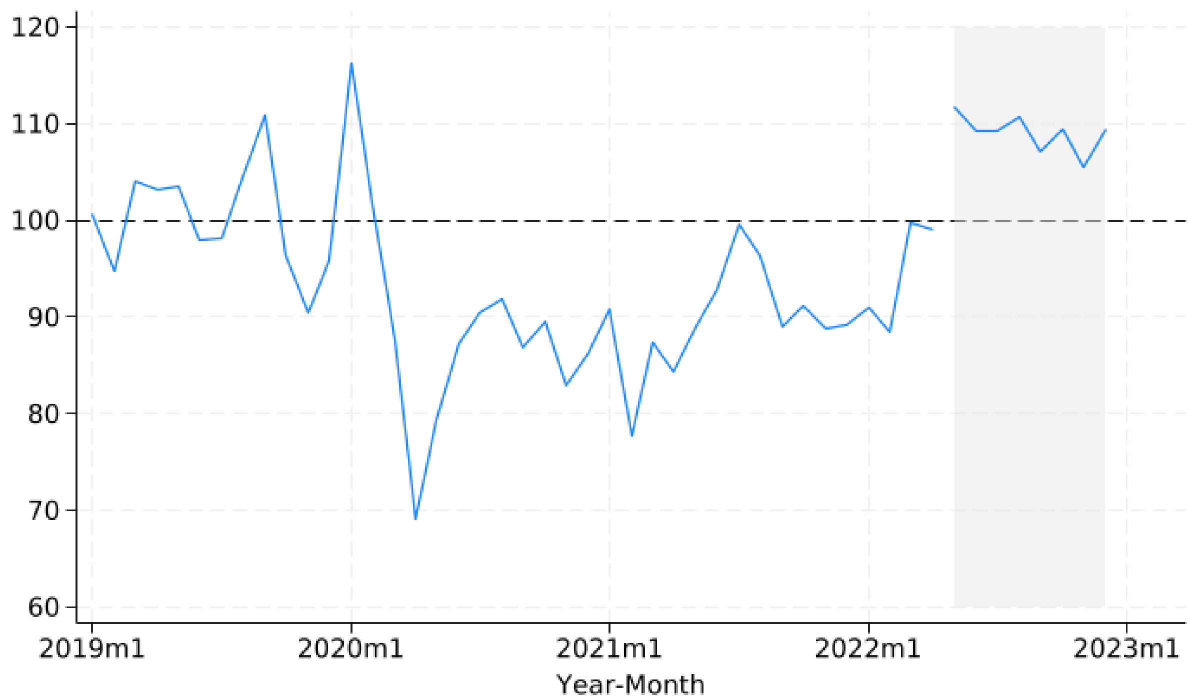


Panel B. Aggregate Employees



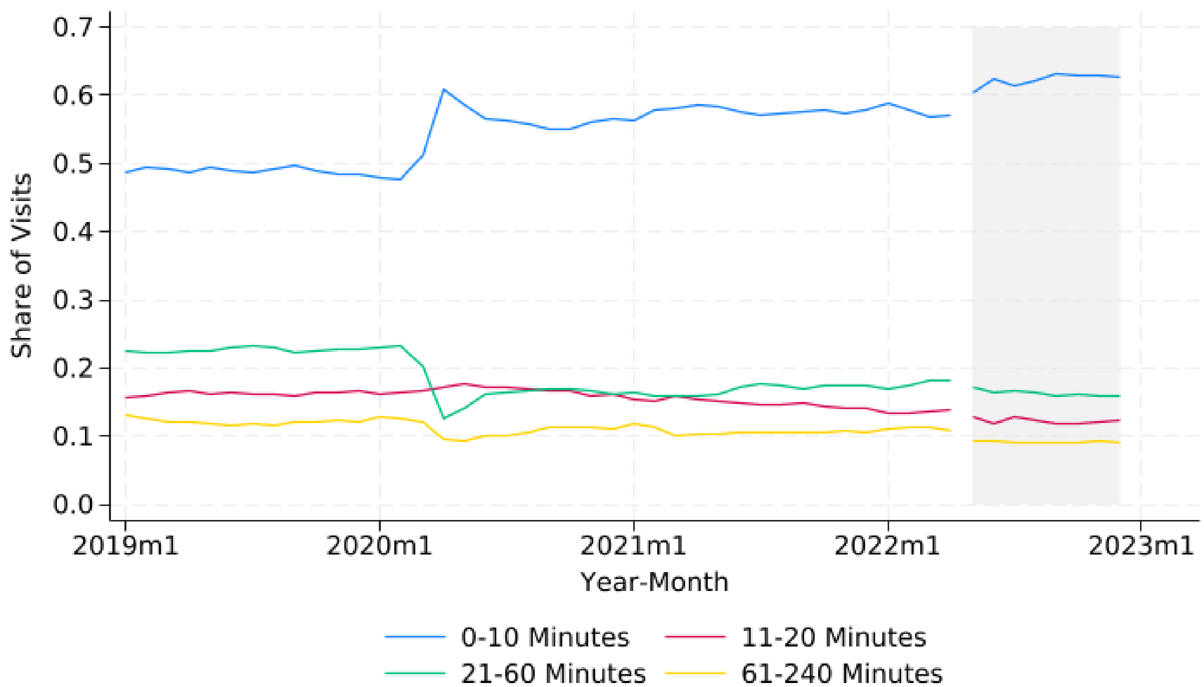
Notes: Figure compares indexes (1992 = 100) of aggregated monthly totals from our restaurant panel to reported aggregates for limited-service eating places industries (NAICS 722513, 722514, and 722515). Panel A compares sales in panel to those from Census Monthly Retail Trade Survey report. Both series are not seasonally adjusted and deflated using the CPI series for Limited Service Meals and Snacks. Panel B compares NSA employment from panel to that reported by the Bureau of Labor Statistics. The shaded area indicates period after processing changes in SafeGraph's *Monthly Patterns* caused a discontinuity in visits data.

Figure 3. Average SafeGraph Employment per Restaurant (2019 Average = 100)



Notes: Figure shows index (1992 = 100) of average employment per restaurant in our restaurant panel. The shaded area indicates period after processing changes in SafeGraph's *Monthly Patterns* caused a discontinuity in visits data.

Figure 4. Average Customer Visit Dwell Time Shares



Notes: Figure shows average share of panel restaurants' customer visits by dwell time category. The shaded area indicates period after processing changes in SafeGraph's Monthly Patterns beginning in May 2022.

Table 1. Dwell Time Changes and Productivity (Real Spending per Employee)

	(1) All Restaurants	(2) McDonald's	(3) Chick-fil-A	(4) Taco Bell	(5) Wendy's	(6) Burger King
0-10 Minutes	4.280	8.734	4.638	9.852	10.55	8.539
	(0.024)	(0.294)	(0.441)	(0.332)	(0.352)	(0.220)
11-20 Minutes	3.661	7.926	3.747	9.244	9.393	7.610
	(0.028)	(0.281)	(0.469)	(0.361)	(0.365)	(0.245)
21-60 Minutes	3.339	8.589	3.559	8.929	10.15	7.929
	(0.029)	(0.399)	(0.515)	(0.400)	(0.411)	(0.277)
N	5,714,426	580,953	88,527	253,143	227,246	233,793
R^2	0.66	0.68	0.78	0.64	0.68	0.61

Average dwell time category share change from 2019 to April 2022 and implied productivity change:

