Appendix A: Proofs and Additional Theoretical Results

A.1. Technical Results

Proposition 1. *Restaurant density effects on sales volume, order wait time, and customer spending (i.e., $\lambda'(\mathcal{N})$, $\frac{\partial t}{\partial \mathcal{N}}(\mathcal{N};x)$, and $\psi'(\mathcal{N})$) can be characterized as:*

$$\lambda'(\mathcal{N}) = \frac{\Lambda'(\mathcal{N})\int_0^{+\infty}\mathbb{P}\left[v\geq h^{-1}(.)|x\right]dF_x(x)+\Lambda(\mathcal{N})\left[\frac{\gamma\mu'(\mathcal{N})}{(\mu(\mathcal{N})-\lambda(\mathcal{N}))^2}-\alpha'(\mathcal{N})\right]\int_0^{+\infty}f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)}{1+\gamma\Lambda(\mathcal{N})\left[(\nu-\lambda(\mathcal{N}))^{-2}+(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\right]\int_0^{+\infty}f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)}, \tag{13}$$

$$\frac{\partial t}{\partial \mathcal{N}}(\mathcal{N};x) = \lambda'(\mathcal{N})\left[(\nu-\lambda(\mathcal{N}))^{-2}+(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\right]-\mu'(\mathcal{N})\left(\mu(\mathcal{N})-\lambda(\mathcal{N})\right)^{-2}, \tag{14}$$

$$\psi'(\mathcal{N}) = \left[\gamma\lambda'(\mathcal{N})\left((\nu-\lambda(\mathcal{N}))^{-2}+(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\right)-\frac{\gamma\mu'(\mathcal{N})}{\left(\mu(\mathcal{N})-\lambda(\mathcal{N})\right)^2}+\alpha'(\mathcal{N})\right] \cdot\int_0^{+\infty}f_v\left[h^{-1}(.)\right]\left(h^{-1}\right)'(.)\cdot\frac{\int_{h^{-1}(.)}^{+\infty}\left[s^*(v)-s^*\left(h^{-1}(.)\right)\right]dF_v(v)}{\mathbb{P}\left[v\geq h^{-1}(.)\right]^2}dF_x(x), \tag{15}$$

where $(.)=(\gamma t(\mathcal{N};x)+\alpha(\mathcal{N}))$.

Proof. We begin by deriving Equation (13). By Equation (5), we first have

$$\lambda'(\mathcal{N}) = \Lambda'(\mathcal{N})\int_0^{+\infty}\mathbb{P}\left[v\geq h^{-1}(.)|x\right]dF_x(x)+\Lambda(\mathcal{N})\int_0^{+\infty}\frac{\partial}{\partial\mathcal{N}}\mathbb{P}\left[v\geq h^{-1}(.)|x\right]dF_x(x).$$

where

$$\frac{\partial}{\partial\mathcal{N}}\mathbb{P}\left[v\geq h^{-1}(.)|x\right] = -f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)\left[\gamma\frac{\partial}{\partial\mathcal{N}}t(\mathcal{N};x)+\alpha'(\mathcal{N})\right].$$

In addition, Equation (2) implies that $\frac{\partial}{\partial\mathcal{N}}t(\mathcal{N};x)=\frac{\lambda'(\mathcal{N})}{(\nu-\lambda(\mathcal{N}))^2}-\frac{\mu'(\mathcal{N})-\lambda'(\mathcal{N})}{(\mu(\mathcal{N})-\lambda(\mathcal{N}))^2}$. Then, $\lambda'(\mathcal{N})$ can be written as:

$$\begin{aligned}\lambda'(\mathcal{N}) =&\Lambda'(\mathcal{N})\int_0^{+\infty}\mathbb{P}\left[v\geq h^{-1}(.)|x\right]dF_x(x)\\ &-\Lambda(\mathcal{N})\left[\frac{\gamma\lambda'(\mathcal{N})}{(\nu-\lambda(\mathcal{N}))^2}-\frac{\gamma\mu'(\mathcal{N})-\gamma\lambda'(\mathcal{N})}{(\mu(\mathcal{N})-\lambda(\mathcal{N}))^2}+\alpha'(\mathcal{N})\right]\int_0^{+\infty}f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x).\end{aligned}$$

Collecting terms of $\lambda'(\mathcal{N})$ and following simple algebra, one can show that the equation above is equivalent to Equation (13).

For Equation (14), it immediately follows from Equation (2); we omit the details for brevity.

Lastly, to establish Equation (15), we first note that:

$$\psi'(\mathcal{N}) = \int_0^{\infty}\frac{\partial}{\partial\mathcal{N}}\mathbb{E}\left[s^*(v)|v\geq h^{-1}(.),x\right]dF_x(x).$$

Within the integral, it immediately follows that

$$\begin{aligned}
&\frac{\partial}{\partial \mathcal{N}}\mathbb{E}\left[s^*(v)|v \geq h^{-1}(.), x\right] \\
=&\left[\gamma\frac{\partial}{\partial \mathcal{N}}t(\mathcal{N};x)+\alpha'(\mathcal{N})\right]\cdot f_v\left[h^{-1}(.)\right]\left(h^{-1}\right)'(.)\cdot\frac{\int_{h^{-1}(.)}^{+\infty}\left[s^*(v)-s^*\left(h^{-1}(.)\right)\right]dF_v(v)}{\mathbb{P}\left[v\geq h^{-1}(.)\right]^2}.
\end{aligned}$$

We thereby obtain Equation (15) by substituting $\frac{\partial}{\partial \mathcal{N}}t(\mathcal{N};x)$ in the expression above with Equation (14). □

The following propositions show the sufficient and necessary conditions for $\frac{\partial}{\partial \mathcal{N}}t(\mathcal{N};x)\geq 0$, $\lambda'(\mathcal{N})\geq 0$, and $\psi'(\mathcal{N})\geq 0$, respectively. To ease notation, we let $(.)=(\gamma t(\mathcal{N};x)+\alpha(\mathcal{N}))$ and let

$$\begin{aligned}
M(\mathcal{N})=&(\nu-\lambda(\mathcal{N}))^{-2}+(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\\
D(\mathcal{N})=&1+\gamma\Lambda(\mathcal{N})\left[(\nu-\lambda(\mathcal{N}))^{-2}+(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\right]\int_0^{+\infty}f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)\\
=&1+\gamma\Lambda(\mathcal{N})M(\mathcal{N})\int_0^{+\infty}f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x),
\end{aligned}$$

in Appendix A.1.

Proposition 2. *The restaurant density positively affects sales volume, $\lambda'(\mathcal{N})\geq 0$ if and only if*

$$\begin{aligned}
&\Lambda'(\mathcal{N})\cdot\int_0^{+\infty}\mathbb{P}\left[v\geq h^{-1}(.)|x\right]dF_x(x)\\
-&\alpha'(\mathcal{N})\cdot\Lambda(\mathcal{N})\int_0^{+\infty}f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)\\
+&\mu'(\mathcal{N})\cdot\frac{\gamma\Lambda(\mathcal{N})}{(\mu(\mathcal{N})-\lambda(\mathcal{N}))^2}\int_0^{+\infty}f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)\\
\geq&0.
\end{aligned}\tag{16}$$

Proof. Note that the denominator of $\lambda'(\mathcal{N})$'s expression in Equation (13) is always positive. Then, it immediately follows that Inequality (16) is equivalent to $\lambda'(\mathcal{N})\geq 0$. □

Proposition 3. *The restaurant density negatively affects the delivery speed, $\frac{\partial}{\partial \mathcal{N}}t(\mathcal{N};x)\geq 0$ if and only if*

$$\begin{aligned}
&\Lambda'(\mathcal{N})\cdot\int_0^{+\infty}\mathbb{P}\left[v\geq h^{-1}(.)|x\right]dF_x(x)\\
-&\alpha'(\mathcal{N})\cdot\Lambda(\mathcal{N})\int_0^{+\infty}f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)\\
-&\mu'(\mathcal{N})\cdot\frac{(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}}{(\nu-\lambda(\mathcal{N}))^{-2}+(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}}\\
\geq&0
\end{aligned}\tag{17}$$

Proof. Combining Equations (13) and (14), we obtain:

$$\frac{\partial}{\partial \mathcal{N}}t(\mathcal{N};x)=\Lambda'(\mathcal{N})\cdot\frac{M(\mathcal{N})}{D(\mathcal{N})}\int_0^{+\infty}\mathbb{P}\left[v\geq h^{-1}(.)|x\right]dF_x(x)$$

$$
\begin{aligned}
&-\alpha'(\mathcal{N})\cdot\frac{M(\mathcal{N})}{D(\mathcal{N})}\Lambda(\mathcal{N})\int_0^{+\infty} f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)\\
&+\mu'(\mathcal{N})\cdot\frac{M(\mathcal{N})}{D(\mathcal{N})}\frac{\gamma\Lambda(\mathcal{N})}{(\mu(\mathcal{N})-\lambda(\mathcal{N}))^2}\int_0^{+\infty} f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)\\
&-\mu'(\mathcal{N})\cdot(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}.
\end{aligned}
$$

Then, we note that the coefficient of $\mu'(\mathcal{N})$ in the expression above can be simplified as:

$$
\begin{aligned}
&\frac{M(\mathcal{N})}{D(\mathcal{N})}\frac{\gamma\Lambda(\mathcal{N})}{(\mu(\mathcal{N})-\lambda(\mathcal{N}))^2}\int_0^{+\infty} f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)-(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\\
=&\frac{1}{D(\mathcal{N})}\left[M(\mathcal{N})\frac{\gamma\Lambda(\mathcal{N})}{(\mu(\mathcal{N})-\lambda(\mathcal{N}))^2}\int_0^{+\infty} f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)-D(\mathcal{N})(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\right]\\
=&-\frac{(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}}{D(\mathcal{N})}.
\end{aligned}
$$

Therefore, Inequality (17) holds by multiplying $D(\mathcal{N})/M(\mathcal{N})$ on both sides of $\frac{\partial}{\partial\mathcal{N}}t(\mathcal{N};x)\geq 0$. □

Proposition 4. *The restaurant density positively affects customer spending, $\psi'(\mathcal{N})\geq 0$ if and only if*

$$
\begin{aligned}
&\Lambda'(\mathcal{N})\cdot\gamma\left[(\nu-\lambda(\mathcal{N}))^{-2}+(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\right]\int_0^{+\infty}\mathbb{P}\left[v\geq h^{-1}(.)|x\right]dF_x(x)\\
&+\alpha'(\mathcal{N})\\
&-\mu'(\mathcal{N})\cdot\gamma(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\\
&\geq 0.
\end{aligned}
\tag{18}
$$

Proof. By Equation (15), we note that $\psi'(\mathcal{N})\geq 0$ is equivalent to

$$
\gamma\lambda'(\mathcal{N})\left((\nu-\lambda(\mathcal{N}))^{-2}+(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\right)-\frac{\gamma\mu'(\mathcal{N})}{\left(\mu(\mathcal{N})-\lambda(\mathcal{N})\right)^2}+\alpha'(\mathcal{N})\geq 0 \tag{19}
$$

because $\int_0^{+\infty} f_v\left[h^{-1}(.)\right]\left(h^{-1}\right)'(.)\cdot\frac{\int_{h^{-1}(.)}^{+\infty}\left[s^*(v)-s^*\left(h^{-1}(.)\right)\right]dF_v(v)}{\mathbb{P}\left[v\geq h^{-1}(.)\right]^2}dF_x(x)\geq 0$ always holds true. Exploiting Equation (13), Inequality (19) becomes:

$$
\begin{aligned}
&\Lambda'(\mathcal{N})\cdot\gamma\frac{M(\mathcal{N})}{D(\mathcal{N})}\int_0^{+\infty}\mathbb{P}\left[v\geq h^{-1}(.)|x\right]dF_x(x)\\
&+\mu'(\mathcal{N})\cdot\left[\gamma^2\Lambda(\mathcal{N})\frac{M(\mathcal{N})}{D(\mathcal{N})}(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\int_0^{+\infty} f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)-\gamma(\mu(\mathcal{N})-\lambda(\mathcal{N}))^{-2}\right]\\
&-\alpha'(\mathcal{N})\cdot\left[\gamma\Lambda(\mathcal{N})\frac{M(\mathcal{N})}{D(\mathcal{N})}\int_0^{+\infty} f_v\left(h^{-1}(.)\right)\left(h^{-1}\right)'(.)dF_x(x)-1\right]\\
&\geq 0,
\end{aligned}
$$

which can be simplified as Inequality (18). □

A.2. Lower Bound on Delivery Pooling Magnitude

It is worth noting that these conditions analytically characterize how the magnitudes of the externalities (i.e., $\Lambda'(\mathcal{N})$, $\alpha'(\mathcal{N})$, and $\mu'(\mathcal{N})$) interact to shape each restaurant density effect. Although Propositions 2, 3, and 4 cannot be readily formulated as testable hypotheses, they can, when combined with empirical evidence, provide a theoretical lower bound on the magnitude of the delivery pooling externality, $\mu'(\mathcal{N})$. Specifically, our empirical results (Table 4) indicate that $\Lambda'(\mathcal{N}) \geq 0$, $\frac{\partial}{\partial \mathcal{N}} t(\mathcal{N}; x) \leq 0$, and $\psi'(\mathcal{N}) \leq 0$. These observations imply the following relationship between delivery pooling and the other two externalities:

$$\mu'(\mathcal{N}) \geq \alpha'(\mathcal{N}) \cdot \frac{(\mu(\mathcal{N}) - \lambda(\mathcal{N}))^2}{\gamma} + \Lambda'(\mathcal{N}) \cdot \left(1 + \frac{(\mu(\mathcal{N}) - \lambda(\mathcal{N}))^2}{(\nu - \lambda(\mathcal{N}))^2}\right) \int_0^{+\infty} \mathbb{P}\left[v \geq h^{-1}(.)|x\right] dF_x(x),$$

which serves as an analytical lower bound on the magnitude of $\mu'(\mathcal{N})$.

