Peer Effects in Product Adoption

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Introduction

- Peer interactions important driver of product adoption decisions
- Specific nature of peer effects central to implications
 - Extra demand or retiming of future demand?
 - Characteristics of influential individuals? Correlation with price sensitity?
 - Peer effects concentrated on product purchased by friends, or positive or negative spill-overs to competing products?
- This project: Explores these and other questions about peer effects in the market for phone purchases

Approach in this paper

- Measurement Challenge: Need to observe both peers and consumption or product adoption decisions in the same data set.
 - Anonymized data from Facebook to measure peers as well as product adoption from log-ins of mobile users.
- Identification Challenge: Homophily \rightarrow common shocks & preferences \rightarrow Correlated Behavior \neq peer effects.
 - Exploiting quasi-random variation in peers purchasing phones induced by
 (i) breaking/losing phones, (ii) contract renewals.

Data Description

- Anonymized network data from Facebook
- Information on phones from mobile-active users
 - Phone model & carrier registered when logging into mobile app
 - Identify switches to new phones
- Unit of observation: Person-week
- Pool across weeks 2016-19, 2016-20, 2016-21, and 2016-22
 - Not close to major device release dates or shopping holidays

Research Design - Phone Purchase

• Baseline Research Questions: Are people more likely to buy any new phone if their friends recently bought a new phone?

$$\mathbb{1}(BuysPhone)_{i,t} = \beta FriendsBuyPhone_{i,t-1} + \gamma X_{i,t} + \varepsilon_{i,t}$$

- Identification challenges (result of homophily):
 - Correlated preferences
 - Correlated shocks
- Our Approach: Find instruments for FriendsBuyPhone that
 - 1 "Quasi-randomly" shifts probability of friends buying
 - 2 Does not affect own probability of buying, except though peer effects.

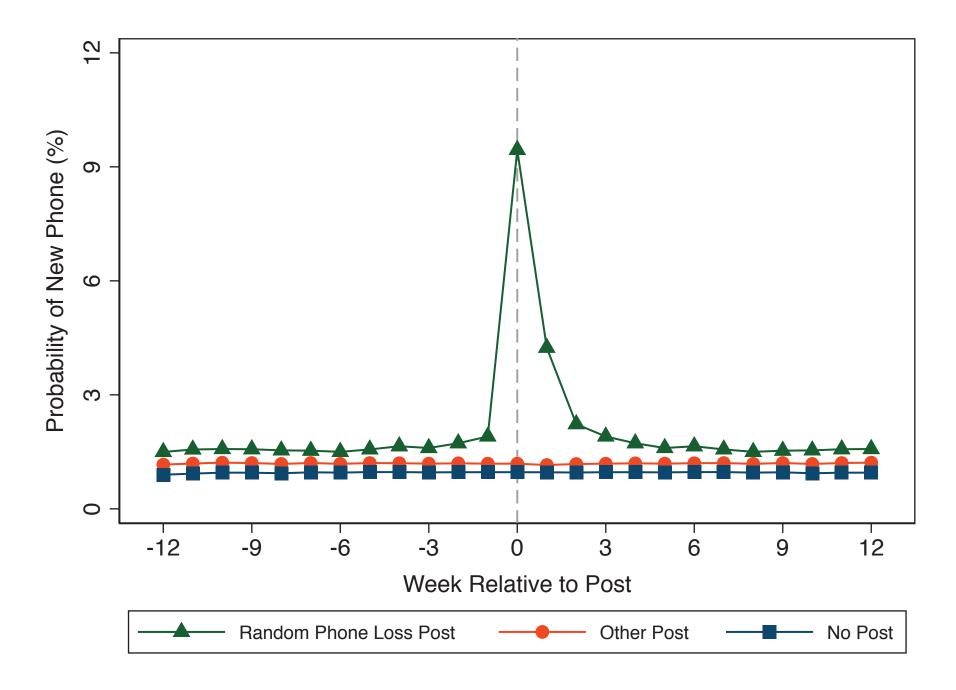
• Use public posts on Facebook that signal "random" loss of phone.



