# E-Commerce Integration and Economic Development: Evidence from China

Victor Couture (UC Berkeley), Ben Faber (UC Berkeley), Yizhen Gu (Jinan University) and Lizhi Liu (Georgetown)

The Sixth IMF Statistical Forum, 20 November 2018

- 400 million online buyers and sellers in China in 2015, rose from  $\approx\!\!0$  in 2000.
  - Most of growth to date has taken place in cities.

- 400 million online buyers and sellers in China in 2015, rose from  $\approx$ 0 in 2000.
  - Most of growth to date has taken place in cities.
- Chinese govt: countryside e-commerce a policy priority to close rural-urban gap.
  - Entered partnership with a large Chinese e-commerce platform.
  - Growing number of countries with similar programs (e.g. India, Vietnam, Egypt).

- 400 million online buyers and sellers in China in 2015, rose from  $\approx$ 0 in 2000.
  - Most of growth to date has taken place in cities.
- Chinese govt: countryside e-commerce a policy priority to close rural-urban gap.
  - Entered partnership with a large Chinese e-commerce platform.
  - Growing number of countries with similar programs (e.g. India, Vietnam, Egypt).
- Policies mainly motivated by case studies of successful "e-commerce villages".
  - Production side: urban market access to raise demand and entrepreneurship
  - Consumption side: evidence of larger e-commerce share in smaller cities.

- 400 million online buyers and sellers in China in 2015, rose from  $\approx$ 0 in 2000.
  - Most of growth to date has taken place in cities.
- Chinese govt: countryside e-commerce a policy priority to close rural-urban gap.
  - Entered partnership with a large Chinese e-commerce platform.
  - Growing number of countries with similar programs (e.g. India, Vietnam, Egypt).
- Policies mainly motivated by case studies of successful "e-commerce villages".
  - Production side: urban market access to raise demand and entrepreneurship
  - Consumption side: evidence of larger e-commerce share in smaller cities.
- Little evidence on economic and welfare effect of e-commerce in developing countries.

# This Paper

### This Paper

- Objective: provide evidence on e-commerce potential to foster economic development in the countryside.
  - What is the impact for average local household welfare?
  - What are the underlying economic channels?
  - What is the distribution of the gains from e-commerce across households and villages?

### This Paper

- Objective: provide evidence on e-commerce potential to foster economic development in the countryside.
  - What is the impact for average local household welfare?
  - What are the underlying economic channels?
  - What is the distribution of the gains from e-commerce across households and villages?
- How we do it:
  - RCT across villages in collaboration with a large Chinese e-commerce firm.
  - New collection of household and store price survey data (3800 households, ≈ 10k local price quotes per round).
  - Universe of transaction records from firm's internal database ( $\approx$  28m transactions).

- E-commerce: ability to buy/sell products online with local parcel delivery or pick-up.
- E-commerce not just about internet access. In our sample:
  - > 50% have smartphones & villages already connected to internet.

- E-commerce: ability to buy/sell products online with local parcel delivery or pick-up.
- E-commerce not just about internet access. In our sample:
  - > 50% have smartphones & villages already connected to internet.
- Two critical barriers to e-commerce:
  - 1. Logistical Barrier: Countryside mostly not serviced by commercial parcel delivery and pick-up.

- E-commerce: ability to buy/sell products online with local parcel delivery or pick-up.
- E-commerce not just about internet access. In our sample:
  - > 50% have smartphones & villages already connected to internet.
- Two critical barriers to e-commerce:
  - 1. Logistical Barrier: Countryside mostly not serviced by commercial parcel delivery and pick-up.
  - 2. Transactional Barrier: Villagers not used to or trusting online interfaces & limited access to online payment systems.

# Program in China

### Program in China

- Program makes two key investments to lift barriers to e-commerce:
  - 1. Logistical barrier: Build warehouses and fully subsidize transport costs to/from the villages.
  - Transactional barrier: Install e-commerce terminal in central village location.
- Objectives of the program:
  - Connect 100,000 villages to e-commerce.
  - Provide same e-commerce access in villages as in counties' main city center.

# Field Experiment

### Field Experiment

• Location: 8 counties in 3 provinces: Anhui, Henan and Guizhou.