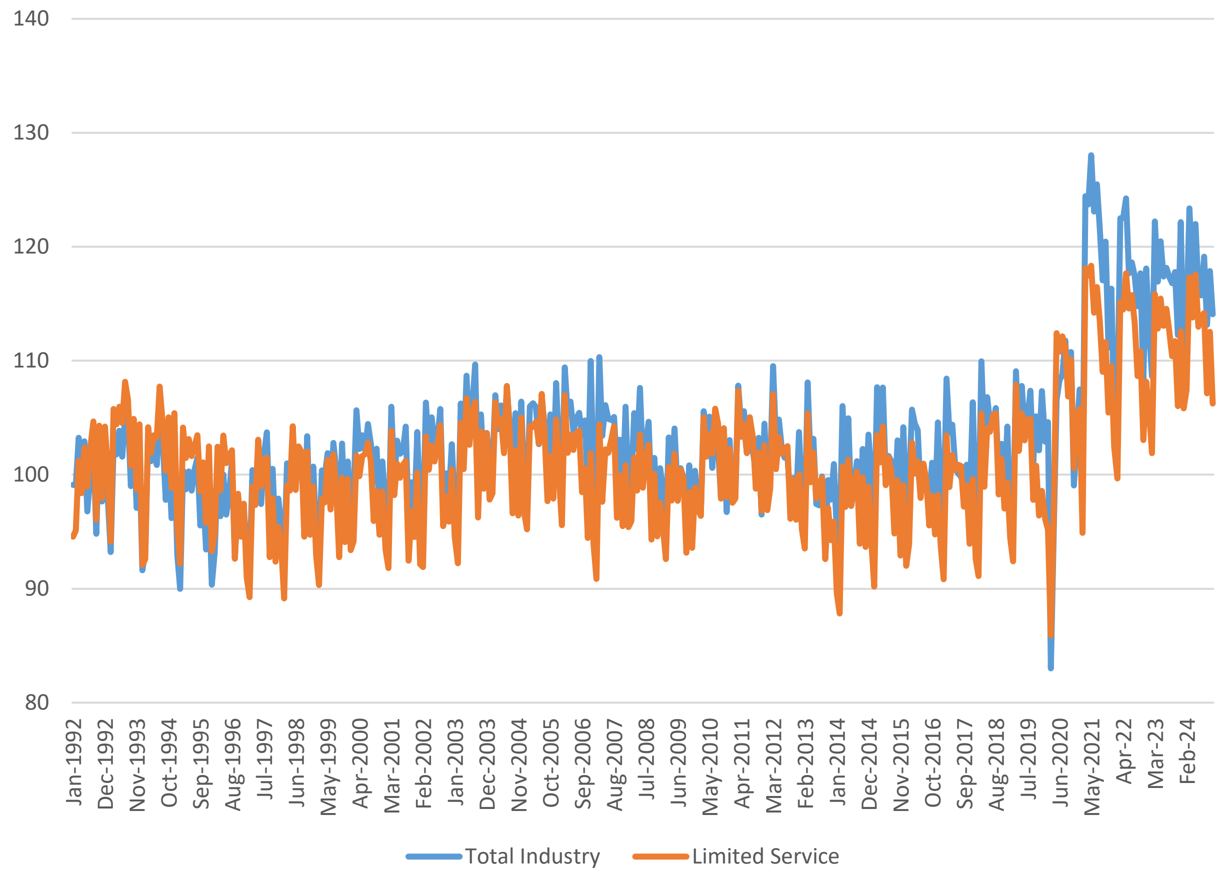
	(1) All Restaurants	(2) McDonald's	(3) Chick-fil-A	(4) Taco Bell	(5) Wendy's	(6) Burger King
0-10 Minutes	0.081	0.099	0.088	0.104	0.121	0.116
11-20 Minutes	-0.023	-0.013	0.004	-0.027	-0.019	-0.026
21-60 Minutes	-0.045	-0.063	-0.080	-0.065	-0.086	-0.071
61-240 Minutes	-0.013	-0.023	-0.013	-0.012	-0.016	-0.019
Impl. Δ% Productivity	11.3	22.4	14.2	19.4	22.4	22.8

Notes: Results from regression of restaurants' logged productivity (real spending per employee) in a month on restaurant fixed effects, indicators for each sample month, and the shares of a restaurant's customers with dwell times in various categories (61-240 minutes is excluded category). Standard errors clustered by restaurant are in parentheses. The lower portion of the table shows the overall change in average dwell shares from 2019 to April 2022 and their implied changes in productivity, calculated by multiplying respective regression coefficients by corresponding change in shares, summing the result, and multiplying by 100.

