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Using Smartphone Location Data for Strategy Research

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Abstract. Smartphones regularly track the precise locations of millions of people worldwide. These data are increasingly used in industry and academic settings to measure firm performance, workplace behavior, social interactions, and other metrics. We demystify this rich data source and explain how these data are constructed, how researchers can obtain access, and best practices when making inferences. Furthermore, we examine mobility data's coverage of business locations against a popular business listing data source (Data Axle) and provide guidelines on matching mobility data to firm financials (Compustat). Finally, we provide sample data, code for illustration, and a website for data exploration (https://www.mobilitydataresearch.com/) and highlight opportunities and limitations of using these data for management and strategy research.

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Keywords: smartphone location data • mobility data • data set construction and analysis • big data • firm competition

1. Introduction

The prevalence of smartphones has dramatically increased in the past decade. In the United States, the share of people owning a smartphone grew from 35% in 2011 to 97% in 2024 (Pew Research Center 2024). Alongside this growth, the time people spend on their devices has also increased. Average daily smartphone usage per person rose from 2.1 hours in 2015 to 3.1 hours in 2019 (App Annie 2020). As smartphones have become ubiquitous, many companies have begun to systematically collect user location data. Prominent firms in this space include Advan, Foursquare, and Mobilewalla.[1]

The widespread availability of mobility data has also sparked a growing body of research across various disciplines, including strategic management (Testoni et al. 2022, Hou and Poliquin 2023), marketing (Wang et al. 2022), public policy (Glaeser et al. 2021), economics (Atkin et al. 2022, Massenkoff and Wilmers 2025), and finance (Bizjak et al. 2022). In particular, in the field of strategic management, Testoni et al. (2022) examine the effect of face-to-face interactions between prospective merging firms on the returns to mergers and acquisitions, and Hou and Poliquin (2023) use mobility data to examine the impact of CEO activism on consumer purchase behavior. These studies underscore the unique advantages of mobility data, particularly their highly granular nature and ability to capture dynamics in near real time.

These characteristics of mobility data offer valuable opportunities for advancing strategy research in several ways. First, mobility data provide enhanced granularity in time frames. Traditional performance metrics are commonly aggregated at the quarterly or yearly levels, making it difficult to capture immediate or short-term trends. This limits researchers' ability to uncover details that may be overlooked by coarser metrics. As an example, future research can build on works such as Conti et al. (2024), who used annual sales and financial information to evaluate the impact of big data analytics on firm performance, by incorporating mobility data to provide deeper insights into additional short-term effects, such as the rate of learning or technology adoption.

Second, mobility data offer greater geographic granularity. By providing point of interest (POI)–level geographic variation, mobility data enable strategy researchers to analyze performance at the establishment level. This granularity allows researchers to incorporate demographic factors (e.g., race, gender, education), economic indicators (e.g., income, employment), and political variables (e.g., voting records) into their analysis to enhance the depth and accuracy of their insights. Although recent studies have leveraged local differences to examine firm behavior (Barber and Blake 2024, Dowell and Lyon 2024), they lack direct performance data. Mobility data bridge this gap by allowing researchers to more effectively connect local trends and policies to firm performance, providing a clearer understanding of their impact.

Third, mobility data provide insights into a company's brand portfolio at a granular level, enabling a deeper understanding of market dynamics. For example, Restaurant Brands International owns multiple restaurant chains, including Burger King, Tim Hortons, Popeyes, and Firehouse Subs. Traditional aggregated data make it difficult to analyze each brand separately. With mobility data, however, researchers can distinguish performance and consumer behavior across brands, leading to more precise insights. To illustrate, in this article, we use Advan data to analyze the introduction of a new product and show how researchers can leverage mobility data to answer strategy-relevant questions. In 2019, fast-food restaurant chains Popeyes and Chick-fil-A feuded over which had invented the original fried chicken sandwich. This led to the "Chicken Sandwich Wars," as Popeyes introduced a new fried chicken sandwich. Using Advan location data aggregated at the POI level, we show that the product launch led to a large increase in foot traffic to Popeyes restaurants. Surprisingly, the "Chicken Sandwich Wars" did not reduce visits to competitors, including Chick-fil-A. Analysis of the demographic profile of Popeyes' customers before and after the product launch reveals that Popeyes attracted younger, richer, and more college-educated consumers following the product introduction. This example highlights the potential of using smartphone location data to uncover insights that are more nuanced than would be possible with firm-level financials. Scholars studying competition can benefit from using mobility data to test theories related to core strategy questions around competition and performance (e.g., Adner and Zemsky 2016, Pontikes 2018).

Finally, mobility data can provide fine-grained measures of social interactions, which may not leave traces in other data sources. Strategy research highlights the importance of social interactions as conduits of information flows capable of influencing firm performance (Sorenson and Stuart 2001, Bell and Zaheer 2007, Rogan and Sorenson 2014). However, research typically relies on indirect proxies for social interactions, such as physical proximity or variation in travel time between locations (Chakrabarti and Mitchell 2013, Catalini 2018, Catalini et al. 2020, Roche 2020). Mobility data provide direct and granular measures of face-to-face interactions by using the proximity of smartphone signals (Testoni et al. 2022, Massenkoff and Wilmers 2025). These granular measures can be used to examine several aspects of firms' corporate strategies, including human resource allocation and interactions between business units (Lim and Audia 2020, Levinthal and Wu 2025), business units and headquarters (Giroud 2013), merging companies (Bingham et al. 2024, Kim 2024), alliance partners (Devarakonda et al. 2022), and knowledge-production teams (Aggarwal et al. 2020), as well as employee turnover and lateral hiring between competitors (Kim 2024). Overall, the richness of mobility data has the potential to better inform theories about the strategic implications of social interactions and associated knowledge flows.

Despite an increasing interest in using mobility data for research, it is difficult to learn nuanced details about the data and to assess advantages over alternatives, best practices, and limitations. Moreover, there are still only a few papers in strategy that leverage this new data source. Thus, the potential of these data to expand our knowledge in strategy is largely untapped. This paper serves as a primer on using mobility data for research in strategy and highlights several promising directions for future exploration. In the following sections, we describe how mobility data are generated, how well they cover firms' establishments, and how well they correlate with firm-level outcomes. Next, we examine how to analyze such data and present best practices. We then provide an example of using mobility data to conduct an event study by analyzing a new product introduction. Finally, we detail how mobility data have unique potential to inform research in strategy, warn researchers of several data limitations, and conclude.

2. Sources and Quality of Smartphone Location Data

2.1. Data Sources

Cellphone carriers were once the only entities that could reliably gather information on population mobility at a broad level (Calabrese et al. 2011, Horanont et al. 2013). However, as smartphone use grew, a wide array of firms began to systematically collect and monetize such data. Recent reports estimate the value of the location intelligence market at $14 billion, with firms of various sizes and capabilities operating in the industry (Grand View Research 2022). Most firms are aggregators that contract with several smartphone application owners and aggregate the data. Other firms, such as Foursquare, collect location information directly from their own apps (e.g., Swarm, CityGuide, Rewards) and proprietary software development kits (SDKs). For example, Foursquare owns the Movement SDK, which is used by popular apps such as

GasBuddy, a gas price comparison app (GasBuddy 2022); Flipp, a couponing app (Flipp 2022); and Checkout 51, a receipt aggregator (Checkout 51 2022). Location information is collected by these apps and subsequently shared with Foursquare (Keegan and Ng 2021).

One popular data set commonly used for research is compiled by Advan, a company that tracks foot traffic to millions of POIs (e.g., stores). Advan relies on application programming interfaces (APIs) and SDKs embedded in mobile apps to collect data (SafeGraph 2021). All individuals tracked by Advan have opted in by allowing an app (such as a weather app) to use their location (Advan 2025).[2] In the United States, Advan estimates coverage of about 10% of the population (Veraset 2021). These data, which Advan acquired in 2023, were previously provided by another company named SafeGraph. Advan data can be obtained with an academic subscription to Dewey Data (Advan 2022, SafeGraph 2022).

Academic research using these data includes Testoni et al. (2022), Hou and Poliquin (2023), and other articles listed on Dewey Data's database of published research.[3] Specifically, Testoni et al. (2022) obtained a microlevel or disaggregated data set from SafeGraph consisting of smartphone "pings," each of which identifies the latitude and longitude of a smartphone at a moment in time. In this data set, smartphones are assigned unique and anonymous identifiers. The authors used this microlevel data set to identify smartphones that appeared in the headquarters of acquiring and target firms during business hours and then measured the frequency of visits between the headquarters of the two firms in the months before the acquisition announcement. They used these data to measure the frequency of interactions between employees and managers of prospective acquiring and target firms in the preacquisition period and assess their impact on acquisition outcomes. Furthermore, Hou and Poliquin (2023) obtained macrolevel (aggregated) data from Advan consisting of counts of visits and unique visitors to POIs. The authors then associated POIs with brands (e.g., Walmart) to measure the impact of CEO support for gun control on changes in visits and visitors to the brands' stores. Table 1 summarizes the main differences between microlevel and macrolevel data.

2.2. Quality of Smartphone Location Data

A primary source of smartphone location data for academic researchers is Advan, which provides foot traffic metrics to millions of POIs. In this section, we assess the quality of Advan data in terms of coverage of smartphone users, coverage of firm establishments, and correlations between Advan metrics and firm revenue from Compustat, a popular source of financial data on publicly traded firms.

