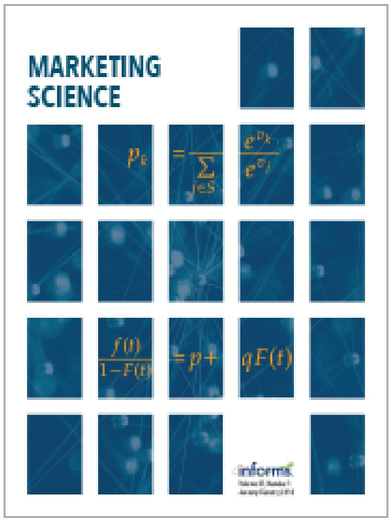

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Learning by Doing and the Demand for Advanced Products

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Abstract. How much does consumer learning by doing affect the demand for advanced products? In the context of digital cameras, I use detailed picture-level data to directly measure changes in picture quality as a result of learning by doing or product switching. Although learning by doing builds up consumer human capital, a fraction of this human capital is product specific, creating consumer switching costs. To quantify the role of consumer human capital, I structurally estimate the demand for digital cameras with consumer learning by doing. The evolution of consumer human capital explains 23% of the sales of advanced digital cameras, whereas brand-specific human capital—arising from incompatibility in product design—explains 15% of consumer brand-choice inertia.

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Supplemental Material: Data and the online appendix are available at https://doi.org/10.1287/mksc.2018.1118.

Keywords: consumer human capital • learning by doing • switching costs • product diffusion • dynamic programming

> I'd get a DSLR based upon my experience level.. . .If your situation is different to mine however. . .you'll probably be quite happy with a cheaper point and shoot.
>
> —Darren Rowse, "Should you buy a DSLR or Point and Shoot Digital Camera?"[1]

> Nikon and Canon are as good as each other overall.. . . The differences lie in ergonomics and how well each camera handles, which is what allows you to get your photo—or miss it forever.. . .And I can't for the life of me figure out the menus of the Nikon Coolpix cameras.
>
> —Ken Rockwell, "Nikon vs. Canon"[2]

1. Introduction

How much does consumer learning by doing affect the consumer's adoption and usage of skill-dependent products? Many examples suggest that consumer skills, or human capital, affect practitioners' marketing strategies. For instance, engineers care about whether their product designs align with existing consumer habits (David 1985), and content creators keep track of consumer learning curve or progression (Albuquerque and Nevskaya 2012). Compared with the theoretical understanding of consumer human capital in marketing and economics literature (Michael 1973, Ratchford 2001), empirical evidence is scarce. This lack of evidence is due to the difficulty of directly measuring consumer human capital evolution. As a consequence, the impact of learning by doing on consumer choices is largely unknown.

In this paper, I measure consumer human capital in the digital camera industry and quantify its impact on consumer demand for advanced products. I exploit novel data on pictures produced by a set of camera users over many years. For each user, I observe camera purchase decisions, the pictures produced using these cameras, and how frequently these pictures are viewed by an online community. I construct a metric for the quality of these pictures and back out the transition dynamics of consumer human capital reflected in the picture quality while simultaneously estimating a dynamic structural model to quantify the role of human capital on demand. I use the model to simulate counterfactual consumer product replacement decisions and to quantify the impact of human capital on product diffusion paths.

My information on picture quality and camera usage history is constructed from picture-level data collected from a popular photo-sharing website, Flickr.com. On Flickr, users upload pictures to share with the public. Information such as the camera used and date taken is automatically recorded at capture and can be seen online. I use this data set for two purposes. First, I recover long histories of product usage and switching by tracking camera usage across a user's uploaded pictures for a median time frame of six years per individual. Second, I compare the number of clicks among pictures uploaded at the same time by the same photographer. Viewers decide which pictures to click on partially based on the appearance of the pictures, without knowing on which dates and by which cameras the pictures were taken. Therefore, picture quality will be driven by experience (at the picture-taking date) and camera, and such variations will be reflected in the number of clicks.[3] I consider the upper bound of picture quality in a given month as combined output of the photographer's human capital and her camera equipment. Conditional on the camera, changes in this upper bound quality measure allow me to back out human capital.

I provide two key pieces of descriptive evidence on the evolution of consumer human capital. First, with the accumulation of experience, picture quality increases but at a decreasing rate. Second, picture quality drops at the point when the consumer adopts a new camera, and the size of the drop depends on existing consumer experience and the direction of the switch. These findings suggest that product usage creates both general and product-specific consumer human capital. I also show that human capital complements the usage of a digital single-lens reflex (DSLR) camera as the more advanced technology—thus, it is rational to expect that the consumer's adoption of a DSLR camera depends on her human capital.

To quantify the extent to which consumer human capital explains product choices, I estimate a dynamic structural model that endogenizes the consumer's choice of product replacement and usage, as well as characterizes the evolution of her human capital as a consequence of these choices. In the model, the consumer uses her camera to produce picture quality through a production function (Michael 1973), in which her human capital complements the camera quality. In using the camera, she learns how to take photos, develops an understanding of photography, and familiarizes herself with the specific camera. Although the accumulation of human capital allows her to better utilize advanced product features and thus increases her utility on the DSLR camera, the increasing product-specific human capital also creates a switching cost that locks her into the current camera type. The model highlights within-consumer evolution in product choices, usage, and picture quality, and allows for rich unobserved heterogeneity in consumer learning curve and preferences to be able to accommodate across-consumer differences.

