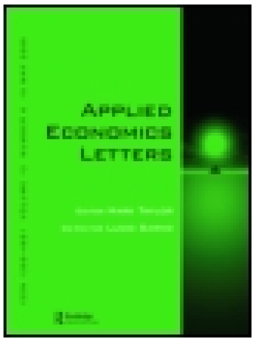

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ARTICLE

Are consumers forward looking? Evidence from used iPhones

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ABSTRACT
This study examines the impact of planned obsolescence – the introduction of new models to make existing models obsolete – on secondary markets for mobile phones. Using data of over 320,000 used iPhones listings on Thailand's largest online marketplace, we document that iPhone prices decrease with age, around 2.8–3.2% for each passing month. We find no evidence that the price decline accelerates after launches of new models (i.e. obsolescence), lending support to the view that consumer in durable goods markets are rational and forward looking.

KEYWORDS
Durable goods; mobile phones; product obsolescence; forward-looking consumer

JEL CLASSIFICATION
D12; L19; L63

I. Introduction

Durable goods such as properties, cars, computers and mobile phones often have secondary markets. When making a purchase decision, a consumer faces the choice of buying a brand-new product in the primary market, or buy a used product – often a good substitute – in the resale market. In order to keep making new sales, firms often resort to planned obsolescence (for example, introducing new models) as a strategy to bring consumers back to the primary market.

New models are often announced in advance, giving resellers some lead time ahead of the actual sale dates. In the case of mobile phones, especially iPhones, new models are launched every year around the same time (around September in the United States and around late October in Thailand). Theory suggests that if consumers are forward looking, have rational expectations and the quality of the new model is known, price adjustments of existing models should occur prior to the launch (Levinthal and Purohit 1989; Purohit 1992).

We employ more than three years of data from Thailand's largest online marketplace to investigate how launches of new mobile phone models affect prices of older models in the secondary market. While there are some studies on this issue, the focus has been on automobiles and college textbooks (Bond and Iizuka 2014; Busse, Knittel, and Zettelmeyer 2013; Chevalier and Goolsbee 2009; Iizuka 2007). To our best knowledge, our study is the first for mobile phones.[1] Our analysis reveals that iPhone resale prices decline predictably with age, and there is no evidence of any sharp change in price after new models become available: the obsolescence seems to be priced in. The finding supports the view that consumers are forward looking, adding to a growing literature that documents price efficiency in non-financial markets.

II. Data and methodology

The dataset for our study is resale iPhone listings on Kaidee – Thailand's largest online marketplace – between 1 January 2014 and 28 February 2017. To use the service, users would write both titles and descriptions of their listings, which are organized in categories. Each listing is location- and time-stamped, and from January 2015, users can also mark the item status in case of cancellation or successful sale. We use an algorithm to parse the data in order to identify the model and memory capacity of the iPhone listings. Listings that do not

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[1]Smartphones have become an indispensable part of modern life, as evidenced by rapidly increasing share of ownership. A study by Pew Research Center in 2017 shows that the share of Americans that own smartphones grew from 35% in 2011 to 77% in 2016. Deloitte Global predicts that used smartphones is a USD 17 billion market in 2016. The ability for consumers to resell their unneeded durable products allow them to retrieve salvage value that otherwise would have been wasted. Online marketplaces reduce transaction costs, which in turn facilitates activities in secondary markets, as explained by Gavazza, Lizzeri, and Roketskiy (2014).

have appropriate model or capacity designations are removed from our sample, leaving 328,087 listings, 87,534 (26.7%) of which are marked as successfully sold on the marketplace. We analyse the listings that were successfully sold separately as the corresponding prices better represent equilibrium prices, which take into account demand from buyers as well.

Data on phone models, memory sizes, launch prices (in THB), launch dates, and summary statistics of listing prices are shown in Table 1.[2] The oldest model in the sample is iPhone 4 and the latest are iPhone 6s and iPhone 6s Plus. As one might expect, average prices in the sample declared as sold are lower than average prices in the full sample across all models.