Table 1. Comparison of Disaggregated and Aggregated Mobility Data

	Disaggregated (micro) data	Aggregated (macro) data
Characteristics	• Data sets consisting of smartphone "pings," each of which identifies the latitude and longitude of a smartphone at a moment in time. Smartphones are assigned unique and anonymous identifiers.	• Data sets consisting of ping data aggregated to visits and visitors at POIs.
Advantages	• Allow a researcher to map the movement of anonymized smartphones across locations and therefore to measure social interactions.	• Readily available and require limited processing. Data vendors already cleaned the data and often provide normalization measures to help in building a representative sample (e.g., removal of moving smartphones, flagging of adjacent POIs, etc.).
Disadvantages	• Privacy concerns and compliance with data policies at research institutions. • Additional data processing steps may be required: geocoding of POIs; removal of moving smartphones in the surroundings; accounting for ping geolocation errors; etc. • Depending on the application and the amount of ping data pulled, may require more computing power.	• Less flexibility to tailor the data set to the specific research question. • Data aggregated at prespecified intervals (e.g., week).
Examples of phenomena that can be studied	• Interactions between companies; monitoring activities between headquarters and subsidiaries; knowledge spillovers derived from face-to-face interactions.	• Effects of companies' decisions or external shocks on consumer visits to retail stores; competitive dynamics in geographically dispersed markets; allocation of human resources in firms with multiple locations.
Examples of published studies	• Chen and Rohla (2018); Testoni et al. (2022); Massenkoff and Wilmers (2025).	• de Vaan et al. (2021); Glaeser et al. (2021); Hou and Poliquin (2023).

2.2.1. Advan's Coverage of Smartphone Users. Because location data are gathered from apps installed by users and shared with app developers only when permitted by users, a key concern is potential sampling bias: some individuals may be more likely to enter the mobility sample than others. Li et al. (2024) conducted a comprehensive analysis of the representativeness of Advan data across five demographic attributes: age, gender, race/ethnicity, education, and income. Their findings indicate that Advan mobility data from 2018 to 2022 at the state level exhibit low bias in these categories when compared with the American Community Survey five-year estimates compiled by the U.S. Census Bureau (U.S. Census Bureau 2022, Li et al. 2024). Bias for most categories ranges within ± 0.05, indicating that, when benchmarked against U.S. Census data, most population groups are not overrepresented or underrepresented in the data by more than 5%.

However, underrepresented groups include populations under the age of 15, those aged 15–17, Hispanic individuals, those without college education, and individuals with incomes below $50,000. The authors attribute the underrepresentation of younger demographics to Advan's policy of excluding devices belonging to children under the age of 16 (SafeGraph 2021, Li et al. 2024). Interestingly, the authors also note that individuals over the age of 65 are not underrepresented, explaining that the age gap between mobile phone and internet users has dramatically decreased (Katz and Rice 2002). Additionally, they observed an outlier in 2022, where mobility data showed an overrepresentation of individuals with lower levels of education and income compared with their higher-educated and higher-income counterparts. We discuss the implications of these biases in Section 3.

2.2.2. Advan's Coverage of Firm Establishments. A major benefit of using mobility data for strategy research is that data providers prioritize comprehensive coverage of business POIs. This focus aligns with their business model, which caters to companies seeking insights into sales performance at specific locations and brands. For instance, Advan positions itself as a service that enables businesses to monitor competitors and select optimal and high-performing locations (Advan 2025). However, despite the intention to provide thorough coverage of business POIs, there is a lack of comprehensive analysis regarding the effectiveness of mobility data in achieving this goal.

To address this gap, we analyze the coverage of mobility data from Advan in detail. First, we download Advan's macro data available through Dewey Data, which contains data from over 550 public companies across more than 24,000 postal codes in the United States, covering approximately 70% of all U.S. Census ZIP Code Tabulation Areas (ZCTAs) nationwide.[4] Over 40% of the firms are in the retail trade sector (North American Industry Classification System (NAICS) code 44-45), which includes Walmart, Amazon, and The Home Depot. Table 2 provides a detailed breakdown of the companies tracked by Advan based on NAICS codes.

Second, to examine the coverage of mobility data, we benchmark Advan's coverage against other business listing providers. Specifically, we compare Advan's coverage to that of Data Axle, formerly known as Infogroup, which is accessible through Wharton Research Data

Table 2. Advan's Coverage of NAICS Sectors

Sector	Definition	Firms	POIs	Postal codes
44–45	Retail Trade	235	388,264	22,396
52	Finance and Insurance	136	227,342	18,342
72	Accommodation and Food Services	65	143,328	13,371
31–33	Manufacturing	48	7,934	5,879
48–49	Transportation and Warehousing	38	115,590	13,876
42	Wholesale Trade	27	10,818	5,578
53	Real Estate and Rental and Leasing	20	30,859	8,408
81	Other Services (except Public Administration)	17	28,153	7,929
51	Information	15	44,817	8,800
62	Healthcare and Social Assistance	15	19,526	7,512
71	Arts, Entertainment, and Recreation	9	3,816	3,178
55	Management of Companies and Enterprises	4	622	567
56	Administrative and Support and Waste Management and Remediation Services	4	1,874	1,446
54	Professional, Scientific, and Technical Services	2	8,838	7,417
61	Educational Services	2	685	660
23	Construction	1	24	24

Notes. Sector classifications are based on the 2017 NAICS definitions. Advan did not track publicly traded companies in the following sectors: Agriculture, Forestry, Fishing and Hunting; Mining, Quarrying, and Oil and Gas Extraction; Utilities; Public Administration.

Services (WRDS 2025). Data Axle compiles information on millions of physical business locations, utilizing a variety of sources, including yellow page directories, phone verifications, new business filings, daily utility connections, press releases, corporate websites, and annual reports. Scholars have leveraged Data Axle to investigate various topics, including the effects of ride sharing on local nightlife, food, recreation, and retail industries (Norris and Xiong 2023); the influence of consumer reviews on local demand (Lee et al. 2022); the potential of blockchain technologies to address contractual incompleteness (Chen et al. 2023); and the effects of vaccine mandate bans on equity markets and political attitudes (Cooper et al. 2023). We compare Advan with Data Axle to better understand the strengths and limitations of mobility data in informing strategy research.

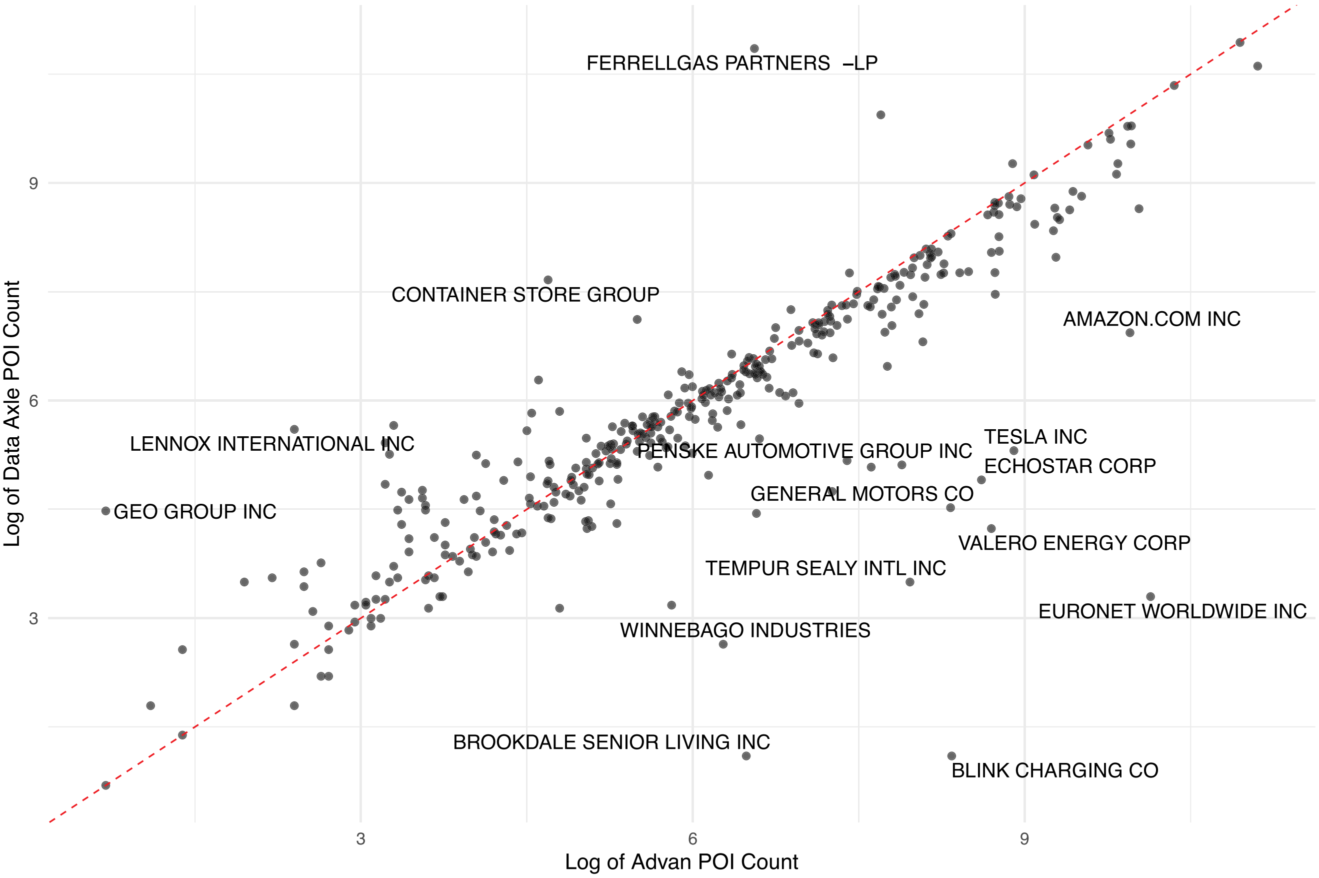
Figure 1 compares the number of POI locations tracked by Advan and Data Axle, revealing a positive correlation between the two data providers. The figure also suggests that Advan tracks more locations for firms with larger geographical footprints compared with Data Axle. Additionally, several outliers are labeled for reference. Amazon and Tesla locations, for example, are more likely to be tracked by Advan than by Data Axle. On the other hand, fewer Lennox International locations are tracked by Advan.

