The Gender Gap in Small Business Performance: Evidence from an Online Food Ordering Platform

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Abstract

Beyond the well-documented gender pay gap among wage earners, female-owned micro-enterprises are consistently found to be less profitable than their male counterparts. This paper examines the gender gap in business performance among freelancers in the gig economy who sell home-cooked meals, a traditionally female-typed domain requiring complex business strategy-making. Using high-quality proprietary data from a Chinese online food ordering platform, we identify a 12% gender gap in daily revenues between male and female sellers. Factors highlighted in the existing literature, such as working hours and experience, explain 63% of this gap. The remaining difference is attributed to male and female freelancers adopting distinct business strategies in pricing, positioning, and market expansion.

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1 Introduction

The gender wage gap has been intensively investigated and well-documented across different countries and job sectors (e.g., Blau and Kahn, 2017; Goldin et al., 2017; Bertrand et al., 2010; Gupta and Rothstein, 2005; Bayard et al., 2003). At the same time, a large share of women, particularly those in developing countries, are self-employed (Fields, 2019) rather than wage earners. Studies comparing male and female entrepreneurs find that they tend to start different types of businesses (Bardasi et al., 2011; Nichter and Goldmark, 2009), with male-owned businesses showing higher profitability (Kalleberg and Leicht, 1991; Bird and Sapp, 2004; Hardy and Kagy, 2018; Delecourt and Fitzpatrick, 2021) and greater returns to capital (De Mel et al., 2008, 2009; Fafchamps et al., 2014).

In this paper, we focus on freelancers who sell home-cooked meals on an online food-ordering platform in Beijing, China. Instead of connecting customers with restaurants, this platform is designed to match individuals who want to sell food prepared in their own kitchens with nearby customers seeking home-cooked meals. Using high-quality proprietary data that records all orders placed on the platform and demographic information about the sellers, we measure the business performance of freelancers and assess the revenue gap between male- and female-owned businesses.

Consistent with the existing literature, we document a raw gender gap of 12.1% in daily revenues, with male freelancers earning an additional 33.7 CNY (5.1 USD) on average. The gender gap in daily revenues is entirely driven by differences in the daily number of orders and is concentrated among younger sellers below the age of 50. Time and location fixed effects, demographics, delivery policies, working hours, and customer reviews together explain 41% of the gap. Additionally, we find that male sellers accumulate experience at a faster rate and achieve higher returns to experience. Controlling for experience accounts for an additional 22% of the gender gap.

Another important factor that may contribute to the gender earnings gap in our setting is the choice of business strategies, as freelancers on the platform independently run their businesses and develop their own business plans. With the help of rich data, we quantify sellers' business strategies along multiple dimensions, including pricing, positioning, and market expansion. Our descriptive evidence shows that male sellers offer smaller but more differentiated

menus at higher prices compared to female sellers. Men are also more ambitious, setting a larger delivery radius to serve more potential customers and maintaining higher stock levels. When we match male and female freelancers on demographics, experience, working hours, and business strategies, the gender gap in daily revenues is fully closed. In other words, business profitability does not differ between men and women with similar demographics, experience levels, work intensity, and business strategies.

In addition to the broad literature documenting the gender gap in labor market outcomes, particularly in small business success, our study contributes to an emerging body of research focusing on the gender earnings gap in the gig economy (Cook et al., 2021; Adams-Prassl et al., 2023). The growth of the gig economy provides job flexibility as well as access to richer and higher-quality data. Previous studies attribute the remaining gender wage gap to "the cost of flexibility" (Goldin, 2014; Goldin and Katz, 2016; Cubas et al., 2023), whereas the gig economy offers the flexibility of choosing when and where to work. Additionally, in our context, all freelancers work from home, which makes it easier for them, especially women, to balance entrepreneurship and household responsibilities. However, similar to Cook et al. (2021) and Adams-Prassl et al. (2023), we find that the gender earnings gap persists even in the gig economy, highlighting the need to incorporate additional factors when studying gender differences.

Our setting differs from most existing studies that document gender earnings differences within job sectors, as providing home-cooked meals is traditionally perceived as a female-typed task. In contrast, many occupations examined in the literature, such as drivers (Cook et al., 2021), bus and train operators (Bolotnyy and Emanuel, 2022), and lawyers (Azmat and Ferrer, 2017), are typically classified as male-typed. The behavioral economics literature has shown that stereotypes associated with male- and female-typed tasks contribute to gender gaps in self-confidence, assessments of others, and behavior in cooperative games (Coffman, 2014; Bordalo et al., 2019). Workplace discrimination is also closely tied to such stereotypes. For instance, Coffman et al. (2021) demonstrates that employers are more likely to hire male workers over female workers for male-typed tasks, even when their resumes are identical. Therefore, we contribute to the literature by re-examining the gender earnings gap in this female-typed domain.

Finally, our study contributes to the literature exploring the reasons behind the lower success rates of female-owned businesses (Bertrand, 2011). Evidence from both laboratory and field studies documents gender differences in bargaining and negotiation (e.g., Exley et al., 2020; Castillo et al., 2013; Biasi and Sarsons, 2022), as well as a tendency for women to shy away from competition (e.g., Niederle and Vesterlund, 2007; Flory et al., 2015). These differences in personal traits can lead to distinct choices of business strategies, which ultimately contribute to the gap in profitability. The uniqueness of our setting allows us to accurately measure the strategies adopted by freelancers across multiple dimensions, including pricing, positioning, and market expansion, and to examine their impact on the gender earnings gap.

2 Setting and Data

2.1 The Platform

We use proprietary data from an online food ordering platform in China. This peer-to-peer platform, founded in Beijing in September 2014, connects freelancers selling home-cooked food with nearby customers. As shown in Appendix Figure D1, the platform has numerous sellers and customers covering most areas of Beijing. By 2020, its operations had expanded to seven major metropolitan areas across China, making it the largest platform for home-cooked food ordering in the country.[1]

The platform works as follows. To become a registered seller and start their own business, freelancers must go through a rigorous screening process that requires them to provide necessary documents, including proof of identity and health certificates, and pass an on-site kitchen sanitation evaluation conducted by the platform. Once the application is approved, sellers upload their self-introduction, which typically contains information such as gender, age group, and a photo of themselves, as well as their menu, which includes the names, pictures, and prices of the dishes they plan to offer, to their online pages. At this point, they are ready for business.