In the data, listing prices decline over time, as illustrated in Figure 1, which suggests model age is likely the main explanatory factor for listing prices. To identify the impact of new model introductions, we estimate regression equations of the following form.

$$y_{it} = \theta_g + \pi_m + \beta_1 Post_t + \beta_2 Age_{it} + \beta_3 Post_t \times Age_{it} + \varepsilon_{it}$$

y_{it} is the natural log of the listing price. $Post_t$ is an indicator variable which takes value of 1 for listing months that follow new model launch. In the sample, there are 3 model launches: iPhone 6 on 31 October 2014, iPhone 6s on 30 October 2015, and iPhone 7 on 21 October 2016. To illustrate, $Post_t$ would take value of 1 for iPhone 5s listings from November 2014 onward. Age_{it} is phone age, which is defined as number of months since the model was launched in Thailand. In this study, we are interested in the coefficient on the interaction of $Post_t$ and Age_{it}. If consumers are not forward looking and do not anticipate the effect of obsolescence before the launch, listing prices should decline more rapidly after new models are introduced: we expect β_3 to be negative.

Because launch prices for each model are different, we include as control variables model-memory fixed effects, π_m. The data is location-stamped up to district level (which is a subdivision of province) in Thailand, allowing us to include geography fixed effects θ_g to control for unobserved differences across the country. The regression equation is estimated for each launch separately, with listings restricted to one year prior and after the launch. We also estimate the regression on a subsample of listings that were sold through the marketplace to allow the incorporation of demand effect as well. SEs are clustered by phone model-memory.

III. Results

The results are displayed in Table 2. Column 1–3 contain results for all listings, separated by different launches. As one moves from column 1 to column 3, the number of model-memory fixed effects increases as more legacy models are available on the market. Consistent with Figure 1, the coefficient on *Age* is negative and statistically significant at 1% level, with adjusted R-square values are greater than 78% across all launches.[3] iPhone listing prices decline by approximately 2.8–3.2% per month. However, the coefficient on the interaction term – our variable of interest – is close to zero and not statistically significant: prices do not decline faster after launch of new models.

Next, we turn to the subsample of phones that were sold on site, as reported in column 4 and 5, where prices more closely reflect transaction prices. The results are similar. It is worth noting that the coefficient on *Post* is statistically significant for column 1–3. The coefficient represents the systematic pricing differences not explained by the increase in *Age*, which may seem to contradict our results of forward-looking consumers. However, in column 4 and 5, where only successful transactions are included, the coefficient is no longer significant, suggesting that in equilibrium, any attempt by sellers to exploit myopic buyers through overpricing (positive coefficient) or undercutting competitors (negative coefficient) are competed away.

Taken together, we interpret this as evidence that consumers are forward looking and anticipate future events (here, model obsolescence) in their decision-making process, consistent with Busse, Knittel, and Zettelmeyer (2013) and Chevalier and Goolsbee (2009) who find similar evidence in automobile and college textbook markets. Since launch dates tend to follow an established pattern, the fact that prices do not follow differential trends after launch is similar to price efficiency in financial markets.

[2]Model-memory combinations with fewer than 1,000 observations are dropped. We also winsorize prices at 0.1 and 99.9% levels.

[3]The high adjusted R-squared values are not due the inclusion of fixed effects. For example, for the model in column 1 of Table 2, the removal of province-district fixed effects reduce the R-squared only to 77%, and further removal of the model-memory fixed effects to 72%.

Table 1. Model information and price statistics.