In addition to comparing the number of POI locations tracked by Advan and Data Axle, we examine the geographic coverage of the two data sources by comparing the number of firms each provider tracks at the ZCTA level. Figure 2 shows that in 85% of ZCTAs across the United States where at least one firm is tracked by either data source, Advan tracks as many as or more firms than Data Axle. Advan's coverage is especially strong along the East and West Coasts, whereas Data Axle has robust coverage in the Midwest.

2.2.3. Correlation Between Advan Foot Traffic Measures and Firm Revenue.

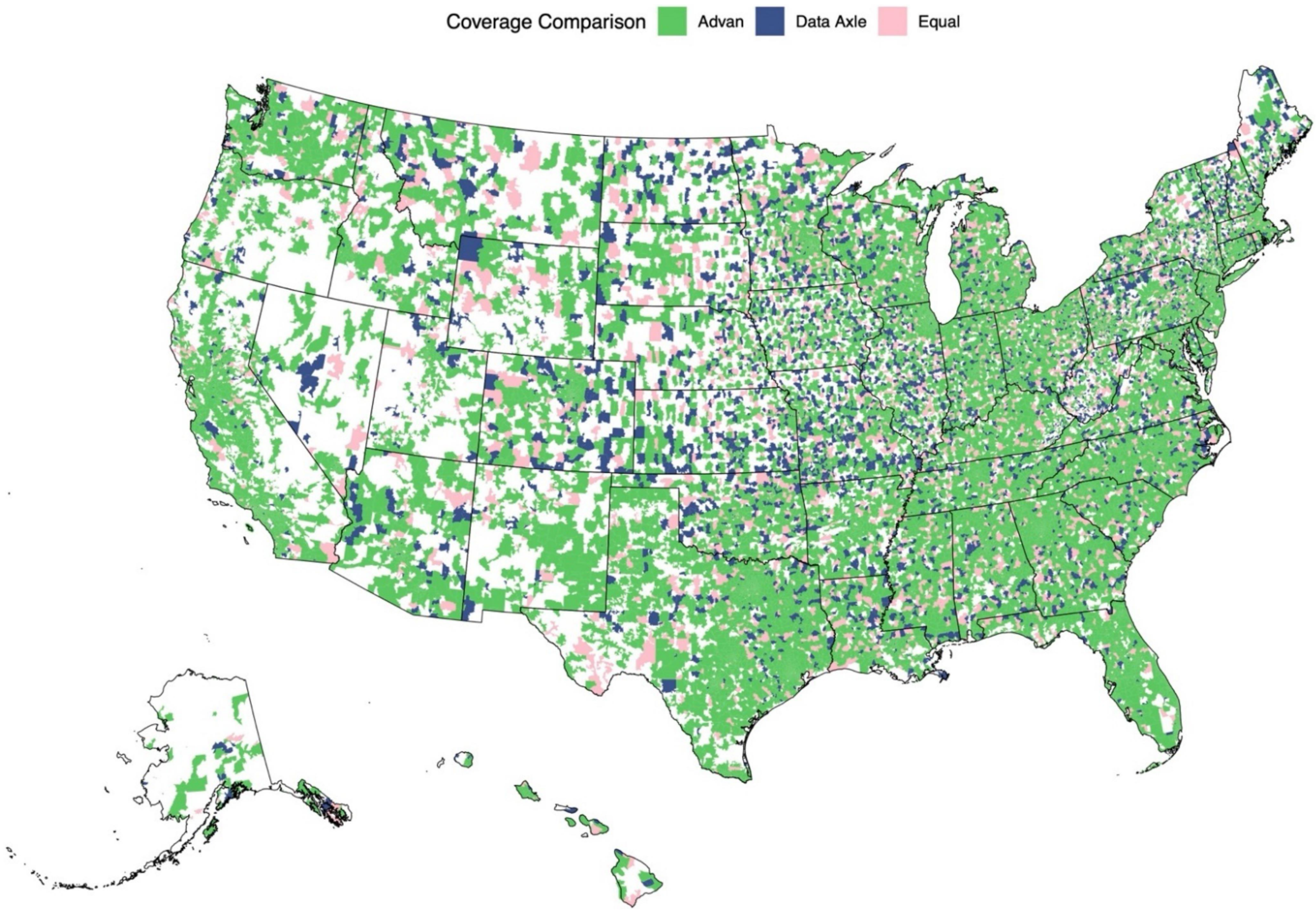
Advan provides different measures of foot traffic to POIs, including the number of visits and the number of unique visitors to the POI. A visit is recorded as long as a smartphone appears inside the geofence polygon of the POI.[5] Whereas a

Figure 1. (Color online) Coverage Comparison: Advan vs. Data Axle



Notes. Dots represent the logarithm of POI counts by firm in Data Axle (vertical axis) and Advan (horizontal axis). The dotted line indicates a 1:1 correlation between the count of POI locations tracked by Advan and Data Axle. Labeled dots represent outliers, defined as firms with POI location counts that differ across the two data sources by more than three standard deviations.

Figure 2. (Color online) Coverage Map: Advan vs. Data Axle



Notes. Coverage comparison is made at the level of U.S. Census ZIP Code Tabulation Areas. Areas where Advan tracks more firms are shown in green, those where Data Axle tracks more firms are shown in blue, and areas with equal coverage from both sources are shown in pink. The map includes only firms present in both Advan and Data Axle. White areas indicate ZCTAs where neither source tracks any firms.

previous version of the database maintained by SafeGraph only counted visits with a minimum dwell time of four minutes, Advan does not impose a minimum dwell time.[6] This is because the observed dwell time may be shorter than the actual one because a user may switch off their smartphone or geolocating app after reaching the POI. Advan reports that removing the dwell time filter increases the correlation between visits and firm performance indicators, such as revenue.[7] This feature implies that Advan relies on the accuracy of the geofence polygon and of the smartphone geolocating signal to measure visits (see Section 3 for a description of the sources of error).

To examine whether location data can be used as a reliable proxy for firm-level performance metrics, we calculate the correlation between Advan foot traffic measures and Compustat quarterly revenue using the following specification:

$$Y_{it} = \beta Advan_{it} + \alpha_i + \lambda_t + \epsilon_{it}, \tag{1}$$

where Y_{it} is the log revenue of firm i in period t, and $Advan_{it}$ is the mobility metric captured by Advan (i.e., log number of visits or log number of visitors). We include fixed effects for firm (α_i) and time (λ_t). The results in Table 3 show a strong correlation between the Advan measures of foot traffic and quarterly revenue.

This result should be highly valuable to strategy researchers, as it implies that mobility metrics can be used as a reliable proxy of firm performance. Mobility metrics have some key advantages over traditional Compustat measures. First, whereas Compustat measures are observable only at yearly or quarterly frequency, mobility variables are measurable at a much higher frequency, even at the daily or hourly level. This high frequency allows researchers to conduct event studies and assess the performance implications of specific events (see Section 4 for an example). Second, whereas Compustat data are available only for public companies, mobility data can represent any sample of firms, public or private. Third, whereas Compustat data provide performance figures aggregated at the company or business segment level, mobility data

Table 3. Foot Traffic as a Predictor of Quarterly Revenue

	(1)	(2)	(3)	(4)
Log *visits*	0.338***	0.536***		
	(0.056)	(0.090)		
Log *visitors*			0.311***	0.579***
			(0.056)	(0.088)
Intercept	7.515***		7.578***	
	(0.128)		(0.139)	
Fixed effects				
Firm	No	Yes	No	Yes
Year-Quarter	No	Yes	No	Yes
Adj. R^2	0.135	0.983	0.118	0.984
Adj. within-R^2		0.212		0.233
Observations	3,807	3,807	3,807	3,807

Notes. Dependent variable = log revenue (in $ mil.). Revenue, visits, and visitors are expressed in millions. Sample excludes firm-quarters with zero or negative revenue. Standard errors in parentheses are clustered by firm. Observations are at the firm-quarter level.
***$p < 0.001$.

enable researchers to assess the performance contribution of each establishment or the effects of localized events (e.g., localized market entries, natural disasters, etc.). Fourth, mobility data allow researchers to estimate the performance contribution of different customer demographics (e.g., see Section 4). Fifth, although it is well known that managers can often manipulate accounting performance measures (e.g., Zang 2012), mobility data can provide an independent measure of performance that is not subject to such manipulations. Overall, given the emphasis of strategy research on firm performance, a more granular measure of performance can be a key step forward for empirical research in strategy.

3. Data Set Preparation, Data Analysis, and Best Practices

Given the novelty of mobility data in academic research, we describe the main data preparation steps, best practices, potential sources of errors, econometric implications, and possible solutions. Researchers may obtain access to microlevel data (identifying the latitude and longitude of a smartphone at a moment in time) or macrolevel data (aggregating smartphone traffic at some POI). Microlevel data can be used, for instance, to map the movement of anonymized smartphones across locations and measure face-to-face interactions (e.g., see Testoni et al. 2022). Macrolevel data, on the other hand, can be more readily used to measure total visits or visitors to specific locations. We describe some key data-processing steps and sources of errors in the smartphone data at the micro and macro levels.