Online Appendix

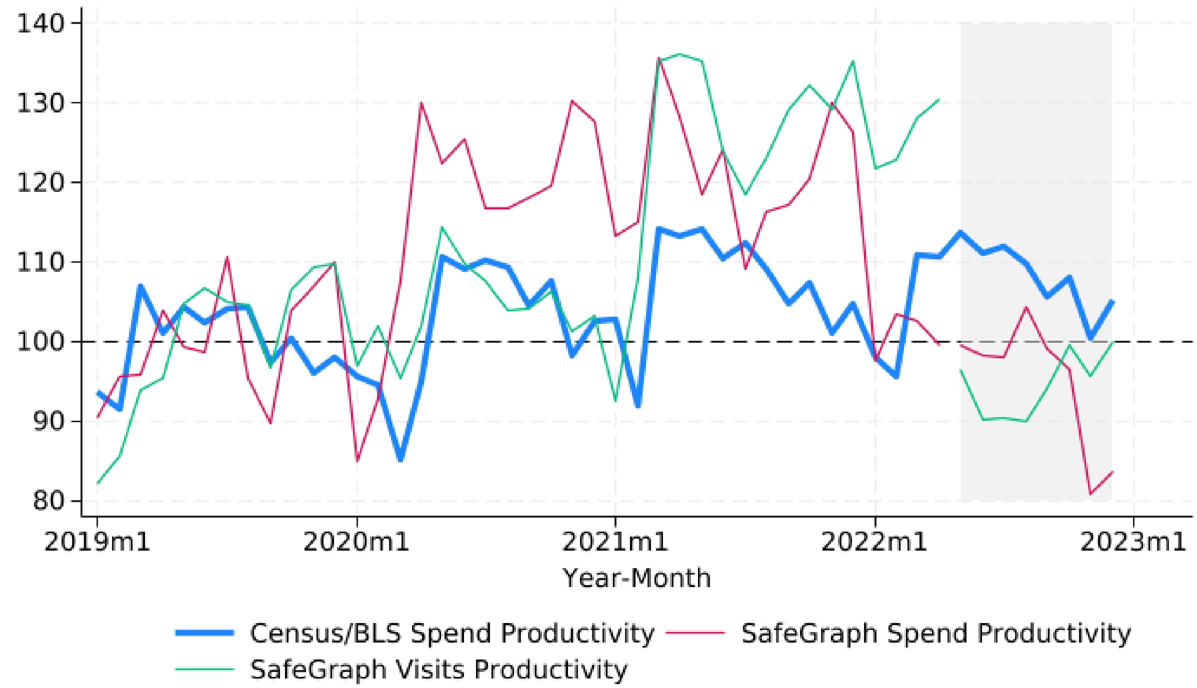
A. Additional Analyses

Figure A1. Annualized Real Restaurant Sales per Employee, Total Industry and Limited Service Eating Places, Not Seasonally Adjusted



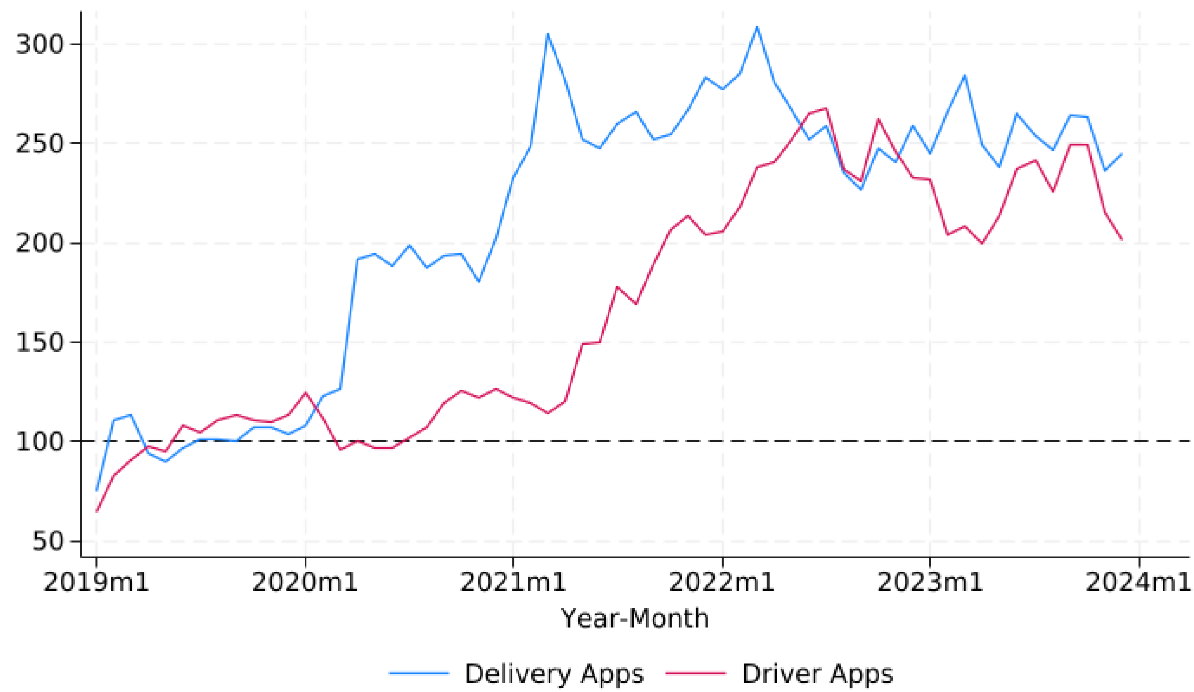
Notes: Figure shows indexes (1992 = 100) of annualized monthly real sales per employee for the entire Food Services and Drinking Places industry as well as for limited-service eating places subindustries (NAICS 722513, 722514, and 722515). Nominal sales are from the Census Monthly Retail Trade Survey report. Real sales obtained by deflating by CPI series for food away from home. Employment from Bureau of Labor Statistics. All series not seasonally adjusted.