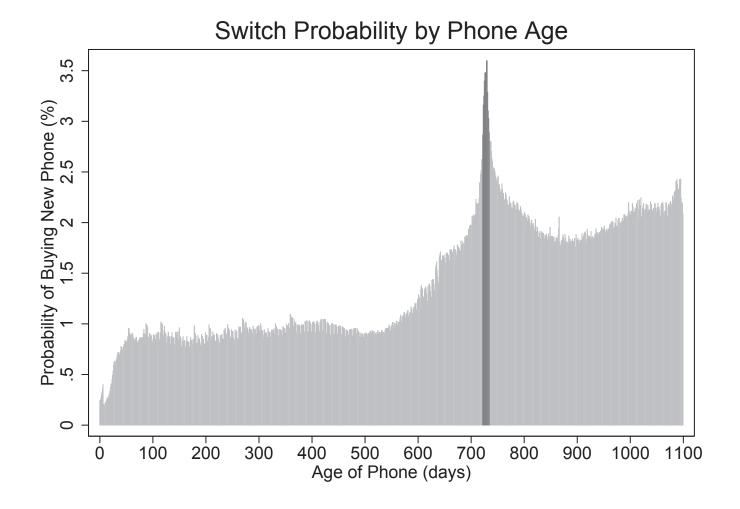
- Identify public posts on Facebook that signal "random" loss of phone.
- Approach: Word Embeddings & Convolutional Neural Networks
 - Neural network trained on about 15k hand-classified posts.

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- Approach: Word Embeddings & Convolutional Neural Networks
 - Neural network trained on about 15k hand-classified posts.
 - Advantages relative to regular expression search
 - Remove some **false positives**:
 - "So...I dropped my phone in the toilet yesterday...!! Still works tho!!"
 - Discover some false negatives:
 - "R.I.P phone. You will be missed."
 - "uggh... water + phone = new phone time.
 - "Long story short, my phone tried to light my house on fire last night and you'll have to reach me on here for a while."
 - Identify ~330,000 posts about "random phone loss"

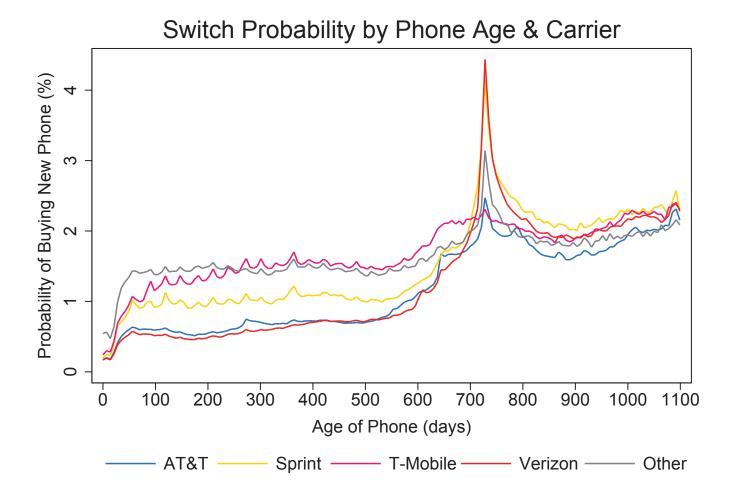
Instrument 1: "Random Phone Loss" – First Stage



Instrument 2: "Contract Renewal" - First Stage



Instrument 2: "Contract Renewal" – First Stage



- Instrument for $FriendsBuyPhone_{i,t-1}$ with number of friends whose phone is aged 720-735 days, and their characteristics
 - E.g., Larger effects at Verizon and Sprint

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Controls in $X_{i,t}$ include:

- User characteristics FE:
 age bucket × gender × education × state × week
- Device characteristics FE:
 device × carrier × phone age bucket × week
- **Friends** characteristics FE: number of friends \times friends switching phones in last 6 months \times week
- Linear controls for
 - Individual probability of buying a new phone
 - Average purchase probability among friends
 - Individual and friend posting behavior (random phone loss instrument)
 - Number and behavior of friends at threshold (contract renewal)

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	OLS	Second Stage DV: Prob Buys New Phone (%)			
	(1)	(2) (3)			
		Broken Phone	Contract Threshold		
# of Friends Buying (t-1 and t)	0.034***	0.041***	0.026**		
	(0.000)	(0.005)	(0.013)		
Controls + Fixed Effects	Υ	Υ	Υ		
Mean Dependent Variable	0.95	0.95	0.95		
Number of Observations	335m	335m 335m			
F-Statistic Instrument		339,156	55,592		