A.3. Proofs of Main Results

Proof of Lemma 1. For a customer of preference v, their optimal spending amount at the focal restaurant can be solved by the first-order condition $\frac{\partial U}{\partial s}(s; v) = vu'(s) - 1 = 0$. Note that $u''(s) < 0$. Then, the solution to the first-order condition is unique, and it can be expressed by $(u')^{-1}(1/v)$. Lastly, we can show that $\frac{\partial^2 U}{\partial s^2}(s; v) = vu''(s) < 0$. Therefore, $s^*(v) = (u')^{-1}(1/v)$ maximizes the customer's utility from the focal restaurant.

Next, we prove the assertion that $s^*(v) = (u')^{-1}\left(\frac{1}{v}\right)$ increases with v. Note that $u'(\cdot)$ is a decreasing function because $u''(\cdot) < 0$. Then, $(u')^{-1}(\cdot)$ is a decreasing function. In addition, $\frac{1}{v}$ decreases with v. Therefore, $s^*(v) = (u')^{-1}\left(\frac{1}{v}\right)$ increases with v. □

Proof of Lemma 2. Following basic algebra, we have:

$$\begin{aligned} h'(v) &= u\left(s^*(v)\right) + vu'(s^*(v))s^{*\prime}(v) - s^{*\prime}(v) \\ &= u(s^*(v)) + \left(vu'(s^*(v)) - 1\right) s^{*\prime}(v) \\ &= u(s^*(v)) \\ &> 0. \end{aligned}$$

The last equation holds because of the first-order condition $vu'(s^*(v)) - 1 = 0$. □

Proof of Theorem 1. The proposition immediately follows given Inequalities (17), (16), and (18). We omit the proof for brevity.

□

Proof of Theorem 2. The proposition immediately follows from Inequalities (17), (16), and (18). We omit the proof for brevity. □

Proof of Corollary 1. This proof follows the same argument as Theorem 1's proof. Hence, we omit it for brevity. □

Appendix B: Supplementary Results

B.1. Examples of restaurant distributions near subway stations

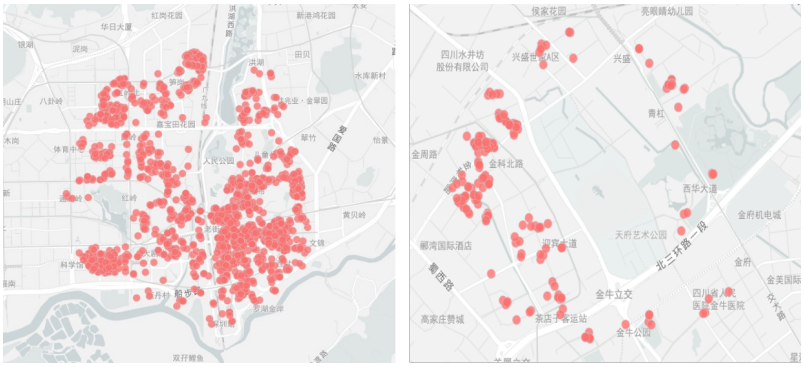


Figure 5. A restaurant-dense region (left) and a restaurant-sparse region (right) located around subway stations.

B.2. Quoted Wait Times for Deliveries to Different Locations



Figure 6. Snapshots of the same quoted wait times for different destination distances.

B.3. First-Stage Regression Results of IV Analysis in Table 8

Variables	Wait Time
$NumberRest$	0.0449^{***}
	(0.0064)
$SubNumberRest$	-0.0415^{***}
	(0.0053)
$Rating\ Score$	-0.3278^{*}
	(0.1973)
$Min\ Spend$	-0.0073
	(0.0059)
$Morning$	-0.4199
	(0.4269)
$Noon$	1.0882
	(0.8465)
$Night$	0.5679
	(0.5908)
$Delivery\ Hours$	-0.1871^{***}
	(0.0505)
$Branded\ Restaurant\ Label$	-0.4826^{**}
	(0.2382)
$New\ Restaurant\ Label$	1.4466^{*}
	(0.7686)
$MainType$	0.6645^{*}
	(0.3512)
$SubType$	0.0367^{***}
	(0.0026)
$Population$	-4.4769^{***}
	(0.8262)
GDP	0.0071
	(0.0093)
$Drivers$	0.4756
	(0.5933)
Restaurant Fixed Effects	Yes
Region-Month Fixed Effects	Yes
Observations	41,679

This table reports the estimated coefficients and standard errors (in parentheses). Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 9. Estimation results of Regression (11).

Appendix C: Robustness Checks

C.1. Instrumental Variable Estimation

In this robustness check, we adopt an instrumental variable (IV) approach for our main estimation in Section 5.2. We exploit the disparity in restaurant density between the city and the subway station region of a focal restaurant to construct our IV (Nevo and Wolfram 2002). Specifically, we first calculate the average restaurant density at the city level, excluding the focal restaurant. We then compute the average restaurant density at the subway station level, also excluding the focal restaurant. Finally, we take the difference between the city-level and subway-station-level average restaurant densities as the instrument, denoted by *Gap_Difference*.

Regarding the *relevance* assumption, *Gap_Difference* captures the extent to which the local market surrounding a subway station is underdeveloped relative to the broader city market. A larger positive gap indicates greater potential for local market expansion: lower relative restaurant density could create attractive entry opportunities and induce platforms or restaurant groups to devote greater resources to the area. We therefore expect a larger *Gap_Difference* to predict subsequent increases in local restaurant density, satisfying the relevance condition. Regarding the *exclusion* assumption, *Gap_Difference* reflects broader market structure rather than restaurant-specific operating conditions or customer preferences. Conditional on our restaurant fixed effects, region-month fixed effects, and observed controls, it is unlikely to directly affect a focal restaurant's wait time, sales, or customer spending. Instead, its primary channel is through the local restaurant entry and resulting changes in restaurant density. This supports the exclusion restriction.

Next, we use the 2SLS method to estimate the effects of restaurant density on the restaurant's end-of-month daytime quoted wait time, sales, and average spending per order, exploiting the IV. The specifications of both stages are given by Regressions (20) and (21), respectively:

$$\mathcal{N}_{ijm} = \beta_0^{(1)} + \beta_1^{(1)} \textit{Gap_Difference}_{ijm} + Control_{im}^{IV} + Restaurant_i + RegionMonth_{jm} + \epsilon_{ijm}^{(1)}, \tag{20}$$

$$Outcome_{ijm} = \beta_0^{(2)} + \beta_1^{(2)} \widehat{\mathcal{N}}_{ijm} + Control_{im}^{IV} + Restaurant_i + RegionMonth_{jm} + \epsilon_{ijm}^{(2)}. \tag{21}$$

To support our theoretical justifications, we implement the weak instrument test (Hausman 1978), and the Cragg–Donald Wald F values are approximately 7,100 and 4,500 for Columns (1) and (2), which exceed the critical threshold suggested by Stock and Yogo (2002). Furthermore, our IV analysis is just-identified, as we have one endogenous independent variable and one IV.

In Table 10, we present the first-stage regression results, which show that our IV has a significant positive effect on restaurant density. The resulting second-stage estimates are presented in Table 11. As shown in the table, the instrumented restaurant density has a significantly negative effect on both restaurant quoted wait time and average spending per order, while it has a significantly positive effect on restaurant sales. These

Variables	$\mathcal{N}$ (Restaurant Density)	
Gap_Difference	521.0216^{***}	524.5327^{***}
	(10.0150)	(13.4792)
Rating Score	-0.1787	-0.3116
	(0.2601)	(0.3059)
Min Spend	-0.0162	-0.0216
	(0.0115)	(0.0190)
Morning	-0.4137	-0.1201
	(0.7108)	(0.7568)
Noon	1.2015	3.0099^{*}
	(1.2472)	(1.6401)
Night	-2.0494^{**}	-2.1612^{**}
	(0.8158)	(1.0230)
Delivery Hours	0.1608^{**}	0.1415
	(0.0789)	(0.0946)
Branded Restaurant Label	0.4103	0.4801^{**}
	(0.2516)	(0.2887)
New Restaurant Label	0.5210	1.5243
	(0.5396)	(1.2798)
Population	-14.3106^{***}	-13.1330^{***}
	(1.1741)	(1.3026)
GDP	0.0064	0.0187^{***}
	(0.0043)	(0.0063)
Drivers	6.0991^{***}	4.7789^{***}
	(1.0422)	(1.2389)
Restaurant Fixed Effects	Yes	Yes
Region-Month Fixed Effects	Yes	Yes
Observations	63,500	41,679

The *Morning*, *Noon*, and *Night* variables are restaurant-month level indicators (i.e., 6 AM-9 AM, 11 AM-2 PM, and 5 PM-8 PM).[a] This table reports the estimated coefficients and standard errors (in parentheses).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 10. First stage of 2SLS analysis for main results in Table 4.

[a] Because a restaurant's platform hours can change over time, these variables capture within-restaurant variation and serve as useful controls in the restaurant-month first-stage regression. For example, a restaurant may expand from breakfast into lunch or evening delivery in response to menu changes or increased local competition. Including these controls helps account for strategic shifts in delivery-time availability that may correlate with both overall platform activity and our endogenous regressor.

results are highly consistent with those in Table 4, providing additional causal evidence in support of our main findings.

Variables	(1) Quoted Wait Time	(2) Sales	(3) Avg. Spending Per Order
$\widehat{\mathcal{N}}$ *(Restaurant Density)*	-0.0108^{***}	0.1887^{***}	-0.0016^{***}
	(0.0032)	(0.0981)	(0.0010)
Control Variables	Yes	Yes	Yes
Restaurant Fixed Effects	Yes	Yes	Yes
Region-Month Fixed Effects	Yes	Yes	Yes
Observations	63,500	63,500	41,679

This table reports the estimated coefficients and robust standard errors (in parentheses).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11. Second stage of 2SLS analysis for main results in Table 4.

C.2. Alternative Definition of Restaurant Density

We examine whether our findings hold when we modify the definition of restaurant density. In particular, we redefine $\mathcal{N}$ over a range of radii centered at 1 km and then re-estimate Regression (7). Table 12 presents the resulting estimates under 6 alternative radii, which include the two extreme ones. We find that both the delivery speed improvement and the restaurant benefits in terms of sales remain significant when the radius varies between 0.75 km and 1.3 km. Hence, Table 12 indicates that the restaurants' delivery speed and sales performance are most significantly influenced by neighboring restaurants on the platform located within a moderate distance.

Variables	(1) Quoted Wait Time	(2) Sales	(3) Avg. Spending Per Order
	$\mathcal{N}$: Neighboring restaurants within 0.75 km		
$\mathcal{N}$ (Restaurant Density)	-0.0103^{***}	0.2280^{***}	-0.0010^{+}
	(0.0025)	(0.0851)	(0.0006)
Observations	63,500	63,500	41,679
	$\mathcal{N}$: Neighboring restaurants within 0.85 km		
$\mathcal{N}$ (Restaurant Density)	-0.0084^{***}	0.2013^{***}	-0.0010^{**}
	(0.0022)	(0.0730)	(0.0005)
Observations	63,500	63,500	41,679
	$\mathcal{N}$: Neighboring restaurants within 0.95 km		
$\mathcal{N}$ (Restaurant Density)	-0.0066^{***}	0.1821^{***}	-0.0011^{**}
	(0.0019)	(0.0630)	(0.0005)
Observations	63,500	63,500	41,679
	$\mathcal{N}$: Neighboring restaurants within 1.1 km		
$\mathcal{N}$ (Restaurant Density)	-0.0051^{***}	0.1135^{**}	-0.0010^{**}
	(0.0017)	(0.0530)	(0.0004)
Observations	59,172	59,172	38,809
	$\mathcal{N}$: Neighboring restaurants within 1.2 km		
$\mathcal{N}$ (Restaurant Density)	-0.0042^{**}	0.1172^{**}	-0.0008^{*}
	(0.0016)	(0.0503)	(0.0004)
Observations	54,860	54,860	36,033
	$\mathcal{N}$: Neighboring restaurants within 1.3 km		
$\mathcal{N}$ (Restaurant Density)	-0.0039^{**}	0.1103^{**}	-0.0008^{**}
	(0.0016)	(0.0506)	(0.0004)
Observations	52,524	52,524	34,596
Control Variables	Yes	Yes	Yes
Restaurant Fixed Effects	Yes	Yes	Yes
Region-Month Fixed Effects	Yes	Yes	Yes

This table reports the estimated coefficients and robust standard errors (in parentheses) using Regression (7).
Significance at $^{+}p < 0.1$ (one-sided test); $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 12. Restaurant density effects with $\mathcal{N}$ measured under different radii.

C.3. Granular Controls for Regional Trends

To assess the sufficiency of using the region-specific monthly fixed effects to account for regional dynamics (e.g., variations in overall demand), we examine whether our findings persist after controlling for regional

trends in a more granular manner. Specifically, we divide each region into smaller sub-regions. Next, we apply monthly fixed effects for each of these sub-regions when estimating the restaurant density effects using Regression (7). This allows a finer characterization of regional dynamics shared across restaurants. Table 13 presents the resulting estimates when each region is divided according to its subway stations' latitude and longitude: into north and south semicircles, east and west semicircles, and further, into quarter circles. As demonstrated in the table, all the effects remain significant in these three cases. Consequently, our findings prove to be robust when implementing more spatially refined temporal controls.

Variables	(1) Quoted Wait Time	(2) Sales	(3) Avg. Spending Per Order
	Regions partitioned by subway's longitude only		
$\mathcal{N}$ (Restaurant Density)	-0.0092^{***}	0.1423^{**}	-0.0010^{**}
	(0.0020)	(0.0669)	(0.0005)
	Regions partitioned by subway's latitude only		
$\mathcal{N}$ (Restaurant Density)	-0.0049^{**}	0.2257^{***}	-0.0012^{**}
	(0.0020)	(0.0638)	(0.0005)
	Regions partitioned by subway's latitude and longitude		
$\mathcal{N}$ (Restaurant Density)	-0.0057^{***}	0.1437^{*}	-0.0014^{**}
	(0.0022)	(0.0746)	(0.0006)
Control Variables	Yes	Yes	Yes
Restaurant Fixed Effects	Yes	Yes	Yes
Sub-Region-Month Fixed Effects	Yes	Yes	Yes
Observations	63,500	63,500	41,679

This table reports the estimated coefficients and robust standard errors (in parentheses) using Regression (7).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 13. Restaurant density effects with granular controls of regional dynamics.