Figure A2. SafeGraph Productivity Aggregates (2019 Average = 100)



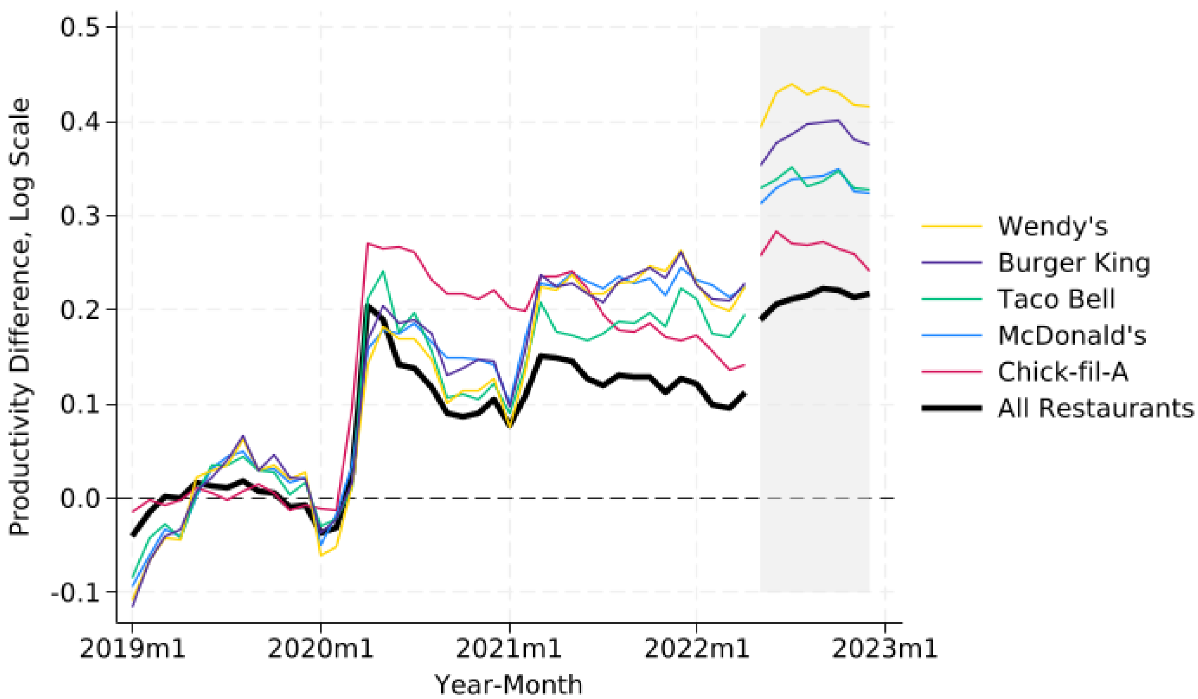
Notes: Comparison of indexes (1992 = 100) for three non seasonally adjusted productivity aggregates for limited service restaurants. One is Census/BLS as reported above; two are aggregated from our SafeGraph monthly restaurant panel. One computes productivity as sales per employee ("spend productivity"); the other as customer visits per employee ("visits productivity"). The shaded area indicates period after processing changes in SafeGraph's *Monthly Patterns* caused a discontinuity in visits data.