				Listed on Marketplace						Sold on Marketplace					
Model-Memory	US Ann. Date	TH Launch Date	Launch Price	Num. Obs.	Mean	SD	5th Pct.	50th Pct.	95th Pct.	Num. Obs.	Mean	SD	5th Pct.	50th Pct.	95th Pct.
iPhone 4 16 GB	6/10/2010	9/24/2010	22,250	33,456	4,202	1,612	2,000	4,000	7,000	8,560	3,350	1,016	1,500	3,500	4,990
iPhone 4 32 GB	6/10/2010	9/24/2010	26,000	13,094	4,710	1,832	2,200	4,500	7,900	3,024	3,654	1,118	1,800	3,700	5,500
iPhone 4s 16 GB	10/4/2011	12/16/2011	20,900	29,130	5,280	1,864	2,800	5,000	8,600	6,828	4,233	1,230	2,400	4,200	6,300
iPhone 4s 32 GB	10/4/2011	12/16/2011	24,900	9,934	5,954	2,106	3,000	5,700	9,700	2,208	4,787	1,321	2,690	4,800	7,000
iPhone 4s 64 GB	10/4/2011	12/16/2011	28,900	2,020	6,606	2,581	3,300	6,200	11,500	405	5,113	1,380	2,990	5,200	7,000
iPhone 5 16 GB	9/12/2012	11/2/2012	22,900	77,647	8,133	2,816	4,500	7,800	13,500	21,218	6,960	2,088	4,000	6,900	10,500
iPhone 5 32 GB	9/12/2012	11/2/2012	26,500	22,693	8,999	3,108	4,900	8,500	14,900	5,239	7,698	2,332	4,500	7,500	12,000
iPhone 5 64 GB	9/12/2012	11/2/2012	29,900	4,797	10,340	3,553	5,500	9,900	16,500	951	8,823	2,893	4,900	8,500	13,500
iPhone 5s 16 GB	9/10/2013	10/25/2013	23,900	40,380	10,610	3,465	5,800	10,200	16,900	10,652	9,103	2,696	5,500	8,900	13,800
iPhone 5s 32 GB	9/10/2013	10/25/2013	27,900	13,994	12,066	3,769	6,500	11,900	18,500	3,270	10,475	2,945	5,999	10,900	15,000
iPhone 5s 64 GB	9/10/2013	10/25/2013	31,900	3,589	13,343	3,985	7,000	12,900	19,990	808	11,643	3,072	6,700	12,500	16,000
iPhone 6 16 GB	9/9/2014	10/31/2014	24,900	26,185	16,169	3,844	10,200	16,000	22,700	8,362	15,238	3,462	9,990	15,500	21,000
iPhone 6 64 GB	9/9/2014	10/31/2014	28,900	15,180	18,514	4,573	11,900	18,300	26,500	4,249	17,383	4,092	11,500	17,500	24,500
iPhone 6 128 GB	9/9/2014	10/31/2014	32,900	2,539	20,030	4,781	13,000	19,800	28,500	602	18,848	4,302	12,590	18,900	26,000
iPhone 6 Plus 16 GB	9/9/2014	10/31/2014	28,900	11,055	18,817	4,029	12,900	18,890	25,900	3,441	17,776	3,761	12,500	17,500	24,500
iPhone 6 Plus 64 GB	9/9/2014	10/31/2014	32,900	8,144	20,905	4,735	14,500	20,500	29,000	2,764	19,878	4,361	13,900	19,800	27,500
iPhone 6 Plus 128 GB	9/9/2014	10/31/2014	36,900	1,426	22,890	5,147	14,900	23,000	31,900	451	21,875	5,079	13,999	22,000	31,500
iPhone 6s 16 GB	9/9/2015	10/30/2015	26,500	4,647	18,566	3,314	13,900	18,500	23,900	1,637	18,336	3,361	13,500	18,000	23,500
iPhone 6s 64 GB	9/9/2015	10/30/2015	30,500	3,587	21,678	4,152	15,900	21,800	28,000	1,207	21,214	4,185	14,990	20,900	27,890
iPhone 6s Plus 16 GB	9/9/2015	10/30/2015	30,500	2,037	21,773	3,684	16,500	21,999	27,500	737	21,391	3,689	16,000	21,500	27,500
iPhone 6s Plus 64 GB	9/9/2015	10/30/2015	34,500	2,563	24,554	4,222	18,500	24,500	31,500	921	24,129	4,254	17,900	23,800	31,000

This table provides descriptive statistics for iPhone models listed for sale on the online marketplace between January 2014 and February 2017. The US announcement dates and Thai launch dates and prices (in THB) for each model are listed, as well as the corresponding descriptive statistics of listing prices. Phone models are classified separately for each memory capacity, totalling 21 model-memories combinations. Model-memory combinations with fewer than 1000 observations are excluded from the sample. Prices are winsorized at 0.1 and 99.9% levels. There are 328,097 listings in total, 87,534 of which are sold on the marketplace (available from January 2015 only).