- Design:
  - For each county, we obtain an extended list of candidate villages (X + 5).
  - Randomly select 5 control and 7-8 treatment villages for data collection.
  - Yields a sample of 40 control villages and 60 treatment villages.
- Timing: Baseline data from late 2015 to mid-2016. Endline 1 year after.
- Stratification: Villages with and without pre-existing parcel delivery.
- Median village population≈2500 (800 households).

# Methodology

### Methodology

- Analysis proceeds in 4 steps:
  - Derive expression of household welfare to guide data collection and analysis.
  - 2. Use RCT to estimate causal effects on a number of economic outcomes.
  - 3. Complement survey data with evidence from firm's internal database.
  - 4. Combine 1-3 for quantification of welfare impact, underlying channels, and distribution.

#### Preview of Results

 $\bullet$  Sizable welfare gains for the 13% of households that adopt e-commerce terminal.

- Sizable welfare gains for the 13% of households that adopt e-commerce terminal.
- Significant heterogeneity in gains:
  - Larger gains for younger, richer households, living closer to terminals and in more remote villages.

- Sizable welfare gains for the 13% of households that adopt e-commerce terminal.
- Significant heterogeneity in gains:
  - Larger gains for younger, richer households, living closer to terminals and in more remote villages.
- Channels:
  - Effects mainly driven by removal of logistical barrier, not transactional.
  - Direct consumption gains but no production gains, and no impact on local store prices.

- Sizable welfare gains for the 13% of households that adopt e-commerce terminal.
- Significant heterogeneity in gains:
  - Larger gains for younger, richer households, living closer to terminals and in more remote villages.
- Channels:
  - Effects mainly driven by removal of logistical barrier, not transactional.
  - Direct consumption gains but no production gains, and no impact on local store prices.
- Firms' transaction data confirm our survey result
  - No evidence of larger impact in full sample or past our survey horizon

### On the Menu Today

- Related literature [skip]
- Theoretical framework [skip]
- Experimental design and data
- Evidence from RCT and survey data
- Additional evidence from transaction database
- Welfare quantification
- Conclusion

#### Related Literature

#### Related Literature

- Recent literature on trade and development.
  - e.g. Topalova (2010), Donaldson (2014), Atkin, Faber, Gonzalez-Navarro (2017).
- Literature on transport infrastructure and development.
  - e.g. Donaldson (2016), Baum-Snow et al (2016), Faber (2014).
- Literature on internet and trade.
  - e.g. Freund & Weinhold (2004), Lendle et al (2016).
- Literature on internet and development.
  - e.g. Goyal (2010), Hjort and Poulson (2016).
- Literature on gains from e-commerce and cost of living across cities.
  - e.g. Couture (2016), Zhou et al. (2016), Einav et al. (2017).
- Recent literature on sources of rural-urban economic divide.
  - e.g. Young (2013), Lagakos et al (2016), Hamory et al (2016).