Figure A3. Delivery and Driver App Usage, Aggregate Minutes per Day



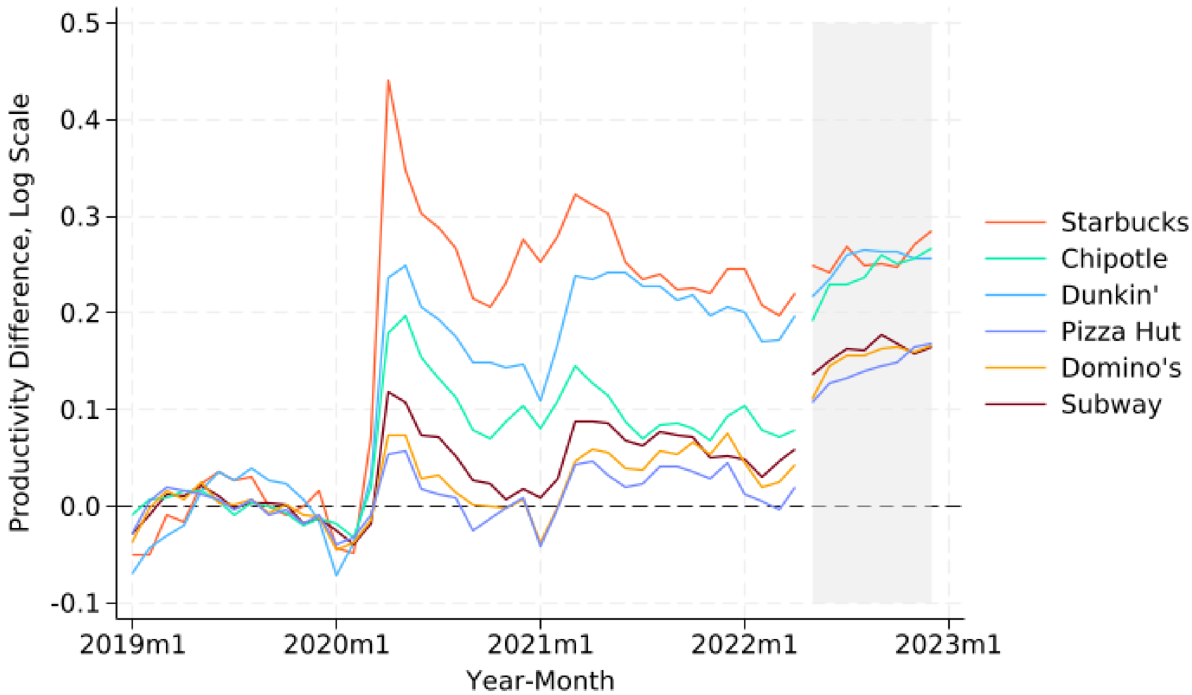
Note: Shows indexes (2019 = 100) of customer and driver usage of delivery apps as reflected in Global Wireless Solutions' Magnify dataset. Customer use is total minutes per day of use, calculated by dividing sum of visible duration of the apps in a given month by the sum of the number of days that each panelist was present. Delivery apps included are: DoorDash, Grubhub, Postmates, and Uber Eats. Driver apps included are: DoorDash-Dasher, Grubhub for Drivers, and Fleet by Postmates. Uber Eats drivers use the Uber-Drive app, the same app used by rideshare drivers, so we do not include it as a driver app.

Figure A4. Implied Productivity Difference from Dwell Time Changes



Notes: Plot of implied difference in productivity for each restaurant chain if their customer visit lengths had remained at their pre-COVID values. This is calculated by multiplying the regression coefficients in Table 1 by the change in dwell shares from their average monthly 2019 values and adding up these values. The shaded area indicates period after processing changes in SafeGraph's *Monthly Patterns* beginning in May 2022.

Figure A5. Implied Productivity Difference from Dwell Time Changes, Additional Restaurants



Notes: Plot of implied difference in productivity for each restaurant chain if their customer visit lengths had remained at their pre-COVID values. This is calculated by multiplying the regression coefficients in Table 1 by the change in dwell shares from their average monthly 2019 values and adding up these values. The shaded area indicates period after processing changes in SafeGraph's *Monthly Patterns* beginning in May 2022.

