

Technical Appendices

Appendix A: Alternative Models

A.1. Model with Delivery Time

We note that the perceived speed of delivery may influence consumers' purchasing decisions, and we recognize the importance of addressing this variable in our analysis.

To account for the potential omitted variable bias, we use a granular measure of delivery time: the 10-day moving average of delivery speed for each listing j on day t . Not only does this measure capture more variation in delivery performance, it also closely reflects the platform's own dynamic estimates shown to customers, as confirmed by our discussions with the platform. We re-estimated our model by including this variable $\log(\text{DeliveryTime}(\text{mins}))$.

The results, presented in Table EC.1, show that using this more granular delivery-time proxy does indeed reduce the magnitude of the *ifFBP* coefficient, thereby confirming that part of FBP's effect on sales is mediated through faster delivery.

Table EC.1 Demand Estimates for Main Model and Model with Delivery Time

	Main Model	Model with Delivery Time
Price	-0.010** (0.005)	-0.009** (0.004)
<i>ifFBP</i>	0.247*** (0.063)	0.200*** (0.080)
$\log(\text{DeliveryTime}(\text{mins}))$		-0.091*** (0.030)
Item (SKU) Fixed Effects	Y	Y
Merchant Fixed Effects	Y	Y
Time Fixed Effects	Y	Y
Random Coefficients	Y	Y
Price Instruments	Lag Price	Lag Price
Control Function	N	N
σ_α	0.0008 (0.0009)	0.0004 (0.0009)

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

The table summarizes results on the demand side using our model. Price in this table is measured in ¥.

We report the cost estimate of *ifFBP* in Table EC.2, which is very close to the estimate in our main model.

Table EC.2 Merchant Supply-Side Estimates (Model with Delivery Time)

	<i>Dependent variable:</i>
	Marginal Cost
<i>ifFBP</i>	13.401*** (1.056)
Merchant Fixed Effects	Y
Time Fixed Effects	Y
Control Function	Y
Item (SKU) Fixed Effects	Y
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

The table shows estimators of the supply side. Coefficient of *ifFBP* shows the *additional* marginal cost incurred with FBP. It is measured in ¥.

We also make a remark: if our goal is to estimate the total effect of FBP on purchasing decisions—capturing both direct and indirect (delivery speed-driven) effects—then excluding delivery time altogether may indeed be preferable. As illustrated in Figure EC.1, omitting delivery speed allows the FBP coefficient to capture both its direct effect and its indirect effect (via faster delivery). This approach facilitates counterfactual simulations in which FBP is absent, without the need for estimating the causal link between FBP status and delivery speed.

A.2. Selection in *ifFBP*: The Control Function Approach

An important concern is that the merchants' choice of adoption of FBP may be endogenous and not fully addressed by the fixed effects and instrumental variables. In this section, we estimate another model where we explicitly model the merchants' decisions to adopt FBP for a product.

We assume the choice to adopt FBP (*ifFBP*) is governed by the latent variable *ifFBP**, which is linearly determined by some observable features W . The merchant adopts FBP if *ifFBP** is non-negative.

Formally, we write our model as follows. We mark the consumer, merchant and market index as superscripts, and omit them in the subsequent discussions.

$$u^{ijt} = f(X^{ijt}) + \beta ifFBP^j + u_1^{ijt} \quad (\text{EC.1})$$

$$ifFBP_j = \mathbb{I}(\gamma_W W^{jt} + e_2^{jt} \geq 0) \quad (\text{EC.2})$$

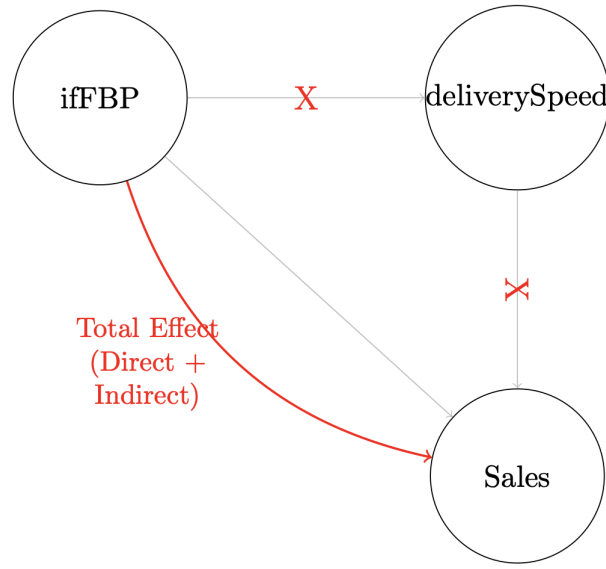


Figure EC.1 The relationship between Fulfillment by Platform (ifFBP), delivery speed, and sales. When delivery speed is omitted from the regression (indicated by X marks), the estimated coefficient of ifFBP captures both its direct effect on sales and its indirect effect through delivery speed (shown by the red curved arrow). The gray arrows represent the true underlying causal relationships in the data generating process.

