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E-commerce and logistics sprawl: A spatial exploration of last-mile logistics platforms

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ABSTRACT

The rise of e-commerce helped fuel consumer appetite for quick home deliveries. One consequence has been the placing of some logistics facilities in proximity to denser consumer markets. The trend departs from prevailing discussion on "logistics sprawl," or the proliferation of warehousing into the urban periphery. This study spatially and statistically explores the facility- and region-level dimensions that characterize the centrality of e-commerce logistics platforms. Analyzing 910 operational Amazon logistics platforms in 89 U.S. metropolitan statistical areas (MSAs) between 2013 and 2021, this study estimates temporal changes in distances to relative, population centroids and population-weighted market densities. Results reveal that although some platforms serving last-mile deliveries locate closer to consumers than upstream distribution platforms to better fulfill time-demands, centrality varies due to facility operating characteristics, market size, and when the platform opened.

1. Introduction

E-commerce has transformed the "consumption geography" of cities (Buldeo Rai, 2021). These transformations have major implications for shopping behaviors and retail channels, last-mile operations and delivery mode choice, the management and pricing of competing uses for street and curb space, and the spatial ordering and functional role of logistics land uses (International Transport Forum, 2022). In the latter case, researchers have observed a diversification of logistics platforms to more efficiently serve home delivery demand. These platforms range from "dark stores" and "microfullfilment centers" that fulfill on-demand deliveries and omni-channeled retail without a consumer facing storefront (Buldeo Rai et al., 2019; Shapiro, 2023), multi-use urban distribution centers that convert unproductive sites (e.g., abandoned rail depots) to more lucrative land uses (Raimbault et al., 2018), and "microhubs" that stage transloading between cargo vans and e-bicycles suited for dense urban neighborhoods (Katsela et al., 2022).

Logistics spaces play an important role in improving urban livability and environmental sustainability. Planning decisions scale geographically from the region-level to the curb. Facilities such as urban consolidation centers (Allen et al., 2012) and loading zones (Dalla Chiara et al., 2022) can mitigate common delivery inefficiencies, such as low delivery densities and "cruising" for parking, respectively. These inefficiencies generate many negative externalities including climate emissions, air and noise pollution, congestion, and heightened collision risks, especially for vulnerable road users such as pedestrians and bicyclists (Browne et al., 2012). Limited commercial data has made it difficult, however, to observe spatial patterns with regards to e-commerce logistics platforms.

Using detailed proprietary data, this paper explores the evolving spatial organization of e-commerce logistics platforms. Given the company's preeminence as the leading online retailer in the U.S., the paper presents Amazon as a case study for understanding warehousing and distribution (W&D) activity in the larger e-commerce space. Utilizing proprietary data on Amazon logistics facilities between 2013 and 2021, this research explores the geographic shape and explanatory dimensions of e-commerce within major U.S. metropolitan areas. In the following section, this study defines the state of research related to broader W&D land use and its implications to e-commerce's distinct consumption geography. Afterwards, two methodologies for measuring logistics centrality are tested: a temporally relative barycenter-based metric, the prevailing method in literature, and another GIS-based, population-weighted service distance metric. The two measurements reveal nuances between facility- and region-level differences in the spatial organization of e-commerce platforms, which has yet to be fully researched. After presenting results from an exploratory regression analysis, this study discusses implications for future urban logistics land use and transport decisions.

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2. Literature review

Woudsma et al. (2008) first spatially analyzed the centrifugal pattern of W&D localization in peri-urban regions, which Dablanc and Rakotonarivo (2010) later described as *logistics sprawl*: "the tendency of warehousing development to move away from inner urban areas toward more suburban and exurban areas" (Dablanc and Browne, 2020). However, patterns of industry and commercial sprawl are not unique to the logistics sector. Research has explored the outward suburban expansion of commercial office spaces (Lang, 2000) and big-box retail (Holmes, 2011; Karamychev and van Reeven, 2009). Meanwhile, the historical sprawl of population and employment, especially in North American cities, is well-evidenced as are the negative externalities (Ewing, 2008). In the past few years, however, sprawl within the logistics sector has received heightened attention among urban transportation and economic geography scholars.

Aljohani and Thompson (2016) and Onstein et al. (2019) provide thorough literature reviews exploring factors that have influenced the geographic structure of regional logistics. These factors range from the globalization of trade and delocalization of production (Hesse and Rodrigue, 2004; Janelle and Beuthe, 1997), growing demand for "just-in-time" delivery, and rapid technological advancements in sorting automation and digital supply chain management. Spurred in part by ground-air freight integrators like FedEx and UPS (Bowen, 2012; Hall, 1989), contemporary "distribution centers" emerged as hubs conducting the directional flow of products along highways, airways, and even within their own walls, on forklifts, conveyor belts, and automated sortation machines (Cidell, 2011; McKinnon, 2009). As Cidell (2011) writes, "parts and products are not meant to sit on a shelf, but to be in constant motion along the supply chain until the final product reaches store shelves" (pp. 835).

Receiver demands for fast deliveries and high-volume throughputs shifted W&D's spatial footprint. W&D operators' appetite for space exploded to leverage economies of scale and reduce supply chain uncertainty (Andreoli et al., 2010). According to data from the U.S. Energy Information Administration (2018), the average square footage of W&D facilities grew from 118,000 square feet in 1946 to over 266,000 ft by 2018, a 125% increase over a 72-year period. Rather than the downtown-adjacent seaports and railyards, highways and airports radiated into the periphery of metropolitan regions and into the interstitial hinterlands between urban mega-regions (Bowen, 2008; Rodrigue, 2004). As such, co-locating around regional corridors and gateways in the metropolitan periphery provided better networked and cheaper siting opportunities than those in the urban core where space was politically contentious and priced at a premium.

Logistics sprawl does not always imply the diminishing density of logistic spaces in the urban core. Case studies in the Ohio River Valley and Greater Toronto Metropolitan Area found substantially higher rates of W&D facility openings in suburban or satellite municipalities than in the urban core, despite the urban core also exhibiting some degree of W&D growth (Cidell, 2011; Woudsma et al., 2016). Subsequent studies have measured logistics sprawl in the greater metropolitan regions of Paris (Dablanc and Rakotonarivo, 2010), Gothenburg (Heitz et al., 2020), Los Angeles (Dablanc et al., 2014; Kang, 2020a), Tokyo (Sakai et al., 2017), Wuhan (Yuan and Zhu, 2019), Brussels (Strale, 2020), Cape Town (Trent and Joubert, 2022), and São Paulo (Guerin et al., 2021), among others.

Not all cities exhibited logistics sprawl equally, with some cities showing lower levels of decentralization or negative decentralization (i.e., centralization). Dablanc et al. (2014) analyzed W&D data from 1998 to 2009 for both the Los Angeles and Seattle metropolitan area and found that while the former city experienced substantial decentralization from its urban center, they found no evidence for sprawl in the latter. Also in comparison to Los Angeles, Giuliano and Kang (2018) found the cities of San Francisco, San Diego, and Sacramento to exhibit only marginal shifts in the geographic center of W&D facilities across time. Krzysztofik et al. (2019) point to Katowice's (Poland) post-Soviet deindustrialization and urban form as a factor in the city's observed "logistics anti-sprawl."

Discrepancies between the spatial organization of W&D activity across cities comes down to local policies, regional economics, and facility attributes. Dablanc et al. (2014) and others (e.g., Aljohani and Thompson, 2016; Cidell, 2011) have discuss how differences in public growth management strategies that coordinate zoning across regional municipalities strongly influence W&D siting decisions. However, discrepancies and effects of W&D zoning policies have yet to be fully explained.