Table A1. Dwell Time Changes and Productivity (Real Spending per Employee), Additional Restaurants

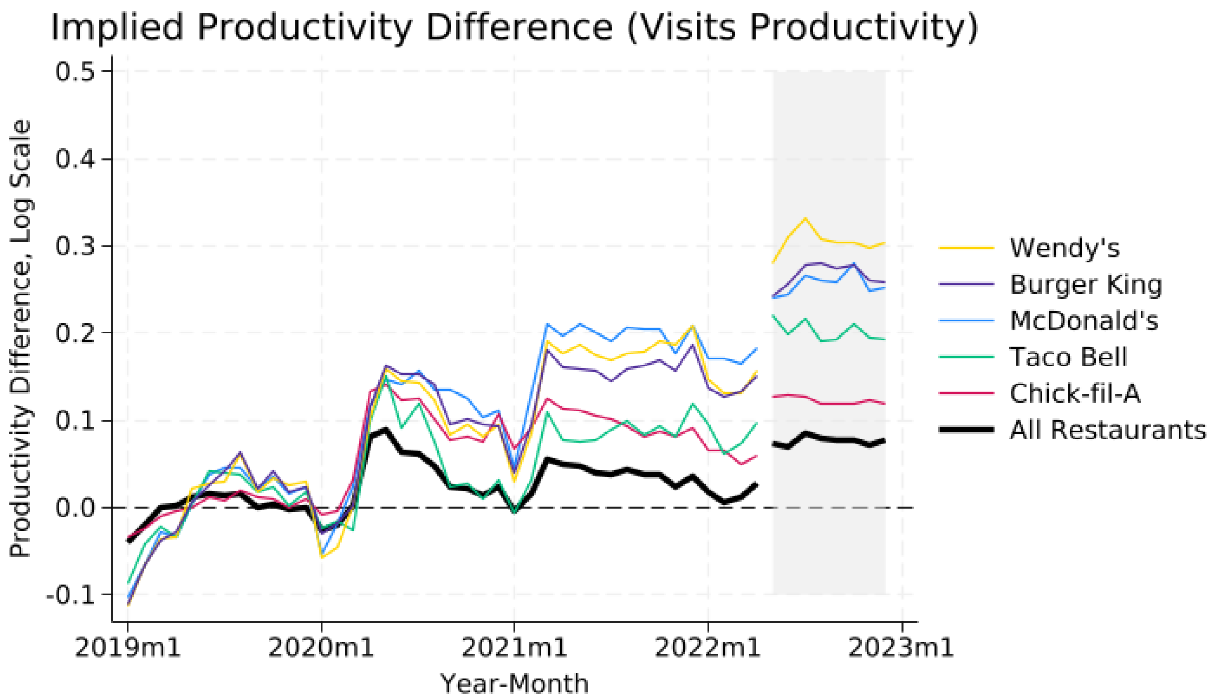
	(1) Starbucks	(2) Dunkin'	(3) Subway	(4) Chipotle	(5) Domino's	(6) Pizza Hut
0-10	5.025	4.665	3.454	5.283	3.101	3.623
Minutes	(0.126)	(0.124)	(0.053)	(0.220)	(0.057)	(0.085)
11-20	4.737	4.007	3.109	4.310	2.605	3.062
Minutes	(0.144)	(0.144)	(0.066)	(0.219)	(0.072)	(0.111)
21-60	4.178	3.083	2.470	4.125	2.071	3.326
Minutes	(0.157)	(0.152)	(0.063)	(0.230)	(0.071)	(0.105)
N	348,344	316,212	568,227	111,568	254,312	159,631
R^2	0.63	0.66	0.59	0.60	0.65	0.64

Average dwell time category share change from 2019 to April 2022 and implied productivity change:

0-10 Minutes	0.091	0.084	0.068	0.065	0.050	0.076
11-20 Minutes	-0.010	-0.021	-0.036	-0.029	-0.032	-0.029
21-60 Minutes	-0.045	-0.036	-0.026	-0.033	-0.014	-0.050
61-240 Minutes	-0.036	-0.027	-0.006	-0.002	-0.004	0.003
Impl. Δ% Productivity	22.0	19.7	6.0	7.9	4.4	1.9

Notes: Results from regression of restaurants' logged productivity (real spending per employee) in a month on restaurant fixed effects, indicators for each sample month, and the shares of a restaurant's customers with dwell times in various categories (61-240 minutes is excluded category). Standard errors clustered by restaurant are in parentheses. The lower portion of the table shows the overall change in average dwell shares from 2019 to April 2022 and their implied changes in productivity, calculated by multiplying respective regression coefficients by corresponding change in shares, summing the result, and multiplying by 100.