To explicit model the endogeneity, we assume u_1 and e_2 are correlated such that

$$u_1 = \rho_1 e_2 + e_1 \quad (\text{EC.3})$$

So,

$$\mathbb{E}(u) = f(X) + \beta \text{ifFBP} + \mathbb{E}(u_1 | \text{ifFBP}, X, W) \quad (\text{EC.4})$$

and we wish to obtain $\mathbb{E}(u_1 | \text{ifFBP}, X, W)$.

Note,

$$\mathbb{E}(u_1 | \text{ifFBP}, X, W) = \mathbb{E}_{e_2}(\mathbb{E}(u_1 | X, Z, e_2) | X, W, \text{ifFBP}) \quad (\text{EC.5})$$

$$= \mathbb{E}_{e_2}(\rho_1 e_2 | X, W, \text{ifFBP}) \quad (\text{EC.6})$$

Assume $e_2 \sim N(0, 1)$, we have:

$$\mathbb{E}(e_2 | X, W, \text{ifFBP}) = \begin{cases} \mathbb{E}(e_2 | e_2 \geq -\gamma_W W) = \frac{\phi(\gamma_W W_{jt})}{\Phi(\gamma_W W_{jt})} & \text{if } \text{ifFBP} = 1 \\ \mathbb{E}(e_2 | e_2 < -\gamma_W W) = \frac{-\phi(\gamma_W W_{jt})}{1 - \Phi(\gamma_W W_{jt})} & \text{if } \text{ifFBP} = 0 \end{cases} \quad (\text{EC.7})$$

In practice, we first estimate the following probit model:

$$ifFBP_j = \Phi(\gamma_W W_{jt}) \quad (\text{EC.8})$$

Then, on the demand side, we add the following term to the RHS of the utility function:

$$ifFBP_j \frac{\phi(\gamma_W W_{jt})}{\Phi(\gamma_W W_{jt})} + (1 - ifFBP_j) \frac{-\phi(\gamma_W W_{jt})}{1 - \Phi(\gamma_W W_{jt})}.$$

where $\phi(\cdot)$ denotes the pdf of the Normal distribution, and $\Phi(\cdot)$ denotes the cdf of the Normal distribution. Hence, the utility function is modeled as:

$$u_{ijt} = x'_{jt}\beta + \alpha_i p_{jt} + \lambda_{sku(j)} + \iota_{m(j)} + \tau_t + \Delta \xi_{jt} + \epsilon_{ijt} + ifFBP_j \frac{\phi(\gamma_W W_{jt})}{\Phi(\gamma_W W_{jt})} + (1 - ifFBP_j) \frac{-\phi(\gamma_W W_{jt})}{1 - \Phi(\gamma_W W_{jt})}. \quad (\text{EC.9})$$

Similarly, on the supply side, the choice of *ifFBP* affects the marginal cost. Therefore, in the model of marginal costs, we make the same modification to the RHS of the cost function, and obtain the following cost-side equation:

$$mc_{jt} = ifFBP_j \cdot \gamma + \kappa_{m(j)} + \zeta_{sku(j)} + \rho_t + \eta_{jt} + ifFBP_j \frac{\phi(\gamma_W W_{jt})}{\Phi(\gamma_W W_{jt})} + (1 - ifFBP_j) \frac{-\phi(\gamma_W W_{jt})}{1 - \Phi(\gamma_W W_{jt})}. \quad (\text{EC.10})$$

To estimate our model, we first estimate the probit model in equation EC.8. We then reconstruct our moment conditions the same way we did earlier with the same set of instruments and estimate the model using a generalized method of moments. We report the results in Table EC.3 and Table EC.4. Our price coefficient and coefficient for *ifFBP* are very similar to what we had without the explicitly modeling the merchants' decision to adopt FBP. We also re-run our counterfactual studies and find all our findings qualitatively hold.