How important is consumer learning by doing to the demand for advanced products? I simulate consumers' camera purchase and usage decisions with or without learning by doing. Keeping prices fixed, I find that learning by doing explains 39% of the share of consumers using advanced products and 23% of firm revenue from these products. The finding that human capital plays a dramatic role in consumer demand suggests that firms should actively invest in consumer human capital through education and training. In fact, for some manufacturers and retailers, this strategy is a routine practice: Apple organizes free product workshops, which give tutorials and tips about its products; Barnes & Noble offers a summer reading program for children and gifts a book to each participant; and Sur La Table (a cookware retail chain) offers regular cooking training sessions.[4]

How much of consumer inertia in product choice can be explained by their product-specific human capital? I measure that a sizable part of consumer human capital is brand specific, arising from the inconvenience of getting used to products in a different brand, created by differences in camera designs across brands.[5] My counterfactual simulations suggest that firm revenue would have been 8% higher if the two major firms in this industry had agreed to adopt identical product designs for their DSLR cameras (or were regulated to do so); in which case, switching to a different type of product in another brand would incur no additional learning cost. Furthermore, whereas there might be other potential sources of inertia in consumers' brand choices—such as learning about brand quality (Erdem and Keane 1996), accumulation of lenses or accessories (Hartmann and Nair 2010, Huang 2018), or other psychological inertia—I quantify that brand-switching costs in human capital are 15% of the total brand-choice inertia. This finding suggests that (the lack of) interoperability due to product design is an important source of switching costs, which could generate path dependence in product diffusion. For example, David (1985) documents the success of the QWERTY keyboard format, attributing a large part to its early market dominance and the creation of user habits.

This paper makes two contributions. First, it is the first paper to directly measure consumer human capital using field data and to quantify the relevance of learning in explaining why product demand can be nonstationary within the consumer. Marketing and economics literature on consumer demand has long recognized that consumer choices are nonstationary, but it either focuses on exogenous changes in prices or technology (Song and Chintagunta 2003, Gordon 2009, Gowrisankaran and Rysman 2012) or rationalizes these nonstationary choice patterns by models with unobserved state variables. This paper provides direct evidence on consumer learning and shows that learning explains a large fraction of adoption and choices. It provides new evidence that supports the Bayesian learning literature (Erdem and Keane 1996, Narayanan and Manchanda 2009) and offers new insights beyond existing learning models.

Second, this is the first paper to directly quantify the source of consumer switching costs. Switching costs are usually quantified through revealed preferences, as the observed inertia in consumer choices after controlling for heterogeneity (Dubé et al. 2009, 2010a; Shcherbakov 2016). In this paper, I measure a specific type of switching costs as the nontransferability of consumer human capital, directly from observing changes in consumer human capital at product switching (while also controlling for implied inertia in choice data). The direct measure adds insight to the explanations behind consumer inertia.

The remainder of this paper is structured as follows. Section 2 reviews the literature. Section 3 describes the institutional detail and data collection process and documents my measure of picture quality. Section 4 presents descriptive evidence on consumer learning by doing. Section 5 presents an empirical model of durable goods demand with learning by doing, and Section 6 presents estimation results. Section 7 evaluates the role of consumer human capital in product diffusion through counterfactual experiments. Section 8 concludes this paper.

2. Related Literature

This paper is most closely related to consumer human capital literature. Michael (1973) discusses the implication of consumer human capital—in a framework related to Becker (1965)—but does not find convincing evidence when using education as a proxy. Ratchford (2001) discusses the implication of this consumer human capital on firm behavior and optimal managerial decisions. Jovanovic and Nyarko (1996) presents a Bayesian version of learning by doing theory and characterizes the consumer's technology adoption decisions when upgrading incurs switching costs. The consumer human capital literature has been mostly theoretical because of the difficulty of empirical measurement. My paper extends the existing models into an empirical framework, provides a direct measure in the context of digital cameras, and relates the measured human capital to consumer product adoption or replacement choices.

My model of consumer demand is related to the large demand estimation literature in marketing and economics. Using aggregate data, Melnikov (2013) combines the dynamic discrete choice framework in Rust (1987) with the differentiated market demand system of Berry et al. (1995) and estimates durable goods demand for forward-looking consumers who are in the market only once. Song and Chintagunta (2003) applies this framework to the digital camera market. Nair (2007) estimates a dynamic model of video game adoption decisions and discusses the implication of consumer rational expectation on firms' intertemporal price discrimination policies. Gowrisankaran and Rysman (2012) extends the Melnikov (2013) framework to allow for replacement decisions. Other related works include Goettler and Gordon (2011) on computer processor replacement choice, Erdem et al. (2003) and Hendel and Nevo (2006) on consumer stockpiling decisions, and Hartmann (2006) and Albuquerque and Nevskaya (2012) on modeling purchase and usage decisions.

More broadly, my paper is related to the (Bayesian) learning literature. Erdem and Keane (1996) estimates the demand of forward-looking consumers when they face the uncertainty of product quality, which is gradually resolved by repeated purchase. Crawford and Shum (2005) models physicians' beliefs on the match value of new drugs. Osborne (2007) estimates a demand system with brand-specific learning and instantaneous switching costs. Narayanan and Manchanda (2009) studies the heterogeneity in consumer learning about new drugs and discusses optimal allocation of marketing communication according to heterogeneity in the learning rate. Goettler and Clay (2011) models consumer tariff choice and shows some consumers will overestimate their long-run usage patterns. Lovett and Staelin (2012) models TV viewing when viewers learn about their own taste. Li (2016) characterizes camera purchase decisions as consumers learn about their preferences to photography. Most of the learning literature does not observe the consumer's evolution in state variables, that is, their belief on product quality. In my paper, however, I directly back out consumer human capital from observed picture quality and can separate preference from human capital changes. Related to my paper, Shin et al. (2012) uses survey methods to directly measure consumer belief and thus separately identify learning from preferences.