# Map of Mainland China



# Sample Villages





### Warehouses



### E-Commerce Terminal





### **E-Commerce Sellers**



# Descriptive Stats: Households

		Full Sample at	Treatment	Control Villages	P-Value	Control Villages
		Baseline	Villages at	at Baseline	(Treat-Control=0)	at Endline
	Median	3.000	3.000	3.000		3.00
Household Size	Mean	3.114	3.053	3.205	0.075	2.987
Household Size	Standard Deviation	1.422	1.420	1.421		1.40
	Number of Obs	2740	1647	1093		1405
	Median	350.000	339.000	375.000		466.67
Household Monthly	Mean	876.412	841.198	929.473	0.365	1028.960
Income Per Capita in RMB	Standard Deviation	1717.456	1687.169	1761.560		2005.31
	Number of Obs	2740	1647	1093		1405
	Median	1.000	1.000	1.000		1.00
Primary Earner Is Peasant	Mean	0.590	0.600	0.577	0.620	0.587
(Yes=1)	Standard Deviation	0.492	0.490	0.494		0.49
	Number of Obs	2549	1531	1018		1348
Any Member of the	Median	0.000	0.000	0.000		0.00
Household Has Ever Used	Mean	0.368	0.354	0.390	0.249	0.427
	Standard Deviation	0.482	0.478	0.488		0.49
the Internet (Yes=1)	Number of Obs	2739	1646	1093		1402
Household Owns a	Median	1.000	1.000	1.000		1.00
	Mean	0.526	0.509	0.552	0.153	0.551
Smartphone (Yes=1)	Standard Deviation	0.499	0.500	0.498		0.50
• ` ` ´	Number of Obs	2731	1642	1089		1400
Share of Household	Median	0.000	0.000	0.000		0.00
Monthly Expenditure on E-	Mean	0.007	0.006	0.007	0.693	0.008
	Standard Deviation	0.050	0.046	0.057		0.05
Commerce Deliveries	Number of Obs	2720	1637	1083		1397
Share of E-Commerce Sales	Median	0.000	0.000	0.000		0.00
in Household Monthly	Mean	0.003	0.001	0.006	0.103	0.003
•	Standard Deviation	0.052	0.030	0.074		0.05
Income	Number of Obs	2055	1244	811		1161
· · · · · · · · · · · · · · · · · · ·	Median	0.553	0.489	0.623		0.60
Share of Retail Expenditure	Mean	0.500	0.470	0.545	0.193	0.531
Outside of Village	Standard Deviation	0.395	0.402	0.379		0.38
č	Number of Obs	2720	1637	1083		1397

### Average Effects on Consumption

Dependent Variables		Intent to Treat	Treatment on Treated	Log Distance (IV using Treat)	Dependent Variables		Intent to Treat	Treatment on Treated	Log Distance (IV using Treat)
Monthly Total Retail	Treat or Log Dist	-21.93 (31.96)	-40.92 (60.19)	11.15 (16.29)	Share of E-Commerce	Treat or Log Dist	-0.00715 (0.00778)	-0.0154 (0.0191)	0.00433 (0.00545)
Expenditure Per Capita	R-Squared First Stage F-Stat Number of Obs	0.038 3,434	43.92 3,434	42.45 3,434	Terminal in Monthly Business Inputs	R-Squared First Stage F-Stat Number of Obs	0.003 1,207	16.46 1,207	14.96 1,207
Household Has Ever Bought Something through Terminal (Yes=1)	Treat or Log Dist	0.0480*** (0.0169)	0.0886*** (0.0271)	-0.0241*** (0.00721)	Share of E-Commerce Terminal in Monthly Non-Durables	Treat or Log Dist	0.00536*** (0.00195)	0.00999*** (0.00355)	-0.00272*** (0.000956)
	R-Squared First Stage F-Stat Number of Obs	0.008 3,518	45.56 3,518	43.80 3,518		R-Squared First Stage F-Stat Number of Obs	0.003 3,433	44.11 3,433	42.33 3,433
Household Has Bought Something through Terminal in Past Month (Yes=1)	Treat or Log Dist	0.0263*** (0.00981)	0.0490*** (0.0171)	-0.0134*** (0.00458)	Share of E-Commerce Terminal in Monthly Durables	Treat or Log Dist	0.0398** (0.0159)	0.0669** (0.0261)	-0.0188** (0.00736)
	R-Squared First Stage F-Stat Number of Obs	0.009 3,482	43.93 3,482	42.23 3,482		R-Squared First Stage F-Stat Number of Obs	0.011 768	52.64 768	41.27 768
Share of E- Commerce Terminal in Total Monthly Retail Expenditure	Treat or Log Dist	0.00666*** (0.00239) 0.006	0.0124*** (0.00434)	-0.00338*** (0.00117)					
	First Stage F-Stat Number of Obs	3,434	44.03 3,434	42.34 3,434					

 <sup>- 9%</sup> of households become users, 5% during month of survey (14% with spillovers added).
 - Average retail expenditure share on new option is 1.24%, 14% among users.

<sup>-</sup> Stongest response for consumer durables (6.7% on average, 44% among users).