C.4. Nonlinear Effects of Restaurant Density

To ensure our results in Table 4 are not sensitive to the scale of restaurant density, we examine the effects of relative changes in restaurant density. We use the logarithmic transformation of restaurant density, $\log(\mathcal{N})$, and substitute $\mathcal{N}$ in Regression (7). The resulting estimates of the modified specification are shown in the upper panel of Table 14. We note that the resulting estimates remain meaningful, and their signs align with those in Table 4. Specifically, a 10% increase in the restaurant density experienced by a restaurant leads to a 0.18-minute decrease in the quoted wait time. Moreover, a 10% increase in restaurant density on the platform results in an increase of 4.80 orders in monthly sales for the restaurant, but it also leads to a decrease in the average spending per order by CNY 0.02. In conclusion, delivery pooling remains the dominant externality, even when we adopt a logarithmic measure for restaurant density.

Next, we add a quadratic term, $\mathcal{N}^2$, to Regression (7) to capture potential nonlinear effects of restaurant density on delivery speed and sales performance. The lower panel of Table 14 shows the resulting estimates. Interestingly, we observe diminishing benefits on delivery speed and restaurant sales as restaurant density increases. In particular, the relationship between quoted wait time and restaurant density follows a U-shaped

curve, which is consistent with the restaurant density effect on driver arrival speed at restaurants estimated in §6.2. In addition, the effect of restaurant density on sales follows an inverted-U-shaped curve, suggesting deteriorating sales gains for restaurants in highly dense areas.

Variables	(1) Quoted Wait Time	(2) Sales	(3) Avg. Spending Per Order
		Logarithmic Specification	
$\log(\mathcal{N})$ (Restaurant Density)	-1.7590^{***}	48.0393^{***}	-0.1801^{+}
	(0.4186)	(13.1362)	(0.1173)
		Quadratic Specification	
$\mathcal{N}$ (Restaurant Density)	-0.0249^{***}	0.3639^{***}	-0.0009
	(0.0040)	(0.1347)	(0.0011)
$\mathcal{N}$ (Restaurant Density)^2	$2.440 \times 10^{-5***}$	-0.0002^{+}	-2.770×10^{-7}
	(4.800×10^{-6})	(0.0002)	(1.350×10^{-6})
Control Variables	Yes	Yes	Yes
Restaurant Fixed Effects	Yes	Yes	Yes
Region-Month Fixed Effects	Yes	Yes	Yes
Observations	63,500	63,500	41,679

This table reports the estimated coefficients and robust standard errors (in parentheses) using Regression (7).
Significance at $^{+}p < 0.1$ (one-sided test); $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 14. The nonlinear effects of restaurant density.

C.5. Estimation without Outliers

We assess whether our findings are influenced by either regions with outlier restaurant densities or restaurants with exceptionally high or low sales revenue. First, to mitigate the influences of regions with extreme restaurant densities, we re-estimate Regression (7) using a subsample that excludes regions falling both below the 5^{th} percentile and above the 95^{th} percentile in restaurant number. The resulting estimates are shown in Table 15. As shown in the table, all findings remain consistent, suggesting that the positive effects of restaurant density resulting from delivery pooling manifest even in regions with moderate restaurant density. Second, to exclude the influences of exceptionally large or very small restaurants, we re-estimate Regression (7) using only restaurants that fall between the 5^{th} and 95^{th} percentiles in monthly revenues. The estimation results are also displayed in Table 15, confirming that all estimated effects persist. Thus, the identification of the predominant role of delivery pooling is not significantly influenced by outliers in terms of restaurant size.

Variables	(1) Quoted Wait Time	(2) Sales	(3) Avg. Spending Per Order
	Excluding regions with extreme restaurant density		
$\mathcal{N}$ (Restaurant Density)	-0.0108^{***}	0.1444^{**}	-0.0011^{**}
	(0.0020)	(0.0620)	(0.0005)
Observations	57,860	57,860	37,876
	Excluding restaurants with extreme revenue		
$\mathcal{N}$ (Restaurant Density)	-0.0070^{***}	0.0996^{**}	-0.0014^{***}
	(0.0019)	(0.0476)	(0.0005)
Observations	59,053	59,053	37,309
Control Variables	Yes	Yes	Yes
Restaurant Fixed Effects	Yes	Yes	Yes
Region-Month Fixed Effects	Yes	Yes	Yes

This table reports the estimated coefficients and robust standard errors (in parentheses) using Regression (7).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 15. Effects of restaurant density estimated using regions of moderate restaurant density and restaurants of moderate size.

Appendix D: External Validity Check

While our primary analysis focuses on the dynamics of food delivery platforms in China, it is crucial to understand the broader applicability of our findings. To examine the external validity of the observed effects, we conducted a similar analysis using a dataset collected from U.S. food delivery platforms. This dataset tracks food delivery platforms' monthly performance at the county level. We utilize the data to identify the effects of restaurant density on restaurants' sales and revenues, as well as on their customers' average spending per order. The estimation results echo our findings in §5 that delivery pooling, rather than customer expansion or cannibalization, is more likely to be the leading externality induced by an increase in restaurant density.

Background and Data. The proprietary dataset records the monthly sales performance of four leading U.S. food delivery platforms across 164 counties from October 2018 to July 2020. For each county and month, we observe the total number of transactions, total transaction value, and the number of partnered restaurants, along with their locations, on each platform. For confidentiality reasons, both the total number of transactions and the total transaction value are stored on a normalized scale in the data. Using these variables, we can compute the average sales and revenues per restaurant, as well as the average spending per order for its customers, on each platform in a given county and month. Additionally, the location information of partnered restaurants, also available in the data, enables us to determine the restaurant density experienced by each restaurant on a platform.

Model Specification. Recall that Theorems 1 and 2 characterize how restaurant density influences restaurant sales and average customer spending per order under different externalities. Building on these theoretical predictions, we aim to infer and compare the magnitudes of these externalities by estimating the corresponding effects using county-level data from four U.S. food delivery platforms. We define

$Outcome_{klm}$ as the dependent variables of interest, which include the average sales per restaurant and average spending per order in county k, platform l, and month m.

On a given platform, a restaurant is called a *dense-region* restaurant if its surrounding restaurant density, denoted as $\mathcal{N}$ (measured on the same platform), is above a given threshold (i.e., the average restaurant density level in the data). Hence, we measure a platform's restaurant density at the county level by counting the number of its dense-region restaurants within the county, denoted by $\mathcal{N}^c_{klm}$. In particular,

$$\mathcal{N}^c_{klm} := \text{No. of dense-region restaurants on platform } l \text{ in county } k \text{ month } m.$$

Subsequently, we control for the platform's regional market size by counting the number of its partnered restaurants in a county per month, denoted by $Control_{klm}$. In addition, we include platform fixed effects to capture the static discrepancy across platforms (e.g., app differences). Moreover, we control for county-specific monthly fixed effects to account for underlying trends of demand and driver supply in the area. Therefore, the regression model can be specified as:

$$Outcome_{klm} = \beta_0 + \beta_1 \mathcal{N}^c_{klm} + Control_{klm} + Platform_l + CountyMonth_{k,m} + \epsilon_{klm}, \tag{22}$$

where the effect of interest is captured by β_1.

Estimation Results. The estimates from Regression (22) are presented in Table 16. As shown in the table, an increase in restaurant density on a platform within a county significantly increases sales, while simultaneously decreasing customers' average spending per order. Comparing these findings to Table 1, we can rule out customer expansion and cannibalization as the dominant externality driving the observed effects. First, if cannibalization were the dominant force, we would expect restaurant sales to decline (as predicted in Column 2 of Table 1), which contradicts the empirical findings. Second, if customer expansion were dominant, average customer spending per order would be expected to increase (as shown in Column 3 of Table 1), yet the data show a significant decline in spending. Furthermore, the estimates rule out the possibility that delivery pooling is dominated by the other two externalities (see Column 3 of Table 2). Notably, all estimated effects align with the theoretical predictions under delivery pooling dominance, suggesting that it is the primary externality at play.

Consistent with our results in the Chinese market, evidence from the U.S. dataset reaffirms the pivotal role of delivery pooling during regional platform expansion. This consistency across two distinct markets highlights the robustness of our conclusions and underscores the significance of delivery pooling as a pivotal externality, which transcends regional or cultural boundaries.

Variables	(1) Sales Per Restaurant	(2) Avg. Spending Per Order
$\mathcal{N}^c$ (County-lvl. Rest. Density)	$6.09 \times 10^{-10***}$	-0.0016^{***}
	(5.75×10^{-11})	(0.0002)
Platform Control Variable	Yes	Yes
Platform Fixed Effects	Yes	Yes
County-Month Fixed Effects	Yes	Yes
Observations	11,786	11,786

This table reports the estimated coefficients and clustered (County-Month) standard errors (in parentheses) using Regression (22).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 16. Restaurant density effects estimated using county-level data from U.S. food delivery platforms.

Appendix E: Effect on Driver Arrival Speed at Restaurants

We next show qualitative empirical evidence that the driver arrival speed at a focal restaurant increases with its surrounding restaurant density (i.e., $\mu'(\mathcal{N}) > 0$). The inference on $\mu'(\mathcal{N}) > 0$ leverages the differential effects of restaurant density on restaurants with different baseline traffic levels. Presumably, restaurant r's customer arrival rate Λ is positively affected by its baseline traffic level, which is denoted by σ. We assume that σ is exogenous and static. Consequently, it follows that $\frac{\partial}{\partial \sigma}\Lambda(\mathcal{N}, \sigma) > 0$.[25] Then, Proposition 5 specifies four possible outcomes resulting from no improvement in driver arrival speed at restaurants (i.e., $\mu'(\mathcal{N}) \leq 0$).

Proposition 5. *Suppose the driver arrival speed at a focal restaurant decreases with its surrounding restaurant density (i.e., $\mu'(\mathcal{N}) \leq 0$). Then, at least one of the following four conditions must hold: (i) $\frac{\partial}{\partial \mathcal{N}}\lambda(\mathcal{N}, \sigma) \leq 0$, (ii) $\frac{\partial}{\partial \sigma}\lambda(\mathcal{N}, \sigma) \leq 0$, (iii) $\frac{\partial^2}{\partial \sigma \partial \mathcal{N}}\lambda(\mathcal{N}, \sigma) \leq 0$, and/or (iv) $\frac{\partial^2}{\partial \sigma \partial \mathcal{N}}t(\mathcal{N}, \sigma; x) \geq 0$ for any given x.*

Proof. We prove this proposition by way of contradiction. Suppose that none of the four conditions in the proposition hold. That is, all of the following opposite premises are true:

(i') $\frac{\partial}{\partial \mathcal{N}}\lambda(\mathcal{N}, \sigma) > 0$

(ii') $\frac{\partial}{\partial \sigma}\lambda(\mathcal{N}, \sigma) > 0$

(iii') $\frac{\partial^2}{\partial \sigma \partial \mathcal{N}}\lambda(\mathcal{N}, \sigma) > 0$

(iv') There exists a x such that $\frac{\partial^2}{\partial \sigma \partial \mathcal{N}}t(\mathcal{N}, \sigma; x) < 0$

Then, we are going to show that conditions (i'), (ii'), (iii'), and (iv') result in $\mu'(\mathcal{N}) > 0$, which yields a contradiction.

First, by Equation (2), we take the partial derivative of the wait time with respect to restaurant density, $\mathcal{N}$, at x such that $\frac{\partial^2}{\partial \sigma \partial \mathcal{N}}t(\mathcal{N}, \sigma; x) < 0$ from Condition (iv'). From this, we derive:

$$\frac{\partial}{\partial \mathcal{N}}t(\mathcal{N}, \sigma; x) = \frac{1}{(\nu - \lambda(\mathcal{N}, \sigma))^2} \cdot \frac{\partial}{\partial \mathcal{N}}\lambda(\mathcal{N}, \sigma) - \frac{1}{(\mu(\mathcal{N}) - \lambda(\mathcal{N}, \sigma))^2} \cdot \left(\mu'(\mathcal{N}) - \frac{\partial}{\partial \mathcal{N}}\lambda(\mathcal{N}, \sigma)\right).$$

[25] It is straightforward to verify that all results in §3.2 hold under this new condition.

Subsequently, we take the second-order derivative with respect to the restaurant's baseline traffic level, σ.

$$\frac{\partial^2}{\partial\sigma\partial\mathcal{N}}t(\mathcal{N},\sigma;x)=$$
$$\underbrace{\frac{\frac{\partial^2}{\partial\sigma\partial\mathcal{N}}\lambda(\mathcal{N},\sigma)\cdot(\nu-\lambda(\mathcal{N},\sigma))^2+2(\nu-\lambda(\mathcal{N},\sigma))\cdot\frac{\partial}{\partial\sigma}\lambda(\mathcal{N},\sigma)\cdot\frac{\partial}{\partial\mathcal{N}}\lambda(\mathcal{N},\sigma)}{(\nu-\lambda(\mathcal{N},\sigma))^4}}_{\text{Term 1}}$$
$$-\underbrace{\frac{-\frac{\partial^2}{\partial\sigma\partial\mathcal{N}}\lambda(\mathcal{N},\sigma)(\mu(\mathcal{N})-\lambda(\mathcal{N},\sigma))^2+2(\mu(\mathcal{N})-\lambda(\mathcal{N},\sigma))\cdot\frac{\partial}{\partial\sigma}\lambda(\mathcal{N},\sigma)\cdot\left(\mu'(\mathcal{N})-\frac{\partial}{\partial\mathcal{N}}\lambda(\mathcal{N},\sigma)\right)}{(\mu(\mathcal{N})-\lambda(\mathcal{N},\sigma))^4}}_{\text{Term 2}}.$$

With Conditions (i'), (ii'), and (iii'), and considering that $\nu-\lambda(\mathcal{N},\sigma)>0$, it immediately follows that Term 1 in the equation above is positive. Given Term 1's positivity and $\frac{\partial^2}{\partial\sigma\partial\mathcal{N}}t(\mathcal{N},\sigma;x)<0$ (i.e., Condition (iv')), we conclude that Term 2 in the equation above must be positive. Then, for Term 2 to be positive under Conditions (i'), (ii'), (iii'), and $\mu(\mathcal{N})-\lambda(\mathcal{N},\sigma)>0$, it must follow that $\mu'(\mathcal{N})>\frac{\partial}{\partial\mathcal{N}}\lambda(\mathcal{N},\sigma)>0$, because the second term on Term 2's numerator needs to be positive. Notably, the result of $\mu'(\mathcal{N})>0$ contradicts the given condition $\mu'(\mathcal{N})\leq 0$. Therefore, Conditions (i'), (ii'), (iii'), and (iv') cannot hold true simultaneously, and we complete the proof of the proposition. □

Conditions (i) and (ii) suggest that the sales of restaurants (i.e., $\lambda(\mathcal{N},\sigma)$) decrease with an increase in restaurant density ($\mathcal{N}$) and the baseline traffic level (σ), respectively. Conditions (iii) and (iv) imply that the benefits of restaurant density on both restaurant sales (i.e., $\partial\lambda(\mathcal{N},\sigma)/\partial\mathcal{N}$) and order wait times (i.e., $\partial t(\mathcal{N},\sigma)/\partial\mathcal{N}$) diminish as σ increases. In other words, compared to low-traffic restaurants, high-traffic restaurants benefit less from a sales boost and delivery speed improvement as their market becomes denser. With these conditions established, we then proceed to explore how they hold up under empirical scrutiny.