Finally, my paper is also related to the empirical switching costs literature. Bronnenberg et al. (2012) documents persistence in consumer brand preferences. Shcherbakov (2016) estimates the magnitude of transaction cost in the cable TV industry. Dubé et al. (2010a) estimates the inertia in consumer choices, controlling for flexible specification of heterogeneity. Most of this literature measures switching costs as state dependence in choices controlling for unobserved heterogeneity. My paper, however, directly measures consumer switching costs as observed changes in their picture quality.

3. Data

3.1. Flickr.com

I extracted picture-level data from a popular photo hosting and sharing website, Flickr.com. Flickr was created by Ludicorp in 2004 and acquired by Yahoo! in 2005. Registered Flickr users upload photos to the website, which can be viewed without the need to register an account.[6] By 2013, Flickr was one of the most commonly visited websites. That year, it ranked 76 in daily traffic and had 87 million registered members who had uploaded a total of 680 million public photos.[7] The website underwent a major interface change in April 2013, at which point it adopted a new way of displaying photos and added many search and social network features. This paper focuses on the period before this interface change.

In my sample period, Flickr offers two types of accounts: a free account and a paid "Pro" account. A free account allows up to 200 pictures to be displayed. The

Pro account costs $24.95 annually (as of 2012) and has no upload or display limit. My paper focuses on the Pro accounts because they upload more pictures. Few Pro account users seem to be professional photographers; in my final sample, only 4% of users had keywords "art," "photo," or "graphic" in their job descriptions (which they elected to fill out in their user profiles).

The top panel of Figure 1 provides an example of a "photostream," a web page that displays photos uploaded by a given user. The photostream shows thumbnail versions of photos together with their titles, copyright information, upload dates, and numbers of comments. Two aspects of the photostream are important to this paper. First, photos are ordered chronologically with the most recently uploaded picture on top. The user or the viewers cannot sort photos differently. Second, the viewer can see limited information besides the thumbnail. To access further information, a viewer must click on a thumbnail to be redirected to a dedicated photo page. A visit to this page will be registered as a "view" on the picture.[8]

The individual photo page reveals more information about the picture. The lower panel of Figure 1 provides an example. On the left, one sees an enlarged version of the picture and comments from the photographer and visitors. On the right, one sees the upload date, number of favorite votes, tags (which are user generated), and camera information. Camera information is recorded at the time a photo is taken according to an industry standard recording format, exchangeable image file format (Exif). This information contains the identity of the camera and a time stamp of when the photo was taken. Note that the picture taking and uploading happen at different points in time. Finally, the last row on the right shows the cumulative number of views since the picture was uploaded to Flickr.

There are two alternative ways to view an individual photo page. First, the user can post the picture to groups within Flickr, which organize photos in the same way as photostreams. Second, when the user uploads a batch of pictures, Flickr notifies accounts that follow the user. I control for the potential impact of these alternative viewing sources, as discussed in Section 3.3.

3.2. Data Collection and Initial Summary Statistics

3.2.1. Data Collection. I collect data from all Pro account users with a username no longer than five letters or digits.[9] Focusing on shorter usernames gives me users who have stayed on Flickr longer,[10] assuming that usernames are exogenous to a user's unobserved preferences. As explained in the previous section, I focus on users with Pro accounts because Flickr shows only the most recent 200 pictures for free account owners, thus limiting my ability to trace the history of these individuals. Initially, this data collection strategy gives me 7,172 individual accounts.