A.3. Exchange Rate as IV for Price

In this section, we report robustness check with respect to our lagged instruments strategy. A limitation of the lagged instrument strategy is that its validity depends on a structural assumption which cannot be empirically validated. In our revised manuscript, we collected additional data on daily CNY/USD exchange rates¹⁰ and use it as an instrument to address price endogeneity. Given that we do not have access to detailed product identities, we cannot argue why exchange rates should affect merchants' pricing decisions. However, we can empirically test if exchange rates do impact pricing by estimating a first-stage regression between the exchange rate and product prices.

¹⁰ We have exchange rate data missing on 6 days.

Table EC.3 Demand Estimates for Model with Control Function

Model with Control Function	
Price	-0.009** (0.004)
<i>ifFBP</i>	0.214*** (0.081)
Item (SKU) Fixed Effects	Y
Merchant Fixed Effects	Y
Time Fixed Effects	Y
Random Coefficients	Y
Price Instruments	Lag Price
Control Function	Y
σ_α	0.0008 (0.0009)

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

The table summarizes results on the demand side using our model. Price in this table is measured in ¥.

Table EC.4 Merchant Supply-Side Estimates (Model with Control Function)

<i>Dependent variable:</i>	
Marginal Cost	
<i>ifFBP</i>	14.867*** (1.078)
Merchant Fixed Effects	Y
Time Fixed Effects	Y
Control Function	Y
Item (SKU) Fixed Effects	Y

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

The table shows estimators of the supply side. Coefficient of *ifFBP* shows the *additional* marginal cost incurred with FBP. It is measured in ¥.

We obtain an F-statistic of 24.49 (see [Table EC.6](#)) from the first-stage regression, indicating the relevance and strength of our instrument. The exclusion restriction follows from the argument that exchange rates act as marginal cost shifters and affect merchants' pricing decisions but do not directly affect the utility a customer derives from a product. We find almost identical results for both the model using lagged prices as instruments and the model using exchange rate instruments. We report the results in [Table EC.5](#). This gives credibility to our structural assumption used for identification.

Table EC.5 Demand Estimates for Model with Exchange Rate as IV

Model with Exchange Rate as IV	
Price	-0.011*** (0.002)
<i>ifFBP</i>	0.211*** (0.063)
Item (SKU) Fixed Effects	Y
Merchant Fixed Effects	Y
Time Fixed Effects	Y
Random Coefficients	Y
Price Instruments	Exchange Rate
Control Function	N
σ_α	0.0008 (0.0009)

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

The table summarizes results on demand side using our model. Price in this table is measured in ¥.

Table EC.6 First Stage Regression: Exchange Rate as IV

<i>Dependent variable:</i>	
	Price
	(2)
Exchange Rate	187.861*** (37.959)
Constant	-1,039.111*** (260.083)
Observations	18,624
R ²	0.001
Adjusted R ²	0.001
Residual Std. Error	285.447 (df = 18622)
F Statistic	24.493*** (df = 1; 18622)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

A.4. Learning Latent Product Characteristics through Factorization

The robustness and validity of our estimates depends on the ability of our demand to capture the substitution patterns between the various products. In the absence of rich product characteristics, we relied on product and merchant fixed effects to capture the substitution patterns across various products. To test if the lack of rich product characteristics affects our estimates and results, we also estimated an alternate model of demand by using consumer transaction history data to learn latent

product characteristics. Recent literature (see [Ruiz et al. \(2020\)](#)) discusses how latent product characteristics can be inferred from customer basket history. We propose a model to estimate latent product characteristics first and then use them in a traditional econometric (BLP) framework.

Extant demand system literature hinges on the assumption that products can be approximated through their respective representation in the characteristics space and such representation can then be used to carry out effective predictions. However, in practice the researcher seldom has access to rich product characteristics and estimating fixed effects for product dummies might not lead to incidental parameter problem if there are a large number of products (see [Bajari et al. \(2001\)](#), [Akerberg and Rysman \(2002\)](#), [Anderson et al. \(1992\)](#), [Caplin and Nalebuff \(1991\)](#), [Berry et al. \(1995\)](#)).

To address the potential concern of lacking observed product characteristics, we use non-negative matrix factorization, aiming to obtain latent product characteristics inferred from observed shopping baskets. The transaction records of consumers' baskets, D , could be factorized to two row-rank matrices: (1) a latent characteristic matrix T of shopping trips, and (2) a latent characteristic matrix P of products. The idea is that there is an underlying substitution pattern, characterized by latent product characteristics, that drives all transactions, and the differences between each shopping basket are driven by trip-specific features.

