

#### TRANSPORT FINDINGS

# Increasing Returns to Scale in Carpool Matching: Evidence from Scoop

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#### Findings

Systems that depend on matching often exhibit scale economies, whereby increased participation leads to improved performance for all users. This paper examines the presence of such increasing returns to scale in carpool matching. Data from Scoop, a carpooling app, is used to demonstrate this phenomenon across various markets using regression. As the number of requests to carpool in a certain market rises, the share of proposed matches that users accept rises, while the extra distance traveled to accommodate these carpools declines. These relationships hold in four specifications of the regression model, and they suggest there are increasing returns to scale in matching.

### 1. Questions

Carpooling in the US steadily declined after the oil crisis of the 1970's (Ferguson 1997), but new technology is hoped to reverse the trend. Services such as Waze Carpool, Carzac, BlaBlaCar and (until recently) Scoop use mobile apps to provide "ridesharing" in a strict sense: "formal or informal shared rides between drivers and passengers with similar origin-destination pairings" (Shaheen and Cohen 2019). Perhaps these apps' primary job is matching: they join a driver and passengers into a carpool within parameters (schedule, travel time, cost, etc.) sufficiently agreeable that all voluntarily participate. Economists have already developed analytical models of matching and applied them to topics such as agglomerations (Zenou 2009), street-hail taxi service (Fréchette, Lizzeri, and Salz 2019) and the labor market (Diamond 1982). A chief concern in this literature is the role of returns to scale in matching. For example, if an activity has increasing returns to scale in matching, then when more people participate, the quality of matches rises. This can lead to positive feedback, as rising usage improves the customer experience and thus invites higher usage. Intuitively, carpool matching should exhibit such returns to scale: the more people choose to carpool, the more likely that one of my neighbors will have a destination and schedule similar to mine, and the more likely I am to carpool in the future. This possibility has received attention in theoretical studies—e.g., by Lehe and Pandey (2020) and de Palma, Stokkink, and Geroliminis (2020)—but no *empirical* study has testified to its existence. Hence, this paper asks: Does a real-world dataset provide evidence that the quality of matches rises with the usage of a carpool service?

## 2. Methods

Our data were provided by Scoop Technologies. Prior to 2021,<sup>1</sup> the firm operated a mobile app for carpooling. The day before traveling, a user would place a trip request specifying their preferred origin, destination, role (passengers or driver), and schedule. Every evening, Scoop used these trip requests to propose matches, and users could accept or reject matches without cost. Passengers paid a small fee to use the service, which would compensate Scoop and also reimburse drivers for gas, tolls, etc. Local governments or employers subsidized many trips. A key motive for many drivers to participate was to use carpool lanes, as well as to network with other employees of a large firm.

The dataset includes average weekly metrics from the first 15-16 weeks of Scoop starting service in seven "markets". A market might be a city or an employer with a large campus, and all represent distinct spatial regions. To preserve anonymity and trade secrets, Scoop has excluded any information about the seven markets and dates (beyond the fact all seven are in the Bay Area or Seattle, and all data is from before 2020), so they are named as letters A-G. Holiday weeks such as American Thanksgiving are flagged, so we have excluded them from analysis. These exclusions result in 103 observations, each representing data from one week in one market.

We study three metrics:

- 1. Trip requests: The number of users who requested a trip.
- 2. Match rate: The fraction of trip requests resulting in a positive match.
- 3. Detour distance: The difference between the distance a driver travels on their carpool and the distance they would traverse if they drove directly to the destination.

As part of the privacy measures, all metrics are normalized to the highest value observed in a given market. For example, if the actual match rate is 40% in some market for some week, and the highest match rate ever observed for the market is 80%, then the match\_rate variable we have is 0.5 (40%/80%) for that week. This normalization makes it impossible to compare absolute scale *across* markets.

Our hypothesis is that the quality of matches improves with the scale of participation. In the context of the dataset, we interpret this to mean that the match rate should rise with the number of trip requests in a market, and the detour distance should decline. We investigate whether this is so by performing

<sup>1</sup> The COVID-19 crisis led Scoop to refocus on a different line of business.