Figure A6. Implied Productivity Difference from Dwell Time Changes, Productivity Measured as Customer Visits per Employee



Notes: Version of Figure A4 using productivity measured as customer visits per employee rather than real spending per employee. Construction process is the same. The shaded area indicates period after processing changes in SafeGraph's *Monthly Patterns* beginning in May 2022.

B. Data Details

Definition of a SafeGraph Visit (verbatim from SafeGraph): A "visit" is based on a set of timestamped latitude/longitude data points ("pings") clustered in space and time and then associated with a POI (the clustering algorithm is discussed in detail in the SafeGraph Store Visit Attribution Whitepaper [https://www.safegraph.com/guides/visit-attribution]). The timespan of the pings of a cluster provide a lower and upper bound on the duration of the corresponding visit based on the time between the first point in the cluster, the last point in the cluster, and the first point in the subsequent cluster. The minimum_dwell (lower bound) is the time between the first ping and last ping in the cluster, and the maximum_dwell (upper bound) is the time between the first ping of the cluster and the first ping of the next cluster in time. SafeGraph uses the minimum_dwell to report on dwell (duration) times. The "start time" of the visit is the timestamp of the first ping in the cluster. More information regarding SafeGraph Patterns documentation can be found at https://docs.safegraph.com/docs/monthly-patterns.

Homebase: Homebase is a free scheduling and time tracking tool used by 100,000+ local businesses and their hourly employees. Homebase's customers in the US primarily consist of restaurant, food & beverage, retail and services and are largely individually owned/operator-managed businesses. They provide a day-worker-establishment level dataset of hours worked. Historical data is available back to January 1, 2018. More information regarding Homebase can be found at https://joinhomebase.com/data/.

National Restaurant Association Restaurant Performance Index: The National Restaurant Association's Restaurant Performance Index (RPI) is a monthly composite index that tracks the health of the U.S. restaurant industry. The Index consists of two components — the Current Situation Index, which measures current trends in four industry indicators (same-store sales, traffic, labor and capital expenditures), and the Expectations Index, which measures restaurant operators' six-month outlook for four industry indicators (same-store sales, employees, capital expenditures and business conditions). The RPI is based on the responses to the National Restaurant Association's Restaurant Industry Tracking Survey, which is fielded monthly among restaurant operators nationwide on a variety of indicators including sales, customer traffic, labor and capital expenditures. We compare SafeGraph Spend and Visits data to the same-store sales, customer traffic, and labor components of the Current Situation Index. The components are defined as follows:

$$Component_t = 100 + \frac{Higher_t\% - Lower_t\%}{10}$$

Where component can be the same-store sales, customer traffic, or labor in year-month *t*. $Higher_t\%$ is the percent of restaurants that reported having more of the component in year-month t compared to the same month in the previous year. $Lower_t\%$ is the percent of restaurants that reported having less of the component in year-month *t* compared to the same month in the previous year. Each component ranges from 90-110. We construct the equivalent of each of these components using our SafeGraph sample. More information about the National Restaurant Association Restaurant Performance Index can be found at https://restaurant.org/research-and-media/research/economists-notebook/restaurant-performance-index/.

Magnify *by Global Wireless Solutions*: *Magnify* by Global Wireless Solutions is a dataset of app usage derived from an opt-in consumer panel of U.S. Android smartphone users. There are an average of nearly 37 thousand daily panelists from 2019 to 2023. Panelists are recruited via mobile advertisement campaigns to download the Global Wireless Solutions OneMeasure Perks app. The app remains on in the background and passively collects data 24/7, including when and where an app is opened and for how long. Panelists are rewarded for data collection and for participating in on-going surveys by earning points to redeem on gift cards. Global Wireless Solutions then weights the panel daily based on demographics and geography. Historical data is available back to January 1, 2019. We calculate the aggregate minutes per day of app usage by dividing the total sum of the visible duration of the apps in a given month by the sum of the number of days that each panelist was in the month. Visible duration is defined as the duration when the app is in the foreground and the screen is turned on. This data was made available by Global Wireless Solutions (GWS) (https://gwsmagnify.com/) via the Dewey Data platform (https://www.deweydata.io/).