### Average Effects on Incomes

Dependent Variables		Intent to Treat	Treatment on Treated	Log Distance (IV using Treat)	Dependent Variables		Intent to Treat	Treatment on Treated	Log Distance (IV using Treat)
Monthly Income Per Capita in RMB	Treat or Log Dist	-7.838	-14.48	3.974		Treat or Log Dist	1.008	1.879	-0.516
		(70.78)	(129.9)	(35.61)	Weekly Hours		(3.383)	(6.285)	(1.723)
	R-Squared	0.038			Worked by Primary	R-Squared	0.000		
	First Stage F-Stat		45.33	42.83	Earner	First Stage F-Stat		43.80	41.21
	Number of Obs	3,437	3,437	3,437		Number of Obs	3,310	3,310	3,310
Annual Income Per Capita in RMB	Treat or Log Dist	-45.95	-85.08	23.33	Member of Household Has Ever Sold through E-Comm (Yes=1)	Treat or Log Dist	-0.00700	-0.0129	0.00353
		(586.9)	(1,080)	(296.3)			(0.00562)	(0.0104)	(0.00282)
	R-Squared	0.046				R-Squared	0.347		
	First Stage F-Stat		44.77	42.23		First Stage F-Stat		45.30	42.71
	Number of Obs	3,388	3,388	3,388		Number of Obs	3,504	3,504	3,504
	Treat or Log Dist	-70.23	-130.3	35.61	Share of E-Comm Sales in Household Monthly Income	Treat or Log Dist	-0.00120	-0.00224	0.000614
Manthile Aminultuml		(140.3)	(257.7)	(70.34)		Treat of Log Dist	(0.00176)	(0.00330)	(0.000901)
Monthly Agricultural	R-Squared	0.033				R-Squared	0.032		
Income Per Capita	First Stage F-Stat		44.23	42.33		First Stage F-Stat		41.62	38.41
	Number of Obs	3,448	3,448	3,448		Number of Obs	2,830	2,830	2,830
Monthly Non- Agricultural Income Per Capita	Treat or Log Dist	-46.65	-86.06	23.55	Member of Household Started a Business Over Last 6 Months (Yes=1)	Treat or Log Dist	-0.00802	-0.0149	0.00407
		(137.3)	(249.6)	(68.28)			(0.00631)	(0.0120)	(0.00327)
	R-Squared	0.157				R-Squared	0.001		
	First Stage F-Stat		45.74	43.51		First Stage F-Stat		44.37	42.34
	Number of Obs	3,441	3,441	3,441		Number of Obs	3,468	3,468	3,468

<sup>-</sup> No evidence of production-side effects.

### Average Effects on Local Retail Prices

Dept Variables		Intent to Treat	Treatment on Treated	Dept Variables		Intent to Treat	Treatment on Treated
	Treat	0.0189 (0.0142)	0.0352 (0.0263)	Store Owner	Treat	-0.00145 (0.0258)	-0.00261 (0.0461)
Log Prices (All)	R-Squared	0.893	0.893	Sources Products	R-Squared	0.000	-0.001
	First Stage F-Stat	41.66 Online (Yes=		Online (Yes=1)	First Stage F-Stat		23.76
	Number of Obs	6,877	6,877		Number of Obs	341	341
Product Replacement	Treat	-0.00516	-0.00983		Treat	0.00229	0.00337
Dummy (Not	Heat	(0.00947)	(0.0181)	Log Prices of		(0.129)	(0.186)
• 1	R-Squared	0.000	-0.002	Business Inputs	R-Squared	0.811	0.811
Counting Store Closures) (Yes=1)	First Stage F-Stat		39.82	business inputs	First Stage F-Stat		24.86
	Number of Obs	8,956	8,956		Number of Obs	237	237
	Tours	0.00124	0.00236		Treat	0.0211	0.0398
Ct (1 (-t	Treat	(0.0294)	(0.0556)	I Di f N		(0.0146)	(0.0276)
Store Closure (at	R-Squared	0.000	0.000	Log Prices of Non-	R-Squared	0.860	0.860
Product Level) (Yes=1	First Stage F-Stat		39.82	Durables	First Stage F-Stat		40.36
	Number of Obs	8,956	8,956		Number of Obs	6,455	6,455
Number of New Products Per Store	m .	2.194**	4.020*		Treat	-0.0320	-0.0522
	Treat	(1.073)	(2.278)	I D C		(0.0711)	(0.115)
	R-Squared	0.277 0.212		Log Prices of	R-Squared	0.951	0.952
	First Stage F-Stat		19.69	Durables	First Stage F-Stat		9.753
	Number of Obs	312	312		Number of Obs	185	185

- No evidence of pro-competitive price effects.
- Some evidence for added new products in local stores.