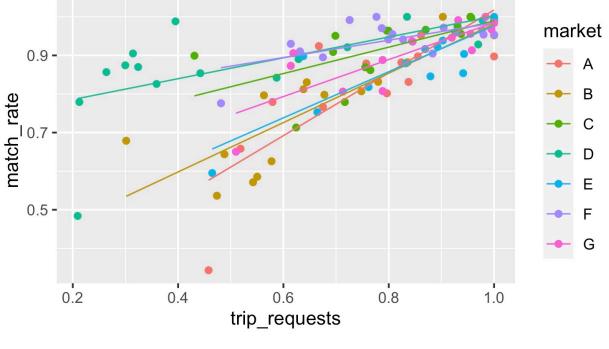


Figure 1. trip requests vs. match rate (both normalized)

regressions on the dataset. While the indexing and scrubbing limits how much can be gleaned from the data, the results of the regressions can at least be suggestive of matching economies, albeit not definitive evidence.

### 3. Findings

In what follows, *trip\_requests*, *match\_rate* and *detour\_distance* refer to the *normalized* trip requests, match rate and detour distance, respectively. We distinguish the two in order to maintain clarity about what the coefficients in the regressions mean.

First we look at the effect of trip\_requests on match\_rate. Fig. 1 shows a plot of the data with a regression line through each market. Clearly, every market's match\_rate rises with trip\_requests.

Table 1 shows the results of four regression models for match rate. Model (1) is an OLS regression of match\_rate on trip\_requests. Model (2) is a two-stage least-squares model with instrumented variables (IV) undertaken to account for obvious endogeneity: if people expect to receive a match good enough to accept, they are more likely to request a trip. Hence, Model (2) uses *week of operation* (that is, how many weeks since Scoop launched in the market) as an instrument for trip\_requests. As Fig. 2 shows, trip\_requests rises over time in every market. The coefficient of week in a regression of trip\_requests on week is .030 (significant at the 99% level). This suggests that in each market, trip\_requests increases by 3% (not compounded) of the maximum value observed per week. Models (3) and (4) are 'fixed effects' versions of (1) and (2), respectively, which give each market its own intercept relative to market

#### Table 1. Match rate models

	Dependent variable:					
	match_rate					
	OLS (1)	IV (2)	OLS (market FE) (3)	IV ( market FE) (4)		
Constant	0.590 ***	0.540 ***	0.484 ***	0.464 ***		
	(0.036)	(0.051)	(0.042)	(0.054)		
trip_requests	0.380 ***	0.457 ***	0.441 ***	0.503 ***		
	(0.046)	(0.065)	(0.047)	(0.063)		
R <sup>2</sup>	0.399	0.379	0.599	0.554		
Adjusted R <sup>2</sup>	0.393	0.373	0.569	0.521		

Note: \*p<0.1, \*\*p<0.05; \*\*\*p<0.01

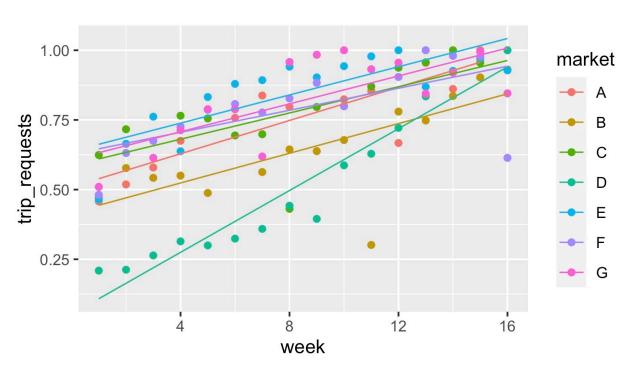


Figure 2. trip requests (normalized) vs (excluding holiday weeks)

A (not printed), so that *Constant* in <u>Table 1</u> is the intercept for market A. All four models have coefficients on trip\_requests that are positive, significant and similarly sized. The *ivreg* R package (Fox, Kleiber, and Zeileis 2021) used to perform the instrumental variable regressions also runs two tests: one for weak instruments and a Wu-Hausman test for endogeneity. For both IV models, the statistics have negligible p-values, suggesting (i) week is not a weak instrument for trip\_requests; and, (ii) trip\_requests and match\_rate are indeed endogenous, as suspected.