Our goal is to find P and T , such that $L = TP + E$, where $T \in \mathbb{R}_+^{I \times R}$, $P \in \mathbb{R}_+^{R \times J}$, and $E = \mathbb{R}^{I \times J}$ is the residual matrix. We assume that each element in the residual matrix follows i.i.d. Normal distribution: $E_{ij} \sim \mathcal{N}(0, \sigma^2)$. Hence the likelihood of observing the data matrix D is

$$p(L|T, P, \sigma^2) = \prod_{i,j} \mathcal{N}(L_{i,j}; (TP)_{i,j}, \sigma^2), \quad (\text{EC.11})$$

where T, P, σ^2 are parameters of interest. Using a Bayesian framework, we set some priors to parameters. We assume T and P are independently exponentially distributed:

$$p(T) = \prod_{i,n} \Lambda(T_{i,n}; \alpha_{i,n}) \quad (\text{EC.12})$$

$$p(P) = \prod_{n,j} \Lambda(P_{n,j}; \beta_{n,j}) \quad (\text{EC.13})$$

where $\Lambda(x; \lambda) = \lambda \exp(-\lambda x) u(x)$ and $u(x)$ is the unit step function. The prior of σ is chosen to be as an inverse gamma distribution with shape k and scale θ .

We then use Gibbs sampling to obtain a posterior of parameters (T, P, σ^2) . For latent product characteristics used in further demand estimation, we use the mean of the posterior distribution.

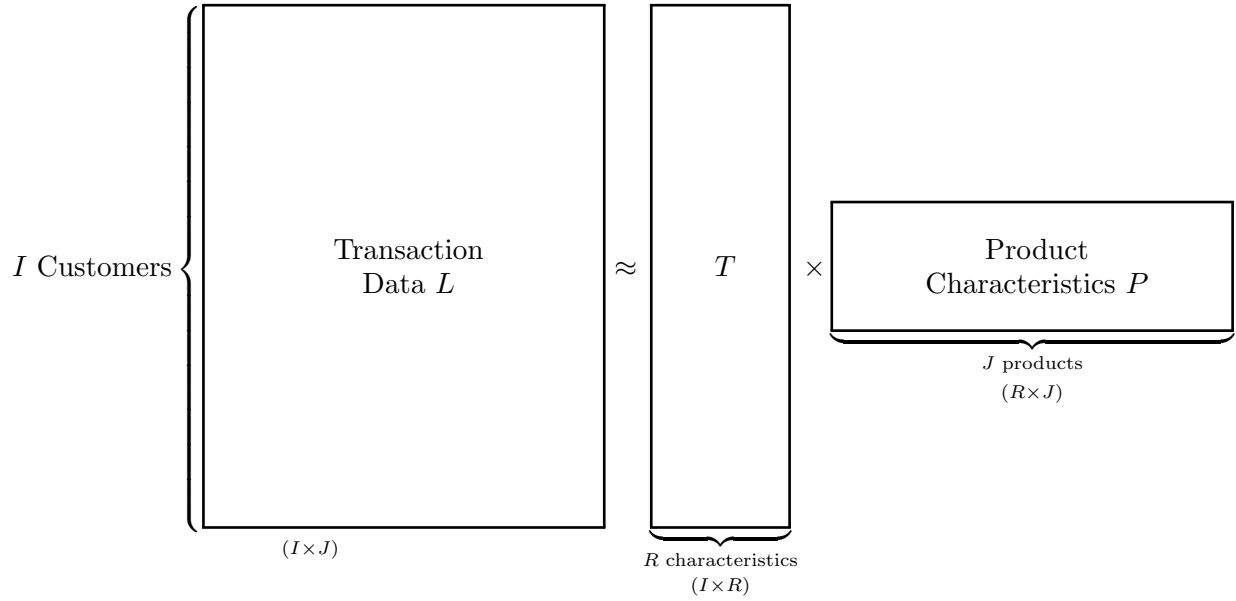


Figure EC.2 An Illustration of Learning Product Characteristic through Matrix Factorization

Table EC.7 Comparison of Demand Estimates: Fixed Effects vs. Latent Product Characteristics

	Logit Model	Latent
Constant	-8.899*** (0.028)	-5.959*** (0.121)
price	-0.001*** (0.000)	-0.012*** (0.001)
<i>ifFBP</i>	1.096*** (0.039)	0.172** (0.055)
Product Fixed Effects	N	N
Merchant Fixed Effects	N	N
Time Fixed Effects	N	Y
Instruments	N	Y
Random Coefficients	N	Y
Latent Product Characteristics	N	Y
σ_α	NA	0.0010*** (0.0002)

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

Note: price in this table is measured in ¥.