### Addressing Three Additional Questions with Survey Data

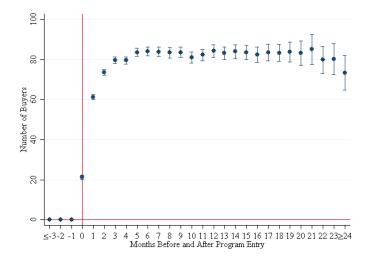
- (1) How does the e-commerce terminal compare with existing stores?
  - Document terminal advantages in prices, variety, travel costs. (Show)
- (2) Could badly managed program implementation affect our result?
  - Find no heterogeneity with respect to terminal manager or other characteristics of implementation. (Show)
- (3) How important are spillovers?
  - Find positive spillovers in consumption usage from nearby terminals, but nothing else. (Show)
  - Estimate tiny fraction of rural market access due to trade with nearby rural markets. (Show)

## Complement RCT with Administrative Data

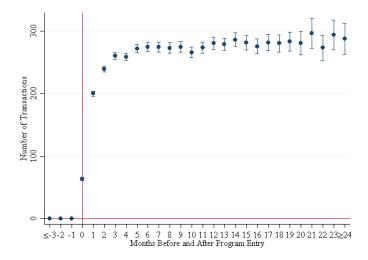
### Complement RCT with Administrative Data

- We use these additional data to answer 4 remaining questions:
  - Are our 100 RCT villages representative of program villages more broadly? (Show)
  - 2. Are our RCT effects subject to seasonality in our endline data?(Show)
  - 3. Is terminal use increasing past our survey's one year window?
  - 4. Are survey data missing highly successful tail events on production side?

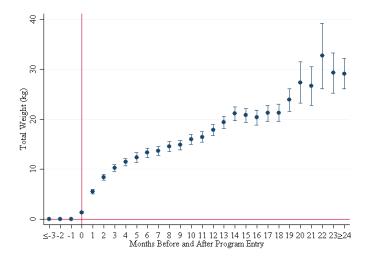
### Q3: Timeline of Adjustment: Number of Buyers



### Q3: Timeline of Adjustment: Number of Purchases



# Q3: Timeline of Adjustment: Village Out-Shipment Weight



## Quantification of Welfare Effect

### Quantification of Welfare Effect

 The "Direct Price Index Effect" (following Atkin, Faber and Gonzalez-Navarro, 2017):

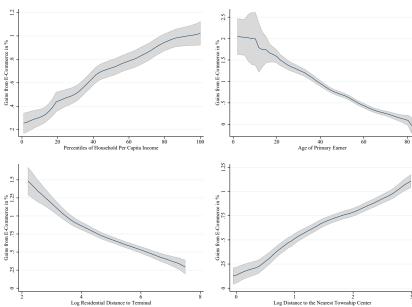
$$\frac{DE}{e(\mathbf{P}_{T}^{0*}, \mathbf{P}_{C}^{0}, \mathbf{P}_{X}^{0}, u_{h}^{0})} = \prod_{g \in G} \left( \left( \sum_{s \in S_{g}^{dc}} \phi_{gsh}^{t1} \right)^{\frac{1}{\sigma_{gh}-1}} \right)^{u_{gh}} - 1$$

- h = household group
- g = product group
- $\sum_{s \in S_{\sigma}^{dc}} \phi_{gsh}^{t1} =$  expenditure share on pre-existing retailers after program entry.
- $\sigma_{gh}$ = elasticity of substitution across retailers.
- $\alpha_{gh}$ = Cobb-Douglas share on product group g.
- Boostrap quantification using point estimates for  $\sum_{s \in S_{qs}^{dc}} \phi_{qs}^{t1}$ .