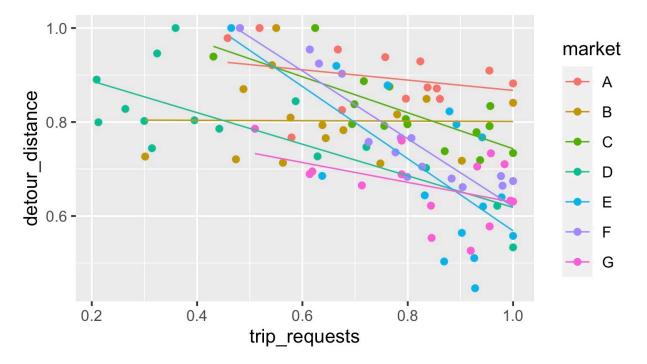


Figure 3. detour distance vs. trip requests (both normalized)

	Dependent variable					
	detour_distance					
	OLS (1)	IV (2)	OLS (market FE) (3)	IV (market FE) (4)		
Constant	0.996 ***	1.141 ***	1.147 ***	1.273 ***		
	(0.040)	(0.081)	(0.045)	(0.061)		
trip_requests	-0.302 ***	-0.484 ***	-0.336 ***	-0.480 ***		
	(0.052)	(0.106)	(0.050)	(0.071)		
R <sup>2</sup>	0.252	0.154	0.542	0.477		
Adjusted R <sup>2</sup>	0.244	0.145	0.508	0.438		

Table 2. Detour distance models

Note: \*p<0.1, \*\*p<0.05; \*\*\*p<0.01

The same exercise was performed with detour\_distance (the normalized detour distance) as the dependent. Fig. 3 shows detour\_distance generally declines with trip\_requests. The resulting estimates appear in Table 2. The  $R^2$  of this model is lower, but the coefficients on trip\_requests are still significant and have the hypothesized negative sign.

Thus, the results provide evidence that carpool matching exhibits increasing returns to scale. These returns to scale open the door to a positive feedback mechanism, whereby usage and quality reinforce each other. While our results do not explicitly confirm the existence of such a virtuous cycle, they do suggest that efforts and technologies that encourage carpooling could have exponential returns.

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#### REFERENCES

Diamond, Peter A. 1982. "Aggregate Demand Management in Search Equilibrium." *Journal of Political Economy* 90 (5): 881–94.

Ferguson, Erik. 1997. "The Rise and Fall of the American Carpool: 1970-1990." *Transportation* 24 (4): 349–76. <u>https://doi.org/10.1023/A:1004928012320</u>.

Fox, John, Christian Kleiber, and Achim Zeileis. 2021. "Ivreg: Instrumental-Variables Regression by '2SLS', '2SM', or '2SMM' with Diagnostics." 2021. <u>https://john-d-fox.github.io/ivreg/</u>.

Fréchette, Guillaume R., Alessandro Lizzeri, and Tobias Salz. 2019. "Frictions in a Competitive, Regulated Market: Evidence from Taxis." *American Economic Review* 109 (8): 2954–92. https://doi.org/10.1257/aer.20161720.

Lehe, Lewis J., and Ayush Pandey. 2020. "Hyperdemand: A Static Traffic Model with Backward-Bending Demand Curves." *Economics of Transportation* 24: 100182. <u>https://doi.org/10.1016/j.ecotra.2020.100182</u>.

Palma, André de, Patrick Stokkink, and Nikolas Geroliminis. 2020. "Influence of Dynamic Congestion on Carpooling Matching." Technical Report. THEMA (THéorie Economique, Modélisation et Applications), Université de....

Shaheen, Susan, and Adam Cohen. 2019. "Shared Ride Services in North America: Definitions, Impacts, and the Future of Pooling." *Transport Reviews* 39 (4): 427–42. <u>https://doi.org/10.1080/01441647.2018.1497728</u>.

Zenou, Yves. 2009. Urban Labor Economics. Cambridge University Press.