We note that Condition (i) is rejected: column 2 of Table 4 shows that restaurant sales increase significantly as restaurant density grows. Next, we use restaurants' sales volume in April 2021 to measure σ, which represents a restaurant's baseline traffic level. Table 17 shows that sales increase with baseline traffic level, rejecting Condition (ii). Moreover, Conditions (iii) and (iv) are rejected by columns (2) and (1) in Panel B of Table 5, respectively. Since all four outcomes in Proposition 5 are rejected, the proposition's premise of no improvement in driver arrival speed (i.e., $\mu'(\mathcal{N})\leq 0$) does not hold in our empirical setting. Therefore, in our data, increasing restaurant density can make drivers arrive at restaurants faster (i.e., $\mu'(\mathcal{N})>0$), thereby reducing order wait times.

Variables	(1) Sales
$SalesApril$	0.9709^{***}
	(0.0041)
Control Variables	Yes
Region-Month Fixed Effects	Yes
Observations	47,524

This table reports the estimated coefficients and robust standard errors (in parentheses).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 17. Traffic effect on restaurant sales.

Appendix F: Assessment of Alternative Explanations

F.1. Restaurant Menu Changes

We begin by ruling out the possibility that potential menu changes in restaurants could be the primary driver of our findings. Compared to other restaurant categories, fast-food chains' menus are unvarying and predictable (Ritzer 1998). Moreover, restaurants that specialize in serving traditional Chinese dishes (e.g., Kung Pao chicken) are unlikely to change their menus. Throughout our four-month observation period, these two types of restaurants were less likely to adjust their menus compared to all other restaurant categories in our data. Therefore, we re-estimate Regression (7) using the subsample of fast-food chains and traditional Chinese restaurants; the results are presented in Table 18. As shown, all estimates in Table 18 are consistent with those presented in Table 4, suggesting that delivery speed remains the dominant factor as restaurant density grows, even when restaurant menus are largely static.

Variables	(1) Quoted Wait Time	(2) Sales	(3) Avg. Spending Per Order
$\mathcal{N}$ (Restaurant Density)	-0.0061^{***}	0.2087^{***}	-0.0010^{**}
	(0.0021)	(0.0722)	(0.0005)
Control Variables	Yes	Yes	Yes
Restaurant Fixed Effects	Yes	Yes	Yes
Region-Month Fixed Effects	Yes	Yes	Yes
Observations	48,024	48,024	32,138

This table reports the estimated coefficients and robust standard errors (in parentheses) using Regression (7).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 18. Effects of restaurant density on fast-food chains and traditional Chinese restaurants' operational performance on the platform.

F.2. Mechanisms through Restaurant Pricing

In this section, we eliminate several plausible mechanisms related to restaurant pricing, using theoretical predictions alongside empirical evidence.

Model Extension with Pricing. We first extend our theoretical model, introduced in §3.1, by factoring in the restaurant's pricing influence.

We let $p > 0$ represent the focal restaurant r's dish price level. When a customer spends s at the restaurant, the purchased quantity can be approximated by s/p. We then use $u_q(s/p)$ to denote the normalized utility function for a customer with $v = 1$. We assume $u_q'(\cdot) > 0$ and $u_q''(\cdot) < 0$ without loss of generality. Following Equation (3), the net utility of a customer with value v and distance x spending s to order from the restaurant can be characterized by:

$$U(s; v, x, p) = v u_q\left(\frac{s}{p}\right) - s - \gamma t(\mathcal{N}; x, p),$$

where $t(\mathcal{N}; x, p)$ denotes the expected delivery time. Similar to Lemma 1, we solve for the customer's optimal spending amount from $\frac{\partial}{\partial s} U(s; v, x, p) = 0$, and we obtain:

$$s^*(v; p) = p\left(u_q'\right)^{-1}\left(\frac{p}{v}\right) > 0.$$

Therefore, the customer will place the order if and only if $U(s^*; v, x, p) \geq \alpha(\mathcal{N})$, which is equivalent to the inequality:

$$v u_q\left(\frac{s^*}{p}\right) - s^* \geq \gamma t(\mathcal{N}; x, p) + \alpha(\mathcal{N}).$$

Besides, the sales volume, $\lambda(\mathcal{N}; p)$, and the expected delivery time for the customer, $t(\mathcal{N}; x, p)$, can be characterized as:

$$\begin{aligned}
\lambda(\mathcal{N}; p) &= \Lambda(\mathcal{N}) \int_0^\infty \mathbb{P}\left[v u_q\left(\frac{s^*}{p}\right) - s^* \geq \gamma t(\mathcal{N}; x, p) + \alpha(\mathcal{N})\right] dF_x(x), \\
t(\mathcal{N}; x, p) &= \frac{1}{\nu - \lambda(\mathcal{N}; p)} + \frac{1}{\mu(\mathcal{N}) - \lambda(\mathcal{N}; p)} + \tau(x).
\end{aligned}$$

Next, we formulate the restaurant's price optimization problem. We assume that the restaurant's goal is to maximize its net revenues generated from the platform, thereby making it equal to the gross revenues minus the commission fee charged by the platform. In practice, the commission fee is often set to be a fraction of the transacted amount (Sharetribe 2023). Hence, we let $\rho \in (0, 1)$ denote the restaurant's rate of margin (i.e., it equals one minus the commission fee rate). Then, the restaurant's expected net revenue can be written as:

$$\Pi(p; \mathcal{N}) = \Lambda(\mathcal{N}) \rho \int_0^\infty s^*(v; p) \mathbb{1}\left\{v u_q\left(\frac{s^*}{p}\right) - s^* \geq \gamma t(\mathcal{N}; x, p) + \alpha(\mathcal{N})\right\} dF_v(v) dF_x(x).$$

Then, the restaurant's optimal price can be obtained by:

$$p^*(\mathcal{N}) = \arg\max_{p > 0} \Pi(p; \mathcal{N}). \tag{23}$$

Restaurant Price Competition. We investigate the revenue implications of price competition for the focal restaurant. For price competition to be a key driver of the restaurant's revenue, the cannibalization externality must necessarily be dominant compared to customer expansion and delivery pooling. In this case, we have the following theoretical projection:

Proposition 6. *Suppose the cannibalization externality dominates and a partnered restaurant optimizes its price per Expression* (23)*. Then, the restaurant's maximum net revenue decreases with restaurant density.*

Proof. To prove the proposition, it suffices if we show that when $\alpha'(\mathcal{N}) > 0$ and $\Lambda'(\mathcal{N}) = \mu'(\mathcal{N}) = 0$ (indicating the dominance of cannibalization), we have $\Pi(p^*(\mathcal{N}_1);\mathcal{N}_1) > \Pi(p^*(\mathcal{N}_2);\mathcal{N}_2)$ for any $\mathcal{N}_1 < \mathcal{N}_2$. To simplify the exposition, we introduce the following notation:

$$\begin{aligned} &p_1 = p^*(\mathcal{N}_1),\ s_1 = s^*(v;p_1),\ \lambda_1 = \lambda(\mathcal{N}_1;p_1),\ \Pi_1 = \Pi(p_1;\mathcal{N}_1) \\ &p_2 = p^*(\mathcal{N}_2),\ s_2 = s^*(v;p_2),\ \lambda_2 = \lambda(\mathcal{N}_2;p_2),\ \Pi_2 = \Pi(p_2;\mathcal{N}_2). \end{aligned}$$

First, we claim that the following function increases with $\mathcal{N}$:

$$g(\mathcal{N};p) := \frac{\gamma}{\nu - \lambda(\mathcal{N};p)} + \frac{\gamma}{\mu - \lambda(\mathcal{N};p)} + \alpha(\mathcal{N}).$$

To show this claim, we first note that the sales volume, $\lambda(\mathcal{N};p)$, can be rewritten as:

$$\lambda(\mathcal{N};p) = \Lambda(\mathcal{N}) \int_0^\infty \mathbb{P}\left[v u_q\left(\frac{s^*}{p}\right) - s^* \geq g(\mathcal{N};p) + \gamma\tau(x) \right] dF_x(x).$$

Then, we prove that $\frac{\partial}{\partial \mathcal{N}} g(\mathcal{N};p) \geq 0$ by contradiction. Suppose $\frac{\partial}{\partial \mathcal{N}} g(\mathcal{N};p) < 0$. It is straightforward to show that $\frac{\partial}{\partial \mathcal{N}} \lambda(\mathcal{N};p) > 0$ (note that s^* is independent of $\mathcal{N}$ and the probability within the integral increases with $\mathcal{N}$). However, this last inequality implies that

$$\frac{\partial}{\partial \mathcal{N}} g(\mathcal{N};p) = \frac{\gamma}{(\nu - \lambda(\mathcal{N};p))^2} \cdot \frac{\partial}{\partial \mathcal{N}} \lambda(\mathcal{N};p) + \frac{\gamma}{(\mu - \lambda(\mathcal{N};p))^2} \cdot \frac{\partial}{\partial \mathcal{N}} \lambda(\mathcal{N};p) + \alpha'(\mathcal{N}) \geq 0,$$

which yields a contradiction. Therefore, $\frac{\partial}{\partial \mathcal{N}} g(\mathcal{N};p) \geq 0$ must hold.

Next, we show $\Pi_1 > \Pi_2$ by contradiction as well. Suppose $\Pi_1 \leq \Pi_2$. First, we observe:

$$\begin{aligned} \Pi(p_2;\mathcal{N}_1) &= \Lambda\rho \int_0^\infty s_2 \mathbb{1}\left\{ v u_q\left(\frac{s_2}{p_2}\right) - s_2 \geq g(\mathcal{N}_1;p_2) + \gamma\tau(x) \right\} dF_v(v) dF_x(x) \\ &\geq \Lambda\rho \int_0^\infty s_2 \mathbb{1}\left\{ v u_q\left(\frac{s_2}{p_2}\right) - s_2 \geq g(\mathcal{N}_2;p_2) + \gamma\tau(x) \right\} dF_v(v) dF_x(x) \\ &= \Pi_2. \end{aligned}$$

Since $\Pi_2 > \Pi_1$, it follows that $\Pi(p_2;\mathcal{N}_1) > \Pi_1$. The last inequality results in a contradiction because Π_1 is the maximum net revenue under $\mathcal{N}_1$. Therefore, it must follow that $\Pi_1 > \Pi_2$. □

As expected, restaurant revenues suffer from escalated competition as restaurant density increases. Although restaurants can optimally adjust their prices in response, Proposition 6 suggests that the price adjustment can only mitigate the revenue loss rather than reverse it.

Moreover, based on Proposition 6, we can hypothesize that if price competition plays a primary role when restaurant density increases, we would expect their revenues to decrease. However, our empirical findings show the opposite. Specifically, we estimate Regression (7) with restaurant monthly revenues as the dependent variable, and the resulting estimate of the restaurant density effect is shown in Table 19. As evident in the table, $\mathcal{N}$ positively affects restaurant monthly revenues, and the effect is statistically significant. By rejecting the hypothesis, we infer that price competition among restaurants is unlikely to play a dominant role in influencing how restaurants perform as more adjacent restaurants join the platform.

Variables	(1) Revenues
$\mathcal{N}$ (Restaurant Density)	5.0852^{**}
	(1.9964)
Control Variables	Yes
Restaurant Fixed Effects	Yes
Region-Month Fixed Effects	Yes
Observations	41,679

This table reports the estimated coefficients and robust standard errors (in parentheses).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 19. Restaurant density effect on restaurant sales revenues.

Furthermore, to directly examine whether restaurants in our data actively adjust their prices in response to changes in surrounding restaurant density, we collected a new data set from Dianping.com, a leading restaurant review platform in China, where the average dish prices of restaurants are regularly reviewed.[26] We then matched the monthly average dish prices from the review platform with the restaurant observations in our original sample based on the similarity in restaurant names. In a given city, names for both platforms that have a similarity rate of more than 80% are considered to be the same restaurant. As a result, we recovered the price information for 32,816 observations, accounting for more than half of our original dataset.

80% Similarity Rate for Name Matching	(1) Dianping Price
$\mathcal{N}$ (Restaurant Density)	0.0008
	(0.0005)
Control Variables	Yes
Restaurant Fixed Effects	Yes
Region-Month Fixed Effects	Yes
Observations	32,816

This table reports the estimated coefficients and robust standard errors (in parentheses).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 20. Restaurant density effect on restaurants' pricing.

[26] Note that our original data from the food delivery platform does not contain the price information of restaurants' dishes.