# Average Effects

	Unweighted (Effects in Sample)			
	Durables	Non-Durables	Total Retail	
	Consumption	Consumption	Consumption	
Reduction in Retail Cost of	3.298%	0.478%	0.812%	
Living for All Households	(0.027)	(0.004)	(0.005)	
Reduction in Retail Cost of	19.331%	3.722%	5.464%	
Living Among Users	(0.215)	(0.029)	(0.035)	

# Heterogeneity of Effects



- Much recent policy attention to e-commerce in developing countries.
  - Can e-commerce integration help close the rural-urban economic divide?

- Much recent policy attention to e-commerce in developing countries.
  - Can e-commerce integration help close the rural-urban economic divide?
- This paper: New microdata and RCT to provide empirical evidence.

- Much recent policy attention to e-commerce in developing countries.
  - Can e-commerce integration help close the rural-urban economic divide?
- This paper: New microdata and RCT to provide empirical evidence.
- Our findings can provide some first insights for current policy debates.

- Much recent policy attention to e-commerce in developing countries.
  - Can e-commerce integration help close the rural-urban economic divide?
- This paper: New microdata and RCT to provide empirical evidence.
- Our findings can provide some first insights for current policy debates.
  - 1. E-commerce leads to significant gains for certain groups of rural households and places, rather than broad-based.

- Much recent policy attention to e-commerce in developing countries.
  - Can e-commerce integration help close the rural-urban economic divide?
- This paper: New microdata and RCT to provide empirical evidence.
- Our findings can provide some first insights for current policy debates.
  - 1. E-commerce leads to significant gains for certain groups of rural households and places, rather than broad-based.
  - 2. Some caution regarding claims about transformation of the countryside via rural entrepreneurship in the absence of complementary interventions (e.g. credit, training, promotions, standardization.)

- Much recent policy attention to e-commerce in developing countries.
  - Can e-commerce integration help close the rural-urban economic divide?
- This paper: New microdata and RCT to provide empirical evidence.
- Our findings can provide some first insights for current policy debates.
  - 1. E-commerce leads to significant gains for certain groups of rural households and places, rather than broad-based.
  - 2. Some caution regarding claims about transformation of the countryside via rural entrepreneurship in the absence of complementary interventions (e.g. credit, training, promotions, standardization.)
  - 3. Investigating how to make local economies thrive under e-commerce is a promising direction for future research!

#### Conclusion

- Much recent policy attention to e-commerce in developing countries.
  - Can e-commerce integration help close the rural-urban economic divide?
- This paper: New microdata and RCT to provide empirical evidence.
- Our findings can provide some first insights for current policy debates.
  - 1. E-commerce leads to significant gains for certain groups of rural households and places, rather than broad-based.
  - 2. Some caution regarding claims about transformation of the countryside via rural entrepreneurship in the absence of complementary interventions (e.g. credit, training, promotions, standardization.)
  - 3. Investigating how to make local economies thrive under e-commerce is a promising direction for future research!

### Thank You!

### Role of Implementation (1)

Could You Have Purchased This Product in	Sample Fraction	0.380	Household Living in Village Without Any	Sample Fraction	0.547	_
Your Village? (Yes=1)	Number Obs	255	Durables on Sale (Yes=1)	Number Obs	3,508	
Log Price Difference Sample Mean -0.166 between Terminal and Sample Median -0.154 Village Retail Number Obs 95	Sample Mean	-0.166		Sample Mean	11.85	
	Sample Median	-0.154	Travel Cost to Nearby Town and Back (RMB)	Sample Median	4	
	95	Town and Back (TaviB)	Number Obs	2,766		
Could You Have	Sample Fraction	0.836	Travel Time to Nearby Town and Back (Minutes)	Sample Mean	58.14	
Purchased This Product in	Sample Praction	0.830		Sample Median	40	
the Nearby Town? (Yes=1)	Number Obs	238	Town and Buck (minutes)	Number Obs	2,366	
Log Price Difference between Terminal and Nearby Town Retail	Sample Mean	-0.227	Travel Distance to Nearby Town and Back (Km)	Sample Mean	20.71	
	Sample Median	-0.182		Sample Median	10.23	
	Number Obs	197	To and Buck (Rin)	Number Obs	2,773	_(Back