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- \uparrow 1 Friend Buys Phone $\rightarrow \uparrow$ P(Buy Phone Next Week) by 0.04ppt
- Effect not driven by family members
- Not caused by advertising responding to instrument

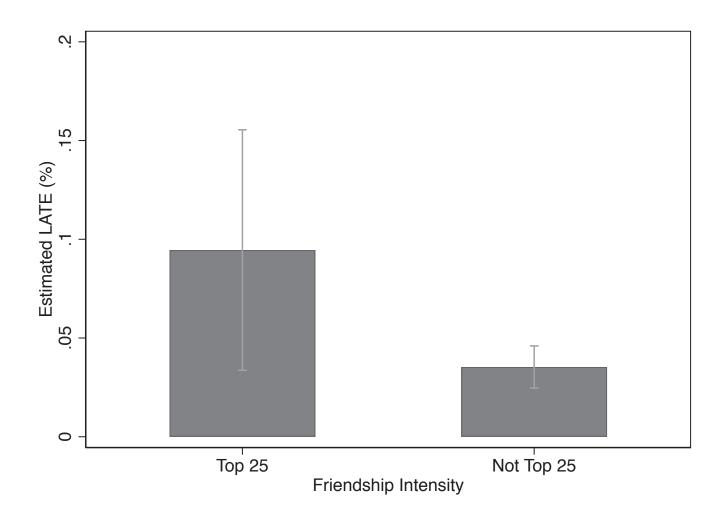
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- \uparrow 1 Friend Buys Phone $\rightarrow \uparrow$ P(Buy Phone Next Week) by 0.04ppt
- OLS \approx IV: Common shocks/preferences less problematic at short horizon (conditional on controls)?
- Different instruments identified off of different individuals

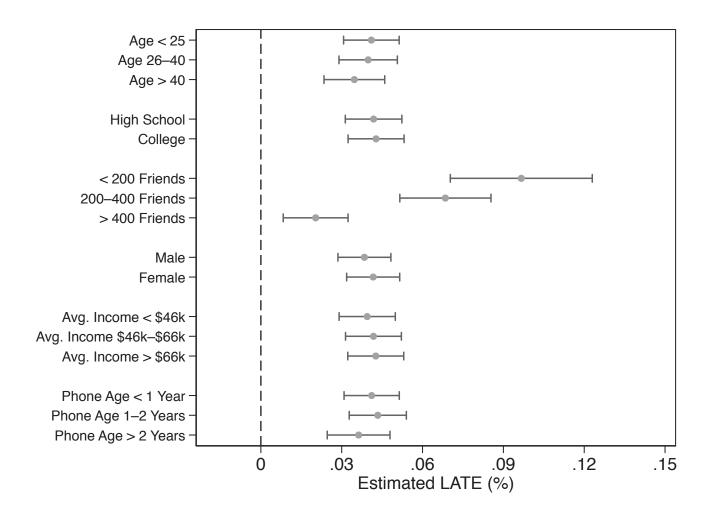


Heterogeneity by Relationship Characteristics



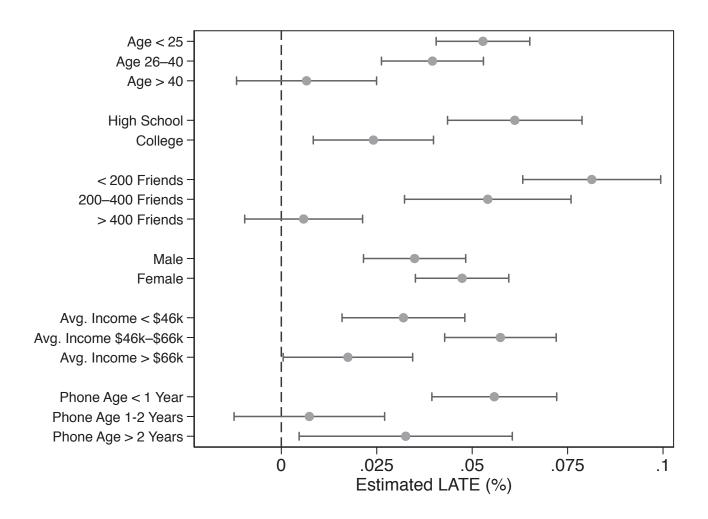
Closer friends are more influential

Heterogeneity by Own Characteristics



- Not much heterogeneity in influencability
- Having more friends: Each friends less close on average