3.1. Obtaining Data and Data Set Preparation

3.1.1. Microlevel Data. For a researcher interested in using microlevel data, the first step is to obtain the data from a data provider. Microlevel data can be obtained from Veraset, which makes microlevel data available via Dewey Data with an institutional subscription, or through ad hoc agreements with other data providers. Possible providers include Advan, Foursquare, and individual apps collecting smartphone geolocation data. For example, Chen and Rohla (2018) and Testoni et al. (2022) obtained microlevel data through an agreement with SafeGraph (the provider of location data later acquired by Advan). These data record the locations of individual smartphones at particular points in time and typically include at least four fields: an anonymous unique ID per smartphone, the latitude and longitude of the geolocation ping, and the Coordinated Universal Time (UTC) timestamp of the ping.[8] Depending on the format and amount of data shared by the provider, these data sets can be very large. For example, SafeGraph covered approximately 10% of the U.S. population of smartphones and included tens of billions of pings for each month of data (Chen and Rohla 2018). Moreover, although smartphone IDs are anonymous, microlevel data may allow personal identification unless safeguards are in place (e.g., by observing movements between residential and work addresses). Hence, extra care is required when handling these data. First, the data provider may share only small portions of the full data sets to prevent deanonymization (e.g., sharing only selected locations with several smartphones and avoiding residential addresses may prevent individual identification). Second, contractual agreements with the data provider, research institutions' policies, and Institutional Review Boards (IRB) may place safeguards to preserve the anonymity of these data. Best practices include keeping data in a secure location, preferably encrypted and accessible with a password; avoiding attempts at individual identification; and publishing only aggregate statistics. Researchers need to check their institution's policies and procedures to implement information-handling safeguards.

A researcher with access to microlevel data typically starts with a list of addresses that are relevant to the research context. These addresses should then be geocoded to define the perimeters of the building of interest. This can be done by using services such as the Google Maps API, the Microsoft Azure Maps API, or Geocodio. These services generally indicate whether the coordinates of the address correspond to a building versus a street center or an interpolation of coordinates. If the coordinates do not match with a building, the researcher would typically need to visualize the addresses and manually correct the geocoding. In small samples, the geocoding of addresses can also be done manually. For instance, Testoni et al. (2022) visually identified the perimeter of buildings on Google Maps and geocoded firm headquarters using the *geohash* system. Geohash is a publicly available geocoding system that assigns a string of letters and numbers to geographic locations. This system subdivides space using a hierarchical grid structure with different levels of precision. As more characters are included in the geohash string, the rectangular cell corresponding to the geohash becomes smaller. In some cases, the point coordinates of an address may be distant from the building of interest (e.g., they can be in the middle of a street, in a parking lot, or at a crossroad). Moreover, some points of interest (e.g., companies' headquarters) could involve multiple buildings of varying shapes. Although labor-intensive, visualizing buildings enables a researcher to ensure that an address corresponds to a building and find the perimeter that best approximates the building or combination of buildings by using a combination of geohashes at different levels of granularity.

Once the building perimeters have been identified, the researcher would typically pull the smartphone data to obtain the smartphone pings inside the buildings. Depending on the research context, the researcher may also impose additional ping selection filters, such as considering only business hours during business days and imposing a minimum dwell time.[9]

3.1.2. Macrolevel Data. Macrolevel data can be obtained, for example, with an academic subscription to Dewey Data, which provides access to Advan, pass_by, and Veraset mobility data (pass_by 2022, Veraset 2022). With macrolevel data, the data provider typically provides a list of POIs linked to a firm brand that have already been geocoded (i.e., the data provider defines the POI geofences). For instance, Advan data are stored across several files that separately contain information on brands and visits (visitors) to the POIs. These files can be downloaded via Dewey Data's API and linked by a unique brand identifier.

Researchers interested in linking macrolevel data with commonly used financial data sources such as Compustat can merge the data using company names and stock tickers provided by Advan. However, we advise researchers to take special caution when using stock tickers to match Advan data with Compustat for several reasons.[10] First, it is possible that the Advan-assigned ticker does not correspond to the company tracked. For example, in Advan, LNT of the NASDAQ stock exchange is assigned to the following brands: Xtramart, Alltown, Jiffy Mart, Honey Farms, Mr. Mikes, T-Bird Mini Mart, and Alliance Energy. However, Global Partners LP, with ticker GLP trading on the New York Stock Exchange (NYSE), is the actual parent company of these brands. Second, Advan does not provide historical information on tickers, which is problematic for companies with ticker changes, delistings, or other major corporate events. For example, Foodarama, a Texas-based supermarket chain, went private in 2006. Its previous ticker—FSM on the American Stock Exchange (AMEX)—is now associated with Fortuna Mining Corporation on the NYSE. Finally, researchers should pay close attention to both the stock exchange and ticker when matching Advan with Compustat to avoid incorrectly matching companies with the same ticker that trade on different exchanges. The tickers AMP and GEO appear in both Advan and Compustat; however, they refer to different entities. In Advan, these tickers correspond to companies trading on the Borsa Italiana, whereas in Compustat North America, they represent different companies listed on the NYSE. A similar discrepancy exists for the tickers RFG and ALD, which are associated with companies on the Australian Securities Exchange in Advan, but they also appear in Compustat North America as NYSE Arca-listed companies. These issues were identified through manual inspection of the tickers provided by Advan. We encourage researchers who match Advan data with Compustat programmatically using tickers to verify the accuracy of their matches. Dewey recently informed subscribers about code available for linking Advan data to Compustat via tickers (Dickmann 2025), but this approach can result in mismatches like those noted above. Therefore, we recommend manual verification.

Although macrolevel foot traffic data do not identify the travel patterns of individual visitors, researchers can still enrich macrolevel data with demographic information to build rich profiles of a firm's or individual store's customers. Data providers like Advan typically provide visit and visitor counts aggregated by visitors' home Census tracts or block groups. Researchers can merge these Census tract distributions with demographic data from Census surveys, such as the five-year American Community Survey (ACS), to estimate the demographic composition of the store's customer base. For example, if 40% of a store's visitors come from Census tracts where the ACS indicates that 30% of residents have college degrees and 60% come from tracts where 10% have degrees, researchers can calculate a weighted average to estimate that approximately 18% of the store's visitors have college degrees. This methodology can be applied across multiple demographic variables or combinations of variables—including income level, race, age, and household characteristics—to construct detailed demographic profiles of a firm's customers without accessing individual-level data. These enriched profiles can then facilitate comparative analyses across store locations, markets, time periods, or firms while maintaining privacy compliance. In Section 4, we demonstrate such an analysis by comparing the age, education, and income of patrons for several fast-food companies.

3.2. Challenges and Sources of Error

3.2.1. Precision of Geocoding. As described above, researchers using microlevel data must geocode addresses and define the perimeters of buildings of interest. With macrolevel data (e.g., from Advan), however, the data provider geocodes the POIs and counts visits. There can be varying degrees of precision in geocoding. When the researchers do the geocoding, precision depends on the system used for geocoding and the level of quality assurance through manual inspection. Precision also depends on where the geocoded buildings are located. For instance, errors are likely to be greater in densely populated areas, those with many adjacent buildings, areas with parking lots, or industrial areas where the buildings of interest (e.g., offices) are surrounded by large empty spaces (e.g., storage spaces, fields, truck parking spots, etc.), particularly when the geocoding process is automated and the output is not verified. Moreover, even when the perimeter of a building of interest is correctly identified, there can be cases in which a building hosts multiple activities, some of which may not be of interest to the researchers. For instance, a company may be in the same building as other companies, housing units, or other facilities (e.g., coffee shops). It is particularly problematic if a building has multiple floors (e.g., shopping malls, skyscrapers). With macrolevel data sets, the level of error depends on the quality of the POI geocoding provided by the data vendor.

3.2.2. Data Coverage. Mobility data aggregators such as Advan rely on the geocoding signals from smartphone apps. This implies that mobility information of certain individuals—those who do not have the geolocating app installed, have switched off the app, have turned off their smartphone, lack a smartphone, or are located in areas with bad reception—will not be tracked. Moreover, the apps included in the portfolio of data aggregators such as Advan, as well as the apps' popularity among users, may vary over time. In addition, there can be differences in data coverage by geographic area, ethnic group, income, or education level, as discussed in Section 2.2. These data-coverage issues are relevant for both microlevel and macrolevel data sets.

3.2.3. Ping Geolocation Errors. Once the building perimeters have been identified, researchers with access to microlevel data would typically pull the data to obtain the smartphone pings inside the buildings. A source of error at this stage is the margin of error in the geolocation of smartphones.[11] In a common geolocation error, for instance, smartphones that are moving along the streets surrounding a building occasionally pop up inside the building of interest. Hence, if researchers are interested in the smartphones appearing inside a building, it is good practice to exclude moving pings from those data. Because macrolevel data sets are built from microlevel data, this source of error also exists for macrolevel data sets.

3.3. Econometric Implications and Best Practices

Overall, these sources of error imply that variables created with microlevel or macrolevel smartphone data sets will inherently have a measurement error. The econometric consequences of this error depend on whether the researchers are using the measure as a dependent or independent variable and the extent to which the measurement error correlates with the independent variables. In some contexts, some sources of error may be considered random (e.g., the precision of geolocating pings), whereas others may correlate with other variables (e.g., the underrepresentation of some population groups) and could bias ordinary least squares (OLS) coefficients (Wooldridge 2010).