## Role of Implementation (2)

Type of Heterogeneity		Intent to Treat	Treatment on the	Log Distance
-	Dependent Variable: Household Has Ev	er Dought Comathing		
	Dependent variable, frouschold fras Ev	0.0480***		
	Treat or Log Dist			
Average Effects	R-Squared	( ,	(0.02/1)	(0.00721)
Average Effects	First Stage F-Stat	0.008	15.56	42.90
	Number of Obs	2.510		
	Number of Obs	- /	- /	- /
	Treat or Log Dist			
	5	(0.147)	(- )	( )
Terminal Manager Test	Treat or Log Dist * Score	-0.000214		
Score	Treat of Log Dist Score	(0.00164)	(0.00270)	(0.000755)
Score	R-Squared	0.006		
	First Stage F-Stat		8.786	8.133
	Number of Obs	8.786 3,042 3,042	3,042	
	Treat or Log Dist	0.0314	0.0616	-0.0172
		(0.0295)	(0.0501)	(0.0136)
m : 114 m :		0.0191	0.0182	-0.00504
Terminal Manager Test	Treat or Log Dist * Above Median	(0.0347)	(0.0583)	
Score Above the Median	R-Squared	0.006	( )	( ,
	First Stage F-Stat		8 654	7 210
	Number of Obs	3,042	to Treat to Treated (IV Using Treatment through E-Commerce Terminal (Yesse)  808*** 0.0886*** -0.0241**  1069) (0.0271) (0.00721)  008  45.56 43.80 518 3,518 3,518 1594 0.104 -0.0297 147) (0.242) (0.0679)  00214 -0.00384 0.000114  0164) (0.00270) (0.000755)  006  8.786 8.133  042 3,042 3,042  3314 0.0616 -0.0172  10295) (0.0501) (0.0136)  1019 0.0182 -0.0504  10347) (0.0583) (0.0158)  006  8.654 7.210  042 3,042 3,042  3347) (0.0583) (0.0158)  006  8.654 7.210  042 3,042 3,042  3392 0.0656* -0.0180*  2047) (0.0357) (0.00941)  1067 0.0486 -0.0131  3335) (0.0554) (0.0149)  009	
•		0.0392	- /-	
	Treat or Log Dist	(0.0247)	(0.0357)	
		0.0167	( )	( ,
County Team Without	Treat or Log Dist * Delay Dummy	(0.0335)		
Smooth Planning	R-Squared	0.009	(0.0554)	(0.0149)
		0.009	10.02	11.46
	First Stage F-Stat	2.510		
	Number of Obs	3,518	3,518	3,318

(Back)

# Estimating GE Effects (1)

## Estimating GE Effects (1)

- · Two approaches:
- 1. Exploit experimental variation similar to Kremer and Miguel (2004).

$$y_{hv}^{Post} = \alpha + \beta_1 \operatorname{\textit{Treat}}_v + \beta_2 \operatorname{\textit{Exposure}}_v^1 + \beta_3 \operatorname{\textit{Exposure}}_v^2 + \gamma y_{hv}^{Pre} + \varepsilon_{hv}$$

where  $Exposure_v^1$  and  $Exposure_v^2$  measure the proximity of village v to other treated villages and to other villages on candidate list of the county.

- 2. In theory, GE effects should be negligible IF village market access is dominated by trade with urban county centers.
  - Compute share of other villages in rural market access in our provinces (using distances and village-level populations or employment).