Heterogeneity by Friend Characteristics



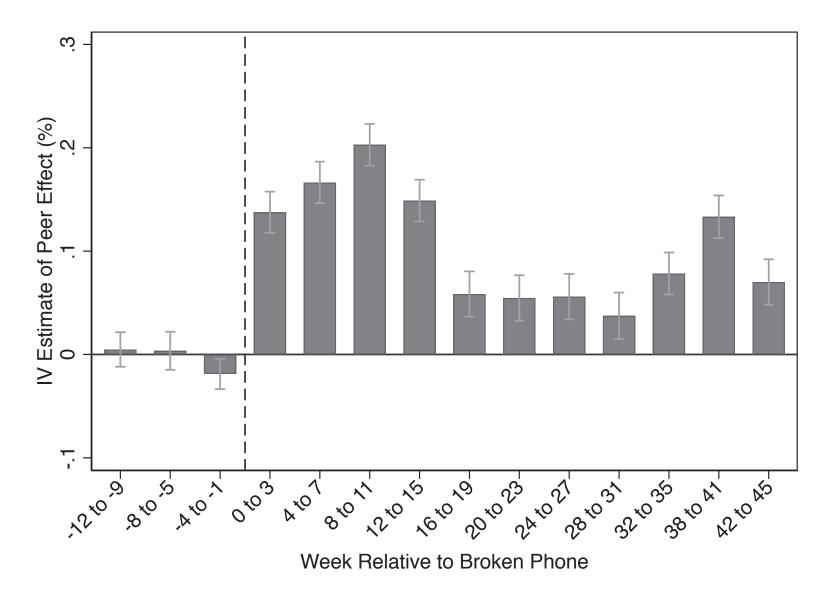
Younger and less educated friends are more influential

Heterogeneity: Implications for Demand

- ullet Peer effects o Aggregate demand more elastic than individual demand
- Key: Correlation between individual price elasticity and peer influence
- Estimate for groups of users
 - Individual price elasticity:
 Increase in purchases following price cut of iPhone 6 in September 2016
 - Peer influence
 - → Correlation between price elasticity and peer influence: 0.45
- Implications
 - Deviation of aggregate and individual price elasticity large
 - Peer effects lead to lower prices ceteris paribus
 - Rationale for queuing

Timing of Peer Effect: New Demand or Pulling Forward?

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- No evidence of a pre-trend, no evidence of reversal over 10 months.
- Implication for firm: Value of customer > Direct effect on profit



Specific Phone Purchase - Motivation

- So far: Effect of friends purchasing any phone on own probability of purchasing any phone.
- Next: Effect of friends purchasing a specific brand of phone (e.g., iPhone) on own probability of purchasing
 - 1 That specific brand of phone
 - 2 A different phone by a competing manufacturer (e.g., Samsung Galaxy)

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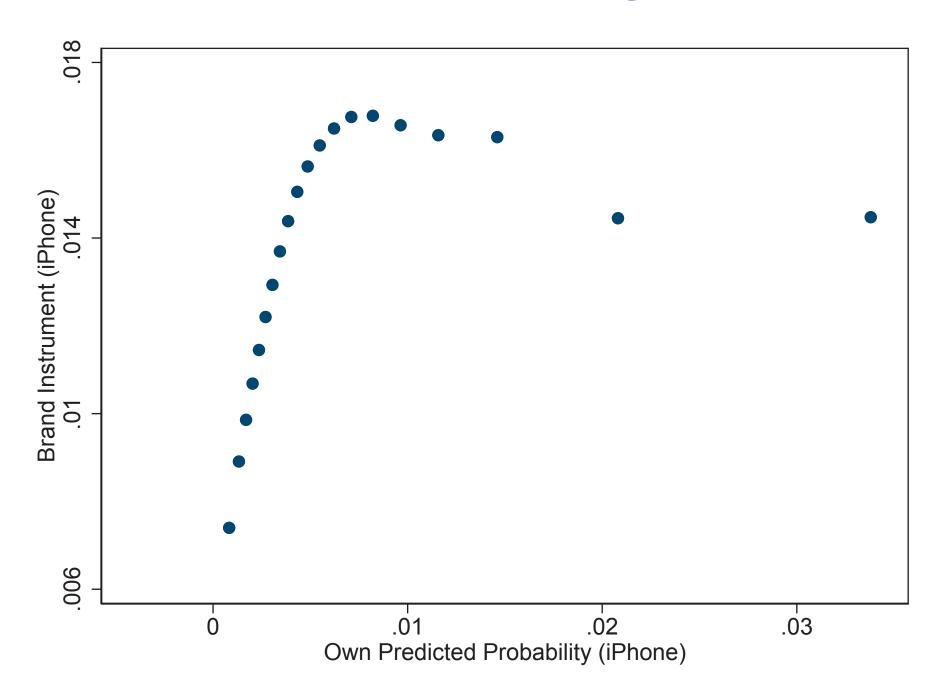
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- Conceptually two effects:
 - 1 Among those who are newly encouraged to buy, how many buy that specific phone vs. another phone (potential for positive demand spillover)
 - 2 Among those who would have bought anyways, what is the effect on the probability of buying that specific phone vs. another phone (potential for negative demand spillover)