National or cross-regional studies have also pinpointed broader economic factors that influence W&D locational discrepancies including the distribution of employment (closer in proximity) and population (further in proximity) (Kang, 2020a), land price differentials (Sivitanidou, 1996), highway density, proximity to airports and other intermodal terminals (Bowen, 2008; Cidell, 2010). Kang (2020a, 2020b) analyzed W&D locations across 48 U.S. metropolitan areas and suggested a positive, non-linear relationship between population size, facility size, land price distributions (using an employment density gradient as a proxy), and commodity flow data. In other words, logistics sprawl is more pronounced for larger metropolises, with larger interregional trade volumes, and for larger W&D facilities.

2.1. A new consumption geography for e-commerce logistics?

A common feature that appears to underline newer e-commerce logistics platforms is their inward expansion into the urban core (Rodrigue, 2020). The economic implication suggests some private last-mile logistics platforms bear and adapt to the higher real estate costs and spatial constraints that dense urban environments entail in exchange for expedient access to home consumers (McKinnon, 2009). This trend departs from discussions surrounding logistics sprawl, which have typically considered the broader W&D sector without analyzing the logistical transformations arising from e-commerce's novel consumption geography.

Consumption geography–how W&Ds, stores, and consumers spatially organize (Buldeo Rai, 2021)–have important consequences for the livability and sustainability of urban environments. For instance, Wygonik and Goodchild (2018) find the spatial configuration and operational characteristics of urban delivery largely determines whether home delivery is more environmentally efficient than the in-person shopping trips that e-commerce is supposedly replacing (see also Jaller and Pahwa, 2020).

Therefore, this paper seeks to measure and explain Amazon centrality, a case study reflecting the the e-commerce sector at-large, within U.S. metropolitan regions. Since logistics sprawl is a longitudinal phenomenon, and the proliferation of Amazon facilities is relativity recent, this paper does not attempt to determine *if* e-commerce logistics platforms are sprawling over time. Rather, this paper explores the facility- and region-level dimensions that characterize platform centrality over the past decade.

3. Methodology

3.1. Data and region-level variables

MWPVL International, a logistics consulting firm, provided proprietary data on Amazon logistics platforms. MWPVL International collects monthly data on over 1199 active Amazon facilities in the U.S. as of February 2022, since the construction of the first fulfillment center in 1997. This study selects facilities opened between 2013 and 2021 (explained in the following section) and filters Amazon platforms that are:

- Currently unoperational or closed;

- co-located logistics platforms that include adjacent, seasonal facilities that manage spill-over demand during holiday spikes (designated in the dataset);
- and distribution centers that serve Amazon-owned retail or grocery (e.g., Whole Foods);

Metropolitan Statistical Areas (MSAs) are urban amalgamations containing economically interrelated municipalities, often with a combined population over 50,000. MSAs are commonly used in urban spatial research over broad metropolitan regions and allows for integration with other public data sources. The consequent sample dataset includes 910 Amazon facilities in 89 MSAs.

To estimate (de)centralization (or centrality), this study utilized a gridded population raster as the weighting factor. WorldPop is an open data source maintained by the University of Southampton, which provides annual, UN-adjusted population data at a one kilometer (0.62 mi) spatial resolution from 2000 to 2020. Opposed to Census-provided population data, the most granular geographic unit being the block group, WorldPop provides higher resolution population information without irregular geographic enumerations. Population is used as the input into the centrality analysis. Since there is no 2021 population data, this study uses 2020 population to analyze the centrality of 2021 facility openings.

This study selects 89 MSAs based on the presence of at least one operational Amazon facility (see *Appendix* for table of included MSAs). According to Kang's (2020a) analysis, MSA population, facility size, and logistics sector strength largely determines the extent to which regions do or do not exhibit logistics sprawl. However, rather than using an employment density gradient and freight flow volume as a proxy for industry land value and strength (the latter data are unavailable for every MSA and for every year in the studied timeframe) (Giuliano et al., 2018), this study opts for a more straightforward geographic concentration metric. LQ captures the employment strength of a region's particular industry cluster relative to other clusters and national employment (Ketels and Protsiv, 2021). The equation to calculate LQ for industry cluster i in region j follows:

$$LQ_{ij} = \frac{employment_j^i}{tot.employment_j} \Big/ \frac{employment_{U.S.}^i}{tot.employment_{U.S.}}$$

Therefore, LQ values greater than one indicates strong relative employment strength of an MSA's industry cluster. This study calculates LQ using North American Industry Classification System (NAICS) code 493 (*Warehousing & Storage*), which includes both W&D facilities and logistics providers (see Giuliano and Kang, 2018).

3.2. Amazon case study and facility-level variables

As an early entrant in the e-commerce space, Amazon's success parallels a growing digitalization of the retail and distribution spaces space (Hagberg et al., 2016; Sullivan, 2021). Rodrigue (2020) identifies four phases of expansion that define Amazon's physical logistics footprint (*See* Fig. 1). The phase encompasses the growth of online shopping and expectation for expedient deliveries, which prioritizes the coverage and speed of last-mile (node-to-consumer) delivery infrastructure. In May 2013, Amazon constructed its first "last-mile delivery station," marking a major step to a growing sophistication of the company's vertical distribution structure. Second, the devaluation of brick-and-mortar commercial real estate, a realignment of conventional retail to digital omni-channels, and a perpendicular growth in W&D facilities. Third, vertical supply chain integration that lent greater autonomy over Amazon's distribution infrastructure and fleets, culminating in 2016 when Amazon ended its contract with long-time logistics integrator, FedEx. Finally, the hyper-specialization of logistical platform functions, including *inter*stitial (i.e., expanding digital and physical networking between facilities) and *intra*stitial sophistication (i.e., high-levels of internal platform automation and specificity of product handling across commodity types, sizes, and seasonality).

Amazon's distribution strategies in the past two decades have molded the modern shape of the company's supply chain: a multi-layered delivery network connecting global and domestic suppliers to consumer doorstops often in the span of 48 h or less. Industry expert, MWPVL International, noted a three-tiered distribution chain that capture a broad range of logistics platform roles, which Fig. 2 also visualizes:

- **Level 1: Procurement and inventory fulfillment (i.e., gateway-to-node)**
  - o *Inbound Cross Dock (IXD):* Large-sized terminals responsible for receiving imported or domestic containerized products. Facilities are often co-located at shipping ports and intermodal terminals.
  - o *Fulfillment center (FC):* Among the largest-sized and most automated facilities, FCs represent the gateway node into Amazon's