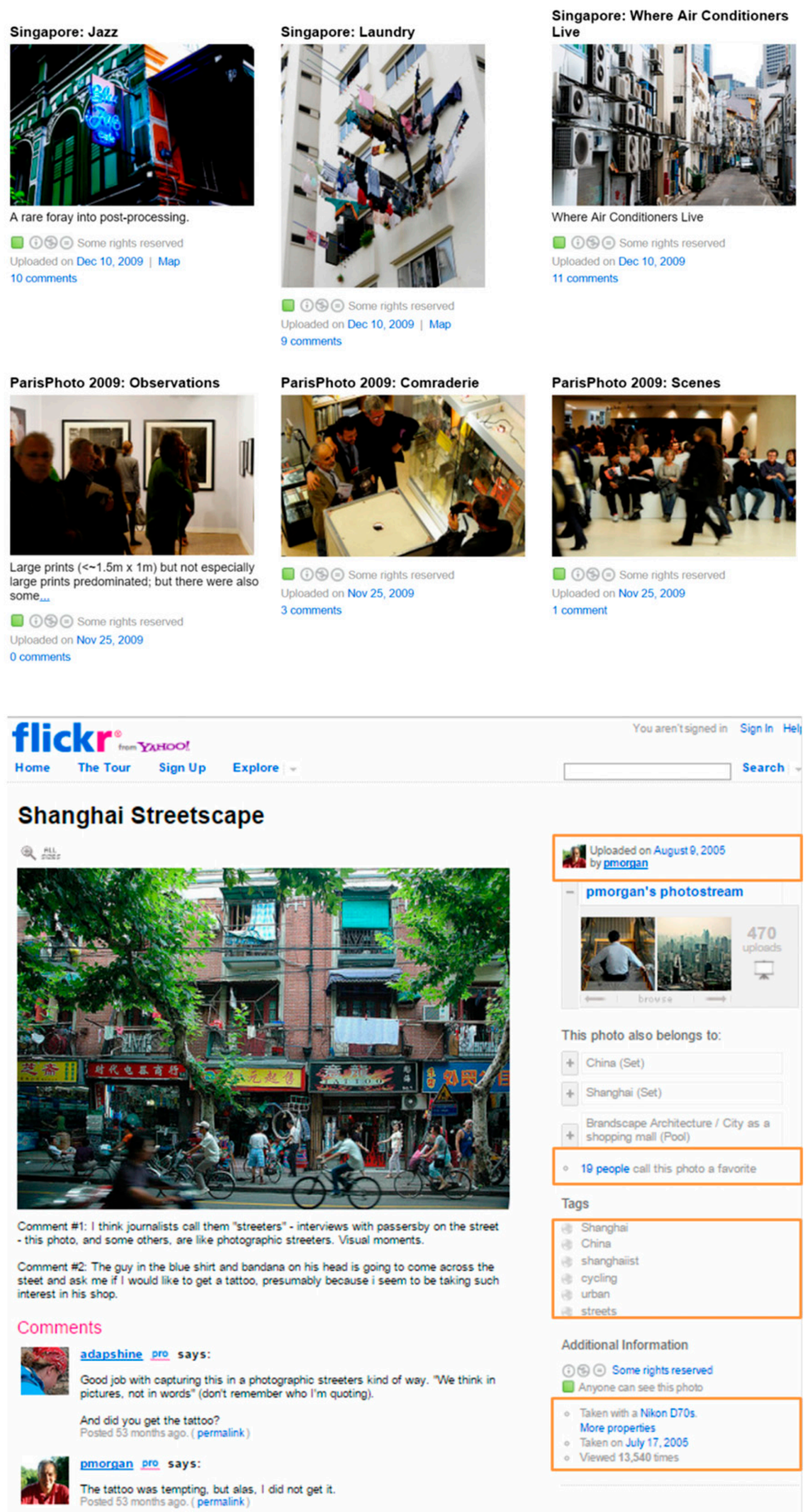
For these users, I sample one in every five pictures according to the order of upload and collect data on each picture once. I do not revisit the pictures, as the time spent collecting information from each picture is large. For each picture, I collect the time of upload, the cumulative number of views, comments and favorite votes since upload, and the Exif data including the camera's identity and the date the picture was taken. This procedure gives me a cross-sectional data set on the picture level, with 2,777,728 observations. For the same set of users, Flickr provides summary statistics on the number of pictures taken and uploaded each month. These data are computed from all uploaded pictures and therefore are more accurate than my sample. My metric of camera usage is computed from these summaries. I also collect cross-sectional data on users' self-reported information, including demographics and occupation.

Furthermore, I collect cross-sectional data on camera characteristics, compiled from the Flickr camera database, DPreview.com, and Cnet.com. In addition, Pixel-peeper.com reports monthly histories for eBay average auction prices by model, starting in late 2006. From this source, I collect average worldwide eBay auction prices (converted to U.S. dollars) and deflate them to 2005 country prices from the Organisation for Economic Co-operation and Development.

3.2.2. Sample Selection. On the picture level, I discard the pictures taken by cell phones, film cameras, camcorders, or digital media players (3.6% of all pictures); those claimed to have been taken prior to year 2000 (11.0%; these are more likely due to recording mistakes in the camera date settings); and those with incomplete Exif data (10.4%). I further discard observations from individuals with fewer than 100 pictures in the sample (4.2%). These sample selection criteria leave me with 2,003,133 pictures from 4,110 individuals.

3.2.3. Initial Description of the Data. Table 1 provides summary statistics for the user-level data after sample selection. Focusing on the median, there are a few notable patterns. First, the duration of observation for a user is above six years. Such a long observation window allows the study of gradual changes in consumer demand as a result of the consumer learning to take pictures. Second, measured by the average market price at adoption, the last camera the consumer used tends to be significantly more expensive than the first. This trend goes against the generally declining market price, suggesting that consumers trade up over time. Third, the per-month number of photo views increases and diverges. The fact that a user's pictures attract more viewers might be due to her picture quality increase (which in turn comes from camera technology or human capital), but could also result from her expanding social networks or the increasing popularity of Flickr.com.

Figure 1. (Color online) Flickr Interface Examples



Notes. The figure shows screenshots from Flickr. The top panel shows a photostream of thumbnails. The bottom panel shows the web page after clicking on a thumbnail (boxes are added to highlight parts of the page). The photos were taken by Peter Morgan (https://www.flickr.com/photos/pmorgan, distributed under CC BY-ND 4.0). The screenshot was captured by https://archive.org/ in April 2010.

Table 1. User-Level Data Summary

	Mean	Median	St. dev.
Months since registered on Flickr	71	76	23
Number of contacts at data extraction	102	24	313
Total number of pictures	2,241	1,495	2,016
Number of in-sample pictures	478	318	438
Number of cameras ever used in-sample	5	4	5
Max views per month, first month	4	1	79
Max views per month, last month	18	4	118
Price of the least expensive camera used	173	137	167
Price of the most expensive camera used	1,070	844	757
Observations	4,110	4,110	4,110

Notes. Summary statistics (mean, median, and standard deviation (st. dev.)) on user-level data are shown. Prices are deflated to 2005 U.S. dollars.