We then apply Regression (7) using the matched sample, with the monthly average dish price, denoted by *Dianping Price*, as the dependent variable, to estimate the effect of restaurant density on restaurants' pricing decisions. The resulting estimate is shown in Table 20. There is no significant effect of restaurant density on the monthly average dish price, suggesting that restaurants tend not to adjust prices in response to changes in restaurant density. The result remains consistent even if we estimate the model using the subsample selected under more stringent similarity thresholds for matching (i.e., 95% and 97.5%). Therefore, we have ruled out price competition as a primary mechanism to explain the restaurant density effects shown in Table 4.

Price Effect on Customer Spending. We then focus on theoretically and empirically investigating how restaurant pricing affects customer spending—the sign of $\partial s^*/\partial p$. We aim to understand how customers adjust their spending amounts when restaurants increase dish prices. We begin by proving that it is impossible for $\partial s^*/\partial p \geq 0$ to hold for all customers and any prices:

Proposition 7. *There does not exist a normalized utility function, $u_q(\cdot)$, satisfying $u_q(\cdot) \geq 0$, $u_q'(\cdot) > 0$, and $u_q''(\cdot) < 0$, such that $\frac{\partial}{\partial p} s^*(v;p) \geq 0$ for any $v > 0$ and any $p > 0$.*

Proof. First of all, the customer's optimal spending s^* satisfies:

$$\frac{\partial}{\partial s} U(s;v,x,p) = v u_q'\left(\frac{s}{p}\right)\frac{1}{p} - 1 = 0.$$

Then, we define:

$$G(s,v,p) := v u_q'\left(\frac{s}{p}\right)\frac{1}{p} - 1 \tag{24}$$

By the implicit function theorem, we thereby have:

$$\frac{\partial s}{\partial p} = -\frac{\partial G/\partial p}{\partial G/\partial s}.$$

Since $\frac{\partial}{\partial s} G(s,v,p) = v u_q''\left(\frac{s}{p}\right)\frac{1}{p^2} < 0$, the sign of $\frac{\partial}{\partial p} s^*(v;p)$ is the same as that of $\frac{\partial}{\partial p} G(s,v,p)$.

Next, we show that there does not exist such $u_q(\cdot)$ such that $\frac{\partial}{\partial p} G(s,v,p) \geq 0$ for any $v > 0$ and $p > 0$. We note that $\frac{\partial}{\partial p} G(s,v,p) \geq 0$ is equivalent to:

$$u_q''\left(\frac{s}{p}\right)\frac{s}{p} + u_q'\left(\frac{s}{p}\right) \leq 0. \tag{25}$$

Since $u_q'(\cdot) > 0$ and it is a decreasing function, the inequality above fails to hold when $\frac{s}{p} \to 0^+$ for any form of $u_q(\cdot)$. As a result, $\frac{\partial}{\partial p} s^*(v;p)$ cannot hold for any $v > 0$ and $p > 0$. □

Proposition 7 suggests that for customers, increasing spending is not necessarily the optimal response to a restaurant's price surge. For any given form of normalized utility function, $u_q(\cdot)$, we can always identify customer value v and price level p such that the optimal reaction to an increase in price is to reduce spending. In addition, Inequality (25) suggests that $\partial s^*/\partial p \geq 0$ is likely to occur when the ratio s^*/p (i.e., order quantity) is very large, which may be rare among meal orders placed by one customer.

Conversely, we establish that, under a mild condition on $u_q(\cdot)$, it is optimal for all customers to reduce spending in response to a price increase at any price level:

Proposition 8. *Suppose the normalized utility function, $u_q(\cdot)$, satisfies $\frac{d}{dx}\left[xu_q'(x)\right] \geq 0$ (in addition to $u_q(\cdot) \geq 0, u_q'(\cdot) > 0$, and $u_q''(\cdot) < 0$). Then, $\frac{\partial}{\partial p}s^*(v;p) \leq 0$ for any $v > 0$ and $p > 0$.*

Proof. Under $\frac{d}{dx}\left[xu_q'(x)\right] \geq 0$, it is straightforward to verify that:

$$u_q''\left(\frac{s}{p}\right)\frac{s}{p} + u_q'\left(\frac{s}{p}\right) \geq 0.$$

Note that the above inequality is equivalent to $\frac{\partial}{\partial p}G(s,v,p) \leq 0$, where $G(s,v,p)$ is defined in Equation (24). Therefore, $\frac{\partial}{\partial p}s^*(v;p) \leq 0$ follows using a similar argument as in Proposition 7's proof; we omit the details for brevity. □

Notably, $\frac{d}{dx}\left[xu_q'(x)\right] \geq 0$ coincides with customers' relative risk aversion, $R(x) = -\frac{xu_q''(x)}{u_q'(x)}$, following $R(x) \leq 1$ (Simon et al. 1994). Hence, quite a few prevalent utility specifications in the literature satisfy the condition, such as power utilities and logarithmic utilities (Ingersoll 1987). Compared to Proposition 7, Proposition 8 suggests that customers are more likely to reduce their spending rather than increase it in response to a restaurant price surge.

Employing the matched sample with *Dianping Price*, we estimate the regression below to determine the association between restaurant dish prices and customer spending:

$$\begin{aligned} AvgSpendingPerOrder_{ijm} =& \beta_0 + \beta_1 DianpingPrice_{im} + Control_{im} \\ &+ Restaurant_i + RegionMonth_{jm} + \epsilon_{ijm}, \end{aligned}$$

where $Control_{im}$ remains the same as that in Regression (7). The resulting estimate of β_1 is shown in Table 21. As we can see, the coefficient is negative, and it is statistically significant. The result continues to hold when the price is measured on a log scale. Hence, Table 21 is consistent with Propositions 7 and 8, which establish that spending reduction is a more probable reaction to price surges by customers rather than spending increases—it is indeed the case in our data.

Variables	DV: Avg. Spending Per Order	
Dianping Price	-0.0123^{+}	
	(0.0090)	
log(*Dianping Price*)		-0.3915^{***}
		(0.1477)
Control Variables	Yes	Yes
Restaurant Fixed Effects	Yes	Yes
Region-Month Fixed Effects	Yes	Yes
Observations	23,378	23,378

This table reports the estimated coefficients and robust standard errors (in parentheses).
Significance at $^{+}p < 0.1$ (one-sided test); $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 21. Association between restaurants' dish prices and customer spending.

General Influences of Pricing. To account for the general influence of restaurant prices (not necessarily in the form of price competition) when identifying and comparing the externalities of customer expansion, cannibalization, and delivery pooling, we re-estimate Regression (7) while controlling for restaurant prices using the matched sample. The resulting estimates are shown in Table 22. Notably, the impact of restaurant density on quoted wait time, sales, and customer spending remains consistent with those revealed in Table 4, suggesting that restaurant pricing cannot explain these restaurant density effects. Table 22 thereby strengthens the robustness of our findings that delivery pooling exists and is likely to dominate customer expansion and cannibalization.

Variables	(1) Quoted Wait Time	(2) Sales	(3) Avg. Spending Per Order
$\mathcal{N}$ (Restaurant Density)	-0.0094^{***}	0.1723^{**}	-0.0013^{**}
	(0.0026)	(0.0790)	(0.0006)
Dianping Price	-0.0231	0.0118	-0.0123
	(0.0248)	(0.6287)	(0.0090)
Control Variables	Yes	Yes	Yes
Restaurant Fixed Effects	Yes	Yes	Yes
Region-Month Fixed Effects	Yes	Yes	Yes
Observations	32,816	32,816	23,378

This table reports the estimated coefficients and robust standard errors (in parentheses).
Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 22. Restaurant density effects estimated using a matched subsample.

F.3. Other Plausible Mechanisms

Several alternative mechanisms could potentially account for the association between restaurant density and delivery speed. First, broad platform- or market-level changes, such as changes in dispatch policies, driver incentives, or aggregate driver supply, are unlikely to drive our estimates because our specification includes region-month fixed effects and controls for district-level driver supply, as discussed in §5.1. Second, restaurant fixed effects absorb persistent operational differences, while our restaurant-level controls help capture observable time-varying operational changes. The stable-menu analysis in Appendix F.1 provides additional evidence against menu adjustments as an explanation. Finally, the IV analysis in Appendix C.1 yields consistent estimates using plausibly exogenous variation in restaurant density. Taken together, these analyses make alternative explanations based on platform-wide shocks or restaurant-specific operational changes less likely.

Appendix G: Data-Driven Simulation Analysis

To derive prescriptive insights, we build a novel, data-driven simulation model by expanding the theoretical framework in §3.1 to incorporate customers' restaurant choice decisions. The model accounts for the spatial distribution of both customers and restaurants (see the model specification in §G.1). Given the available data, we estimate the model's parameters using a nonlinear least squares approach (see estimation details and results in §G.2). Through simulation, we isolate the effects of density on restaurant sales and customer utility under scenarios where only one of the three externalities—customer expansion, cannibalization, or delivery pooling—is present. Additionally, we solve for each restaurant's sales-maximizing density and examine how the optimal density varies with regional characteristics (see detailed analyses and results in §G.3).

G.1. Model Specification

Preliminaries. Restaurants and customers are distributed on a two-dimensional plane. For a given restaurant i, located at $\boldsymbol{l}_i = (l_i^x, l_i^y)$, we assume that its *entire* sales are generated from customers located within 3 km of its location $\boldsymbol{l}_i$; this area is denoted by $\mathcal{D}_i$. When customers in $\mathcal{D}_i$ decide whether or not to purchase from restaurant i, they compare it with other restaurants located within 1 km of restaurant i. We refer to $\mathcal{D}_i$ and its customers as the *local market* of restaurant i.

In restaurant i's local market, we assume that customers are uniformly distributed over $\mathcal{D}_i$, with the corresponding cumulative distribution function (CDF) denoted by $F_{\mathcal{D}}(\tilde{\boldsymbol{l}})$. The total mass of restaurant i's customers in month m, denoted by Λ_{im}, is given by:

$$\Lambda_{im} = \exp\left(\beta_0^{\Lambda} + \beta_1^{\Lambda}\log\left(\bar{\lambda}_{i1}\right) + \beta_2^{\Lambda}\log\left(\bar{\lambda}_{i1}\right)^2 + \beta_3^{\Lambda}\log\left(\mathcal{N}_{im}\right) + \beta_4^{\Lambda}\log\left(\mathcal{N}_{im}\right)^2\right), \tag{26}$$

where $\bar{\lambda}_{i1}$ denotes the total sales volume of all the restaurants located within 1 km from restaurant i in the initial month (i.e., April 2021 in our data). The term $\exp\left(\beta_0^{\Lambda} + \beta_1^{\Lambda}\log\left(\bar{\lambda}_{i1}\right) + \beta_2^{\Lambda}\log\left(\bar{\lambda}_{i1}\right)^2\right)$ captures the baseline market size for restaurant i, while the term $\exp\left(\beta_3^{\Lambda}\log(\mathcal{N}_{im}) + \beta_4^{\Lambda}\log(\mathcal{N}_{im})^2\right)$ captures the customer expansion externality. Then, Expression (26) thus implies that the mass of the local market, Λ_{im}, can vary across restaurants (i.e., locations) and over time (i.e., months). Finally, we let $\mathcal{J}_{im}$ denote the set of restaurants within 1 km from restaurant i in month m, including restaurant i itself, which collectively serve demand in restaurant i's local market.

For a customer n located at $\tilde{\boldsymbol{l}}_n = (\tilde{l}_n^x, \tilde{l}_n^y) \in \mathcal{D}_i$, we let $v_{i'm}$ denote their valuation for restaurant i' in month m, where $i' \in \mathcal{J}_{im}$. Then, we assume:

$$v_{i'm} = \exp\left(X_{i'm}^T \boldsymbol{\beta}^v\right)\eta_{i'}, \tag{27}$$

where $\eta_{i'}$ represents the normalized idiosyncratic valuation, and $\eta_{i'} \sim$ Fréchet(1), independently distributed from the customer's location;[27] vector $X_{i'm}$ denotes the restaurant's characteristics in month m, as defined in Equation (10).

[27] Specifically, the Fréchet distribution has a shape 1, a location 0, and a scale 1.