All transactions take place via the platform's mobile application. After downloading the mobile application and signing up, buyers can browse the list of kitchens open for business

[1]The platform was closed due to health and safety concerns related to the COVID-19 pandemic.

in nearby regions, click to view their menus, and place orders. Additionally, buyers can read each seller's self-introduction, ratings, and customer reviews, as well as leave their own reviews after the order is complete. Once an order is placed by a customer, the seller prepares the dishes in their home kitchen and arranges third-party delivery for the meal. The majority of orders are delivered by a third-party service cooperating with the platform, with the delivery cost split equally between the customer and the seller; only a negligible share is directly picked up by the customer or delivered by the seller themselves.

2.2 Data

We combine several datasets from the platform for analysis. The primary dataset includes detailed records of all orders placed by customers on the platform in the city of Beijing from November 2014 to December 2017. For each individual order, we observe the identities and locations of the seller and the customer, the exact time of the order, the dishes ordered, the total payment, delivery fees, as well as the rating and review from the customer. We merge the order records with a second dataset that provides demographic information about the sellers, including their age group, gender, and home address. Additionally, we have access to each seller's menu, which includes the names and prices of the dishes they offer.

Table 1 displays the summary statistics of our main sample of analysis, which includes the universe of sellers with at least 100 complete orders.[2] Both seller-level and order-level characteristics are reported for the full sample, and separately for male and female sellers. Consistent with our prior assumption that women do more home cooking than men, the freelancers in our sample are predominantly female (71%) with an average age of around 40. On average, a seller has a rating of 4.84 out of 5, and is open for business 60% of the time, with male sellers working more days compared to female sellers. In addition, men set a larger delivery radius (2.48 km), which covers more customers, set higher prices, and have more dishes in stock, while female sellers offer a larger variety of dishes.

Although we don't observe significant differences in order-level characteristics such as revenues per order, delivery fees, and coupons, female freelancers overall exhibit lower business

[2] 50.2% of businesses owned by males and 49.0% of businesses owned by females in our data have at least 100 complete orders. We don't see significantly different rates of selection into our sample by gender.

success. They receive fewer orders (6.28 versus 7.47) and earn lower revenues (209 versus 238 CNY) per day. These differences persist even after accounting for the shorter hours worked by women daily and when comparing outcomes based on hourly revenues and order counts instead of daily figures. Our observations of a gender gap in the raw data align with existing evidence (e.g., Hardy and Kagy, 2018; Delecourt and Fitzpatrick, 2021). We plan to explore these discrepancies thoroughly in our empirical analysis, focusing on daily business metrics.[3]

3 The Gender Gap in Business Performances

3.1 The Gender Earnings Gap

To empirically quantify the gender earnings gap, taking into consideration the differences in characteristics such as demographics and work intensity, we construct seller-day-level data which is restricted to the days when the seller is open for business, with outcome variables measuring their daily business performance. Specifically, we estimate the following OLS model:

$$R_{st} = \beta \text{male}_s + \alpha X_{st} + \gamma v_s + \pi_t + \varepsilon_{st}, \tag{1}$$

where the outcome variable R_{st} measures the business performance of seller s on day t conditional on being open for business. We consider measures such as total revenue, number of orders, and average revenue per order. The key independent variable male_s is a dummy variable indicating whether the seller s is male, and β is the coefficient of interest that captures the gender gap in business performance. X_{st} represents the covariates that change over time, including the number of working hours each day, and v_s denotes seller-level characteristics that are time-invariant, including the seller's age group, geographic location, the prespecified delivery method and delivery radius, as well as the seller's average customer rating.[4] We additionally include π_t, the year, week, and day-of-week fixed effects, to absorb possible time

[3] We use daily business outcomes as our main variables of interest because our measurement of working hours is imprecise. Instead of using hourly business outcomes directly, we incorporate control for working hours in our regression analyses to adjust for the differences in work intensity between genders.

[4] It has been documented in the literature that review systems can be biased against women. For example, female instructors receive systematically lower teaching evaluations (Boring, 2017; Mengel et al., 2019; Keng, 2020). Therefore, male- and female-owned businesses with similar ratings might have systematically different quality.

trends and seasonality. The standard error ε_{st} is clustered at the seller level.

Panel A of Table 2 reports the gender gap in daily revenues. Column (1) shows that, on average, male sellers earn 33.7 CNY (5.1 USD) more than female sellers, which is equivalent to a 12.1% raw gender gap. From columns (2) to (4), we additionally control for year, week, and day-of-week fixed effects, demographics of sellers (including geographic location and age group fixed effects), and sellers' delivery options and radius. Comparing column (4) to column (1) suggests that 25% of the gender gap in daily revenues can be explained by these factors, mostly driven by the fact that men set a larger delivery radius, which is positively correlated with daily revenues. In column (5), we add the number of working hours to the regression, which further explains 17% of the gender gap, as men, on average, work longer hours and have higher revenues. Finally, we add the average customer rating to the regression in column (6), but there remains a 7.2% gender earnings gap, which is of a similar magnitude as the gender pay gap among Uber drivers (Cook et al., 2021).

To explore the cause of the gender earnings gap, we decompose the outcome, daily revenue, into average revenue per order and daily number of orders:

$$\text{Daily Revenue} = \text{Average Revenue/Order} \times \text{Daily Number of Orders},$$

and separately use them as the outcome variables in Panel B and Panel C of Table 2. We can conclude from Panel B that there is no meaningful gap in average revenue per order between male and female sellers, as long as we adjust for time trends and seasonality. The gender earnings gap observed in Panel A is entirely driven by the difference in the number of orders, which is roughly 8.9%, as shown in column (6) of Panel C.

Gender Earnings Gap by Age Groups We conduct heterogeneity analyses by documenting the gender gap in business performance separately for sellers in each age group. In Appendix Figure D2, we plot the coefficients and 95% confidence intervals of the gender gap in daily revenues and number of orders based on the specification in column (6) of Table 2. Compared to sellers above age 50, younger sellers on average have higher daily revenues and complete more orders, possibly because they are more likely to treat this self-employment as the main source of income rather than a hobby. The gender earnings gap is also mostly con-

centrated among younger sellers. The gaps in daily revenue and in daily number of orders are above 20% for sellers in their 20s and are roughly 10% for sellers between age 30 and 49, while the gaps become small and insignificant for those above age 50. The heterogeneity analysis provides suggestive evidence that the gender gap in business performance could be even larger if we focus on serious and full-time entrepreneurs. It's also possible that the gender earnings gap is larger among younger sellers because young women are disproportionately more likely to be affected by childcare and household duties.