Fourth, the median individual subscribes to only 24 other users. It seems that a defined social network is not as prevalent a feature on Flickr compared with other settings.[11]

3.3. Implied Picture Quality

3.3.1. Measure. I measure picture quality by the difference in the number of views across pictures uploaded at the same time, referred to as a batch. On Flickr, pictures are presented in fixed chronological order by the upload date. Pictures uploaded in the same batch are shown for the same duration and, if their thumbnails look equally attractive to viewers, should be clicked on with equal probability. Therefore, among pictures uploaded in the same batch, differences in the cumulative number of views reflect differences in picture quality.

With this intuition, for picture p captured by individual i, I estimate a linear model of the log number of views on individual fixed effects, a set of time window dummies, and control variables,

$$\log(views_{ip}) = \alpha_i + \Phi_{t_{p0}t_{p1}} + z_{ip}\psi + \omega_{ip}, \tag{1}$$

and will later refer to the sum of individual fixed effects and residual as picture quality:

$$q_{ip} = \alpha_i + \omega_{ip}. \tag{2}$$

In particular, I count the persistent heterogeneity α_i in the individual picture quality, because I observe the initial establishment of these accounts, but not the very first time one takes pictures. Thus, it is likely that α_i captures heterogeneity in initial experience (and thus picture quality) rather than initial social network differences. As robustness checks in past versions of this paper, I measure picture quality using only ω_{ip} and get similar results.

In Equation (1), $\Phi_{t_{p0}t_{p1}}$ is a set of dummy variables that capture the time (year-month) window between when picture p was uploaded, t_{p0}, and when data on p were extracted, t_{p1}. Naturally, pictures shown on Flickr for longer durations, or pictures uploaded when Flickr became more popular, will have a higher cumulative number of views. These view differences are not associated with picture quality and will be captured by $\Phi_{t_{p0}t_{p1}}$. However, within an upload–data extraction time window, there might be alternative mechanisms that drive the decision about which picture to click on. I control for a collection of dummy variables, z_{ip}, capturing (1) the upload order within a batch, (2) the number of pictures uploaded in the month, (3) the number of comments on a given picture, (4) tags, (5) the number of months between the first batch uploaded and the current batch, and (6) the number of pictures captured in the month (that are eventually uploaded). These six groups address, respectively, six potential alternative mechanisms:

First, pictures shown at different positions on a screen will draw different levels of attention and views. Since photostreams sort pictures based only on upload time, I control for within-batch upload order coded in dummy variables (computed from the day of upload within batch), in addition to controlling for the time window $\Phi_{t_{p0}t_{p1}}$.

Second, pictures uploaded together might crowd out the views of each other. I control for the number of pictures uploaded within a batch, and thus my measure of picture quality focuses on pictures uploaded in batches of similar size.

Third, I control for the number of comments, because viewers can see the number and might be attracted to pictures with more comments.

Fourth, pictures on certain subjects might draw more attention than others. For example, pictures of people or pets are more popular than pictures of landscapes or architecture. Conceptually, one should distinguish interesting subjects from high picture quality as drivers of views. I control for tag dummies to control for subject popularity.

Fifth, individuals with more followers will receive more attention and thus views. Note that the upload–data extraction windows $\Phi_{t_{p0}t_{p1}}$ are assumed to be common across individuals, and thus cannot capture heterogeneous popularity at the same point in time. To address this alternative explanation, I leverage the variation that different accounts are created at different points in time and flexibly control for the number of months since the individual registered her Flickr account until the upload of a given picture. Time since registration can control for the growth of attention on a user, to the extent that such growth rate is common across individuals. In Section 4.3, I further check the robustness of this assumption by estimating the learning rate using variations only within individual and upload batch.

Sixth, because individuals selectively upload pictures and their selection criteria might change over time, variations in picture quality do not reflect only human capital evolution or camera quality change. For example, more pictures uploaded on Flickr are taken immediately after an individual switches to a different camera, potentially because they want to experiment with their new camera or its different features, and therefore might have different standards on which pictures "qualify" to be uploaded compared with a usual month. To address this concern, I first control for the number of pictures taken in each month (that are eventually uploaded). In addition, I take the upper bound of the quality measure, among pictures taken in the same month:

$$Q_{it} = \max_{p \in t} \hat{q}_{ip}. \tag{3}$$

Assuming that one always uploads the best possible pictures, Q_{it} measures the frontier of individuals' picture quality production process and can be used to infer human capital. As robustness checks, I replace the upper bound with the mean, median, and 90th percentile of picture quality distribution and find qualitatively similar results.[12]

3.3.2. Summary Statistics of the Implied Picture Quality.

Focusing on a balanced panel of individuals who have been on Flickr for at least five years, Table 2 summarizes, by year, the implied picture quality and other variables. I find that quality increases with experience but the slope is decreasing, which is intuitive and is consistent with existing learning by doing evidence in the contexts of consumers (Johnson et al. 2003), labor (Shaw and Lazear 2008, Levitt et al. 2013), and firms (Benkard 2000, Kellogg 2011). Also, I examine the correlation between the maximum implied picture quality (within individual-month) and the maximum number of favorites one gets. For the same individual in a given year, this correlation is averaged around 0.35–0.41. This correlation indicates my picture quality measure coincides with observed ratings.