Customer Utility and Restaurant Choice. For a customer n from $\mathcal{D}_i$, who chooses restaurant $i' \in \mathcal{J}_{im}$, Equation (3) implies that their received utility after spending s follows:

$$U\left(s; v_{i'm}, \mathcal{N}_{i'm}, X_{i'm}, \bar{\lambda}_{i'm}, \boldsymbol{l}_{i'}, \tilde{\boldsymbol{l}}_n\right) = v_{i'm}u(s) - s - \gamma t\left(\mathcal{N}_{i'm}; X_{i'm}, \bar{\lambda}_{i'm}, \boldsymbol{l}_{i'}, \tilde{\boldsymbol{l}}_n\right).$$

We assume $u(s) = \sqrt{s}$, which satisfies $u'(s) > 0$ and $u''(s) < 0$. The order wait time, $t(\mathcal{N}_{im}; X_{i'm}, \bar{\lambda}_{i'm}, \boldsymbol{l}_{i'}, \tilde{\boldsymbol{l}}_n)$, is estimated using Equation (10). For notational simplicity, we define $t_{im}(\tilde{\boldsymbol{l}}_n) := t\left(\mathcal{N}_{im}; X_{im}, \bar{\lambda}_{im}, \boldsymbol{l}_i, \tilde{\boldsymbol{l}}_n\right)$. Then, by Lemma 1, the customer's optimal spending and resulting maximum utility at restaurant i', month m are:

$$s^*_{i'm} = v^2_{i'm}/4 \text{ and } U\left(s^*_{i'm}; v_{i'm}, \mathcal{N}_{i'm}, X_{i'm}, \bar{\lambda}_{i'm}, \boldsymbol{l}_{i'}, \tilde{\boldsymbol{l}}_n\right) = v^2_{i'm}/4 - \gamma t_{i'm}(\tilde{\boldsymbol{l}}_n).$$

Therefore, the customer n's restaurant choice decision can be characterized as:

$$i^*_n = \arg\max_{i' \in \mathcal{J}_{im}} \left\{U\left(s^*_{i'm}; v_{i'm}, \mathcal{N}_{i'm}, X_{i'm}, \bar{\lambda}_{i'm}, \boldsymbol{l}_{i'}, \tilde{\boldsymbol{l}}_n\right)\right\}.$$

G.2. Model Estimation

We begin by noting that the CDF and PDF of a customer's valuation for restaurant i', $v_{i'm}$, are given by:

$$F^v_{i'm}(v) = \exp\left(-\exp\left(X^T_{i'm}\boldsymbol{\beta}^v\right)v^{-1}\right) \text{ and } f^v_{i'm}(v) = \exp\left(X^T_{i'm}\boldsymbol{\beta}^v\right)v^{-2}\exp\left(-\exp\left(X^T_{i'm}\boldsymbol{\beta}^v\right)v^{-1}\right).$$

That is, $v_{i'm}$ follows a Fréchet distribution with a shape of 1, a location of 0, and a scale $\exp(X^T_{i'm}\boldsymbol{\beta}^v)$. Then, among restaurants in $\mathcal{J}_{im}$, the customer n at $\tilde{\boldsymbol{l}}_n$ chooses the one that provides the highest utility in month m. Therefore, the probability that the customer chooses restaurant i:

$$\mathbb{P}\left(\frac{v^2_{im}}{4} - \gamma t_{im}(\tilde{\boldsymbol{l}}_n) \geq \frac{v^2_{i'm}}{4} - \gamma t_{i'm}(\tilde{\boldsymbol{l}}_n), \forall i' \in \mathcal{J}_{im} \setminus \{i\}\right). \tag{28}$$

Accordingly, restaurant i's expected sales volume and expected sales revenues in month m are given by:

$$\mathbb{E}[\lambda_{im}] = \Lambda_{im}\int_{\tilde{\boldsymbol{l}}\in\mathcal{D}_i} \mathbb{P}\left(\begin{array}{c}\frac{v^2_{im}}{4} - \gamma t_{im}(\tilde{\boldsymbol{l}}_n) \geq \frac{v^2_{i'm}}{4} - \gamma t_{i'm}(\tilde{\boldsymbol{l}}_n),\\ \forall i' \in \mathcal{J}_{im} \setminus \{i\}\end{array}\right) dF_{\mathcal{D}}(\tilde{\boldsymbol{l}}), \tag{29}$$

$$\text{and } \mathbb{E}[\Pi_{im}] = \frac{\Lambda_{im}}{4}\int_{\tilde{\boldsymbol{l}}\in\mathcal{D}_i}\left(\int_0^\infty v^2_{im}\mathbb{P}\left(\begin{array}{c}\frac{v^2_{i'm}}{4} - \gamma t_{i'm}(\tilde{\boldsymbol{l}}) \leq \frac{v^2_{im}}{4} - \gamma t_{im}(\tilde{\boldsymbol{l}}),\\ \forall i' \in \mathcal{J}_{im} \setminus \{i\}\end{array}\middle| v_{im}\right) dF^v_{im}(v_{im})\right) dF_{\mathcal{D}}(\tilde{\boldsymbol{l}}).$$

In the model, the unknown parameters are $\boldsymbol{\beta}^\Lambda$, $\boldsymbol{\beta}^v$, and γ, introduced in Expressions (26), (27), and (28), respectively. In the data, we observe each restaurant's sales volume λ_{im}, sales revenue Π_{im}, attributes X_{im}, and regional features $\bar{\lambda}$ and $\mathcal{N}_{im}$ for a given month. Additionally, restaurant i's location, $\boldsymbol{l}_i$, is observable, and the wait time function for a customer at $\tilde{\boldsymbol{l}}_n$ is predicted by the function $t_{im}(\tilde{\boldsymbol{l}}_n)$ from Equation (10).

We then adopt the nonlinear least squares (NLS) method to estimate $\boldsymbol{\beta}^\Lambda$, $\boldsymbol{\beta}^v$, γ using the following objective function:

$$\left(\hat{\boldsymbol{\beta}}^\Lambda, \hat{\boldsymbol{\beta}}^v, \hat{\gamma}\right) = \arg\min_{\boldsymbol{\beta}^\Lambda, \boldsymbol{\beta}^v, \gamma} \sum_{i,m}\left\|\begin{pmatrix}\lambda_{im}\\ \Pi_{im}\end{pmatrix} - \begin{pmatrix}\mathbb{E}[\lambda_{im}]\\ \mathbb{E}[\Pi_{im}]\end{pmatrix}\right\|^2_2.$$

To improve computational efficiency, we first derive the analytical forms of $\mathbb{E}[\lambda_{im}]$ and $\mathbb{E}[\Pi_{im}]$, which substantially improves the computational speed. Then, to ensure scalability to large datasets, we adopt a distributed estimation approach following Chen and Xie (2014). For brevity, we omit the technical details of the estimation procedure. The resulting NLS estimates are:

$$\hat{\beta}^{\Lambda} = \begin{bmatrix} 0.00121 \\ -0.09292 \\ 0.01341 \\ -0.00005 \\ 0.00651 \end{bmatrix}, \quad \hat{\beta}^{v} = \begin{bmatrix} -0.01540 \\ -0.00929 \\ 0.13249 \\ -0.00006 \\ 0.02405 \\ 0.00763 \\ -0.00799 \\ -0.01148 \\ -0.00289 \end{bmatrix}, \quad \text{and } \hat{\gamma} = 37.00194.$$

To assess the empirical fit of the simulation model, we compare simulated and observed restaurant-level sales and revenues in the estimation sample. Because both variables are strongly right-skewed (see Table 3), we report both conventional and robust fit measures. Specifically, we compute the ratio of mean absolute error to the standard deviation (MAE/SD) and the ratio of median absolute error to the interquartile range (Median AE/IQR). For sales, the MAE/SD is 58.7%, and the Median AE/IQR is 24.7%; for revenues, the corresponding values are 62.9% and 25.2%. These results indicate that the model fits the bulk of restaurants well, while the fit is less precise for a small number of high-volume outliers in the right tail.

G.3. Counterfactual Simulation Analysis

Marginal Effects of Restaurant Density. To derive welfare implications, we simulate the marginal effects of restaurant density on (i) the expected sales volume of a restaurant and (ii) the expected utility of a customer under scenarios in which only one of the three externalities—customer expansion, cannibalization, or delivery pooling—is active. Exploiting the estimated spatial-choice model, we isolate the influence of restaurant density via each externality, separately. In particular, for customer expansion, restaurant density exerts an effect via term $\hat{\beta}_3^{\Lambda}\log(\mathcal{N}_{im}) + \hat{\beta}_4^{\Lambda}\log(\mathcal{N}_{im})^2$ in function Λ_{im} (Equation (26)). For cannibalization, we add or remove a generic competitor from the choice set $\mathcal{J}_{im}$ (a device that mitigates independence-of-irrelevant-alternatives concerns when $\mathcal{J}_{im}$ changes). The competitor's attractiveness is scaled by the change in restaurant density. For delivery pooling, restaurant density's effect is manifested through the term $\hat{\beta}_1^{\mu}\mathcal{N}_{im} + \hat{\beta}_2^{\mu}\mathcal{N}_{im}^2$ in the driver arrival rate function μ (Equation (9)). Then, we can pin down the effect of each mechanism separately by holding the two externalities fixed at their baseline values (observed in the data).[28]

Figure 7 reports the simulated range of percentage change in a restaurant's sales resulting from a 1% increase in its surrounding restaurant density, under scenarios in which only one of the three externalities is

[28] In each restaurant's counterfactual simulation, its steady-state sales volume is computed, and it is solved from Equation (29).

active. Both customer expansion and delivery pooling lead to sales increases, with median effects of 0.06% and 0.93%, respectively. In contrast, under cannibalization, the same density increase reduces sales by a median of 0.10%. These results suggest that the sales impact induced by delivery pooling is substantially larger than those associated with customer expansion or cannibalization.

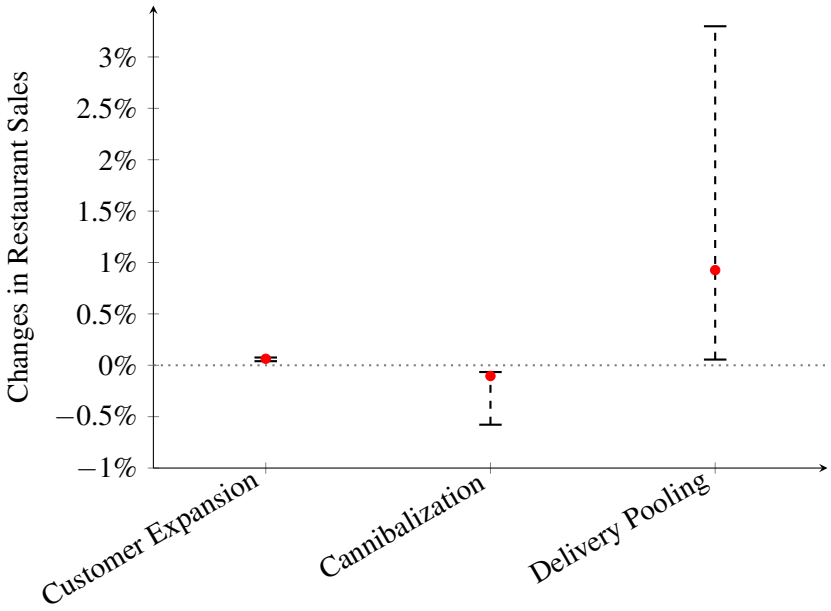


Figure 7. Effect on expected per-restaurant sales volume of a 1% increase in restaurant density, when only customer expansion, cannibalization, or delivery pooling is active.

Note: Each red dot denotes the median change and each interval represents a 95%-confidence interval.

Next, we isolate the effect of the three externalities on the expected utility of a customer in the local market of restaurant i in month m. For a customer located at $\tilde{\boldsymbol{l}}$, let $\boldsymbol{v}_{im} = (v_{i'm})_{i' \in \mathcal{J}im}$ denote the vector of her valuations for all restaurants in $\mathcal{J}_{im}$. Her utility from transacting with restaurant $i' \in \mathcal{J}_{im}$ is given by $v_{i'm}^2/4 - \gamma t_{i'm}(\tilde{\boldsymbol{l}})$. Accordingly, the customer's expected maximum utility from choosing one restaurant in $\mathcal{J}_{im}$ (i.e., restaurant i or its alternatives) is:

$$\sigma_{im} = \mathbb{E}\left[\max_{i' \in \mathcal{J}_{im}} \left(v_{i'm}^2/4 - \gamma t_{i'm}(\tilde{\boldsymbol{l}})\right)\right].$$

In Figure 8, we present the simulated range of changes in σ_{im} induced by a 1% increase in restaurant i's surrounding density, under the assumption that only one of the three externalities is active. First, customer expansion has a negative effect. This is because an increase in customer mass raises the restaurant's sales, which in turn prolongs the order wait time. However, since the sales increase is marginal (Figure 7), the resulting loss in each customer's utility is small. Second, cannibalization has a positive effect on customer utility, driven by two mechanisms: an increase in the value of alternatives and a reduction in order wait

time (due to decreased sales, as shown in Figure 7). Third, delivery pooling also increases customer utility, primarily due to a significant reduction in order wait time. Notably, its effect magnitude is the largest among the three externalities.

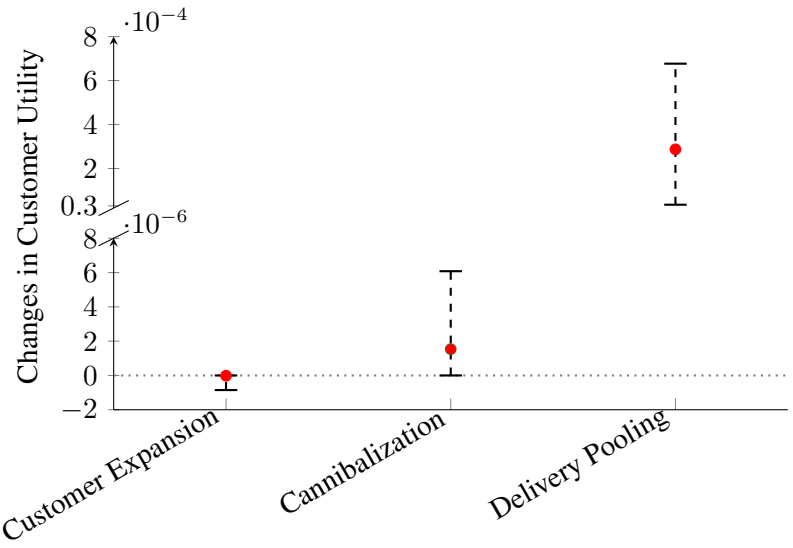


Figure 8. Effect on expected per-customer utility of a 1% increase in restaurant density, when only customer expansion, cannibalization, or delivery pooling is active.

Note: Each red dot denotes the median change and each interval represents a 95%-confidence interval.

Sales-Maximizing Restaurant Density. We focus on identifying the restaurant density that maximizes restaurant sales because restaurant sales are a key determinant of both restaurant retention on the platform and the platform's own profitability. Platforms like ours succeed only when their partnered restaurants thrive—high sales improve restaurants' incentives to stay engaged, reduce churn, and strengthen long-term relationships. Moreover, as the platform typically earns revenue through commissions on order value, increasing restaurant sales directly enhances the platform's financial performance. Therefore, optimizing restaurant density to improve restaurant sales yields benefits for both the platform and its restaurant partners.

Utilizing the estimated model, we simulate the sales volume of each restaurant while varying the surrounding restaurant density over a wide range. Specifically, we vary density relative to the baseline level observed in the data, from -99% to 300%. For each restaurant and each density level, we compute its steady-state sales volume. To facilitate comparison across restaurants, we normalize each restaurant's sales volume by its own maximum value.

Figure 9's left panel displays the simulated sales curves for three restaurants. All the sales curves are unimodal over the range of restaurant density changes considered. When restaurant density decreases drastically, the benefits from customer expansion and delivery pooling diminish. At the same time, the

reduction in cannibalization is not sufficient to offset the resulting sales loss, leading to a lower overall sales volume. Conversely, when restaurant density increases significantly, sales also decline or even vanish. This is partly because the benefit from delivery pooling diminishes or even reverses as density rises (see Table 7). These patterns suggest that, at high levels of restaurant density, cannibalization outweighs the benefits from customer expansion and delivery pooling. The right panel of Figure 9 shows a histogram of the sales-maximizing restaurant density for each restaurant, revealing substantial variation. Most restaurants in our data would benefit from an increase in surrounding restaurant density.