In general, it is good practice to examine how the coverage of smartphone data varies in the population studied. For instance, researchers can plot maps to check whether the smartphone density is proportional to population. Moreover, researchers can verify whether data coverage varies systematically with other observables. If the researchers suspect that the coverage is higher or lower for some groups of observations, it is good practice to include fixed effects for the observation groups within which the coverage is expected to be approximately constant in the regressions. Indeed, although the coverage may vary with some observables, the variation in coverage could be quasi-random conditioning on those observables. The fixed effects allow the researchers to estimate the regression coefficients by comparing observations among which the error in measurement due to coverage is approximately constant and more likely to be random. For instance, as mentioned, the Advan data coverage has been increasing over time. Hence, it is good practice to include a time fixed effect in regressions to estimate within-period regression coefficients. Similarly, researchers could include a location or location × period fixed effect to control for possible differences in coverage across locations or locations and periods. However, in some research contexts, researchers may be interested in comparing observations across time and locations, and in those contexts, a fixed-effect estimator (which considers variation within groups) may not be the appropriate regression design. In these cases, researchers can apply normalization procedures to account for the sampling bias of the Advan data.[12]

The sources of error described in Section 3.2 imply that there can be false negatives in the data (i.e., smartphones in a POI that are not observed). However, there can also be false positives. For instance, because of geolocation error, a smartphone can appear in the POI even if it is outside or in an adjacent POI. Several factors affect the likelihood of false positives. For instance, when using macrolevel data, researchers may not be able to accurately attribute visits or visitors to a particular POI when multiple POIs share the same polygon (e.g., a Pizza Hut and a Taco Bell sharing the same location). Depending on the research objective, researchers may want to filter out POIs with a shared polygon so that measures are not inflated.[13]

Overall, when the measurement error is nonrandom and correlates with other variables, it can bias the OLS regression coefficients (Wooldridge 2010). To deal with this issue, the researchers can use an instrumental variable approach.[14]

Moreover, depending on the research design, mobility data may sometimes be used to define the study sample rather than simply to define some measures (e.g., when selecting a sample of firms or stores with observed smartphone location data). In these cases, differences in data coverage can induce sample selection biases in OLS regressions. To deal with this issue, the researchers can apply a Heckman selection model to correct for the sample selection bias (Certo et al. 2016).

4. Example: New Product Introductions

To illustrate best practices for working with smartphone location data and show how these data can be used to conduct an event study, we analyze the effects of the Chicken Sandwich Wars following Popeyes' introduction of a new fried chicken sandwich in 2019. The new sandwich became a sensation on social media after Popeyes and Chick-fil-A began feuding over which chain first served such a sandwich. In fact, the new item was so popular that Popeyes ran out of sandwiches after two weeks and had to temporarily discontinue the item before relaunching two months later. Using macrolevel mobility data, we show that the new product launch (and relaunch following the initial stockout) led to a large increase in foot traffic to Popeyes restaurants, but that little of this increase appears to have come at the expense of competitors. Furthermore, we analyze the demographic profile of Popeyes' customers before and after the product launch, finding evidence that Popeyes attracted younger, richer, and more college-educated consumers following the product introduction. We provide data and R code for replicating these analyses in the Online Appendix, enabling researchers who are new to location data to easily get started and understand the data's potential.

Figure 3 shows foot traffic patterns at Popeyes and several prominent competitors around the time of the sandwich launch on August 12, 2019; the subsequent stockout on August 27; and the relaunch on November 2.

To assess how foot traffic changed around the time of the product launch, we use a multiplicative difference-in-differences model:

$$E[Y_{it}|X_{it}] = \exp(\beta_1 Launch_{it} + \beta_2 Stockout_{it} + \beta_3 Relaunch_{it} + \alpha_i + \lambda_t), \quad (2)$$

where Y_{it} is visits to store (or brand) i in week t; α_i and λ_t denote store/brand and week fixed effects; and the β coefficients capture the effects of the initial product launch, initial stockout, and subsequent relaunch of the new chicken sandwich at Popeyes. The details of these dummy variables are explained in Table 4.

Table 4, Models 1–3 show coefficient estimates of Equation (2) at the brand (Model 1) and store (Models 2 and 3) levels, using either all competitor stores (Models 1

Figure 3. (Color online) Weekly Foot Traffic at Popeyes and Select Competitors in 2019

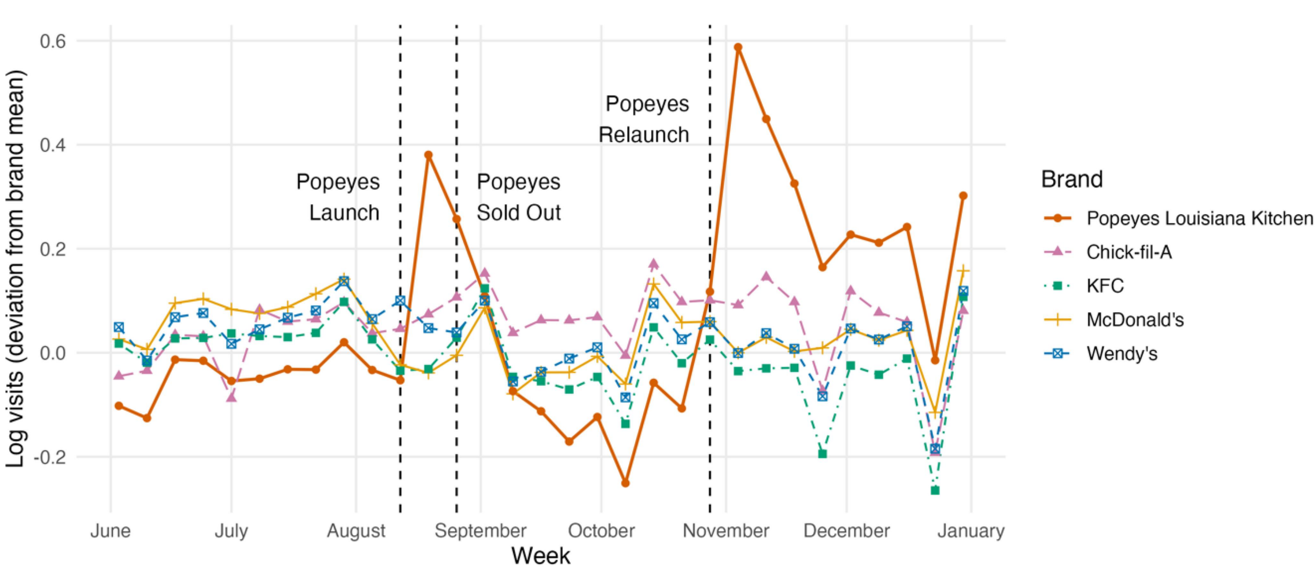


Table 4. Effect of Popeyes' Chicken Sandwich Launch

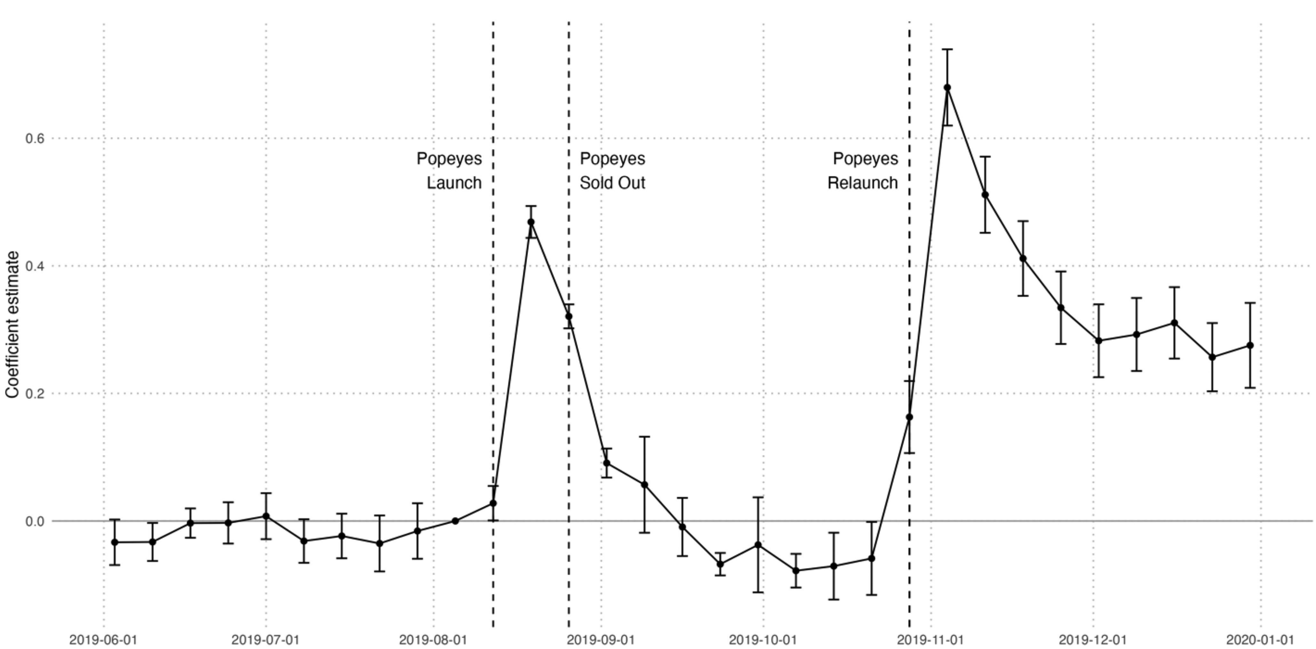
	Effects on Popeyes			Effects on competitors
	Brand-level	Store-level		Store-level
	(1)	(2)	(3)	(4)
Product launch	0.305***	0.305***	0.320***	0.018***
	(0.016)	(0.012)	(0.013)	(0.006)
Stockout	0.019	0.020	0.045**	0.031***
	(0.017)	(0.017)	(0.017)	(0.006)
Relaunch	0.397***	0.400***	0.427***	0.034***
	(0.018)	(0.017)	(0.018)	(0.004)
Fixed effects				
Brand	Yes	No	No	No
Store	No	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Pseudo-R^2	0.32	0.04	0.03	0.04
Observations	14,787	4,292,235	1,097,713	4,216,570

Notes. Dependent variable = weekly store visits. *Product launch* refers to the period between the introduction of the new chicken sandwich at Popeyes and the stockout. *Stockout* refers to the period between the stockout and the relaunch of the sandwich. *Relaunch* refers to the period following the relaunch of the sandwich after the stockout. Model 1 is brand-level and includes a single observation per brand-week. Models 2 and 3 are store-level and include observations for each store-week; Model 2 includes all store-weeks, whereas Model 3 omits competitor stores within 10 miles of a Popeyes location. Standard errors in parentheses are clustered by brand (Model 1) or store (Models 2 and 3). Model 4 reestimates Model 2, but period dummies are for competitor stores within 10 miles of a Popeyes location and omit observations of Popeyes.