3.4. Camera Replacement

I use camera identity embedded in the picture's Exif data to infer camera replacement history. When a new camera appears to have taken at least two pictures on a user's photostream, I assume this camera was purchased in the month the first picture was taken, and that it replaced the previous camera. I check the data to see whether a camera still takes pictures after a new camera has appeared (my assumption would imply the previous camera will never be used). Only in 6.3% of individual-camera combinations do I see the previous camera takes more than half the pictures in any month. In fact, in 75% of individual-camera combinations, the previous camera never appears in the sample. Therefore, assuming camera replacement does not seem to violate the data to a noticeable extent.

I also examine the degree of which the implied camera purchases in my data match with industry insights. For example, the probability of product replacement is about 4% per month (or 88% per three years) and matches with the conventional belief that the product life cycle for a digital camera is about three to four years.[13] In addition, although many consumers choose the same camera brand format they owned previously when making replacement decisions, many others choose to buy a different brand format, providing variations that are necessary to measure the transferability of human capital. For example, for Canon point-and-shoot camera owners, there are 541 purchase occasions for another Canon point-and-shoot camera (which take 1.64% of the sample), 510 occasions (1.55%) of purchasing a Canon DSLR camera, and 308 occasions (0.94%) of purchasing a Nikon DSLR camera. Table A3 of the online appendix tabulates the incidence of consumer choices.

3.5. Price Indices

In consumer durable goods contexts, it is impossible to observe individual prices that consumers paid. I use eBay average auction price data to proxy the prices, in contrast to the existing literature on digital cameras (Song and Chintagunta 2003, Carranza 2010), which uses average new product prices in the NPD point-of-sale data. It is useful to compare these measures. First, one might be concerned that auction prices follow different time trends compared with what consumers pay. I find that prices (for given cameras) in my data decline at an average rate of 21% per year. This trend is

Table 2. Summary Statistics by Time

	Max quality	St. dev.	Max favs.	Corr. with quality	DSLR share	Take pic.
1 year in sample	0.780	1.326	0.659	0.402	0.279	0.177
2 years	1.057	1.389	0.746	0.409	0.368	0.223
3 years	1.147	1.403	0.838	0.405	0.438	0.248
4 years	1.158	1.382	0.845	0.353	0.488	0.361
5 years	1.142	1.373	0.819	0.365	0.525	0.324

Notes. Summary statistics by time since first picture are shown. The first two columns show the mean and standard deviation (st. dev.) of monthly best picture quality. The third and fourth columns show the maximum number of favorites (favs.) on pictures taken in a month and its correlation (corr.) with implied quality within individual-year. The fifth column shows the share of individuals taking pictures.

comparable to that in Carranza (2010), which focuses on data from 1998 to 2002. Second, one might be concerned that auction prices are too low compared with retail prices. Although I do not have full retail data, I examine examples of new and used good prices on Amazon. Figure 2 presents the comparison for the Canon Rebel XSi, a popular DSLR model. The left panel shows that Amazon new-good prices are comparable to used-good prices when the product is available new. However, for the majority of a product's life cycle, it is only sold as used, with further declining prices. In addition, the right panel shows that used prices on Amazon are very close to eBay prices in my data, for the same camera model. I verified a few other popular models in my data and on Amazon to make sure the comparisons were similar.

Next, I compute average monthly prices weighted by the number of auctions for each camera model, separately for DSLR and point-and-shoot cameras. The price data start from January 2007, but observations of the consumer's picture quality and camera choices can start before then. I interpolate the missing values for prices in or before 2006,[14] to simulate camera choices before observing the actual prices. However, when estimating the structural model, I use data from 2007 to compute the discrete choice part of the likelihood function.

4. Descriptive Analysis

4.1. Overview

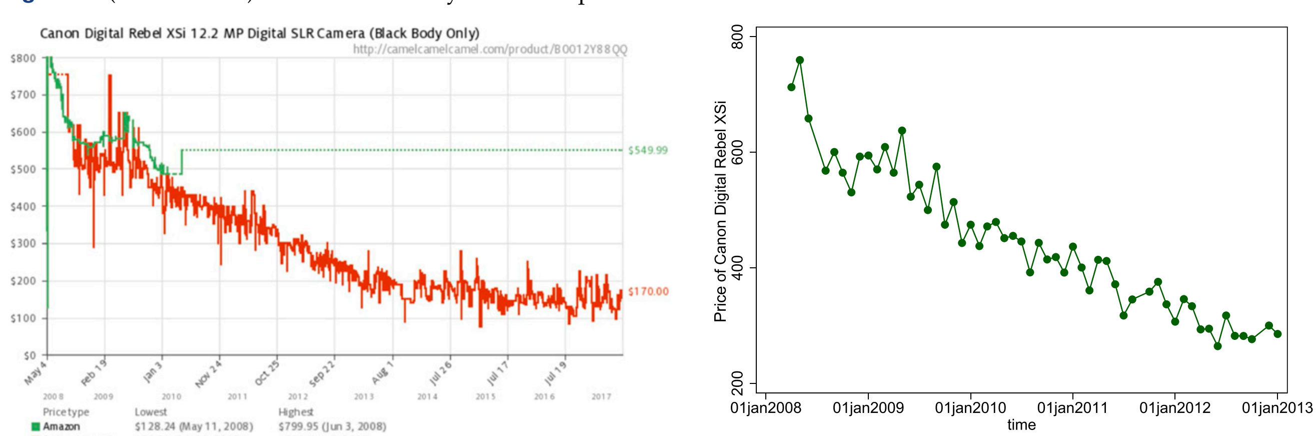
This section presents descriptive analysis on the role of consumer human capital in photography. I first examine the way picture quality changes with general and product-specific experience, by visually plotting average picture quality, respectively, over time since the first picture and time since camera switching. I then decompose the roles of general and product-specific human capital, as well as camera technology. Finally, I perform robustness checks to address several concerns in the measure of picture quality.