3.2 Experience

The roles of experience and the non-linearity of returns to experience have been recognized as important factors behind the gender gap (Goldin, 2014). We explore whether and how experience helps to explain the gender gap in business performance observed in Table 2 by including different measures of experience in the regression. Column (1) of Table 3 is identical to column (6) of Table 2 and serves as a baseline.[5] In column (2), we include the variable experience, which is measured as the total number of orders completed by the seller before the given day of work.[6] The results show that there are indeed large and significant returns to experience, which explain at least half of the remaining gender earnings gap in our baseline model. In column (3), rather than adding the linear term of experience, we include category dummies for different levels of experience to allow for non-linear returns to experience, which reduces the gender gap in daily revenues to 4.5%.

In columns (4) and (5) of Table 3, we run OLS regressions separately for male and female sellers. The coefficients suggest that male sellers have higher returns to experience than female sellers at all levels of experience. This finding differs from Cook et al. (2021), where the authors find no gender differences in the actual learning process. The discrepancy might stem from differences in the settings, as the freelancers in our sample have much more flexibility regarding their own business strategies and thus more to learn, compared to Uber drivers who are paid according to a fixed formula.

[5]Because we do not see gender differences in average revenue per order, in our following analysis, we focus on daily revenue as our main outcome of interest. The results are robust if we use daily number of orders instead.

[6]Similar to Cook et al. (2021), our measure of experience is precise and will not lead to biased estimates of returns to experience.

Overall, controlling for experience explains a large portion of the gender difference but does not fully close the gap. In column (6) of Table 3, in which we focus on the least experienced sellers who have completed no more than 30 orders, there is still a 3.7% gap in their daily revenues.

4 The Gender Gap in Business Strategies

As small business owners, the sellers in our sample can set their own strategies, including pricing, positioning, and expansion. This section provides descriptive evidence of the gender gap in entrepreneurial strategies and examines how these differences contribute to disparities in business performance.

4.1 Descriptive Evidence of Differences in Business Strategies

First, we consider two seller-level strategies that are time-invariant: delivery radius, which determines the number of potential customers a seller can serve, and a similarity index, which summarizes their positioning strategy. The similarity index is constructed using Natural Language Processing to analyze each seller's menu and calculate the cosine similarity between pairs of menus.[7] A menu exhibits high similarity when its average distance to other menus is small. Column (1) of Table 4 confirms the gap observed in the summary statistics: male sellers set a significantly larger delivery radius, controlling for age group and geographic location fixed effects. This larger radius enables male sellers to serve more customers compared to female sellers. Column (2) indicates that male sellers offer more differentiated menus, with their dishes being less similar to those of other sellers. Appendix Figure D3 further illustrates this, showing that male sellers are more likely to specialize in less common cuisine types on the platform, while female sellers are more concentrated in competitive cuisine types. These findings suggest that male and female freelancers adopt different positioning strategies.

Next, we quantify other time-varying business strategies, including the number of working days, dish variety, price levels, and dish stock. These strategies are measured monthly, with gender gaps reported in columns (3)-(6) of Table 4. On average, kitchens operated by male

[7]Details on the construction of the similarity index are provided in Appendix Section A.

sellers open 0.76 more days per month, suggesting that the gender earnings gap would widen further if monthly revenues, rather than daily revenues, were the key outcome. Columns (4), (5), and (6) show that men list fewer dishes on their menus, charge higher prices, and maintain higher dish stock levels compared to women. These results align with the hypothesis that male freelancers demonstrate greater business sophistication—they focus on producing fewer dishes at a larger scale and offer more differentiated dishes, enabling them to charge higher prices. Together, these strategies may explain why male freelancers achieve higher sales and earn greater revenues than female freelancers.

4.2 Earnings Gap and Differences in Business Strategies

To investigate whether the gender differences in business strategies identified in Table 4 help explain the gap in business performance, we incorporate these strategies into our model (1). The results in Table 5 show that menu similarity, dish variety, price levels, and stock levels are all positively correlated with revenues. However, adding these strategies individually (columns (2)-(5)) or collectively (column (6)) does not reduce the earnings gap compared to the baseline specification in column (1). Nevertheless, we cannot conclude from Table 5 alone that these business strategies do not influence the gender gap. It is possible that these factors affect performance non-linearly or interact in complex ways.

To address potential non-linearity and interactions, we adopt a matching method. Specifically, we use Exact Matching and Euclidean distance to pair each male seller with the most similar female counterpart.[8] We first perform exact matching based on age group and geographic location. Next, we apply coarsened exact matching on the date of business start to control for experience (tenure on the platform). Finally, we match each male seller to the closest female seller using Euclidean distance, which measures the similarity of their daily working hours and business strategies. Business strategies include dish prices, menu similarity, the number of dishes offered, stock levels, and customer ratings (used as a proxy for service quality). Additionally, we ensure that the covariate distances fall within the specified calipers.[9] Table 6 shows that after matching, the male and female groups are balanced across

[8] For a review of matching methods, see Imbens (2004) and Stuart (2010).
[9] Appendix Section B provides detailed information on the matching sample construction.

most observable characteristics.

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Table 7 reports the estimates of model (1) using the matched sample. Panels A and B present the results where the outcome variables are daily revenue and daily number of orders, respectively. To provide a benchmark, column (1) replicates the baseline estimates from column (6) of Table 5, controlling for demographics, working hours, and all business strategies linearly. Columns (2)-(4) report estimates of model (1) based on samples matched on different sets of variables, while controlling for time fixed effects, demographics, and delivery options.

In column (2), male and female sellers are matched only on demographics (age group and geographic location) and experience (business start date). The gender gap remains large, consistent with the results in Table 2, which show that controlling for time, age group, and location fixed effects does not reduce the gender gap. Column (3) indicates that when sellers are additionally matched on average working hours, the gender earnings gap decreases by over 50% but remains substantial and statistically significant. In column (4), sellers are matched on demographics, experience, working hours, and business strategies. In this specification, the gender gap in daily revenue (daily orders) decreases to no more than 1.4% (2.4%) and is no longer statistically significant.

Appendix C demonstrates that these results are robust to alternative matching methods and specifications, including using Mahalanobis distance to measure similarity, applying different calipers, and not excluding outliers.