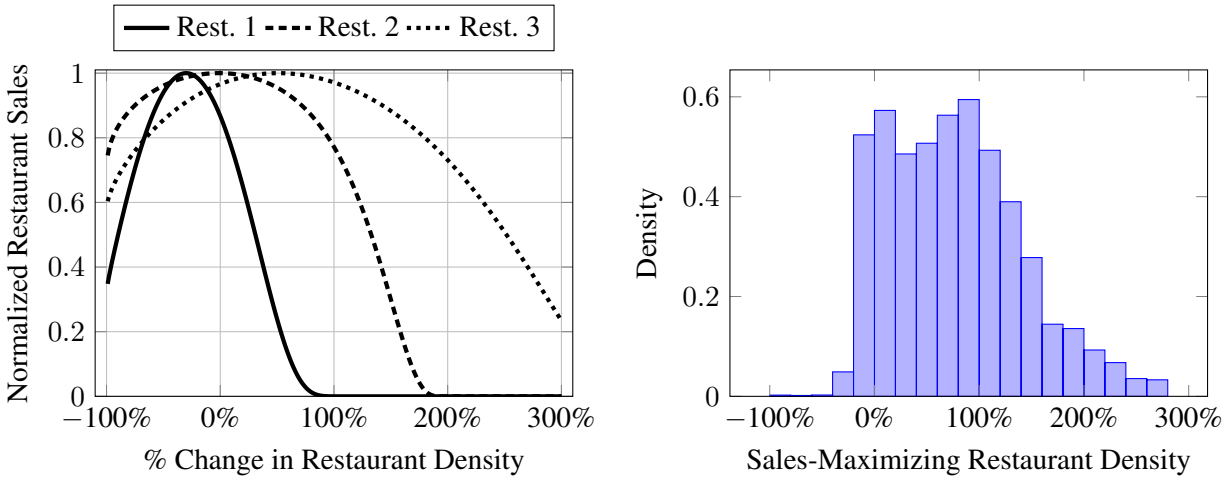


Figure 9. Normalized sales curves of three restaurants with respect to changes in the surrounding restaurant density (left) and histogram of restaurant density change rates that maximize each restaurant's sales (right).

To examine how sales-maximizing restaurant density varies across regions, we regress each restaurant's optimal density on its region index. The regression results are presented in Table 23. The results show that a restaurant's region is a strong predictor of its optimal density. Compared to Region 1 (the baseline), Regions 2, 3, and 28 have lower optimal densities, while all other regions exhibit higher optimal densities. All estimated region coefficients are statistically significant.

In Figure 10, we plot the regional averages of sales-maximizing restaurant density against region size, measured by the number of restaurants within 2 km of the central subway station. As shown in the figure, optimal density decreases as region size increases—that is, restaurants in denser areas require smaller increases in surrounding density to maximize sales. This pattern likely arises because restaurants in highly dense areas tend to experience weaker benefits of delivery pooling (see Table 7) and more intense competition compared to moderately dense regions. Therefore, to amplify the positive externalities of delivery pooling and boost restaurant sales, the platform should focus on proactively attracting restaurants in relatively low-density areas (e.g., fewer than 500 restaurants), while expanding cautiously—or even maintaining current density levels—in high-density regions (e.g., more than 750 restaurants).

Dependent variable: Sales-Maximizing Restaurant Density					
Region	Coefficient	Region	Coefficient	Region	Coefficient
Region 2	-0.229^{***} (0.024)	Region 15	0.690^{***} (0.030)	Region 28	-0.095^{***} (0.025)
Region 3	-0.068^{***} (0.024)	Region 16	0.866^{***} (0.028)	Region 29	0.749^{***} (0.025)
Region 4	0.966^{***} (0.030)	Region 17	0.918^{***} (0.234)	Region 30	0.933^{***} (0.026)
Region 5	0.337^{***} (0.026)	Region 18	1.133^{***} (0.032)	Region 31	1.426^{***} (0.029)
Region 6	0.254^{***} (0.030)	Region 19	0.525^{***} (0.030)	Region 32	0.643^{***} (0.025)
Region 7	1.228^{***} (0.033)	Region 20	0.649^{***} (0.031)	Region 33	1.430^{***} (0.031)
Region 8	0.745^{***} (0.030)	Region 21	0.947^{***} (0.032)	Region 34	0.733^{***} (0.034)
Region 9	0.716^{***} (0.028)	Region 22	0.644^{***} (0.029)	Region 35	0.194^{***} (0.026)
Region 10	0.537^{***} (0.027)	Region 23	0.930^{***} (0.031)	Region 36	1.157^{***} (0.028)
Region 11	0.368^{***} (0.029)	Region 24	0.147^{***} (0.024)	Region 37	0.838^{***} (0.032)
Region 12	1.031^{***} (0.032)	Region 25	0.714^{***} (0.039)		
Region 13	0.559^{***} (0.026)	Region 26	1.222^{***} (0.028)		
Region 14	0.982^{***} (0.053)	Region 27	0.670^{***} (0.027)		
Constant: 0.241^{***} (0.020)					
Observations: 22,356					

Note. Significance at $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 23. Association between sales-maximizing restaurant density and region.



Figure 10. Relationship between average sales-maximizing change in restaurant density and the number of incumbent restaurants in a region.

Note: The slope of the fitted regression line (red) is -1.2164×10^{-3} *with p-value less than 0.001.*

Examples of Platform Expansion Strategies. For a given region, we project the total monthly sales of incumbent restaurants under different platform expansion rates, where the expansion rate is defined as the percentage increase in restaurant density relative to the incumbent level. The two examples below illustrate not only that platforms should prioritize some low- and medium-density regions over dense ones, but also that density alone is insufficient for determining an effective expansion strategy.

Example 1. We begin by illustrating the key implication from Figure 10: the platform should prioritize low- and medium-density regions rather than uniformly favoring the densest ones. In this example, we compare Region 14, which had 23 incumbent restaurants in April 2021, with Region 22, which had 134 incumbent restaurants in the same month. As shown in Figure 11, Region 22 was substantially denser than Region 14.

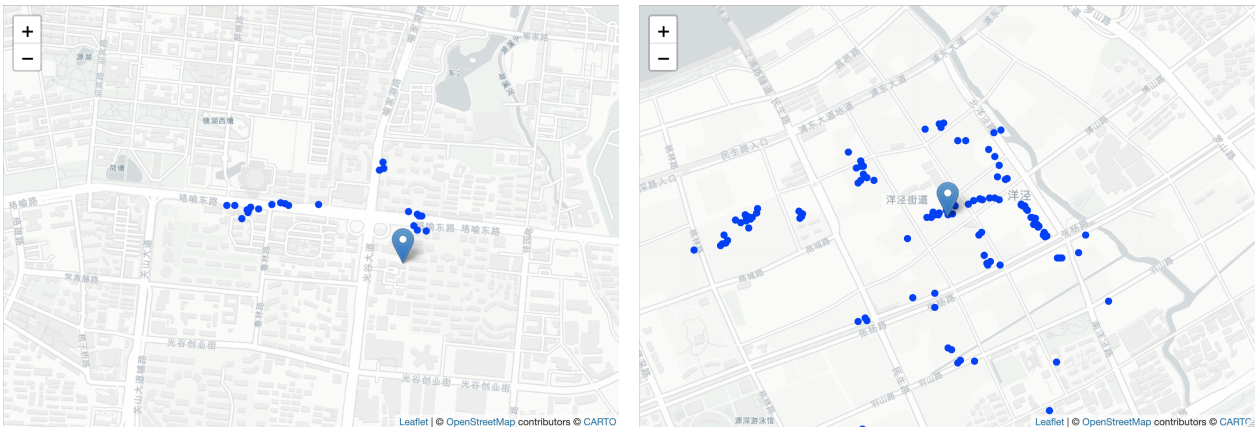


Figure 11. Locations of incumbent restaurants in Regions 14 (left) and 22 (right). Note. Region 14 has 23 restaurants, and Region 22 has 134 restaurants.

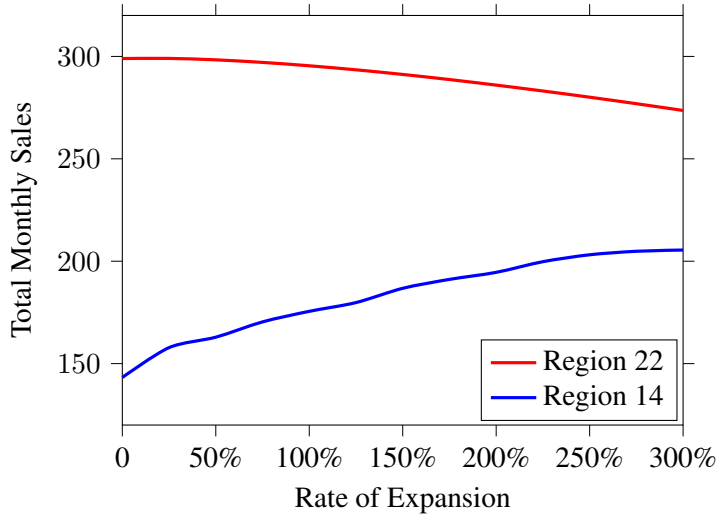


Figure 12. Total monthly sales of incumbent restaurants under different rates of platform expansion in the region. Note. Region 14 has 23 restaurants, and Region 22 has 134 restaurants.

Using our simulation model, we project the total monthly sales of incumbent restaurants under various expansion rates, with the results shown in Figure 12. As the figure shows, total sales in Region 14, the sparser region, increase substantially with the rate of expansion, indicating that customer expansion and delivery pooling outweigh cannibalization. By contrast, total sales in Region 22, the denser region, decline gradually as the expansion rate increases. In this case, cannibalization is the dominant force, and adding more nearby restaurants erodes the sales of incumbents. At a 100% expansion rate, the total monthly sales of incumbent restaurants increase from 143.23 to 175.53 in Region 14, a gain of about 22.6%, but decrease from 298.97 to 295.43 in Region 22, a decline of about 1.2%.

Therefore, if the platform aims to increase incumbent restaurants' sales, it should prioritize expansion in Region 14 rather than Region 22. Moreover, because Region 14 has far fewer incumbent restaurants, the

same expansion rate requires onboarding fewer additional restaurants, implying a lower expansion cost than in Region 22.

Example 2. This example goes beyond Example 1 by showing that restaurant density rankings alone are not sufficient to guide expansion decisions. We compare Region 8 and Region 19 (shown in Figure 13), which had similar numbers of incumbent restaurants in April 2021 (118 and 111, respectively), yet exhibit markedly different responses to platform expansion in our simulations.

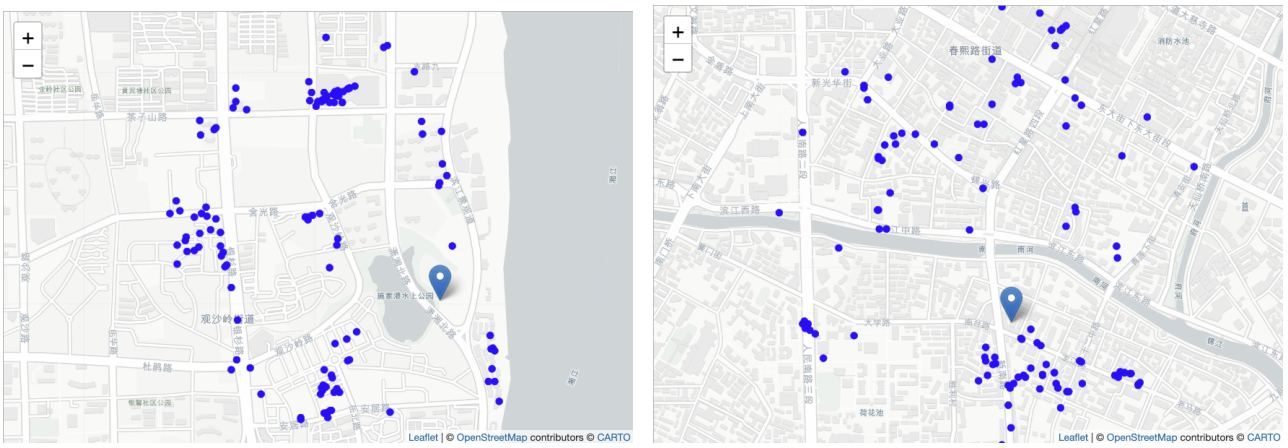


Figure 13. Locations of incumbent restaurants in Regions 8 (left) and 19 (right). Note. Region 8 has 118 restaurants, and Region 19 has 111 restaurants.

As shown in Figure 14, the total monthly sales of incumbent restaurants in Region 8 decline substantially as the expansion rate increases, whereas those in Region 19 increase steadily. At a 100% expansion rate, the total monthly sales of incumbent restaurants decrease from 1124.52 to 1086.27 in Region 8, a decline of about 3.4%, whereas they increase from 267.25 to 482.59 in Region 19, a gain of about 80.6%. This contrast suggests that even regions with similar restaurant density can warrant very different expansion strategies.

A key reason is that the expansion problem is inherently multidimensional. Beyond restaurant density, the impact of expansion also depends on the characteristics of incumbent and entrant restaurants, their geographic distribution and composition, and the competitive relationships among them. On the demand side, expansion outcomes are likewise shaped by local market conditions, such as the number of potential users, their spatial distribution, and their purchasing power. Therefore, a reliable projection of expansion outcomes cannot rely on density alone; it must account for the broader configuration of local supply and demand.