Specific Phone Purchase - Research Design

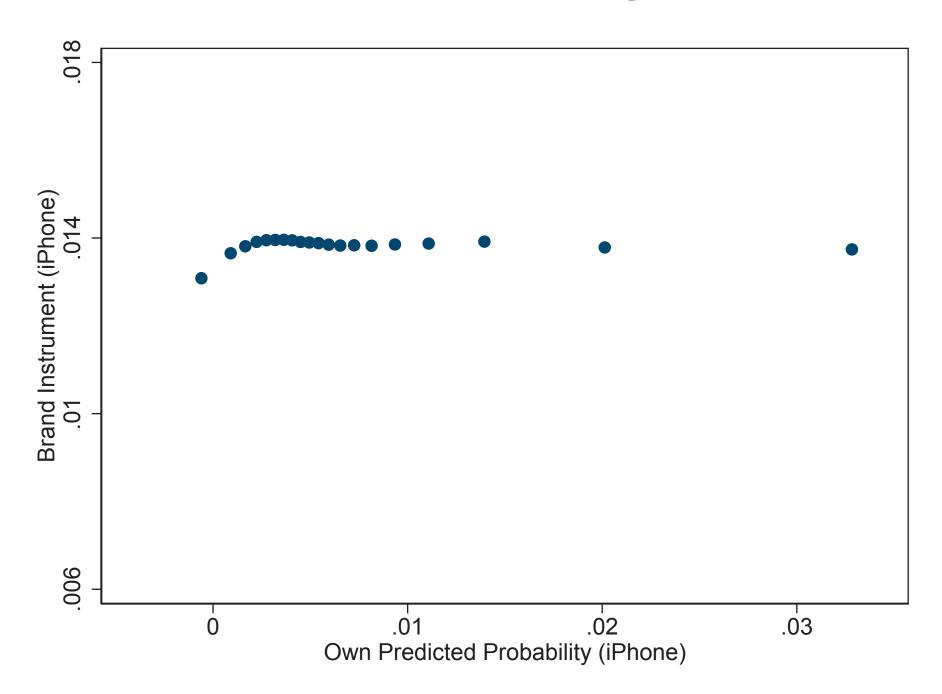
$$\mathbb{1}(BuysX)_{i,t} = \beta_1 FrBuysX_{i,t-1} + \beta_2 FrBuysY_{i,t-1} + \gamma X_{i,t} + \varepsilon_{i,t}$$

- Common shocks + homophily: You are more likely to buy the same phone as your friends, even in the absence of peer effects.
- **Observation:** Individuals differ in their (conditional) propensity to buy particular phones, *PropX*
 - Current iPhone users more likely to buy another iPhone
- Identification Idea:
 - IV: *PropX* among all people who post about randomly losing their phone
 - Control for average of *PropX* among all friends

Specific Phone Purchase - Research Design



Specific Phone Purchase - Research Design



	Dependent Variable: Buys between t and t+24 (%)			
	iPhone	Galaxy	Other	Any Phone
Friends buy iPhone	0.331*** (0.024)	-0.003 (0.018)	-0.121*** (0.017)	0.207*** (0.033)
Friends Buy Galaxy	-0.196*** (0.043)	0.670*** (0.037)	0.403*** (0.036)	0.877*** (0.063)
Friends buy Other	-0.470*** (0.032)	0.081*** (0.030)	1.438*** (0.033)	1.049*** (0.051)
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Mean Dependent Variable	11.74	6.58	5.91	24.23
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- Largest positive peer effects for same brand
- Same brand effect smallest for iPhone (social learning?)