To summarize, when male and female freelancers are matched on demographics, experience, work intensity, and business strategies, the gender gaps in daily business performance are no longer economically or statistically significant in the matched sample. While we cannot specify a functional form that captures how business strategies jointly determine micro-enterprise success in this context, we conclude that the choice of business strategies plays a critical role in shaping the gender gap in business profitability.

5 Discussion

The gender earnings gap and its underlying causes have been extensively studied and remain a central topic in economics literature. The gap persists even when focusing on individuals working in the gig economy or operating their own small businesses (e.g., Cook et al., 2021; Hardy and Kagy, 2018).

In this study, we examine the gender gap in business performance among freelancers and micro-entrepreneurs who sell home-cooked meals on an online platform in Beijing, China. Our setting is unique in that these entrepreneurs operate in a traditionally female-typed domain (home cooking) and independently set their business strategies, which can be quantified using our data. Comparing the daily revenues of male and female sellers, we document a 12.1% gender gap, entirely driven by differences in the daily number of orders rather than variations in average revenue per order. Adjusting for time trends, seller demographics, delivery options, working hours, and customer ratings reduces the gender earnings gap by 41%, with an additional 22% reduction achieved by controlling for experience.

To investigate the remaining gender gap, we analyze differences in business strategies between male and female sellers and find that male sellers demonstrate greater business sophistication. They offer smaller but more differentiated menus at higher prices and tend to be more ambitious in setting delivery radii and managing inventory. Although controlling for linear terms of business strategies does not reduce the gender earnings gap, matching male and female sellers on demographics, experience, working hours, and business strategies successfully eliminates the gap in daily revenues.

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Tables

Table 1: Summary Statistics

	Full	Male	Female
A. Kitchen-level Characteristics			
Male	0.29	1.00	0.00
Age	42.20	40.88	42.74
Rating	4.84	4.83	4.84
Num of Days Open	175.15	179.84	173.21
Share of Days Open	0.67	0.69	0.66
Delivery Radius	2.32	2.48	2.25
Num of Dishes Available	39.17	36.55	40.25
Avrg Price of Dishes	22.90	23.29	22.74
Num of Dishes in Stock	12.08	13.68	11.42
Daily Total Revenue	217	238	209
Daily Num of Orders	6.63	7.47	6.28
Hourly Total Revenue	36.49	38.54	35.65
Hourly Num of Orders	1.09	1.22	1.04
Num of Observations	5,529	1,618	3,911
B. Order-level Characteristics			
Total Payment	40.06	40.26	39.97
Delivery Fee	2.72	2.73	2.71
Coupon	6.55	6.69	6.48
Num of Observations	7,196,049	2,333,313	4,862,736

Notes: This table presents summary statistics of the key variables in our analysis. Panel A summarizes seller-level characteristics, for the full sample and separately for male and female sellers. Panel B summarizes order-level characteristics, for orders in our full sample and separately for orders from male and female sellers.

Table 2: Gender Gap in Business Performances

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Daily Revenue						
Male	33.732***	31.098***	29.299***	25.311***	19.606***	19.871***
	(10.466)	(10.378)	(9.865)	(9.537)	(7.378)	(7.391)
Working Hours					31.323***	31.282***
					(0.653)	(0.658)
Rating						38.396*
						(22.458)
Time FEs		x	x	x	x	x
Demographics			x	x	x	x
Delivery				x	x	x
Mean(Y)	277.662	277.662	277.662	277.662	277.662	277.662
N	967,655	967,655	967,655	967,655	967,655	967,655
Panel B: Average Revenue per Order						
Male	1.032**	0.432	0.321	-0.067	-0.052	0.009
	(0.429)	(0.343)	(0.331)	(0.315)	(0.315)	(0.311)
Working Hours					-0.083***	-0.093***
					(0.020)	(0.021)
Rating						8.902***
						(1.419)
Time FEs		x	x	x	x	x
Demographics			x	x	x	x
Delivery				x	x	x
Mean(Y)	39.420	39.420	39.420	39.420	39.420	39.420
N	967,655	967,655	967,655	967,655	967,655	967,655
Panel C: Daily Number of Orders						
Male	0.843***	0.897***	0.867***	0.820***	0.667***	0.660***
	(0.255)	(0.257)	(0.244)	(0.239)	(0.182)	(0.182)
Working Hours					0.840***	0.841***
					(0.016)	(0.016)
Rating						-1.030
						(0.627)
Time FEs		x	x	x	x	x
Demographics			x	x	x	x
Delivery				x	x	x
Mean(Y)	7.433	7.433	7.433	7.433	7.433	7.433
N	967,655	967,655	967,655	967,655	967,655	967,655

Notes: This table presents the estimates of equation (1). The unit of observation is at the seller-day level. The outcome variables are daily revenue, average revenue per order, and daily number of orders for Panels A, B, and C, respectively. Time fixed effects include year fixed effects, week fixed effects, and day of week fixed effects. Demographic variables include age group fixed effects and geographic location fixed effects. Delivery information includes delivery options, delivery prices, and delivery radius. Standard errors (in parentheses) are clustered at the seller level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table 3: Gender Gap in Daily Revenues, Controlling for Experience

	(1)	(2)	(3)	(4)	(5)	(6)
Male	19.871***	9.504**	12.369**			4.450***
	(7.391)	(4.748)	(6.217)			(1.564)
Experience		0.056***				
		(0.004)				
Completed Orders: 150-400			31.466***	38.526***	28.127***	
			(1.358)	(2.640)	(1.561)	
Completed Orders: 400-1000			72.343***	86.526***	66.287***	
			(2.461)	(4.934)	(2.838)	
Completed Orders: 1000-2500			141.787***	157.453***	134.993***	
			(4.461)	(8.713)	(5.085)	
Completed Orders: >2500			332.059***	370.130***	312.858***	
			(12.208)	(21.323)	(14.681)	
Sample	Full Sample	Full Sample	Full Sample	Male Sellers	Female Sellers	Inexperienced
Mean(Y)	277.662	277.662	277.662	301.265	267.533	121.598
N	967,655	967,655	967,655	290,556	677,099	47,561

Notes: This table presents the estimates of equation (1). The unit of observation is at the seller-day level. The outcome variable is daily revenue. Experience is measured as the number of orders completed prior to the given day of work. In columns (3), (4), and (5), sellers with fewer than 150 orders are the excluded category. In columns (4) and (5), the sample of analysis is restricted to male and female sellers, respectively. In column (6), the sample is restricted to sellers when they have no more than 30 completed orders. Time fixed effects, demographics, delivery information, working hours, and average customer ratings are controlled in all columns. Standard errors (in parentheses) are clustered at the seller level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table 4: Gender Gap in Business Strategies