Our data-driven simulation model provides a tractable framework for incorporating these factors and projecting restaurant sales under alternative expansion scenarios. Built on the estimated spatial-choice structure, the model explicitly incorporates customers' restaurant choices based on location, wait time, and restaurant characteristics, while also capturing the three key externalities of customer expansion,

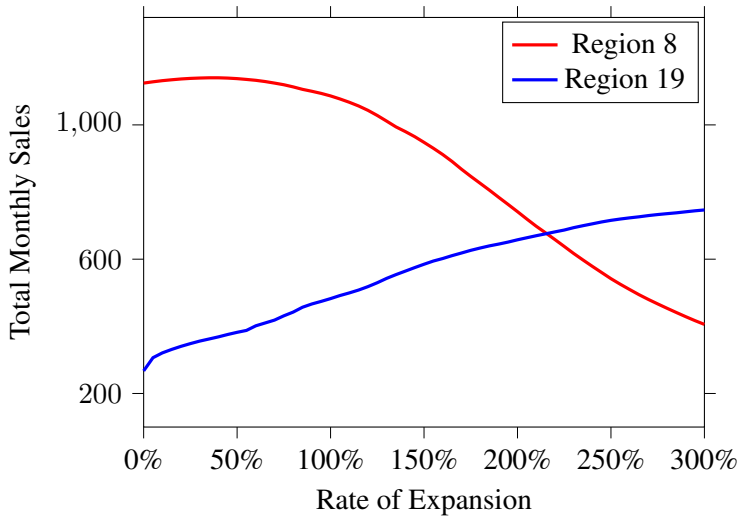


Figure 14. Total monthly sales of incumbent restaurants under different rates of platform expansion in the region.

cannibalization, and delivery pooling. Because of this, it can translate rich local information into region-specific counterfactual predictions of how incumbent restaurants would perform under different expansion rates.

Therefore, the main managerial implication from Example 2 is not simply that density should be interpreted with caution, but that platforms should assess expansion strategies using a broader, data-driven evaluation of local market conditions. We emphasize that the numerical projections in Examples 1 and 2 are model-based counterfactual illustrations calibrated to the observed characteristics of the selected regions, rather than universal point predictions. Their purpose is to illustrate the broader qualitative insight that the desirability of further expansion is region-specific and need not vary monotonically with existing restaurant density. In this regard, our data-driven simulation model offers a viable and practical tool for platforms to conduct such assessments, compare region-specific expansion scenarios, and identify where further expansion is likely to strengthen incumbent restaurant performance rather than undermine it.

Taken together, Example 1 shows that the platform should not uniformly prioritize denser regions, while Example 2 shows that density itself should not be used as a stand-alone rule for expansion. Instead, platforms should evaluate expansion opportunities through a broader, data-driven assessment of local market conditions.

Sensitivity Checks. To assess whether our prescriptive implications are robust to moderate perturbations of key parameters, we conducted a local sensitivity analysis around the baseline simulation estimates. Specifically, we perturbed three key components of the model, one at a time, by $\pm 10\%$: (i) the customer expansion parameters (β_3^Λ and β_4^Λ from Equation (26)), which govern how restaurant density affects the size of the local customer base; (ii) the wait-time sensitivity parameter (γ from Equation (3)), which governs how

strongly customers respond to delivery delays; and (iii) the delivery-pooling parameters (the coefficients on N and N^2 in $\boldsymbol{\beta}^{\mu}$ from Equation (9)), which govern how restaurant density affects driver arrival speed. Under each perturbation, we recomputed every restaurant's sales-maximizing density change using the same simulation procedure as in the baseline specification. Table 24 reports the average absolute difference between the perturbed and baseline optimal density change across restaurants. The resulting differences are small, ranging from 1.81% to 4.09%, indicating that the sales-maximizing density recommendations are stable to moderate perturbations of the key parameters.

Parameter perturbation	Average absolute difference in optimal density change (%)
Customer expansion parameters $+10\%$	3.07%
Customer expansion parameters -10%	3.14%
Wait-time sensitivity (γ) $+10\%$	3.87%
Wait-time sensitivity (γ) -10%	4.09%
Delivery pooling parameters $+10\%$	1.81%
Delivery pooling parameters -10%	2.15%

Note: The second column reports the average absolute difference in each restaurant's sales-maximizing density change (%) relative to the baseline specification.

Table 24. Sensitivity of sales-maximizing density change (%) to moderate parameter perturbations.

To complement the restaurant-level sensitivity analysis in Table 24, we re-run the two region-level examples above under the same six perturbations. That is, for each perturbation, we kept the example setup unchanged—including the same regions, the same definition of the expansion rate, and the same projection of incumbent restaurants' total monthly sales across alternative expansion rates—and recomputed the corresponding counterfactual sales curves. Figures 15 and 16 summarize these results for Examples 1 and 2, respectively. Across all perturbations, the qualitative recommendations remain unchanged: in Example 1, the sparser Region 14 continues to benefit more from expansion than the denser Region 22, and in Example 2, Region 19 continues to respond more favorably to expansion than Region 8. These results show that the example-based managerial implications are robust to moderate changes in the model's key parameters.

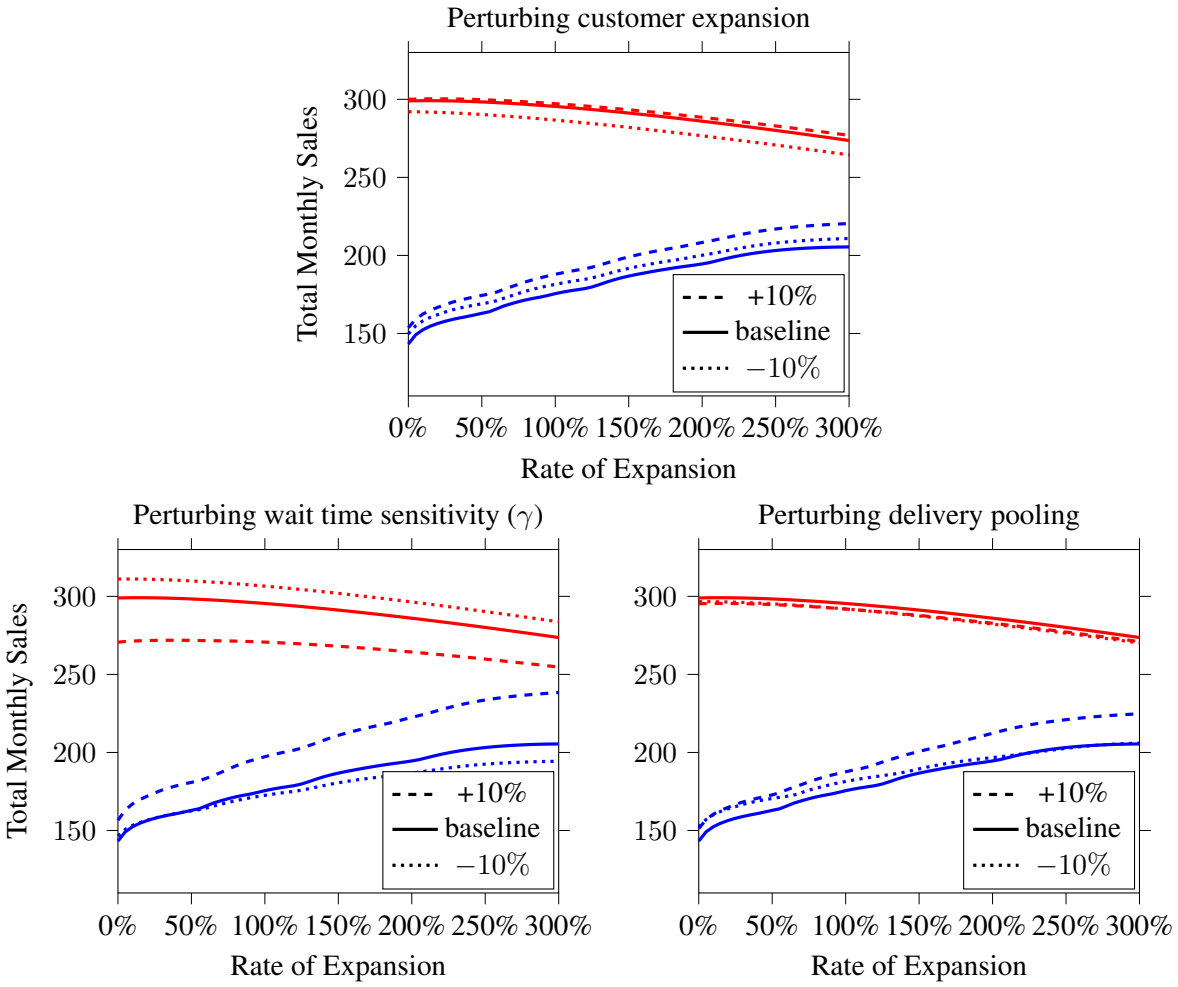


Figure 15. Total monthly sales of incumbent restaurants under different rates of platform expansion in Region 22 (red) and Region 14 (blue) under perturbations in key parameters.

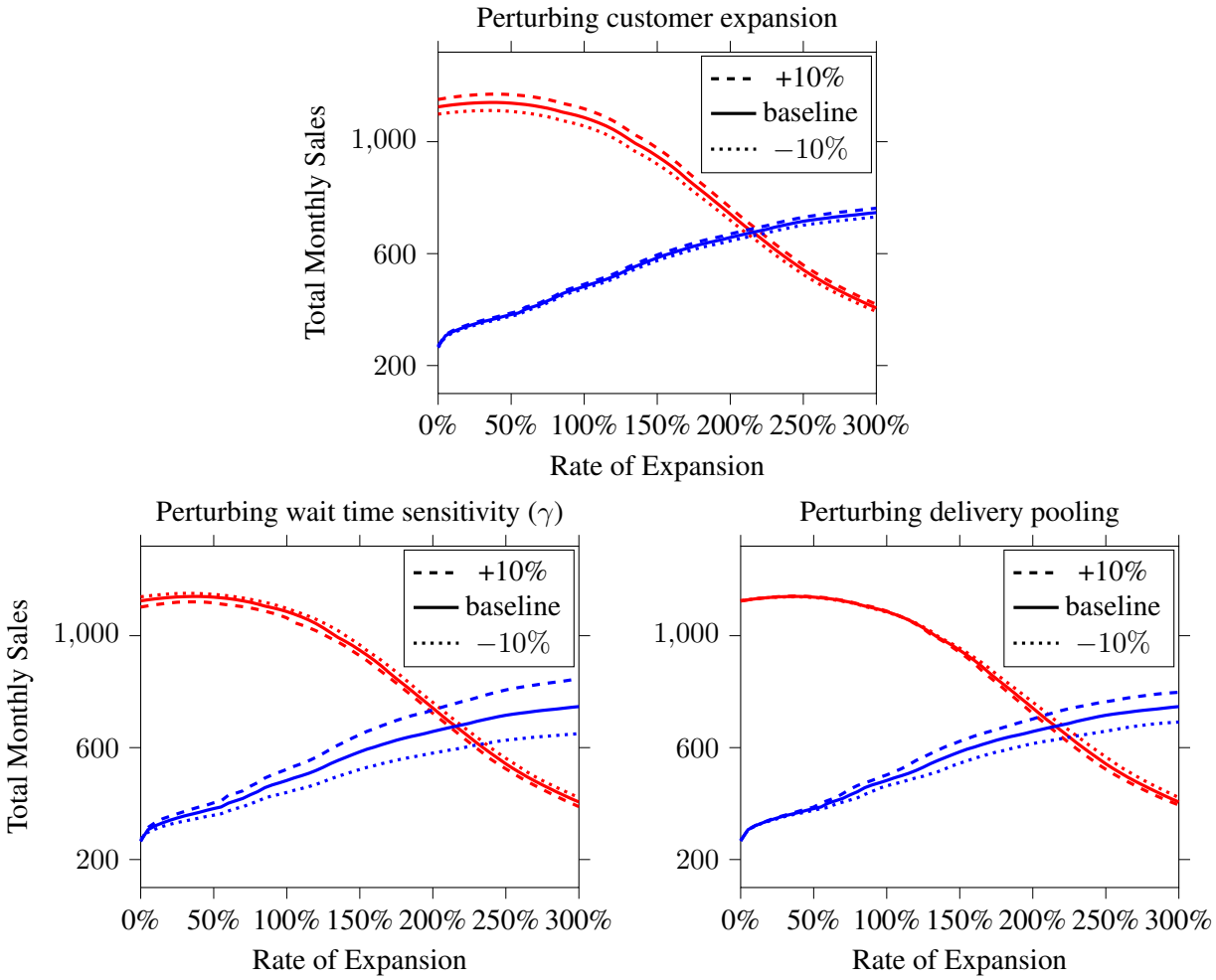


Figure 16. Total monthly sales of incumbent restaurants under different rates of platform expansion in Region 8 (red) and Region 19 (blue) under perturbations in key parameters.

Appendix H: Details of Survey

In this section, we provide additional details on the driver survey. Specifically, Figure 17 presents the full questionnaire, which consists entirely of self-reported yes/no items. Although our main analysis focuses on items 3–6, we also report responses to item 2, which focuses on whether, conditional on the opportunities presented by the platform, drivers retain discretion over acceptance decisions. We find that 94.7% of drivers answered yes to item 2, providing suggestive evidence that drivers retain meaningful discretion in order acceptance decisions.

This survey aims to investigate the behaviors of food delivery drivers during the order fulfillment process. Please be assured that all personal information and survey responses will be kept strictly confidential. We sincerely appreciate your time and thoughtful participation in answering these questions.

1. Do you have experience fulfilling delivery orders for our focal platform?

☐ Yes ☐ No

2. When delivering online food orders, do you typically decide independently whether to accept an order based on its specific conditions?

☐ Yes ☐ No

3. When delivering online food orders, do you engage in "order pooling" (i.e., collecting multiple orders at once and delivering them sequentially)?

☐ Yes ☐ No

4. If the density of restaurants offering food delivery were to increase in a specific region, would this lead to a greater chance of you pooling orders during your delivery process?

☐ Yes ☐ No

5. If the number of restaurants offering food delivery were to increase in a particular region, would you be able to perceive this change and consequently choose to move towards that region?

☐ Yes ☐ No

6. In the absence of available delivery orders, would you relocate to a region with a higher restaurant density?

☐ Yes ☐ No

Figure 17. Survey questionnaire.