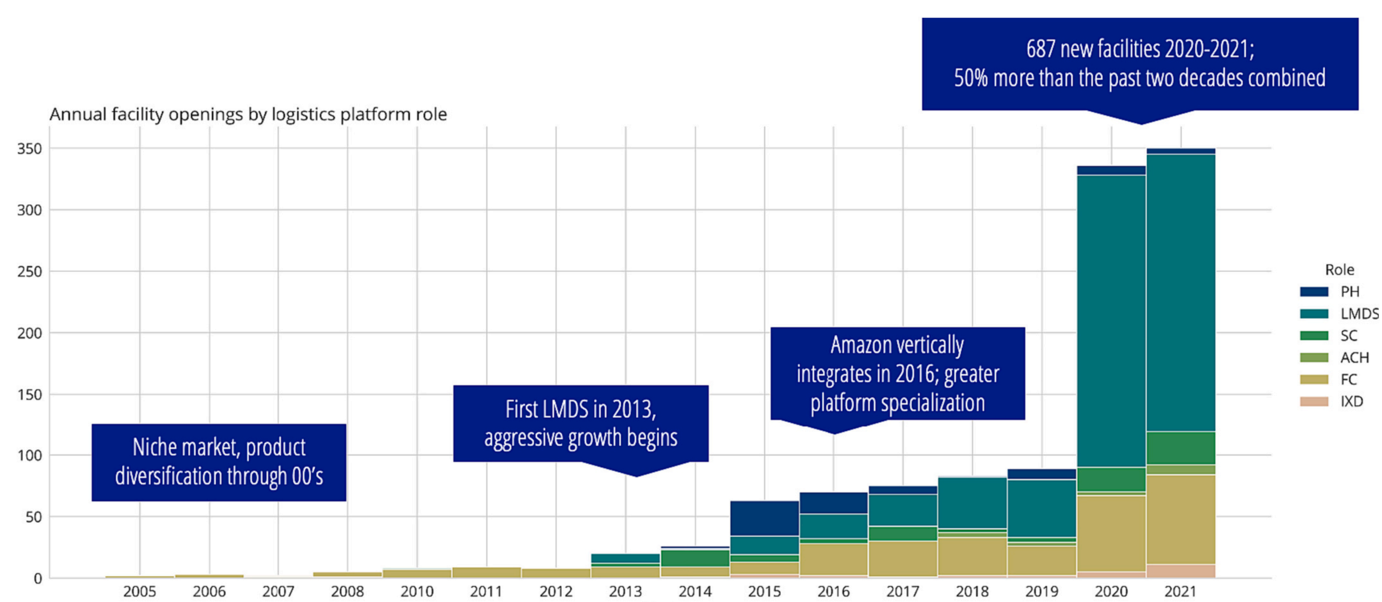

Fig. 1. Annual facility openings by logistics platform role, 2005–2021.

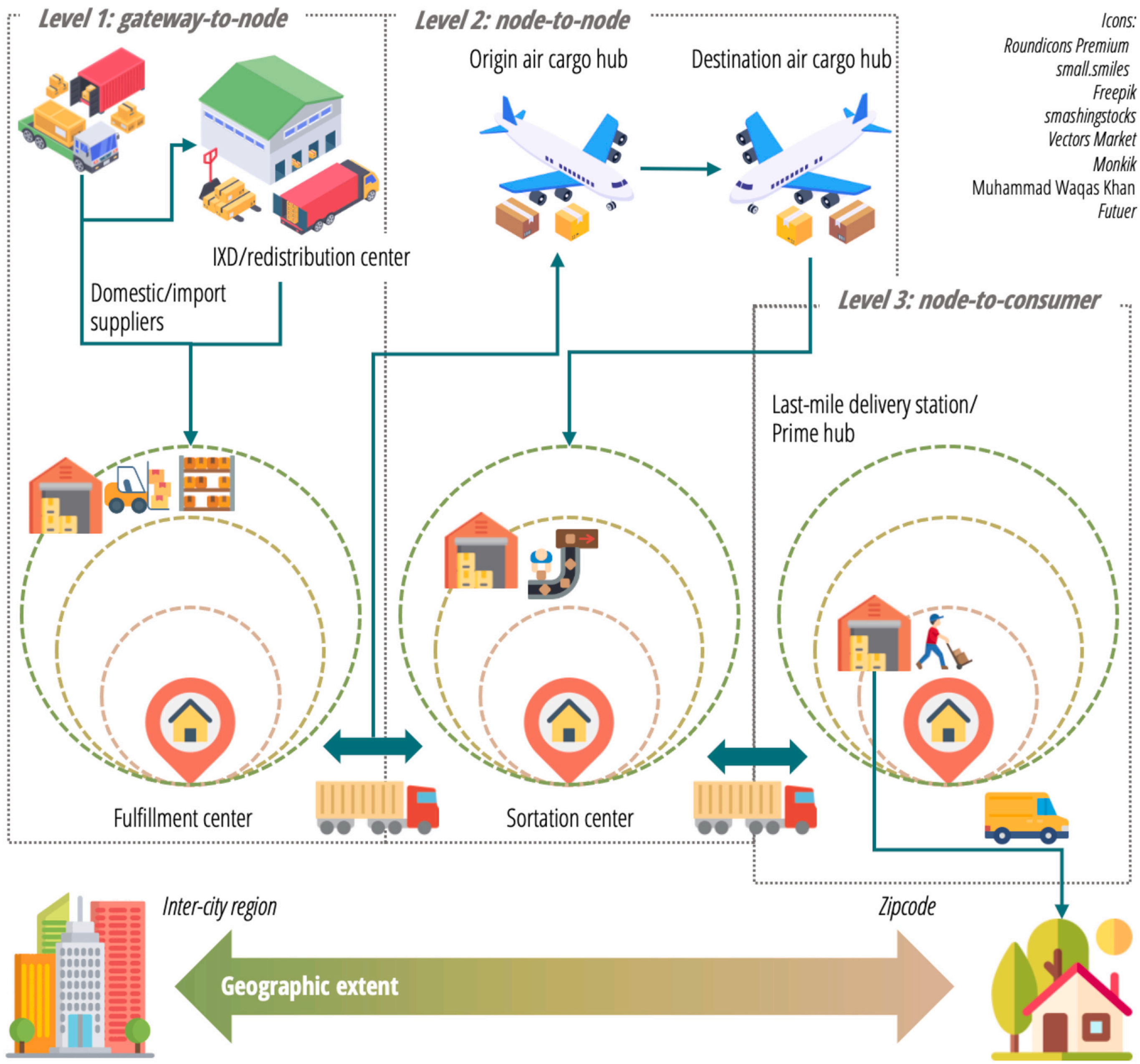

Fig. 2. Amazon's multi-layered physical distribution network across geographic extents (Adapted from MWPVL International, 2021).

distribution channel. Since many products require custom handling equipment, transportation/storage needs, or spillover inventory space, Amazon specialized some facilities (a) by size (small boxed sortables <10 kg, large boxed sortables <25 kg, and larger non-conveyable items), (b) by commodity types (e.g., jewelry and perishables), and/or (c) by time, which include newer sub-same day facilities often located inside FCs and seasonal facilities that service holiday spikes in demand.

- **Level 2: Sorting and distribution (i.e., node-to-node)**
  - o *Sortation center (SC)*: Large-sized, cross-docking facilities (i.e., serving in-bound trucks on one side, outbound on the other) that sort parcels bound for smaller geographic service areas.
  - o *Air cargo hub (ACH):* Cross-docking facilities serving domestic cargo airports.
- **Level 3: Last-mile logistic centers (i.e., node-to-consumer)**
  - o *Last-mile delivery station (LMDS)*: Medium-sized facilities that serve inbound trucks and outbound cargo vans adapted for dense urban street networks. These often include separate facilities for smaller parcels and heavier bulk items (e.g., furniture and large appliances).
  - o *Prime hubs (PH):* Small facilities designed to meet on-demand delivery needs for high-demand consumables.

Amazon has entered a new phase of horizontal growth. Since 2020, Amazon has accelerated platform openings in response to shifting consumer behaviors spurred by contagion concerns, new travel and remote work opportunities, entertainment and education patterns, and the long-term behavioral effects of in-store shopping restrictions (Gu et al., 2021; Kohli et al., 2020). In addition to building *more* logistics platforms, Amazon is building *out*: expanding its distribution footprint in most major cities and suburbs while also filling the service gaps in small urban and rural markets (e.g., the Upper Midwest and Great Plains), especially for FC and LMDS facilities (Schorung, 2021). Therefore, the remainder of this study focuses on the time period between 2013 and 2021 where

Amazon exerted greater control on its own supply chain while reaching new heights in their economies of scale.