	Kitchen Level		Kitchen-month Level			
	(1)	(2)	(3)	(4)	(5)	(6)
	Deli Radius	Similarity	Days Open	Dish Variety	Avrg Dish Price	Dish Stock
Male	203.169***	-0.017***	0.761***	-6.597***	0.546***	1.201***
	(36.020)	(0.002)	(0.090)	(0.322)	(0.041)	(0.107)
Mean(Y)	2316.253	0.219	19.173	46.955	22.296	11.720
N	5,525	5,526	50,484	50,484	50,484	50,484

Notes: This table presents the estimates of gender gap in business strategies. For columns (1) and (2), the unit of observation is at the seller level; while for columns (3), (4), (5), and (6), the unit of observation is at the seller-month level. In columns (1) and (2), we control for age group fixed effects and geographic location fixed effects; while in columns (3), (4), (5), and (6), we control for age group fixed effects, geographic location fixed effects, and month fixed effects. Robust standard errors are reported in parentheses.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table 5: Gender Gap in Daily Revenues, Controlling for Business Strategies

	(1)	(2)	(3)	(4)	(5)	(6)
Male	19.871***	25.110***	26.259***	18.233**	18.782**	25.747***
	(7.391)	(7.290)	(7.241)	(7.418)	(7.355)	(7.161)
Working Hours	31.282***	30.540***	30.280***	31.284***	31.195***	29.769***
	(0.658)	(0.610)	(0.610)	(0.659)	(0.653)	(0.574)
Rating	38.396*	70.403***	63.174***	19.061	58.844***	93.340***
	(22.458)	(22.099)	(22.639)	(22.561)	(22.084)	(22.017)
Similarity		353.776***				272.341***
		(39.061)				(39.209)
# of Dishes Available			0.909***			0.737***
			(0.133)			(0.134)
Average Price of Dishes				4.259***		4.465***
				(0.613)		(0.578)
Average Stock of Dishes					1.334***	1.989***
					(0.289)	(0.297)
Time FEs	x	x	x	x	x	x
Demographics	x	x	x	x	x	x
Delivery	x	x	x	x	x	x
Mean(Y)	277.662	277.662	277.662	277.662	277.662	277.662
N	967,655	967,655	967,655	967,655	967,655	967,655

Notes: This table presents the estimates of equation (1). The unit of observation is at the seller-day level. The outcome variable is daily revenue. Time fixed effects include year fixed effects, week fixed effects, and day of week fixed effects. Demographic variables include age group fixed effects and geographic location fixed effects. Delivery information includes delivery options, delivery prices, and delivery radius. Similarity is constructed by measuring the cosine distance between the menus of kitchen pairs. Number of dishes available, average price of dishes, and average stock of dishes are calculated based on their menus each month. Standard errors (in parentheses) are clustered at the seller level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table 6: Covariate Balance between Matched Male and Female Sellers

	Male sellers		Female sellers				
Covariates	Mean	SD	Mean	SD	Difference	SE	p-value
Business Start Date	20434.31	156.582	20433.47	155.341	-0.839	7.473	0.911
Working hours	7.320	2.262	7.287	2.144	0.033	0.105	0.754
Rating	4.853	0.088	4.854	0.086	-0.001	0.004	0.852
Price	21.669	3.077	21.403	2.934	0.265	0.144	0.066
Variety	33.253	20.250	33.397	18.920	-0.144	0.939	0.878
Menu Similarity	0.219	0.072	0.224	0.074	-0.005	0.003	0.164
Dish stock	10.626	7.375	9.849	6.912	0.777	0.342	0.023
Observations	871		871				

Notes: This tables presents covariate balance between the matched male and female sellers. Columns (1) and (2) report male sellers' group mean and standard deviation. Columns (3) and (4) report the matched female sellers' group mean and standard deviation. Column (5) reports the mean of covariate difference. Column (6) reports the standard error of this difference. Column (7) reports the p-value from t-test.

Table 7: Gender Gap in Business Performances, Matched Samples

	Baseline	Matching		
	(1)	(2) Demo + Exper	(3) + Hours	(4) + Strategies
Panel A: Daily Revenue				
Male	25.747***	39.193***	20.073*	3.736
	(7.161)	(11.666)	(11.901)	(12.031)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	277.662	281.990	273.858	264.480
N	967,655	542,438	493,581	303,423
Panel B: Daily Number of Orders				
Male	0.815***	1.138***	0.560*	0.173
	(0.177)	(0.297)	(0.301)	(0.294)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	7.433	7.551	7.378	7.198
N	967,655	542,438	493,581	303,423

Notes: This table presents the estimates of equation (1). The unit of observation is at the seller-day level. The outcome variable in Panel A is daily revenue, and the outcome variable in Panel B is daily number of orders. Column (1) reports the baseline coefficients when we control for all business strategies linearly in addition to working hours and ratings as in column (6) of Table 5. Columns (2) - (4) report coefficients from the matched samples. Male and female sellers are matched on demographics as well as the time entering the platform as a proxy for experience in column (2). They are matched on demographics and average working hours in column (3), and on demographics, average working hours, and business strategies in column (4). Time fixed effects include year fixed effects, week fixed effects, and day of week fixed effects. Demographic variables include age group fixed effects and geographic location fixed effects. Delivery information includes delivery options, delivery prices, and delivery radius. Standard errors (in parentheses) are clustered at the seller level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

ONLINE APPENDIX

A Cosine Similarity

We use cosine similarity score to measure the closeness of menus offered by sellers. This is a standard method for computing text similarity and has been used in numerous economics research (Hoberg and Phillips, 2016; Gentzkow et al., 2019; Kelly et al., 2021; Biasi and Ma, 202w). We calculate the score in the following steps.

- We use a Chinese text segmentation package "jieba" to create a corpus of dishes from all menus in the data.[10] The package helps split each dish name into a series of words. For example, the dish "Stir-fried tomato and eggs" would be broken up into three parts "stir-fried", "tomato", and "eggs". Some commonly seen dish names like "Kung Pao chicken" will stay as it is and be treated as a single word. Stop words like "and" are removed. We eventually get a vector of 26,694 dish words.