To avoid concerns of potential endogeneity, (we also randomly select three months to learn latent product characteristics from those days. We run our subsequent demand analysis on rest of the data. We show model estimates using latent product characteristics in Table EC.7. We find that estimates using fixed effects are almost identical to the estimates from model with product characteristics.

A.5. Random Coefficients on *ifFBP*

In this section, we report the robustness check on our demand estimation, where we include random coefficients on *ifFBP*. Demand and supply side results are reported in Table EC.8 and EC.9, respectively. Overall, we observe very similar coefficients as our main model. Counterfactual results also hold qualitatively.

Table EC.8 Demand Estimates (with Random Coefficient on *ifFBP*)

Model with RC on <i>ifFBP</i>	
Price	-0.010** (0.005)
<i>ifFBP</i>	0.224*** (0.078)
Item (SKU) Fixed Effects	Y
Merchant Fixed Effects	Y
Time Fixed Effects	Y
Instruments	Y
Random Coefficients	Y
σ_α	0.0002 (0.0008)
σ_{ifFBP}	0.019 (0.020)

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

The table summarizes results on the demand side using our model. Price in this table is measured in ¥.

Table EC.9 Merchant Supply-Side Estimates (with Random Coefficient on *ifFBP*)

<i>Dependent variable:</i>	
Marginal Cost	
<i>ifFBP</i>	12.868*** (0.716)
Merchant Fixed Effects	Y
Time Fixed Effects	Y
Control Function	Y
Item (SKU) Fixed Effects	Y

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

The table shows estimators of the supply side. Coefficient of *ifFBP* shows the *additional* marginal cost incurred with FBP. It is measured in ¥.

Appendix B: Out-of-Sample Test

In this section, we report the out-of-sample performance of our structural model.

We first note that, our structural model uses information of pairs (j, j', l, l') for estimating model parameters of *ifFBP* and price elasticity. There are SKUs not associated with such pairs. Hence, they naturally serve as units in the test set. We use our model to predict the market shares s_{jt} , and achieve a mean squared error (MSE) of 3.09×10^{-6} .

As a benchmark, we compare with the out-of-sample results of the Logit Model reported in Table 6. The MSE of the predicted market share using the logit model is 8.50×10^{-6} . If we include all fixed effects in the logit model, the MSE is 3.57×10^{-6} .

Appendix C: First Stage Regression Results for Instruments

In this section, we report the first stage IV regression results for price and *ifFBP* in Tables EC.10 and EC.11 respectively. The F-stat in both regressions exceeds 10, indicating the instruments are strong enough for identification.

Table EC.10 First Stage Regression: Lagged Price as IV	
	<i>Dependent variable:</i>
	Diff. Price
	(1)
$\log(\text{price}_{jt-2})$	-5.030^{***} (0.945)
price_{jt-3}	0.086^{***} (0.018)
$\log(\text{price}_{jt-2}) : \text{price}_{jt-3}$	-0.010^{***} (0.002)
Constant	19.447^{***} (3.712)
Observations	17,963
R ²	0.002
Adjusted R ²	0.002
Residual Std. Error	24.160 (df = 17959)
F Statistic	10.195 ^{***} (df = 3; 17959)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01	

Table EC.11 First Stage Regression: Network instruments as IV

	<i>Dependent variable:</i>
	Sum Diff. <i>ifFBP</i>
Closeness Centrality m, j'	-2,015.652*** (126.281)
Closeness Centrality m, j'	2,609.708*** (144.807)
Closeness Centrality m', l'	1,862.424*** (130.226)
Closeness Centrality m', l'	-3,500.847*** (121.656)
Aggregate Centrality m	-1.465*** (0.185)
Aggregate Centrality m'	13.218*** (0.768)
Constant	-6.327*** (0.352)
Observations	14,894
R ²	0.152
Adjusted R ²	0.152
Residual Std. Error	1.075 (df = 14887)
F Statistic	444.969*** (df = 6; 14887)

Note:

*p<0.1; **p<0.05; ***p<0.01

Closeness centrality is calculated for each merchant-item pair. As there are 4 merchant-item pairs in equation (34) that identifies the cost of *ifFBP*, we use the closeness centrality to predict the sum of difference. Aggregate centrality is closeness centrality aggregated on the merchant level.