3.3. Finding center

This research experiments with two methodologies to measure e-commerce centrality. The first method is rooted in centrographic techniques, which measures the degree of dispersion around a weighted centroid using spatial statistics (Bachi, 1963). There is limited consensus on what metrics and reference inputs to utilize in centrographic analyses, with studies often adopting one or multiple comparative metrics. Dablanc's work generally analyzed the relative barycenter (i.e. center of gravity) of W&D establishment distribution, which proved useful as a comparative metric across international case studies (Dablanc et al., 2014; Dablanc and Rakotonarivo, 2010; Dablanc and Ross, 2012).

Kang (2020b) estimated the centrality of Los Angeles W&D facilities using a change in distance from the absolute barycenter, related transportation sector businesses, and population centroids. Kang found that W&D facilities sprawled in relation to each metric but to a lesser degree than the absolute barycenter, implying that logistics are paralleling a decentralization of other related industries, employment, and population. As in, it is not just warehouses that are sprawling but also demand for freight (see also Sakai et al., 2017).

Research generally estimates intra-metropolitan freight activity as a function of population, employment, and transportation supply (Giuliano et al., 2018). Since home consumers are the primary market for e-commerce, population can appropriately proxy market demand. In-line with prevailing centrographic techniques in logistics research, this study measures the Euclidean distance from Amazon platforms to an MSA's population-weighted centroid (i.e., market center) relative to the year the platform opened. However, despite centroid distances being an important aspect to measuring centrographic dispersion, they assume monocentric urban form with uniform distance decay. Therefore, this study selects a population-weighted distance metric based on a Thiessen-defined service area allocation (Church and Murray, 2009).

With delivery drivers assuming the role of traveling shoppers, the study assumes Amazon will deliver to consumers closest to the origin platform. Therefore, the equation to measure an Amazon platform's (j) temporally relative, mean population-weighted distance (d) away from all gridded population points (p_i) within a service area follows:

$$Pop.weighted\ distance = \sum_i T_i{*}p_i{*}d_{ij} \Big/ \sum_i p_i{*}T_i \ \ while \sum_i p_i < k = \frac{Tot.MSA\ population}{Tot.MSA\ logistics\ platforms}$$

Where $T_i = 1$ if p_i is in a non-co-located, Thiessen-defined service area and $T_i = 0$ if p_i falls outside the boundaries. To ensure Thiessen polygons do not fracture service areas for co-located platforms, platforms sharing the same zipcode would also share the same Thiessen polygon. Moreover, the equation adds a population-based threshold break-point (k) to prevent distance inflation of more centrally located platforms.

Since both metrics use population proxies for home consumer access, this study labels the centroid-based metric as "distance to market centroid" and the population-weighted distance as "distance to market densities." When compared, both metrics reveal nuances to how Amazon platforms have spatially organized across facilities and within MSAs over time.

3.4. Exploratory regression approach

Table 1 summarizes several variables present in the MWPVL dataset, including:

- Floorspace square footage, including ground and mezzanine area;
- Leasing costs per square foot;
- Capital expenditures (CAPEX), such as fixed equipment costs;
- Annual operating expenditures (OPEX), not including leasing (e.g., labor and packaging costs);
- Number of full-time staff, not including temporary seasonal workers;
- Daily average packages shipped, not including holiday peaks;
- Advanced automation (i.e., the facility contained Kiva automated guided vehicles);
- and whether facility received some form of public incentive, mainly property tax abatement, hiring subsides, road construction, and/or other tax-related subsidies.

The study selects these variables based on their completeness in the dataset and relative independence from one another using variance inflation factor testing. The exception is facility floorspace, which had a strong collinear effect on most continuous variables. Larger platforms have larger everything: staffing, package throughput, lease costs, and CAPEX/OPEX. Several variables showed NAs in the dataset. Particularly, floorspace was 9.2% incomplete. This study uses a Multivariate Imputation By Chained Equations (MICE) algorithm to simulate missing data. The algorithm only uses determining variables with correlations, $|R^2|$, >0.25 to improve predictive accuracy. The study then inputs the facility-level variables into an exploratory Ordinary Least Squares (OLS) regression analysis.

To infer the most impactful variables, the analysis takes an exhaustive subset approach to OLS regression. The approach identifies variables for inclusion in best-fitting models by minimizing the Bayesian Information Criterion (BIC). The variable's inclusion, strength, and significance can then compare across models. Since platform role appears to largely influence centrality, the analysis conducts separate models for Level 3 platforms ($n = 574$), Level 1&2 ($n = 336$), and all three together ($n = 910$) for both density and centroid metrics, totaling six models.

Level 3 platforms are included as a dummy indicator for the latter models (*L3*). Additionally, the analysis includes a dummy variable indicating whether the facility opened after 2020 (*post-2020*). *Section 4* describes the reasoning for the timeseries variable inclusion. The analysis also includes two region-level dummy indicators for high population MSAs (*metro*) and strong relative employment strength in the NAICS

Table 1
Summary of variables for observed logistics platforms, 2013–2021 (MWPVL, 2021).

	Count	Avg. floorspace (mil. sq. ft.)	Avg. CAPEX ($ mil.)	Avg. OPEX ($ mil.)	Avg. Staff	Kiva automation (count)	Public incentives (count)	Avg. lease cost ($ per sq. ft)	Avg. daily packages shipped (thousand)
IXD	23	0.65	8.3	50.6	1163	0	5	7.5	NA
FC	223	1.2	134.9	102.5	1482	96	57	6.1	151.7
SC	78	0.36	52.7	41.8	787	6	9	6.0	195.6
ACH	12	0.48	185.5	35.5	784	1	1	5.1	NA
LMDS	513	0.18	15.2	7.9	182	3	3	8.1	26.8
PH	61	0.05	5.9	3.9	95	0	1	10.3	7.1
TOT.	910	0.47	49.6	34.4	570	106	76	7.5	75.2

493 sector (*LQ*). Moreover, to control for non-linear residuals and multicollinearity, the model log-transforms and normalizes continuous variables by square footage. In total, the exploratory regression includes 12 variables.

4. Results

4.1. Logistics centrality across platform roles and time: Summary statistics

Centrality varied across platform roles. On average, Level 3 platforms (i.e., LMDS and PH) were closer both to market centroids and densities (see Table 2). PH facilities, which have the most stringent delivery time windows, were substantially more centralized: the average PH was 7.9 mi and 3.5 mi from market centroids and densities, respectively. While LMDS were generally more decentral than PHs, their average distance from market centroids (12.8 mi) and densities (5.7 mi) still positioned them more centrally than Level 1 and 2 platforms. There was limited statistical difference in centrality across Level 1 and 2 platforms. Therefore, the subsequent OLS regression analysis groups Level 1 and Level 2 together, despite their distinct logistical functions. Market centroid and density distances between Level 1&2 and Level 3 platforms presented statistically significant differences in means according to an unequal variance *t*-test. In other words, platforms that serve a last-mile logistical function (i.e., node-to-consumer) are closer to consumers than platforms upstream in the distribution chain.

Note that platforms generally showed closer proximity to consumer market densities than they did market centroids. On average, platforms were roughly 12.9 mi from a market center (median = 11.1 mi). Whereas the mean distance from market densities was 6.2 mi (median = 5.3 mi). Centroid metrics also showed a higher degree of variance, with the minimum distance at roughly 0.4 mi and the maximum at 54.5 mi. Moreover, density and centroid distances have a moderate and statistically significant positive correlation ($R^2 = 0.31$; Pearson's *p*-value <0.001). Results suggest that while the two metrics moderately interrelate, there is still some degree of unaccounted variance.