4.2. Evolution of Consumer Human Capital

4.2.1. Does Consumer Human Capital Increase Over Time? I first visually examine the way average picture quality increases with experience, that is, time since taking the first picture in the sample. In the top panel of Figure 3, the solid line shows the evolution of the quality of pictures taken with a camera that the consumer has been using for more than three months. It indicates that the consumer's picture quality increases as she develops human capital in photography, but the rate of increase slows down as she learns. In other words, consumer human capital evolution generates a conventional learning curve. However, when focusing on picture quality generated using cameras owned for less than three months, I find that average picture quality evolves along with the dashed curve. Specifically, with little experience, picture quality from a new camera or from a familiar one are virtually the same. Yet, as the consumer develops more experience, picture quality produced by a newly adopted camera diverges from, and largely stays below, the solid curve. For example, pictures produced using a new camera in year 2 are better than those produced in year 0, but worse than those that would have been produced in year 2 were the consumer using a familiar camera. This finding suggests that consumer human capital is imperfectly transferable between cameras.

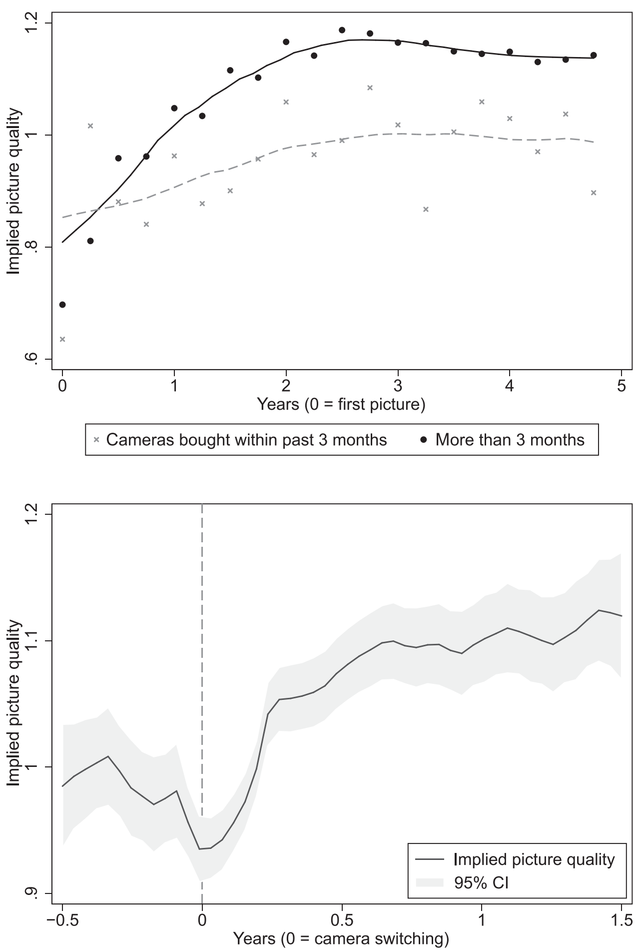
A potential alternative explanation for this trend is that consumers who like photography more tend to have higher human capital and also stay in the sample longer, resulting in a selection problem. My descriptive analysis focuses on a balanced subsample of individuals who remain in sample for at least five years, and also

Figure 2. (Color online) Amazon and eBay Price Comparison



Notes. The left panel shows Canon Digital Rebel XSi prices from Amazon.com. The lighter color line (solid green online), Amazon prices, where dashed means the product is not available; the darker color line (red online), third-party prices (new or used; this is a screenshot from https://camelcamelcamel.com, extracted in July 2017). The right panel shows eBay average auction prices for the same model (from my data).

Figure 3. Implied Picture Quality over Time and Across Cameras



Notes. The top panel shows implied picture quality (adjusted log views) against years since the first picture was posted on Flickr, by cameras adopted for more than three months (solid line) and cameras adopted in the past two months (dashed line). The bottom panel shows picture quality around the time when one switches cameras (normalized as year 0).

focuses on their first five years of data. Therefore, my analysis is not subject to this concern. Another alternative explanation for this adoption trend is the evolution in camera technology; I control for it in Section 4.3, where I decompose various drivers of picture quality.

4.2.2. Is Consumer Human Capital Product Specific?

Next, I further examine whether consumer human capital is product specific. The top panel of Figure 3 already shows that picture quality differs between a newly adopted camera and a camera that the consumer is familiar with, indicating that there is nontransferable human capital across cameras. As a different way to look at the data, the lower panel presents changes in picture quality around the time when the consumer switches to a new camera, normalized to year 0. I find that there is an immediate drop in picture quality at switching, which accounts for about 4% of views. This dip is recovered in two to three months, and then picture quality gradually increases in the next year and a half. This finding further confirms that, at the instance of camera switching, the individual loses a certain amount of camera-specific human capital. Such product-specific human capital might include explicit knowledge on menu and button layout, as well as implicit experience on how to best circumvent certain product limitations.