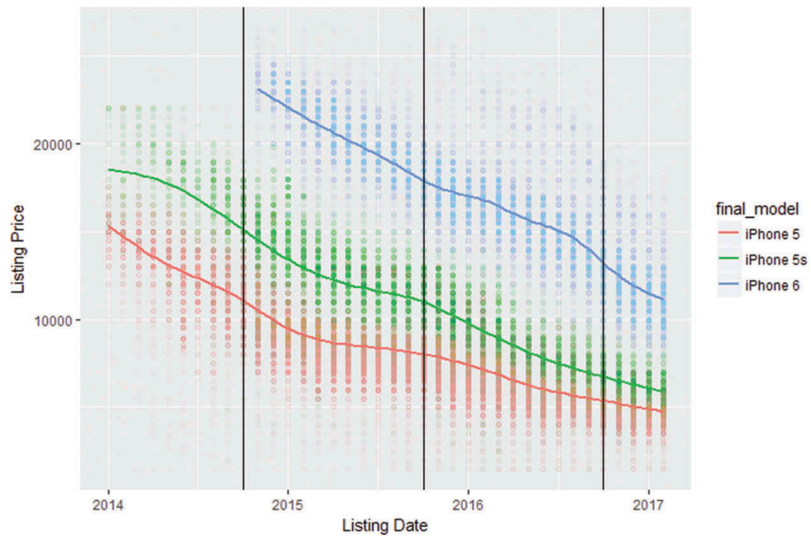

Figure 1. Listing prices over time.

This figure shows the scatter plot of listing prices between January 2014 and February 2017 for three most popular iPhone models on the marketplace: iPhone 5 16 GB, iPhone 5s 16 GB and iPhone 6 16 GB. The opacity of the points correspond to density, and the lines are average listing prices. The vertical lines correspond to the launch dates of iPhone 6, iPhone 6s and iPhone 7 in Thailand, which are October 31, 30 October 2014, 2015, and 21 October 2016 respectively.

Table 2. Impact of new model launches on prices of older models.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Ln(price)	Ln(price)	Ln(price)	Ln(price)	Ln(price)
Model launched	iPhone 6	iPhone 6s	iPhone 7	iPhone 6s	iPhone 7
Window	01/14–10/15	11/14–10/16	11/15–02/17	1/15–10/16	11/15–02/17
Sample	All listings	All listings	All listings	Sold on mkt.	Sold on mkt.
Post	−0.0593**	0.0545***	−0.0285*	0.0343	−0.0199
	(0.0191)	(0.0181)	(0.0138)	(0.0197)	(0.0162)
Age	−0.0276***	−0.0293***	−0.0323***	−0.0310***	−0.0339***
	(0.0015)	(0.0011)	(0.0020)	(0.0013)	(0.0016)
Post * Age	−0.0005	−0.0006	0.0002	−0.0002	0.0001
	(0.0005)	(0.0005)	(0.0003)	(0.0005)	(0.0003)
Observations	144,181	246,351	166,666	70,626	60,791
Model-memory fixed effects	11	17	21	17	21
Province-district fixed effects	914	919	897	797	734
Adjusted R-squared	0.780	0.871	0.896	0.876	0.899

The following table reports the results from estimating fixed effects regressions with the natural log of listing prices as the dependent variable. Each model launch is analysed separately, with listings restricted to one year prior and after launch date. The analysis in column 1–3 uses all listings, while column 4 and 5 restrict the sample to listings sold on the marketplace only. The sample starts from January 2015 since the data field was not available prior to this date. All specifications include model-memory fixed effects and province-district fixed effects. SEs are clustered at the model-memory level and reported in parentheses. *, **, and ***denote statistical significance at the 10%, 5%, and 1% levels, respectively.

IV. Conclusion

This study investigates the impact of new iPhone launches on prices of older models sold on the secondary market. We document that prices decline with phone age, but there is no evidence that prices decline faster after new model launches. The finding supports the view that consumers are rational and forward looking. The market for used smartphones is large and significant (Deloitte 2016 estimates it to be USD 17 billion), and an increasing proportion of adults now own smartphones. The fact that prices for used iPhones are efficient with respect to launches of new models makes the resale decision simpler for potential sellers, as they do not have to worry about market timing.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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