Centrality also fluctuated over time (see Fig. 3). Level 3 platforms openings trended further away from market centers and densities during the observed timeframe. For instance, between 2014 and 2021, distance from market centroids and densities for PH platforms increased by 1.9 mi and 2.5 mi respectively, constituting a 29% and 136% increase in respective distances. For LMDS, the percent increase in distances from market centroids and densities between 2013 and 2021 increased by 46% (9.6 mi to 14.1 mi) and 114% (2.7 mi to 5.8 mi).

On the other hand, market centroid distances for Level 1 and 2 platforms exhibited only weak changes between start and end years. FCs opened *closer* to market centroids and densities, decreasing by 5% (14.7 mi to 14.0 mi) and 20% (9.5 mi to 7.6 mi), respectively. Meanwhile, SC increased their market density difference by 80% (4.7 mi to 8.5 mi). Except for FCs, however, most platforms opened after 2020 were further from their region's market centroid and density.

This initial analysis indicates there are significant differences in centrality between a) platform roles, especially Level 3, and b) platforms opened after 2020, which also marked a substantial acceleration in new facility openings. Fig. 4 shows the cumulative frequencies of both distance metrics by platform role (Level 1&2 versus Level 3) and timeframe (2013–2019 versus 2020–2021). While both metrics exhibit yearly fluctuations, they differ in relative magnitude. Table 3 validates the differences in means between the two timeframes for both Level 1&2 and Level 3, as well as corresponding Welch's (unequal variance) *t*-tests.

The results confirm that Level 1&2 and Level 3 platforms opened after 2020 were significantly more decentralized. The exception is Level 1&2 platforms did not show significant differences in centroid distances. The results also validate a significant difference in mean relative distances between Level 1&2 and Level 3 platforms, especially relative to centroid distances. Level 3 platforms opened between 2020 and 2021 decentralized to a larger degree around market centroids (Δ mean = 3.1 mi), whereas centroid distance remained static across most new Level 1&2 openings. Meanwhile, both Level 1&2 and Level 3 platforms that opened after 2020 decentralized around market densities, although the difference between them is less substantial (albeit significant).

4.2. Facility- and region-level factors for centrality: OLS regression

The degree and significance of platform decentralization varied across market density and centroid metrics. Table 4 presents the results of the best model subsets. The table also presents the R^2, log-likelihood, and BIC of the null model (subscript *0*), which includes all variables. All best subsets show small to moderate improvements in model fitness compared to the null. The paper summarizes the findings below.

4.2.1. Finding 1: Floorspace and leasing costs were among the strongest facility-level determinants for centrality across metrics and platform roles

Similar to other studies that examined at facility-level W&D characteristics (Kang, 2020a; Sivitanidou, 1996), platform size and leasing costs largely determined how far facilities located from the urban core. Model 1 and 2 (all levels) showed positive, non-linear relationships between centrality and floorspace and the inverse for leasing costs per square foot. Platforms opened further away from consumer market densities and centroids were generally able to leverage higher land availability and lower land values to build large facilities, enhancing their economies of scale (Andreoli et al., 2010).

However, the correlation strength and significance of these factors were not constant across all relationships. In L1&2 models, floorspace was insignificant for density distance (model 3); conversely, leasing costs were insignificant for centroid distance (model 4). In L3 models, high floorspace and low leasing costs strongly determined density decentralization (model 5); however, only leasing costs had a significant influence on centroid distance in the best subset (model 6). Although it is difficult to generalize a pattern from these observed discrepancies, results do suggest e-commerce platforms follow similar siting decisions as those made for general W&D facilities. Although the strength of these factors varied by metric used and what logistical role the platform played.

Table 2
Summary statistics of market density and centroid distances across platform roles.

	Market density distance (mi)					Market centroid distance (mi)				
	mean	med	range	var	Welch's t-test (H0:Level1&2 = Level3)	mean	med	range	var	Welch's t-test (H0:Level1&2 = Level3)
IXD	6.33	6.59	2.99–9.20	2.48		16.35	14.72	3.27–35.56	67.01	
FC	7.43	6.24	1.45–27.76	16.30		13.70	12.39	1.28–41.26	50.34	
ACH	7.87	7.42	3.74–12.98	7.32		13.09	13.23	7.10–22.23	23.24	
SC	7.35	6.16	2.57–20.71	13.77		14.12	12.80	2.27–38.19	48.86	
LMDS	5.71	5.03	0.94–23.59	10.97		12.80	10.66	0.38–54.50	71.47	
PH	3.54	3.49	1.06–7.77	2.24		7.87	6.14	0.36–25.66	31.84	
Level 1&2	**7.35**	**6.25**	**1.45–27.76**	**14.45**	**<0.001 *****	**13.95**	**12.61**	**1.28–41.26**	**50.23**	**<0.001 *****
Level 3	**5.48**	**4.80**	**0.94–23.59**	**10.49**		**12.27**	**10.00**	**0.36–54.50**	**61.51**	

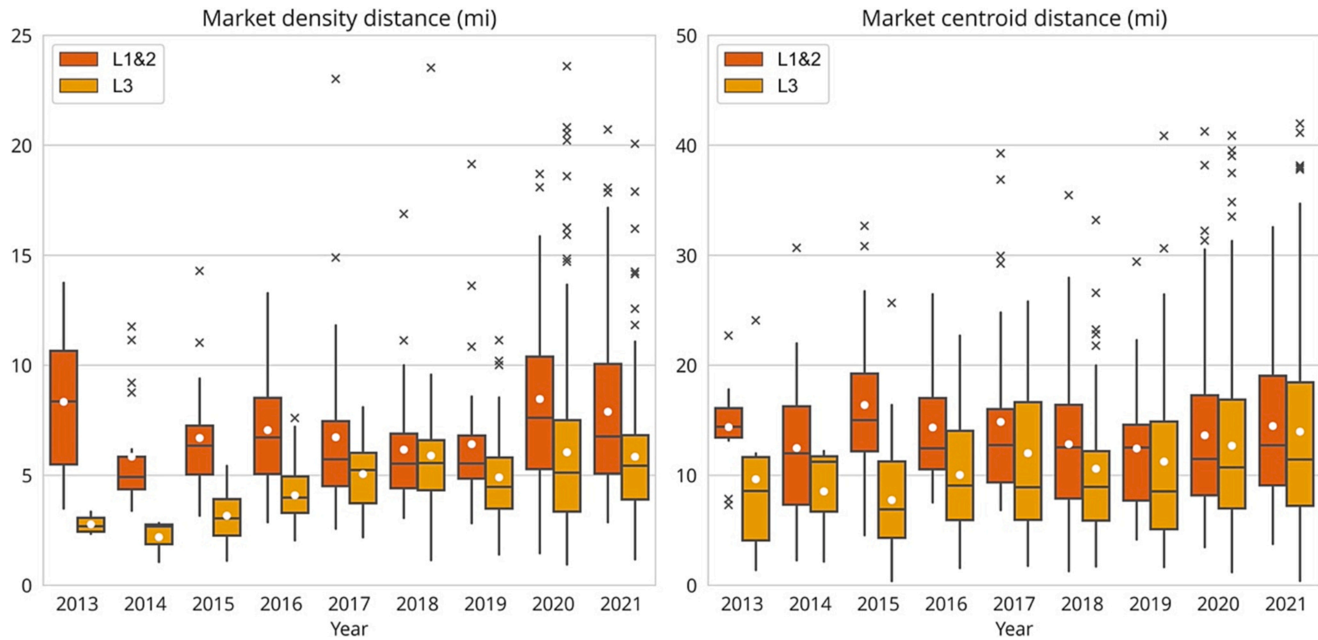

Fig. 3. Annual change in density and centroid distances by logistics platform role, 2013–2021 (NOTE: white dot represents mean).