- We then collapse all kitchen menus into a matrix M (also known as "bag-of-words"), where a row represents the menu of a seller $s \in S$ and a column represents the total number of times word j occurs in this menu. There are 5,529 kitchens in our dataset. Thus the dimension of the matrix is 5,529-by-26,694.

- The pairwise cosine similarity score between row m_s and m_k is computed as

$$CS_{s,k} = \frac{m_s \cdot m_k'}{|m_s||m_k'|}.$$

  The score measures the angle between the vectors of these two menus and can take any value between 0 and 1. If the score is zero, it means the vectors are orthogonal to each other and the menus have nothing in common. A larger score indicates that there is more similarity between the two menus.

- We compute the pairwise cosine similarity score between each row m_s and all other rows in M. Seller s's average menu similarity is calculated by taking an average of her cosine

[10] https://github.com/fxsjy/jieba

similarity score with all other sellers as below.

$$\text{Similarity}_s = \frac{1}{|S|-1} \sum_{k \neq s, k \in S,} CS_{s,k}$$

B Matching Procedure

In our main analysis, we use Exact Matching and Euclidean distance to create a group of female sellers and a group of male sellers that are similar in observed demographics, working hours, and business strategies. We implement the matching as follows.

For each male seller, we first find all female sellers that share the same age group and geographic location with him, and started their business within 30 days before/after the male seller did.

Next, we calculate the pairwise standardized Euclidean distance between this male seller and all female sellers who satisfy the exact matching criteria, to measure their closeness on working hours and business strategies. Business strategies include kitchen rating, dish price, similarity in menus, number of dishes offered (variety), and dish stocks.

In order to compare the relative importance of working hours and business strategies in explaining the revenue gap, we put 50% weight on working hours and the rest 50% weight on all of the five business strategy choices equally when calculating the Euclidean distance. To ensure balance between each covariate, we also impose a caliper of 1 to make sure that the absolute difference between each standardized covariate is smaller than one (i.e., one standard deviation of the un-standardized covariates).

We then match each male seller with his nearest female seller (with replacement) in terms of the Euclidean distance. We further drop matches with distances lying outside the 95th percentile. Eventually, 871 male sellers are matched to 721 female sellers.

C Robustness Check

This section provides a range of robustness checks for our main matching results. We use different matching specifications such as choosing a different distance measure, selecting dif-

ferent calipers, and reconstructing the sample. We find that our results are robust to all of these alternative specifications.

- Table C1 shows the results when we use Mahalanobis distance to measure the closeness on working hours and business strategies. Unlike Euclidean distance, Mahalanobis distance uses full variance-covariance matrix, allowing it to account for redundancy due to correlations between covariates (Rosenbaum and Rubin, 1985). Besides, we do not put any extra weight on the working hours when calculating Mahalanobis distance, i.e., each covariate has the same weight.

- Table C2 shows the results when we use a caliper of 1.5 instead of 1 for each standardized covariate pair.

- Table C3 shows the results when we relax the business start date criterion from 30 days to 90 days.

- Table C4 shows the results when we do not drop matches whose distance lies outside the 95th percentile.

Table C1: Gender Gap in Business Performances, Matched Samples (Mahalanobis Distance)

	Baseline	Matching		
	(1)	(2) Demo + Exper	(3) + Hours	(4) + Strategies
Panel A: Daily Revenue				
Male	25.747***	39.193***	20.073*	4.759
	(7.161)	(11.666)	(11.901)	(12.451)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	277.662	281.990	273.858	265.788
N	967,655	542,438	493,581	305,905
Panel B: Daily Number of Orders				
Male	0.815***	1.138***	0.560*	0.211
	(0.177)	(0.297)	(0.301)	(0.304)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	7.433	7.551	7.378	7.214
N	967,655	542,438	493,581	305,905

Notes: This table presents the estimates of equation (1). The unit of observation is at the seller-day level. The outcome variable in Panel A is daily revenue, and the outcome variable in Panel B is daily number of orders. Column (1) reports the baseline coefficients when we control for all business strategies linearly in addition to working hours and ratings as in column (6) of Table 5. Columns (2) - (4) report coefficients from the matched samples. Male and female sellers are matched on demographics as well as the time entering the platform as a proxy for experience in column (2). They are matched on demographics and average working hours in column (3), and on demographics, average working hours, and business strategies in column (4). Time fixed effects include year fixed effects, week fixed effects, and day of week fixed effects. Demographic variables include age group fixed effects and geographic location fixed effects. Delivery information includes delivery options, delivery prices, and delivery radius. Standard errors (in parentheses) are clustered at the seller level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table C2: Gender Gap in Business Performances, Matched Samples (Calipers=1.5)

	Baseline	Matching		
	(1)	(2) Demo + Exper	(3) + Hours	(4) + Strategies
Panel A: Daily Revenue				
Male	25.747***	39.193***	19.955*	2.203
	(7.161)	(11.666)	(11.766)	(13.998)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	277.662	281.990	275.247	280.624
N	967,655	542,438	504,549	426,995
Panel B: Daily Number of Orders				
Male	0.815***	1.138***	0.569*	0.085
	(0.177)	(0.297)	(0.297)	(0.343)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	7.433	7.551	7.404	7.559
N	967,655	542,438	504,549	426,995

Notes: This table presents the estimates of equation (1). The unit of observation is at the seller-day level. The outcome variable in Panel A is daily revenue, and the outcome variable in Panel B is daily number of orders. Column (1) reports the baseline coefficients when we control for all business strategies linearly in addition to working hours and ratings as in column (6) of Table 5. Columns (2) - (4) report coefficients from the matched samples. Male and female sellers are matched on demographics as well as the time entering the platform as a proxy for experience in column (2). They are matched on demographics and average working hours in column (3), and on demographics, average working hours, and business strategies in column (4). Time fixed effects include year fixed effects, week fixed effects, and day of week fixed effects. Demographic variables include age group fixed effects and geographic location fixed effects. Delivery information includes delivery options, delivery prices, and delivery radius. Standard errors (in parentheses) are clustered at the seller level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table C3: Gender Gap in Business Performances, Matched Samples (Start Date Gap $\leq$ 90)

	Baseline	Matching		
	(1)	(2) Demo + Exper	(3) + Hours	(4) + Strategies
Panel A: Daily Revenue				
Male	25.747***	31.918**	21.622*	-0.978
	(7.161)	(12.487)	(12.539)	(12.627)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	277.662	286.742	278.316	273.520
N	967,655	556,445	524,364	375,125
Panel B: Daily Number of Orders				
Male	0.815***	1.018***	0.597*	0.039
	(0.177)	(0.304)	(0.314)	(0.331)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	7.433	7.592	7.495	7.399
N	967,655	556,445	524,364	375,125