Cumulative Effects over 24 Weeks

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Negative across-OS spillover

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- Losing customers to a rival firm hurts me due to
 - Loss of future sales through positive peer effects from this person
 - Loss of customers this person will bring to competitor who would have otherwise bought my product

Cumulative Effects over 24 Weeks

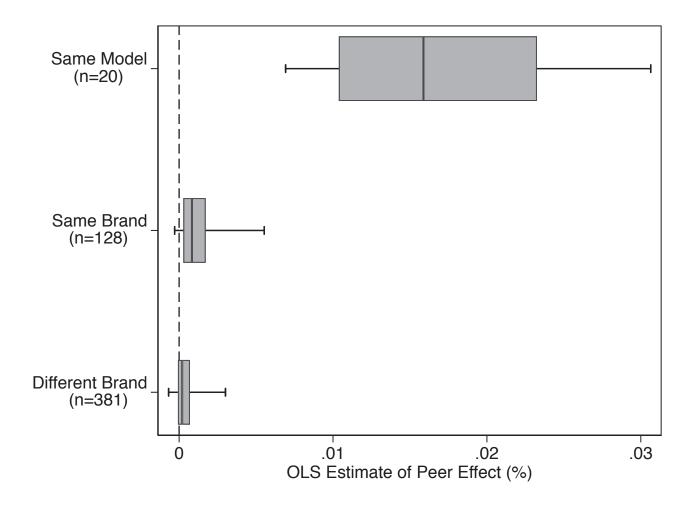
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Positive across-brand spillovers for Android phones (social learning?)

Specific Phone Purchase - Model vs. Brand

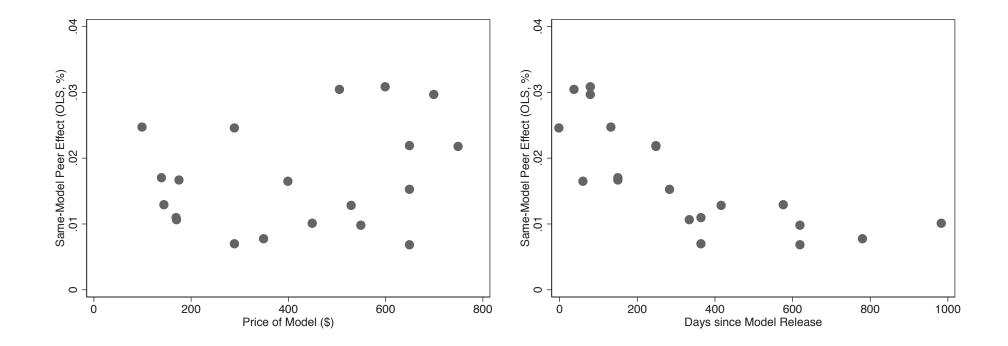
- Next: Can we split up effect further? Effect of friends purchasing a specific model of phone (e.g., iPhone 6s) on own probability of purchasing
 - 1 That specific model of phone (e.g., iPhone 6s)
 - 2 A different phone by the same manufacturer (e.g., iPhone 6)
 - 3 A different phone by a competing manufacturer (e.g., Samsung Galaxy)
- Empirical Challenge:
 - Predicted propensities for iPhone and iPhone 6s are highly correlated
 - → No separate shifter for "friend buys iPhone 6s" and "friend buys iPhone"
 - Can still study the OLS (with all appropriate caveats)

Within and Across Model Peer Effects



Concentrated on same model, some positive same-brand spillovers

Within Model Peer Effects



- Same model peer effects independent of price
- Same model peer effects larger for newer phones
- → Social learning plays important role

Conclusion

- More likely to buy any new phone if friends recently bought new phone
- Largest effect on specific device, some positive within-brand spillovers
- Negative across-brand spillovers, but substantial new overall demand
- Most price elastic individuals are most influential
- → Value of customers; competitive implications; price setting
- → Understanding precise nature of peer effects important for implications
 - Follow-on project to explore similarities across products