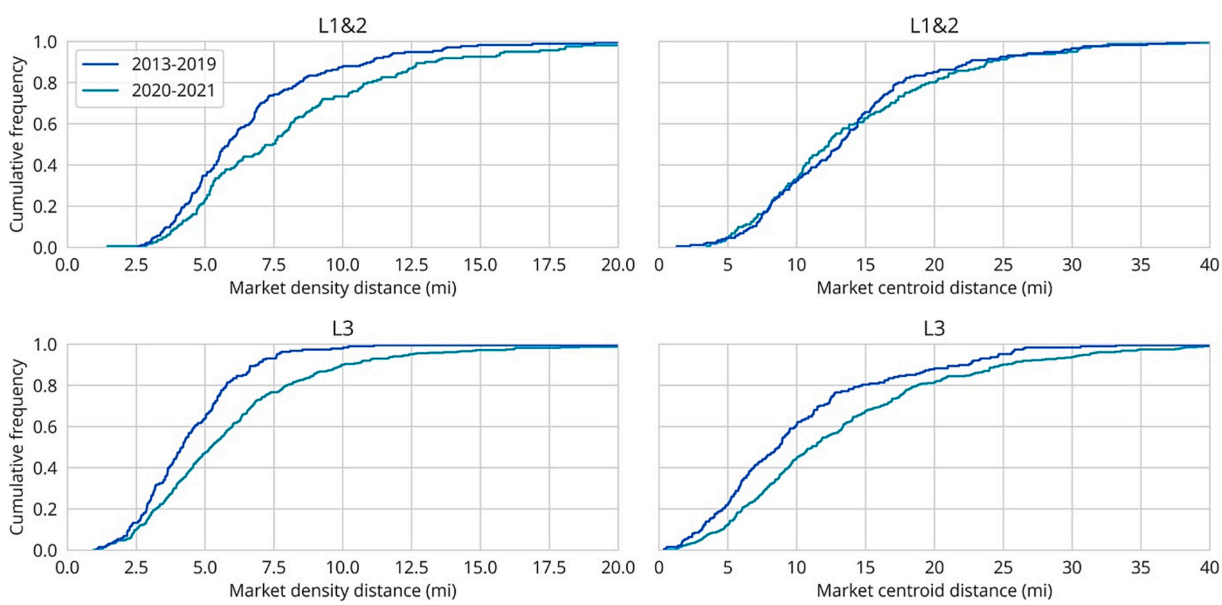

Fig. 4. Cumulative distances from market densities (left) and centroid (right) for different logistics platform functions and timeframes.

Table 3
Mean differences in relative distance measurements (mi), 2013–2019 and 2020–2021.

	Logistics function	N	Δ mean	Δ median	Welch's t-test (H0: ΔD = 0)	Welch's t-test (H0: ΔD Level 1&2 = ΔD Level 3)
Δ Centroid distance	Level 1&2	336	0.23	−0.87	0.765	<0.001***
	Level 3	574	3.05	2.42	<0.001***	
Δ Density distance	Level 1&2	336	1.54	1.62	<0.001***	<0.001***
	Level 3	574	1.46	1.03	<0.001***	

4.2.2. *Finding 2: Post-2020 openings influenced platform centrality*

The OLS regression validates the observation made in *Section 4.1*: platforms opened after 2020 located further away from both market densities and centroids, especially for L3 platforms. The dummy indicator, *post-2020*, showed positive significance for five out of six models. Generally, platforms opened between 2020 and 2021 located 17–20% further away from consumer markets than those built in years prior, depending on model subset and metric used. The exception is model 4, which showed no significance, and model 6, which showed a substantially stronger effect. In other words, post-2020 siting did not

Table 4
Best subset models for density and centroid distance measurements across logistics facility function (NOTE: continuous log-transformed variables normalized by floorspace sq. ft.;

	Density mi[log]		Centroid mi[log]		Density mi[log]		Centroid mi[log]		Density mi[log]		Centroid mi[log]	
	All levels [model 1]		All levels [model 2]		L1&2 [model 3]		L1&2 [model 4]		L3 [model 5]		L3 [model 6]	
	Coef.	*Std.e*	*Coef.*	*Std.e*	*Coef.*	*Std.e*	*Coef.*	*Std.e*	*Coef.*	*Std.e*	*Coef.*	*Std.e*
Intercept	2.06***	0.24	0.92***	0.33	1.71***	0.25	1.10***	0.39	1.71***	0.28	3.39***	0.34
floorspace[log]	0.06***	0.02	0.12***	0.02	–	–	0.09***	0.03	0.09***	0.03	–	–
lease cost[log]	−0.29***	0.04	−0.17***	0.06	−0.18**	0.07	–	–	−0.36***	0.05	−0.20**	0.07
packages[log]	−0.03	0.02	–	–	−0.05**	0.02	–	–	–	–	0.11***	0.04
staff[log]	0.06**	0.03	–	–	–	–	–	–	0.06*	0.03	–	–
post-2020	0.18***	0.03	0.17***	0.05	0.16***	0.05	–	–	0.18***	0.04	0.27***	0.07
metro>2.2mil+	−0.31***	0.03	0.43***	0.05	−0.32***	0.05	0.32***	0.06	−0.32***	0.05	0.47***	0.7
LQ > 1	0.06**	0.03	–	–	0.08*	0.05	–	–	–	–	–	–
L3	−0.16***	0.04	−0.13**	0.06	–	–	–	–	–	–	–	–
kiva auto.	–	–	−0.21***	0.08	–	–	−0.19***	0.06	–	–	–	–
public incentive	–	–	−0.09	0.08	–	–	–	–	−0.52***	0.17	–	–
opex[log]	–	–	–	–	0.12**	0.04	–	–	–	–	−0.25***	0.06
capex[log]	–	–	–	–	–	–	–	–	–	–	–	–
R^2 adj.	0.28		0.16		0.20		0.10		0.23		0.15	
LL	−565.03		−866.50		−172.85		−236.60		−378.30		−601.30	
BIC	1198.19		1794.33		392.23		502.28		807.42		1247.08	
R^2 adj.$_0$	0.28		0.15		0.19		0.10		0.23		0.15	
LL_0	−562.00		−865.05		−171.63		−233.03		−377.20		−597.05	
BIC_0	1221.39		1825.49		418.89		541.68		836.98		1276.68	

**** p < 0.1, ** p < 0.05, *** p < 0.01; + 2.2 million people derives from a natural break in population, see Kang, 2020a).***

significantly influence observed centroid decentralization for L1&2. Whereas post-2020 siting for L3 platforms decentralized roughly 31% on average from market centroids, controlling for other facility attributes.

4.2.3. Finding 3: MSA population was the strongest region-level determinant for centrality

Again in-line with Kang (2020a), the OLS regression modelling revealed MSA population substantially influenced platform centrality. Interestingly, however, the relationship sign differed across metrics. Platforms sited in large MSAs (population >2.2 million people) located 38–60% further away from market centroids on average, depending on platform role. Conversely, platforms in small MSA were roughly 27% *closer* to market densities, regardless of platform role. At first glance, this observation appears obvious. Kang (2020a) observed W&D facilities sprawl from urban centroids in larger metropolitan regions; however, higher population densities in large MSA means logistics platforms are still likely to open near denser consumer markets than smaller MSAs.

4.2.4. Finding 4: Level 3 (L3) platforms were more centralized than level 1 and 2 (L1&2) platforms, but explanatory factors varied

A platform's logistical role largely influenced its centrality. The *L3* dummy indicator Model 1 and 2 was negative and significant, providing further evidence for the assumption that last-mile e-commerce platforms (i.e., node-to-consumer facilities) localize closer to urban consumers than upstream distribution facilities. When controlling for variables in the best subset, L3 facilities were roughly 15% and 12% closer to market densities and centroids on average, respectively.