Notes: This table presents the estimates of equation (1). The unit of observation is at the seller-day level. The outcome variable in Panel A is daily revenue, and the outcome variable in Panel B is daily number of orders. Column (1) reports the baseline coefficients when we control for all business strategies linearly in addition to working hours and ratings as in column (6) of Table 5. Columns (2) - (4) report coefficients from the matched samples. Male and female sellers are matched on demographics as well as the time entering the platform as a proxy for experience in column (2). They are matched on demographics and average working hours in column (3), and on demographics, average working hours, and business strategies in column (4). Time fixed effects include year fixed effects, week fixed effects, and day of week fixed effects. Demographic variables include age group fixed effects and geographic location fixed effects. Delivery information includes delivery options, delivery prices, and delivery radius. Standard errors (in parentheses) are clustered at the seller level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

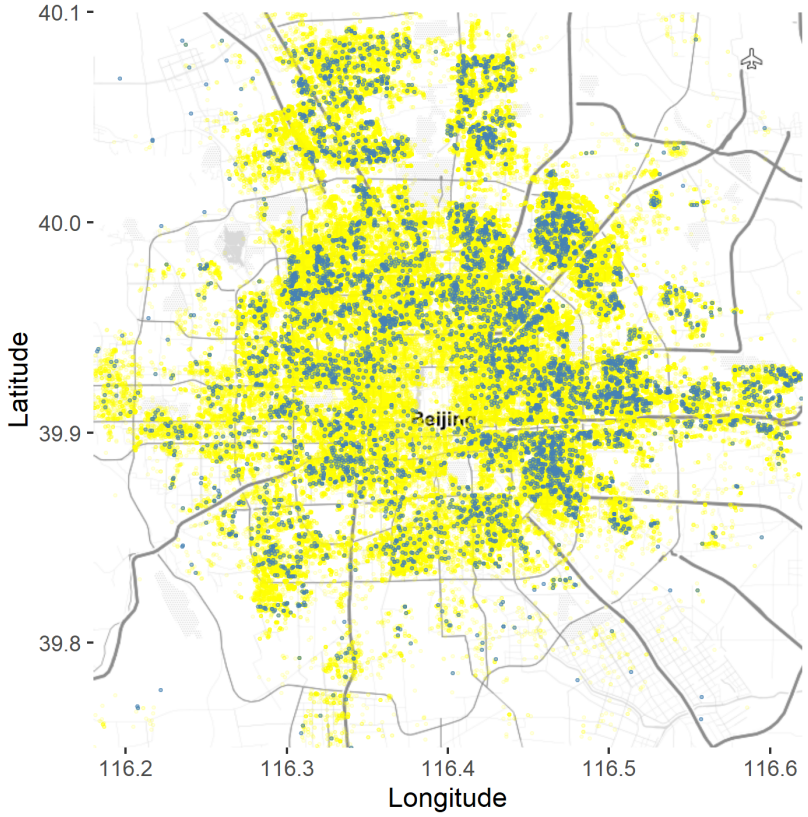
Table C4: Gender Gap in Business Performances, Matched Samples (Full Sample)

	Baseline	Matching		
	(1)	(2) Demo + Exper	(3) + Hours	(4) + Strategies
Panel A: Daily Revenue				
Male	25.747***	39.193***	24.575**	6.258
	(7.161)	(11.666)	(11.732)	(12.080)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	277.662	281.990	278.593	268.189
N	967,655	542,438	521,389	316,390
Panel B: Daily Number of Orders				
Male	0.815***	1.138***	0.707**	0.274
	(0.177)	(0.297)	(0.297)	(0.293)
Time FEs	x	x	x	x
Demographics	x	x	x	x
Delivery	x	x	x	x
Mean(Y)	7.433	7.551	7.483	7.293
N	967,655	542,438	521,389	316,390

Notes: This table presents the estimates of equation (1). The unit of observation is at the seller-day level. The outcome variable in Panel A is daily revenue, and the outcome variable in Panel B is daily number of orders. Column (1) reports the baseline coefficients when we control for all business strategies linearly in addition to working hours and ratings as in column (6) of Table 5. Columns (2) - (4) report coefficients from the matched samples. Male and female sellers are matched on demographics as well as the time entering the platform as a proxy for experience in column (2). They are matched on demographics and average working hours in column (3), and on demographics, average working hours, and business strategies in column (4). Time fixed effects include year fixed effects, week fixed effects, and day of week fixed effects. Demographic variables include age group fixed effects and geographic location fixed effects. Delivery information includes delivery options, delivery prices, and delivery radius. Standard errors (in parentheses) are clustered at the seller level.
Significance levels: *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

D Additional Figures

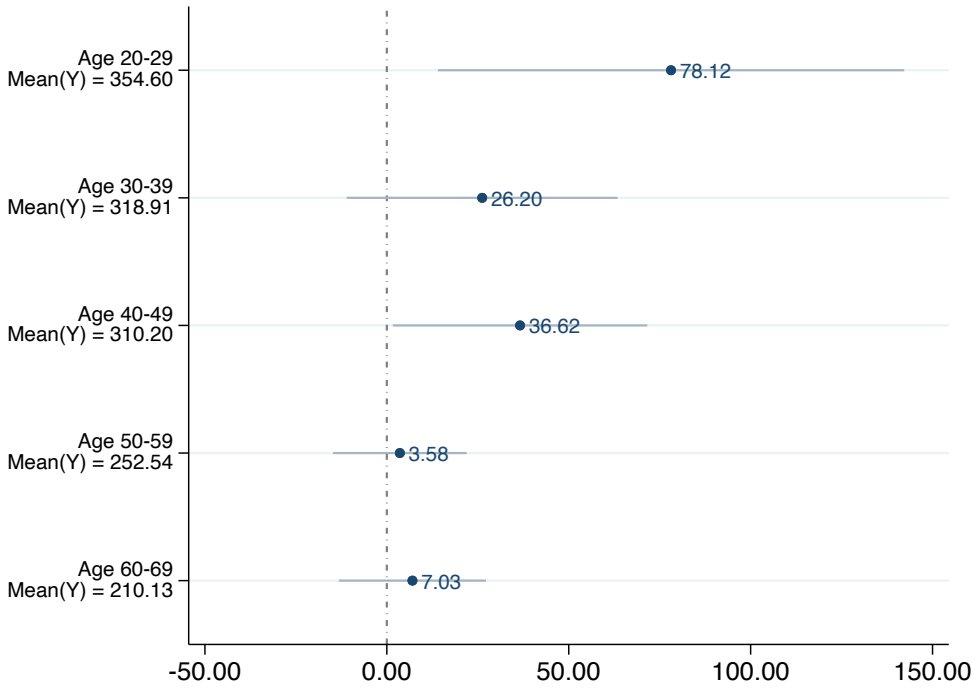
Figure D1: Map of Sellers and Customers in Beijing