# Estimating GE Effects (2)

			ToT with Spillovers:	ToT with Spillovers:
Dependent		Treatment on Treated		Number of Terminals
Variables		without Spillovers	within 3 km Outside of	within 10 km Outside
			Village	of Village
	Treat Dummy	-0.0129	-0.0135	-0.0148
Any Member	rreat Dulling	(0.0104)	(0.0101)	(0.0101)
of Household	Exposure to Terminals		-0.00142	-0.00233
Has Ever Sold	Outside the Village		(0.0102)	(0.00202)
through	Exposure to Other		-0.00335***	-0.000285
E-Commerce	Villages		(0.00102)	(0.000363)
(Yes=1)	First Stage F-Stat	45.30	47.63	44.61
	Number of Obs	3,504	3,504	3,504
Household	T . D	0.0886***	0.0786***	0.0862***
Has Ever	Treat Dummy	(0.0271)	(0.0266)	(0.0267)
Bought	Exposure to Terminals		0.0655**	-0.00611
Something	Outside the Village		(0.0311)	(0.00568)
through	Exposure to Other		-0.00245	0.00252**
E-Commerce	Villages		(0.00538)	(0.00111)
Terminal	First Stage F-Stat	45.56	48.11	44.91
(Yes=1)	Number of Obs	3,518	3,518	3,518
	Treat Dummy	0.0124***	0.0101**	0.0119***
Share of	Treat Dummy	(0.00434)	(0.00398)	(0.00422)
Snare of E-Commerce	Exposure to Terminals		0.0159*	-0.00128
E-Commerce Terminal in	Outside the Village		(0.00834)	(0.000923)
Terminal in Total Retail	Exposure to Other		-0.000594	0.000506**
	Villages		(0.000523)	(0.000228)
Expenditure	First Stage F-Stat	44.03	46.57	43.50
	Number of Obs	3,434	3,434	3,434
	m . n	0.0352	0.0338	0.0386
	Treat Dummy	(0.0263)	(0.0258)	(0.0252)
	Exposure to Terminals		0.00353	0.00382
Log Local	Outside the Village		(0.0314)	(0.00562)
Retail Prices	Exposure to Other		-0.00318	-0.00135
(All Prices)	Villages		(0.00314)	(0.000950)
	First Stage F-Stat	41.66	43.89	43.95

(Back)

Q1: Are Our Sample Villages Representative? (1)

## Q1: Are Our Sample Villages Representative? (1)

• Run following regression using firm database:

$$y_{vm} = \theta_m + \beta RCTSample_v + \gamma MonthsSinceEntry_{vm} + \varepsilon_{vm}$$

- v = terminal (village)
- m = month

## Q1: Are Our Sample Villages Representative? (2)

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Full Sample	Full Sample	3 Provinces	3 Provinces	3 Provinces
VARIABLES	N Users	N Transactions	Sales (RMB)	N Users	N Transactions	Sales (RMB)
RCT_Sample	-4.110	0.0605	-6,034	0.149	12.65	-3,747
	(7.751)	(25.33)	(4,061)	(7.734)	(25.32)	(4,066)
Observations	125,204	125,204	125,204	100,098	100,098	100,098
R-squared	0.037	0.047	0.029	0.031	0.046	0.030
N Cluster	11731	11731	11731	8471	8471	8471

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	3 Provinces	3 Provinces
VARIABLES	N Transactions	Weight (kg)	N Transactions	Weight (kg)
RCT_Sample	1.712**	5.154	1.364*	4.680
	(0.753)	(4.332)	(0.752)	(4.333)
Observations	120,483	120,483	95,744	95,744
R-squared	0.060	0.023	0.067	0.026
N Cluster	11904	11904	8591	8591

- Sample of RCT villages do not appear to be particular.(Back)

Q2: Seasonality (1)

## Q2: Seasonality (1)

• Run following regression using firm database:

$$y_{vm} = \theta_v + \beta RCTMonth_m + \gamma MonthsSinceEntry_{vm} + \varepsilon_{vm}$$

- v = terminal (village)
- $\bullet$  m = month

## Q2: Seasonality (2)

					I	
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Full Sample	Full Sample	3 Provinces	3 Provinces	3 Provinces
VARIABLES	N Users	N Transactions	Sales (RMB)	N Users	N Transactions	Sales (RMB)
RCT_Month	0.893***	-4.671***	-1,565***	0.568**	-5.290***	-585.9
	(0.255)	(0.818)	(451.5)	(0.274)	(0.863)	(458.0)
Observations	125,204	125,204	125,204	100,098	100,098	100,098
R-squared	0.694	0.680	0.219	0.679	0.667	0.227
N Cluster	11731	11731	11731	8471	8471	8471

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	3 Provinces	3 Provinces
VARIABLES	N Transactions	Weight (kg)	N Transactions	Weight (kg)
RCT_Month	-0.387***	-1.256***	-0.498***	-1.407***
	(0.0225)	(0.125)	(0.0261)	(0.138)
Observations	120,483	120,483	95,744	95,744
R-squared	0.592	0.432	0.570	0.422
N Cluster	11904	11904	8591	8591

- Point estimates on seasonality very small.(Back)