$^{**}p < 0.01$; $^{***}p < 0.001$.

and 2) or only distant competitors (Model 3) as a control group for Popeyes' stores. Figure 4 plots per-period, "event-study" coefficients using the store-level sample from Table 4, Model 2. As is clear from the figure and table, visits to Popeyes surged following the introduction of the new chicken sandwich, plunged immediately after the restaurants ran out of sandwiches on August 27, and surged again once the sandwich was relaunched on November 2. This analysis illustrates how smartphone location data enable researchers to examine firm performance at a high level of granularity. The compressed time window over which Popeyes launched, sold out, and relaunched the item would make independent analysis of these events using firm-level

Figure 4. Effects of Chicken Sandwich Launch and Relaunch on Popeyes



Note. Vertical bars represent 95% confidence intervals.

financials nearly impossible. Furthermore, the use of high-frequency (weekly) observation allows researchers to credibly conduct the study, showing that increases in foot traffic coincided with the launch and relaunch of the sandwich.

Beyond high-frequency observations, smartphone location data provide granular information about visitors to a company's individual locations. From this, researchers can analyze changes in the demographics of a firm's consumers and see how events at one firm can affect nearby competitors. To illustrate, we use the fact that consumers are assigned to their most likely Census tract of residence to construct demographic profiles of visitors to Popeyes and competing restaurants around the time of the initial sandwich launch. To do so, we merge the Census tracts of visitors to demographics of interest from the five-year ACS, then calculate the share of visitors with selected attributes.

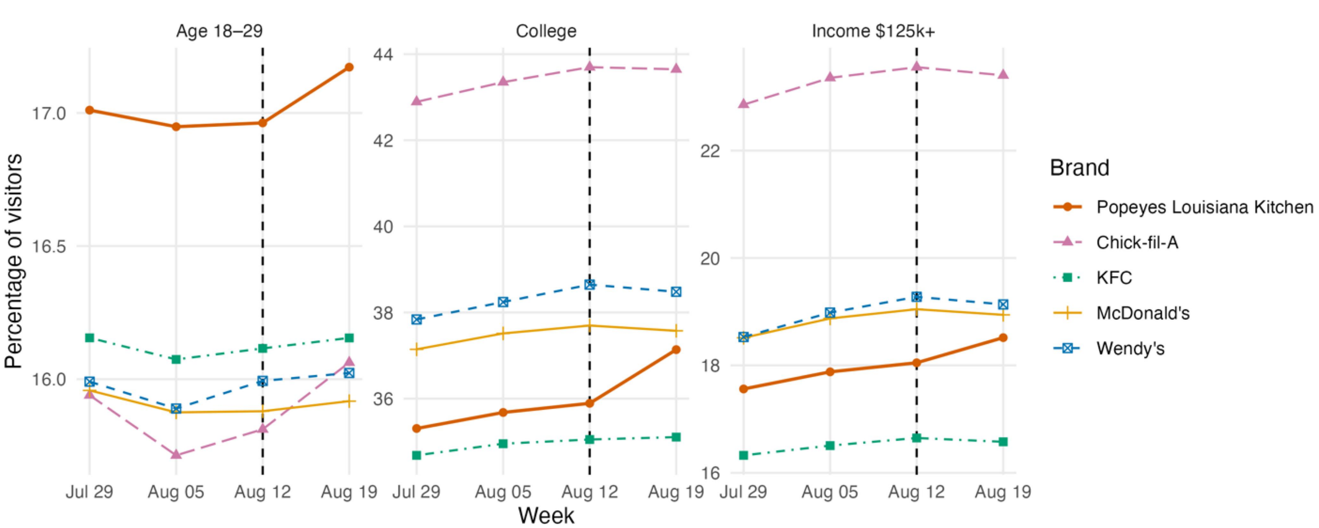
The results, shown in Figure 5, suggest that Popeyes saw an increase in the share of customers aged 18–29, the share with a college degree, and the share with annual household income above $125,000 after launching the new sandwich. Additionally, the figure reveals differences in the customer bases of each brand, with Chick-fil-A generally serving older, better-educated, and richer consumers than Popeyes. This illustrates how researchers can use smartphone location data to measure whether two seemingly similar firms—such as Popeyes and Chick-fil-A—compete for different customers, an analysis that is impossible with aggregate financial data.

The geographic granularity of the data allows us to further explore how Popeyes' new product affected other fast-food restaurants. The patterns in Figure 5 suggest that the surge of interest in Popeyes did little to change store visits to other chains. We can assess this claim more rigorously by comparing foot traffic at competitor restaurants that are geographically close to a Popeyes store (within 10 miles) to foot traffic at competitor restaurants that are not co-located with Popeyes and rerunning the model in Equation (2) but with the $Launch_{it}$, $Stockout_{it}$, and $Relaunch_{it}$ variables denoting competitor stores that are close to Popeyes during the respective postlaunch periods. The results in Table 4, Model 4 show that competing fast-food outlets close to Popeyes did not lose customers during the Chicken Sandwich Wars relative to outlets geographically distant from Popeyes. In fact, the positive coefficients on each variable suggest that nearby fast-food outlets saw positive spillovers from Popeyes' new product introduction, with foot traffic increasing 2%–4% at locations co-located with Popeyes.[15] This analysis illustrates how observing individual stores in the data facilitates the estimation of otherwise hard-to-measure effects (such as spillovers) using comparisons that would be impossible without such data.

5. The Value of Smartphone Location Data for Research in Strategy

In this section, we outline how mobility data can be leveraged to derive measures central to strategy research. First, we discuss how mobility data enable the development of fine-grained measures for theoretical constructs that serve as core dependent variables in strategy research. Next, we explore how mobility data can be used to quantify social interactions, which strategy research recognizes as critical channels for information flows within and across firms that influence firm performance. Finally, we highlight important limitations of mobility data that strategy scholars should consider when integrating these measures into their research.

Figure 5. (Color online) Customer Demographics Before and After Popeyes Chicken Sandwich Launch



5.1. Strategy-Relevant Dependent Variables

5.1.1. Demand. A firm delivers value by supplying products or services to customers, and strategy scholars investigate how firms can deliver superior value to customers vis-à-vis competitors. Consequently, firm-specific demand, its trajectory over time, and its relative performance against competitors are central theoretical variables of interest in strategy. In a recent quest to identify the dependent variable most relevant to strategic management, Helfat (2024, p. 2) underscores that "[i]n the absence of growth, firms can improve their performance only by reducing costs or raising prices … —and firms may reach their limits to do both." Thus, a fine-grained measure of demand—and demand growth in particular—should be highly valuable to empirical researchers in strategy.

Researchers often rely on revenues reported in the financial statements of public companies to measure firm-specific demand. Section 2.2.3 establishes that mobility metrics correlate well with revenues reported in Compustat. Yet, the former have some key advantages over the latter. First, whereas revenues measure prices and quantities jointly, mobility metrics provide information about the size of the firm's customer base. Understanding the growth of a firm's customer base can be a more reliable predictor of the firm's long-term success (Helfat 2024). Second, financial statements are available only for public firms and are typically consolidated at the firm level. By contrast, mobility metrics are also available for firms with no publicly available financial statements and provide fine-grained measures at the location level. These features make mobility data particularly valuable to researchers interested in investigating the demand of private firms or subunits within firms (e.g., branches and subsidiaries). Third, financial statements are available with a low frequency—yearly or quarterly—whereas mobility data are available almost continuously. This feature allows a researcher to conduct event studies to investigate the immediate impact of firms' strategic actions. For example, de Vaan et al. (2021) used mobility data to infer store-closing decisions (an otherwise hard-to-measure variable) and analyzed spillovers across geographically co-located businesses (an otherwise hard-to-measure level and outcome). Key to this study was the ability to accurately identify a broad array of community establishments, their neighboring establishments, and the date of closure, all of which can be inferred from location data. The authors found that stores are more likely to be open if nearby establishments are open. Moreover, Glaeser et al. (2021) estimated the impact of stay-at-home orders during the COVID-19 pandemic using mobility data and found an asymmetric response to regulation. Specifically, there was a limited impact of states' initial shutdown orders but a meaningful increase in activities after reopening decisions. The authors highlighted shortcomings of traditional economic measures, such as the U.S. Census Monthly Retail Trade Report, as it would be "difficult to tell whether the response to lockdown and reopening is symmetric" (U.S. Census Bureau 2022) with macrolevel statistics because these statistics tend to reflect national changes and do not account for the timing and reopening of local lockdown orders. Fourth, revenues reported in financial statements do not provide information about the characteristics of the firm's customer segments. In contrast, as shown in Section 4, mobility metrics can provide key information about the heterogeneity of competitors' demand. This feature can be especially valuable in studying questions about strategic positioning (Hou and Yao 2022), pricing (Miller et al. 2021), and branding (Bronnenberg et al. 2009). For example, Hou and Poliquin (2023) used aggregated Advan POI data to measure weekly changes in consumer visits to retail stores in Democratic- and Republican-leaning counties after multiple CEOs of large retail chains voiced their support for stronger gun-control regulation. The authors find asymmetric consumer response across Democratic- and Republican-leaning counties within 4 weeks but no net effect beyond 10 weeks—nuanced effects that would be difficult to detect otherwise. Finally, although managers can manipulate accounting data (Zang 2012), mobility data provide a proxy for earnings over which managers do not have much control.