4.2.5. Finding 5: Other variables differed in strength, significance, and even sign across density/centroid metrics and facility role

Beyond the variables already discussed, several present different implications across models. For instance, number of staff per square foot of floorspace (*staff*) was positively significant in the base density distance model and for L3 platforms (model 1 and 5). L3 facilities closer to dense urban markets were less staffed. Conversely, L3 facilities closer to market centroids had higher package volumes (*packages*) when normalized by facility size (model 6).

Administering public incentives (mainly, property tax abatement) helped bring L3 platforms over 40% closer to market densities than platforms that received zero subsidies (model 5). The finding provides some empirical credence—and intriguing insight—to the influence of public planning practices on W&D siting decisions. Yuan (2019) shows how favorable and often lax zoning, taxes, and environmental regulations helped drive W&D firms deeper into the economically opportunistic suburbs of Southern California's Inland Empire. More direct public incentives likely have to counteract urban municipalities' higher financial and political costs to nudge L3 platforms closer to dense consumer markets.

Meanwhile, L1 or L2 facilities that contained advanced, Kiva robotic automation showed negative and significant coefficients (model 2 and 4). Since most Kiva-outfitted facilities are FCs, the implication is that FCs located closer to market centers were more automated. Non-lease related OPEX showed positive significance for model 3, but negative significance in model 6. Density decentralized L1 and L2 platforms had higher annual operating costs, while centroid decentralized L3 platforms had lower costs. Finally, CAPEX did not show any significance across best subsets.

4.2.6. Finding 6: Market density metrics produced better fitting models than centroid metrics

As the dependent variable, density distance created best-fitted models. For instance, model 1 presents the highest adjusted R^2, accounting for 28% of the variance. In the absence of additional metrics, cost-optimal distance away from market densities, rather than market cores, may more closely reflect Amazon platform siting decisions.

5. Discussion and conclusion

This study spatially explored Amazon's growing logistics footprint by using two distinct centrographic methods: distance from market (i.e., population) centroids and densities. While Amazon has pioneered innovative models for distribution and inventory management, Amazon's platform siting has followed similar geographic pathways outlined in past studies on broader W&D activity (e.g., Bowen, 2008; Cidell, 2011; Giuliano and Kang, 2018; Kang, 2020b). Platforms with larger floorspace needs generally opened further from market centroids where leasing costs were cheaper, especially in bigger metropolitan areas. These platforms did not necessarily open in less consumer-dense regions, however.

Moreover, facility attributes unique to e-commerce space also influenced platform centrality, which this study is the first to analyze in detail. Particularly, certain platforms strategically localized in closer proximity to urban consumer markets to expediently fulfill home delivery demand. Between 2013 and 2015, Amazon aggressively built out their logistics network to manage inventory and staging for last-mile delivery. Level 3 platforms (i.e., LMDS and PH) located moderately closer to market centers and densities than Amazon's Level 1 and 2 cross-docks, air hubs, fulfillment and sortation centers. In a short time period, however, Level 3 platforms showed signs of decentralization. On average, Level 3 platforms opened after 2020—a year that marked another major uptick in Amazon's horizontal expansion—dispersed 20% (11.1 to 13.4 mi) from market centroids and 23% (4.9 to 6.0 mi) from market densities.

The explanation is familiar: decentralizing last-mile platforms paralleled ballooning facility floorspaces and, to a lesser extent, falling land values. Between 2013 and 2020, for instance, the mean, annual rate of change for Level 3 floorspace and leasing costs was 21.8% and − 6.8%, respectively (see Fig. 5). However, this study does not claim a trend toward logistics sprawl. In fact, the future of "e-commerce sprawl" seems uncertain as Level 3 platforms opened in 2021 showed signs of decreasing floorspaces and increasing rents.

This study also found that state and municipal incentives play an important role in pulling Level 3 facilities closer to dense consumer markets, which departs from previous discussion of public sector's more passive role in W&D development (Yuan, 2019). Moreover, since the spatial analysis finds the market density metric has stronger explanatory power for platform siting decisions than the market centroid metric, this study provides evidence for observations of Amazon's "fill the gap" strategy in recent years (Schorung, 2021). That is, the horizontal integration of logistics activities across less consumer-dense regions.

5.1. Implications for logistics transport and land use

The effects of logistics sprawl, both positive and negative, are not well-quantified. Compact distances between W&D and consumer markets brings network optimizations that could reduce freight vehicle-miles-traveled (VMT) and consequent emission intensities (Dablanc and Rakotonarivo, 2010; Rivera-Gonzalez et al., 2023). However, it is not always intuitive to isolate the phenomenon from decentralizing freight demand. As Sakai et al. (2017) demonstrates, logistics sprawl does not imply increasing distances between platforms and demand and, thus, nonoptimal freight efficiencies (see also Robichet and Nierat, 2021). Even with longer distances between origin and market destinations, possible efficiency trade-offs occur as larger, more automated platforms leverage higher average loads per truck than their smaller, urban counterparts. In a scenario of decentralizing freight demand, optimized inventory sorting and truck loading procedures, decentralized logistics platforms could hypothetically bring operational efficiencies that create freight network improvements.

Conversely, inward expansion of urban logistics platforms puts freight activity in closer proximity to high population densities and sensitive urban land uses, which would magnify the effect of negative, local externalities (Holguín-Veras et al., 2021). Considering diesel truck exhaust constitutes a major fraction of urban mobility-source air pollution (Kozawa et al., 2009; Minet et al., 2020), facility localization would have important implications for pollutant-related respiratory and heart disease morbidity and social costs (HEI, 2010; Vohra et al., 2021). Additional externalities include urban heat island (Voogt and Oke, 2003), noise pollution (Münzel et al., 2021), traffic congestion and collisions, and surface runoff pollution (Müller et al., 2020), creating undesirable and potentially dangerous neighborhood conditions.

Therefore, last-mile logistics platforms' inward move toward denser, urban neighborhoods raises proximity concerns. Emerging research on Freight Efficient Land Uses (FELUs) presents public and private strategies for balancing competing land use, transport, and community priorities (Holguín-Veras et al., 2021). For instance, multi-use urban distribution centers maximize economically productive land uses while simultaneously mitigating external costs associated with "proximity logistics" (Buldeo Rai et al., 2022). Nature-based buffers or "complete streets" road design around logistics platforms can also enhance safe interactions between commercial vehicles and vulnerable road users, such as pedestrians or bicyclists (Conway et al., 2013; Pitera et al., 2017).

There is also an opportunity to adapt public health language, air quality/traffic monitoring, and Health Impact Assessments (HIA) into municipal permitting for freight-intensive land uses (Garcia et al., 2013; Nowlan, 2023; Schneller et al., 2022). Doing so can help planners and private operators better understand the community impacts of e-commerce logistics. In 2021, for example, the South Coast Air Quality Management District, Los Angeles metro's air pollution regulatory board, adopted the Warehouse Indirect Source Rule (ISR). ISR requires W&D operators to report truck traffic impacts and incentivizes large platforms to offset freight emissions in vulnerable neighborhoods via a point-or-fee system (South Coast AQMD, 2021).