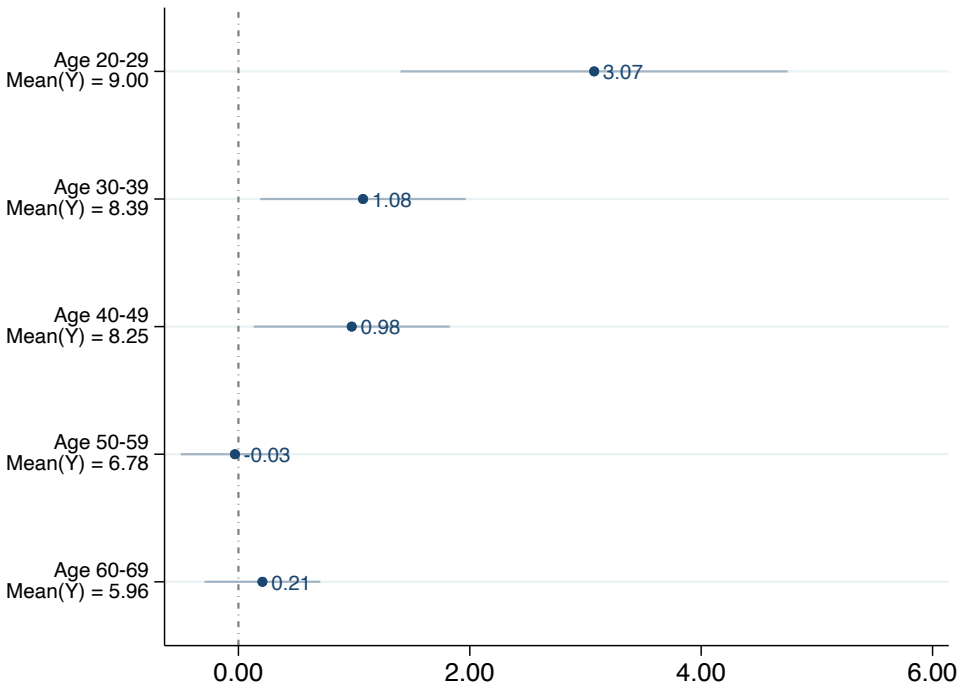
Notes: This figure presents a map of all sellers (in blue) and customers (in yellow) in Beijing in Year 2016.

Figure D2: Gender Gap in Business Performances, by Age Groups

(a) Daily Revenue

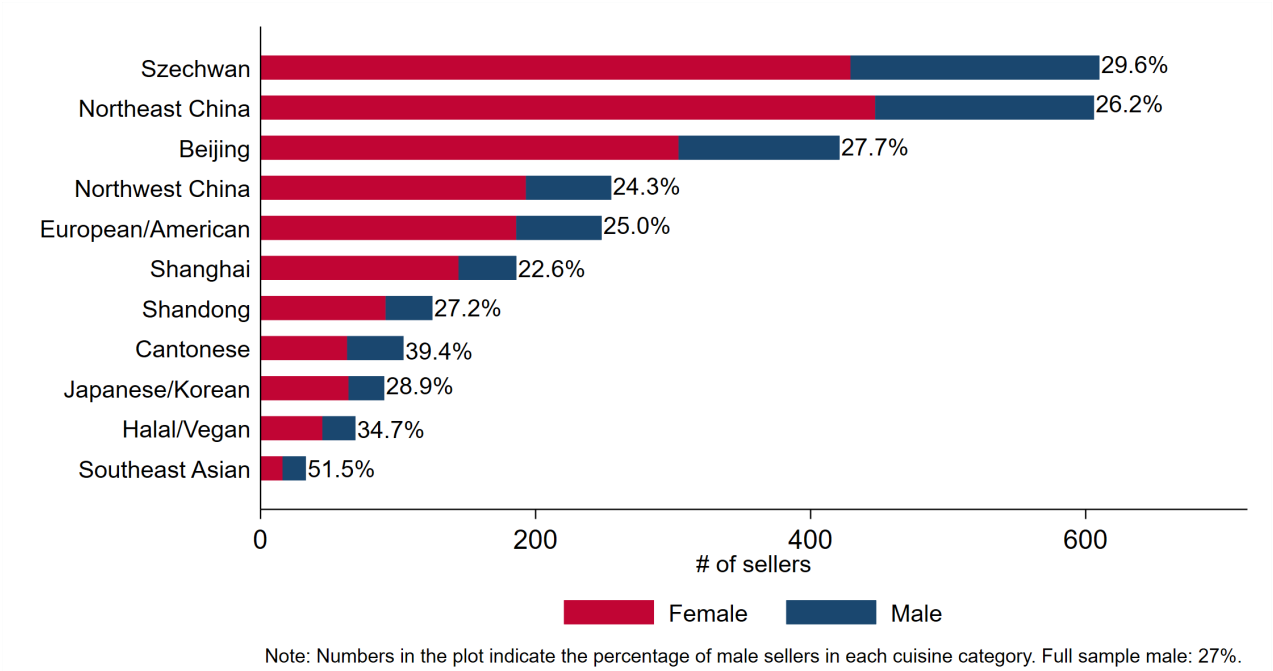


(b) Daily Number of Orders



Notes: This figure presents the estimates of β in equation (1), separately for each age group. The coefficients and 95% confidence intervals in the plot correspond to the specification in column (6) of Table 2. The outcome variables are daily revenue and daily number of orders for Panels A and B, respectively.

Figure D3: Share of Male and Female Sellers by Cuisine Type



Notes: This figure presents the share of male and female sellers by cuisine types. The cuisine types are ranked in descending order by the number of sellers who are characterized into each type. The total number of sellers within each cuisine type is decomposed into the number of female sellers (in red) and male sellers (in blue). Numbers in the plot indicate the share of male sellers within each cuisine type.