An alternative source of demand information that can provide granular, high-frequency observations is scanner data (Chevalier et al. 2003). Yet, scanner data are limited to a selected set of retailers and convenience stores, and licensing agreements for such data nearly always preclude identifying the retailers. Given that mobility data provide accurate information on the identity of establishments they track, one area of future research is to examine competition beyond retailers. For example, it would be valuable to learn how clustering can benefit or disadvantage different firms and under what conditions. Moreover, mobility data can also be valuable for studying competitive dynamics in geographically dispersed markets (Chuang et al. 2023).

5.1.2. Profitability and Valuation. Although mobility data provide a direct measure of a firm's demand, they can also be used to estimate other measures of performance commonly used in strategy research, such as profitability and valuation. It can be useful to measure these constructs for firms or subunits within firms with no publicly available data or at a higher frequency than publicly available data. For example, suppose a researcher has access to data on profitability or valuation for a sample of public firms from

Compustat. Because profitability or valuation is a function of demand, we can express it with the following equation:

$$y_{i\tau} = f(d_{i\tau}, X_{i\tau}, \varepsilon_{i\tau}), \quad (3)$$

where $y_{i\tau}$ is the profitability or valuation of firm i in period τ as measured with Compustat data; f is a function of $d_{i\tau}$, the firm's demand as proxied by Advan metrics; $X_{i\tau}$ is a vector of firm characteristics; and $\varepsilon_{i\tau}$ is an error term. $X_{i\tau}$ could include elements such as industry dummies, location dummies, and period dummies, which may be observed not only for public firms, but also for private firms or subunits of public firms. A researcher could estimate the function f with a machine-learning method (e.g., random forest). The machine-learning method could model interactions between $d_{i\tau}$ and the vector of predictors $X_{i\tau}$. These interactions may capture differences, for example, in the average effect of demand (as proxied by Advan data) on $y_{i\tau}$ across industries or locations (e.g., due to differences in average spending by customers across industries or locations, or differences in profit margins). After estimating Model 3 on the sample of public firms for which $y_{i\tau}$ is observed, Model 3 can also be used to predict $y_{i\tau}$ for private firms or subunits within public firms for which y is not observed. This would allow a researcher to leverage the fact that $d_{i\tau}$ from Advan data is also observed for firms or business units with no publicly available financial statements. In addition, whereas $y_{i\tau}$ can be observed only once for each period τ (e.g., quarterly or yearly), $d_{i\tau}$ can be observed at a much higher frequency (e.g., daily). Hence, a researcher may also use the estimated Equation (3) to create a time series of y at higher frequencies than normally observed (e.g., from quarterly to daily frequency).

5.2. Social Interactions as a Determinant of Firm Performance

A long tradition in strategy has highlighted the importance of social interactions as channels through which tacit information can flow within and across firms (Sorenson and Stuart 2001, Bell and Zaheer 2007, Rogan and Sorenson 2014). Hence, social interactions are an important factor shaping firm performance and, therefore, a variable of interest to strategy scholars. Common measures of social interactions between firms include observable relationships, such as alliances (Gulati 1995, Zaheer et al. 2010) and board interlocks (Cai and Sevilir 2012), or geographic proximity (Ragozzino and Reuer 2011, Chakrabarti and Mitchell 2013). However, managers and employees may interact with firms with which they do not have a contractual relationship or that are not in their near surroundings. Mobility data have a key advantage over traditional data sources because they allow a researcher to measure actual social interactions, as inferred by the physical proximity of smartphones at some points in time. Indeed, social interactions can often be temporary and may not leave traces in other data sources. For example, Testoni et al. (2022) hypothesized that social interactions with the management of a prospective acquisition target can benefit the acquiring company by mitigating competition in the bidding process. Although anecdotal evidence suggests that these social interactions in the preacquisition phase can occur and be advantageous for acquirers (Share 1998, Wheelwright et al. 2000, Cullinan et al. 2004), they were largely unmeasured and escaped empirical examinations in previous research. To overcome this problem, Testoni et al. (2022) used smartphone geolocation data to measure the frequency of face-to-face interactions between the acquirer and the target in the months preceding the acquisition announcement; they found that these interactions improve the acquirer's returns by reducing the acquisition premium and the probability of competing bids.

Social interactions can be key conduits of knowledge spillovers between firms. Previous research traditionally relied on physical proximity or variations in travel time to assess the role of social interactions on knowledge spillovers (Catalini 2018, Catalini et al. 2020, Roche 2020). Yet, smartphone location data can be used to provide more precise and granular measures of social interactions. For example, Atkin et al. (2022) use smartphone location data to measure face-to-face interactions between workers at different establishments in Silicon Valley and assess the impact of these interactions on patent citations between firms. The granularity of these data allows the authors to disentangle the benefits of face-to-face interactions from other agglomeration benefits. Social interactions and the development of social networks can also foster entrepreneurship. For instance, Choi et al. (2024) find that the introduction of Starbucks cafés into U.S. neighborhoods increased entrepreneurship by facilitating social interactions. The authors validate their findings using smartphone location data to measure visits to Starbucks cafés. Moreover, social and economic segregation can be an important barrier to social interactions and the flow of ideas. Massenkoff and Wilmers (2025) use smartphone location data to study which locations increase or decrease the chances of encounters between individuals of different social classes.

Overall, mobility data can be used to measure social interactions and temporary human capital movements between places and firms. Although such movements may not leave traces in traditional data sources, they can be highly valuable for firms and should therefore be investigated. Mobility data can illuminate many important aspects of firms' corporate strategies, including human resource allocation among geographically dispersed business units (Lim and Audia 2020, Levinthal and Wu 2025), employee turnover (Kim 2024), headquarters-subsidiary monitoring (Giroud 2013), postacquisition organizational integration (Bingham et al. 2024, Kim 2024), frequency of social interactions in alliances (Devarakonda et al. 2022), and knowledge spillovers induced by interactions within and across firms (Aggarwal et al. 2020, Devarakonda et al. 2022). Given the centrality of these topics to strategy research, smartphone location data have the potential to push substantially the boundaries of our knowledge in strategy.

5.3. Limitations

Several limitations are worth considering when using mobility data. As discussed in Section 3, because mobility data rely on cellular or Wi-Fi connections, the data can be less accurate in areas with poor connections and do not cover individuals who do not have a geolocating app installed, have switched off the app, have switched off their smartphone, or do not have a smartphone. In these cases, mobility information may be less representative of the general population for a specific area. For example, as detailed in Section 2.2.1, there is evidence that Advan data can underrepresent younger individuals, Hispanic populations, low-income households, and individuals with low levels of education (Li et al. 2024). These biases have important implications for strategy research. In particular, researchers using mobility data to measure demand must exercise caution when drawing conclusions about target-market behavior. For instance, the underrepresentation of younger demographics can lead to inaccurate conclusions about their preferences and behavior, particularly in industries with a high percentage of younger consumers, such as entertainment, technology, fast food, and retail. Similarly, the overrepresentation of higher-educated and higher-income groups may result in an underemphasis on price-sensitive segments, potentially causing researchers to misjudge the behaviors and needs of lower-income consumers. Not adjusting for bias can also lead to flawed conclusions about optimal resource allocation. For businesses, insufficient resource allocation to younger individuals, lower-income consumers, less-educated populations, and Hispanic communities may result in missed opportunities to serve these groups effectively. Similarly, policies aimed at fostering equity across demographics may fail to allocate sufficient resources (e.g., capital, talent, innovative efforts) to address these underrepresented populations' needs. Moreover, the underrepresentation of these groups may cause researchers to mistakenly conclude that businesses and policy should deprioritize investment in these communities. This can create blind spots when developing strategies to promote inclusivity and unlock opportunities for growth and innovation within underserved communities. Similar coverage concerns may affect researchers using mobility data to measure the social interactions of employees within and between firms. For example, whereas mobility data may overrepresent the social interactions of white-collar employees and managers, who are likely to be higher-income and more educated individuals, they may underrepresent the social interactions of blue-collar employees.

Another limitation of mobility data as a proxy for sales is that they do not capture online activity. E-commerce represents a growing share of retail sales in the United States. As of 2024, online sales accounted for roughly 16% of retail sales, up from just 4% in 2000.[16] However, the implications of e-commerce for research using foot traffic to measure firm performance vary by industry and researchers' goals. Whereas e-commerce accounts for about 40% of electronics and appliance sales in the United States, it accounts for less than 10% of sales of building materials, gardening equipment, and related supplies.[17] Importantly, foot traffic can still be a good indicator of sales in settings where e-commerce is a large percentage of revenue. For example, even though digital sales account for more than 30% of Starbucks Corp. transactions, nearly all these orders eventually result in visits to a café.[18] Moreover, the fact that foot traffic accounts for only a share of revenue can be a feature rather than an impediment for some research questions. Scholars are often interested in the effects of business decisions that may be poorly represented in total revenue. For example, companies like Starbucks often earn income from secondary channels, such as licensing agreements, or operate stores in multiple geographic locations that are heavily aggregated in year-end financial reports. Researchers interested in Starbucks' decision to pilot the sale of Fair Trade coffee in its domestic, company-owned stores (Argenti 2004) or in whether opening Starbucks cafés facilitates interactions that spur entrepreneurship (Choi et al. 2024) are likely to find the granular and local nature of cellphone location data more useful than the aggregate figures captured in databases like Compustat. For these types of research questions, the ability to isolate consumer foot traffic from online sales is likely to be an advantage rather than a liability.