5.2. Conclusion

This study presents a first effort to reveal spatial nuance in e-commerce platform siting decisions around U.S. metropolitan areas. The study hones in on Amazon's recent build out of last-mile delivery stations, which differ from conventional distribution centers in their ability to more expediently serve home delivery. Namely, these facilities have

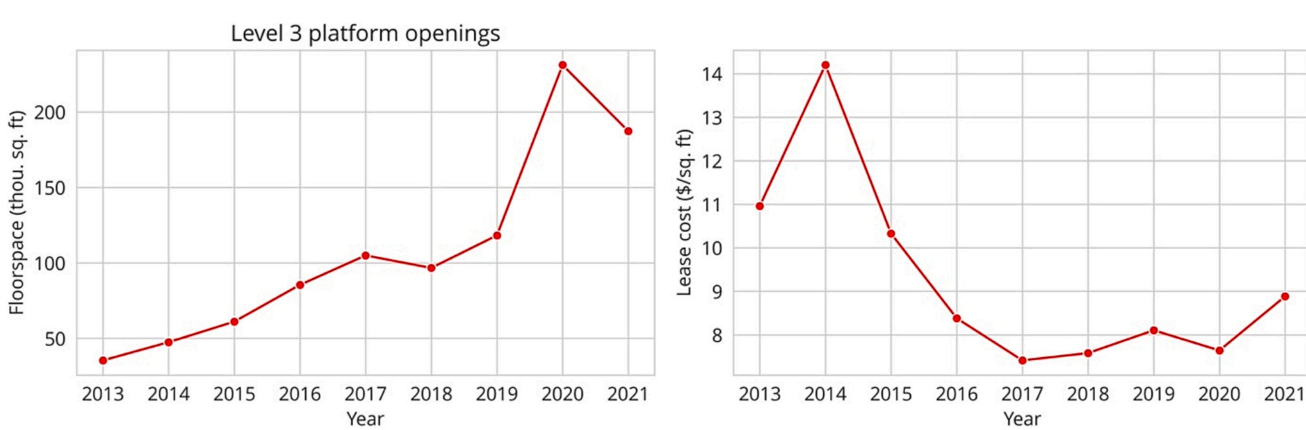

Fig. 5. Annual change in mean floorspace and leasing costs for Level 3 platform openings.

moved moderately closer to consumer households, forgoing the larger floorspace and lower rents that suburban locations accommodate—sometimes. More recently, LMDS have shown signs of decentralization matching the spatial trends of more upstream logistics facilities and W&D spaces more generally, indicative of a new phase in Amazon's horizontal integration to smaller markets. Robichet et al. (2021) also show in their analysis of microhub allocation in Paris that high real estate prices can eventually render urban siting unattractive as platforms near the city core become more saturated.

Amazon's newness limits this study's temporal scope, and this study does not attempt to make long-term projections regarding future e-commerce platform localization. Moreover, while this study measures the extent of e-commerce logistics (de)centralization, it does not causally explain *why* Amazon is sprawling in some cities and centralizing in others. However, the results do present implications that extend beyond any one e-commerce platform. The observed spatial trends reflect the restructuring of retail and logistics spaces that have generated heightened commercial competition for real estate, curb and street access in the urban core, leading to a supposed “space race” for freight carriers (ITF, 2022). But this has not been at the expense of e-commerce's sprawling logistical footprint in the exurbs. As the analysis itself reveal a heterogeneity of cases across facility types and cities, which future studies can and should explore.

CRediT authorship contribution statement

Travis Fried: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Visualization. **Anne Goodchild:** Supervision, Writing – review & editing.

Data availability

The data that has been used is confidential.

Appendix A. Appendix

Appendix Table 1
Observed MSAs and region-level variables.

MSA name, state (largest city)	Pop., 2020 (mil.)	LQ NAICS493	# logistics platforms	MSA name, state (largest city)	Pop., 2020 (mil.)	LQ NAICS493	# logistics platforms
New York City, NY	19.22	0.59	65	Birmingham, AL	1.09	0.56	5
Los Angeles, CA	13.21	0.68	36	Grand Rapids, MI	1.08	0.47	5
Chicago, IL	9.46	1.23	49	Rochester, NY	1.07	0.18	3
Dallas, TX	7.57	1.60	40	Tucson, AZ	1.05	0.94	5
Houston, TX	7.07	0.99	26	Fresno, CA	1.00	1.18	2
Washington, DC	6.28	0.29	16	Tulsa, OK	1.00	0.87	3
Miami, FL	6.17	0.49	24	Omaha, NE	0.95	0.53	3
Philadelphia, PA	6.10	1.21	37	Worcester, MA	0.95	1.82	6
Atlanta, GA	6.02	1.61	27	Bridgeport, CT	0.94	0.15	3
Phoenix, AZ	4.95	1.14	27	Greenville, SC	0.92	1.19	1
Boston, MA	4.87	0.45	17	Albuquerque, NM	0.92	0.44	3
San Francisco, CA	4.73	0.43	19	Albany, NY	0.88	0.96	4
Riverside, CA	4.65	6.19	39	Knoxville, TN	0.87	0.47	1
Detroit, MA	4.32	0.81	17	McAllen, TX	0.87	0.73	1
Seattle, WA	3.98	0.82	28	New Haven, CT	0.85	1.11	4
Minneapolis, MN	3.64	0.55	13	Oxnard, CA	0.85	0.36	5
Denver, CO	2.97	0.84	15	El Paso, TX	0.84	0.66	1
St. Louis, MO	2.80	0.94	13	Columbia, SC	0.84	0.94	2
Baltimore, MD	2.80	0.99	22	North Port, FL	0.84	0.88	4
Charlotte, SC	2.64	1.68	13	Dayton, OH	0.81	NA	2
Orlando, FL	2.61	0.58	9	Greensboro, NC	0.77	1.25	4
San Antonio, TX	2.55	1.41	13	Cape Coral, FL	0.77	0.35	3
Portland, OR	2.49	0.75	12	Stockton, CA	0.76	7.44	12
Sacramento, CA	2.36	1.95	10	Boise City, ID	0.75	0.59	5
Pittsburgh, PA	2.32	0.65	7	Little Rock, AR	0.74	0.39	5
Las Vegas, NV	2.27	1.28	17	Lakeland, FL	0.72	5.68	7
Cincinnati, OH	2.22	1.77	15	Akron, OH	0.70	1.33	4
Kansas City, MO	2.16	1.54	13	Des Moines, IA	0.70	0.57	5
Columbus, OH	2.12	3.45	14	Ogden, UT	0.68	1.80	1
Indianapolis, IN	2.07	2.73	16	Poughkeepsie, NY	0.68	NA	2
Cleveland, OH	2.05	0.48	8	Deltona, FL	0.67	0.38	2
San Jose, CA	1.99	0.14	10	Madison, WI	0.66	0.58	2
Nashville, TN	1.93	1.81	12	Syracuse, NY	0.65	0.59	2
Virginia Beach, VA	1.77	1.13	6	Provo, UT	0.65	0.42	1
Providence, RI	1.62	0.99	5	Durham, NC	0.64	0.76	5
Milwaukee, WI	1.58	0.67	4	Toledo, OH	0.64	1.14	3
Jacksonville, FL	1.56	2.13	9	Wichita, KS	0.64	0.26	2
Oklahoma City, OK	1.41	0.37	7	Harrisburg, PA	0.58	2.24	4
Raleigh, NC	1.39	0.26	4	Spokane, WA	0.57	0.35	4
Memphis, TN	1.35	4.63	8	Chattanooga, TN	0.57	0.49	1
New Orleans, LA	1.27	0.76	3	Modesto, CA	0.55	1.42	1
Louisville, KY	1.27	0.98	5	Youngstown, OH	0.54	0.81	1
Salt Lake City, UT	1.23	1.30	10	Lexington\, KY	0.52	2.34	2
Hartford, CT	1.20	1.18	6	Pensacola, FL	0.50	0.12	1
Buffalo, NY	1.13	0.71	2				

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