Similarly, although mobility data can provide a good proxy for demand in consumer retail businesses, they cannot serve the same purpose in business-to-business (B2B) businesses, where foot traffic is likely to be a less reliable measure of demand and revenues. Moreover, even for brick-and-mortar consumer stores where foot traffic can be a good proxy for demand, the strength of the correlation between foot traffic measures and revenues may differ among firms, because the probability of purchase as well as the average amount spent per visit can differ among industries or among firms within the same industry. Hence, accounting for these differences with industry or firm fixed effects (i.e., exploiting longitudinal rather than cross-sectional variations in foot traffic measures) is likely necessary in many research contexts. For example, in the Chicken Sandwich Wars application, we used store or brand fixed effects to rely on the within-store or within-brand variation in foot traffic to assess the effect of the product launch (see Equation (2)). However, it is also worth noting that although mobility data may be a poor proxy for demand in some contexts (e.g., e-commerce and B2B firms), they can still be used to track employees' movements and social interactions in these industries.

Moreover, because large-scale mobility data aggregation is in its infancy, historical data are limited. This may hinder researchers' ability to study questions that require a long time series or past events. Relatedly, for researchers interested in examining firm openings and closings, Advan's macrolevel data do provide indicators for when POIs opened and closed at the monthly level. Advan states that if a POI from an existing source repeatedly appears (disappears) in its build pipeline, it is flagged as *opened_on* (*closed_on*) during the month in which it first appeared (disappeared). The *opened_on* dates are only referred to for POIs with a *SafeGraph_brand_id*, whereas *closed_on* dates are attempted for both branded and nonbranded POIs (Advan 2022). These variables, however, have a low fill rate, given that Advan only recently started collecting this information. We expect these limitations to become less binding as time progresses and more mobility data are collected over the next years. In addition, given that regulation and smartphone usage differ by country, data that can be easily standardized across borders are currently limited.

Mobility data also do not convey contextual information. Although researchers may be able to observe where an individual has traveled, information on the individual's motive, purpose, or actions is unavailable. For example, although the researcher may be able to observe that an individual has visited a particular store, the researcher cannot observe if the individual has made a purchase, what products the individual bought, how much the individual spent, or the impact of external factors such as advertising on the individual's action. To answer these questions, researchers will likely need to merge mobility data with other data sources.

The lack of transparency of data aggregators regarding the data collection process, including which apps are used to track smartphones, also poses concerns. These concerns can be mitigated by assessing the coverage of smartphone data using third-party data as benchmarks and assessing possible biases. The analyses reported in Section 2.2 to assess the quality of Advan data represent a step forward in this respect.

Finally, researchers contemplating using mobility data may need to consider potential threats to data availability. Apple, which has a significant market share in smartphones, recently began limiting the degree to which third-party apps can access user locations (Apple 2023a). Third-party apps must now seek permission to access a user's location, and the user can also opt to provide only an "approximate location" (Apple 2023b). Furthermore, several regulations aimed at protecting consumer privacy have been recently implemented or are pending. Among these are the California Consumer Privacy Act (California 2023), the European Union (EU) General Data Protection Regulation bills (EU 2018), the Online Privacy Act (Congress 2019), and the Consumer Data Privacy and Security Act (Congress 2021), all of which require companies to inform consumers and obtain their explicit consent before collecting and sharing their location. Given the sensitivity of mobility data, especially microlevel data, researchers should consult their institutions (e.g., an IRB) on how to handle and store mobility data.

6. Conclusion

With smartphones nearing ubiquity, researchers can now tap into previously unavailable data on population mobility. As many firms have begun to systematically gather and compile user location data, researchers are beginning to leverage such data to answer unique questions that were previously difficult or impossible to address. These data are appealing because they are highly granular and reflect dynamics in near real time. In our study, we find mobility metrics tracked by companies such as Advan to be highly correlated with quarterly revenue. The strong correlation between mobility metrics and revenue suggests that mobility data are a powerful option for researchers studying questions in strategic management. We hope that validating mobility metrics as a proxy for firm performance will be useful to strategy scholars in need of more granular performance measures. Indeed, mobility metrics have some clear advantages over traditional Compustat metrics: they are available with high temporal frequency (which allows the performance of event studies) and high geographic granularity (which allows assessment of the performance contribution of specific establishments or customer groups), and they offer visibility into not just public firms, but also private companies, nonprofit organizations, and other points of interest.

In our example, we show how to use mobility data to perform event studies. Specifically, we examine the effects of the Chicken Sandwich Wars following

Popeyes' introduction of a new fried chicken sandwich in 2019. We explain how to use macrolevel smartphone location data to show that the product launch (and relaunch following the initial stockout) led to a large increase in foot traffic to Popeyes restaurants. Interestingly, the Chicken Sandwich Wars do not appear to have come at the expense of competitors, as no significant decrease in foot traffic among them was observed. Additionally, our analysis of the demographic profile of Popeyes customers before and after the product launch reveals that Popeyes attracted younger, richer, and more educated consumers following the product introduction. Through this example, we hope to illustrate the potential of using smartphone location data to reveal what are often nuanced insights that require granular, high-frequency observations beyond aggregated firm-level financials.

Finally, we highlight opportunities and limitations of using mobility data for academic research in strategy, and we call attention to areas where special attention should be paid due to the data's unique features. As we demonstrate, mobility data can measure consumer or employee behavior and social interactions at a level that has not been observable in past studies. This opens new research opportunities. We hope this study will encourage further strategy research using mobility data.

Acknowledgments

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Endnotes

[1] See Thompson and Warzel (2019) for an extensive list of firms operating in the mobility data space.

[2] Researchers do not know which applications Advan partners with. The weather app here is used as an example.

[3] See https://www.deweydata.io/resources (accessed April 9, 2025).

[4] For our analysis, we downloaded the Global Places file and the Brand Info file from Dewey in July 2024. Because not all public companies listed in the Brand Info file appear in the Global Places file, we restrict our analysis to public companies present in both data sets.

[5] A "geofence polygon" is a virtual boundary drawn around a physical location (such as a grocery store) that allows a smartphone's latitude and longitude coordinates to be classified as inside or outside the location.

[6] "Dwell time" refers to the amount of time a smartphone is observed within the boundaries of a given location.

[7] Advan Neighborhood Patterns documentation, v1.6, available at https://drive.google.com/drive/folders/1EmJaE31hO4SY2CUDlXpoCKevxZTc4U_f (accessed November 1, 2024).

[8] The UTC timestamps can be converted to local times using the coordinates, considering the time zone and the daylight saving time adjustment (which can vary by location within the same time zone).

[9] If a smartphone is continuously observed in the data set, dwell time can be measured with relative precision because it is known when the smartphone moved from one location to the focal POI and when it left the focal POI to move to another location. However, because users may switch off their smartphone or geolocating app before or after reaching the POI, a smartphone may appear in the focal POI without being tracked in another location before or after, making it impossible to precisely measure the dwell time. How to deal with these cases depends on the research context and the researcher's assessment of the relative probability of false positives and false negatives. For example, Advan reports that removing the filter based on dwell time improves the correlation between store foot traffic measures and firm revenues. Moreover, if a researcher is interested in studying visits of employees between two companies or subsidiaries, visits that are false positives (i.e., a smartphone that appeared in the building while it was moving in the surroundings) may be less likely if companies or subsidiaries are located in cities far away or sparsely populated areas.

[10] As part of our verification process, we manually reviewed tickers in the Advan file to ensure their accuracy.

[11] The horizontal accuracy of smartphone pings can vary by device (e.g., iOS versus Android) and location (i.e., it can worsen if underground or inside buildings) and depending on whether the smartphone is moving or still (i.e., it can be more precise if the smartphone is moving). As a consequence, some smartphone pings inside the building of interest may occasionally appear outside of the geocoded perimeter and vice versa.

[12] Since January 2022, Advan has included normalized visit count as an additional data field. Alternatively, researchers can apply their own normalization (e.g., see https://community.deweydata.io/t/panel-normalization-for-longitudinal-analysis-sampling-bias-corrections-and-extrapolation/13473, accessed May 22, 2024).

[13] Similarly, researchers with microlevel data may be interested in measuring the movements of people between company A and company B. Because of geolocation error, some smartphones that are in streets close to A and B could appear in A and B, respectively. Intuitively, these false positives are more likely if A and B are in close proximity or in the same city. In these scenarios, one way to verify the robustness of the results is to consider subsamples where false positives are less likely (e.g., excluding companies in close proximity or in the same city, or excluding companies in crowded areas or in skyscrapers).

[14] For instance, suppose the researchers are interested in measuring the effect of face-to-face interactions between the headquarters of companies on some outcome variable and use microlevel smartphone data to measure interactions. To obtain unbiased coefficients in the presence of a systematic error in measurement, the researchers would need to instrument the smartphone-movement variable with a variable affecting the probability of interactions between the companies. Different instruments for the ease of face-to-face interaction have been proposed in the literature, such as flight introductions (Giroud 2013, Catalini et al. 2020, Testoni et al. 2022), weather conditions (Testoni et al. 2022), historic city planning (Roche 2020), road infrastructure planning (Agrawal et al. 2017), and building structural changes (Catalini 2018).

[15] Results are similar if we use competitors within five miles of a Popeyes location.

[16] U.S. Census Bureau, E-Commerce Retail Sales as a Percent of Total Sales [ECOMPCTSA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/ECOMPCTSA, February 20, 2025.

[17] Estimates based on the Census Annual Retail Trade Survey for 2022, which is the most recent release.

[18] Starbucks Corporation, Q1 2024 earnings call (transcript), January 30, 2024, Starbucks Investor Relations, https://s203.q4cdn.com/326826266/files/doc_events/2024/01/1/SBUX-Q1-2024-Earnings-Call.pdf (accessed April 19, 2025).

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