A potential alternative explanation is that an individual takes and uploads a different number of pictures when she starts using a new camera. Note that I measure monthly picture quality using the upper bound among the pictures a user uploads, so the evidence presented here is robust to changes in the selection criteria as long as it does not affect the upper bound. In addition, I show that consumers take and upload more pictures after switching to a new camera (Figure A4 in the online appendix). Consequently, they should be more likely to find a "lucky draw" and produce high picture quality immediately after switching. Therefore, my upper bound measure is a conservative measure of switching costs.

4.2.3. Does Consumer Human Capital Complement Camera Technology?

Third, I examine whether consumer human capital complements camera technology. I focus on individuals who used both DSLR and point-and-shoot camera formats and compute the difference in picture quality for the given individual-year. I find that, within individual-year, using a DSLR corresponds to producing pictures that are better received by Flickr audiences. In addition, using a DSLR corresponds to a 35% increase in views for consumers with more than one year of experience, whereas the gain is a modest 10% in views for consumers within their first year.[15]

The observation that consumers with more experience find higher returns to DSLR technology shows that advanced cameras complement rather than substitute human capital. A potential concern is that camera format is selected even within individual-year. The structural model will further control for selection.

4.3. Decomposition of Consumer Picture Quality Evolution

I further decompose the evolution of general and product-specific human capital and separate them from the contribution of camera quality, and other factors, to the number of views. Specifically, I estimate

$$\begin{aligned}\log(views_{ip}) = {} & \alpha_i + \theta_1 year\_expr_{ip} + \theta_2 year\_expr_{ip}^2 \\ & + \gamma_0 switch_{ip} + \gamma_1 month\_since\_switch_{ip} \\ & + \gamma_2 month\_since\_switch_{ip}^2 + \Phi_{t_{p0}t_{p1}} + z_{ip}\psi \\ & + camera_{ip} + \omega_{ip}.\end{aligned} \tag{4}$$

Above, α_i are individual fixed effects, $year\_expr_{ip}$ measures years since the first picture (in the sample), and $month\_since\_switch_{ip}$ measures the number of months since last camera switching. Among the control variables, $\Phi_{t_{p0}t_{p1}}$ are display time window dummies indicating the combination of the time when the picture p was uploaded and the time when data on the picture p were collected, and z_{ip} are additional control variables discussed in Section 3.3. These are the same set of controls as in Section 3.3, and given these controls, the remaining variations in log views should reflect picture quality. In addition, I control for camera dummies, $camera_{ip}$, in Equation (4) to focus only on human capital evolution.

Covariate $year\_expr_{ip}$ measures the consumer's general experience in photography, as the length of time between current picture p and the her first picture. From the top panel of Figure 3, one should expect human capital to be concave in the consumers' general experience. To measure product-specific experience, $switch_{ip}$ indicates whether the consumer has switched to a new camera in the past 18 months, and, if so, $month\_since\_switch_{ip}$ captures the number of months since the consumer has switched to this camera. If the consumer has not switched to a new camera, $camera, switch_{ip}$ and $month\_since\_switch_{ip}$ will both be zero. From the bottom panel of the same figure, one should expect that human capital is generally lower when the consumer uses a new camera, but recovers as the consumer uses the new camera longer.

I present estimates of the key covariates in Table 3. First, I find that for a given camera, the first year of general experience increases the views of a consumer's picture by 7.7%, and additional experience has a decreasing marginal effect. This increase is interpreted as an outcome of learning because we focus on pictures uploaded and displayed in the same time window $[t_{p0}, t_{p1}]$ and with similar additional controls z_{ip}. In addition, using a new camera for the first time is associated with a drop in picture quality, reflected in a 2.5% drop in views,[16] which is gradually recovered in approximately four months. These results are in line with the descriptive patterns in Section 4.

Furthermore, in the third and fourth columns of Table 3, I distinguish cases of product switching depending on the direction: within or across brands, or within or across product formats. I find that when a consumer switches to a camera in a different brand, the drop in picture quality is a degree of magnitude larger: the consumer loses 19.8% of views in the first month, and the loss is not recovered until month 7 after the switch. Furthermore, I find evidence for switching costs when the consumer trades up from a point-and-shoot camera to a DSLR camera and when she switches between DSLR cameras. I do not find evidence of switching costs when the consumer buys a point-and-shoot camera. These findings suggest that the majority of consumer switching costs in human capital are incurred when she switches to a different brand or when she switches to an advanced camera. I choose the specification of my structural model according to this result.

Finally, one might be concerned about heterogeneity in the rate of which individuals gain popularity in the social network. If these heterogeneous trends cannot be captured by common display window dummies $\Phi_{t_{p0}t_{p1}}$, they will be reflected as trends in picture quality and lead me to overestimate learning. Although I need to compare picture quality across batches and therefore cannot control for full individual-specific display window fixed effects, $\Phi_{i,t_{p0},t_{p1}}$, I can estimate Equation (4) controlling for these fixed effects to see the impact on the implied learning rate.[17] As shown in the second column of Table 3, I find that learning rate in the first year is only 1.4 percentage points smaller than the baseline estimates. Therefore, not controlling for individual-batch fixed effects will lead to only a small bias in the implied learning rate, suggesting that heterogeneity in social network trends is not a major concern.

I summarize the estimates of other control variables in the online appendix.

5. A Model of Durable Goods Demand with Learning by Doing

5.1. Overview and Timing

I estimate a structural model to characterize the relationship between consumer human capital and product choice, and to understand the extent to which human capital explains the diffusion of advanced products. The model is presented in the context of digital camera markets for concreteness. In the model, consumers derive utility from picture quality, producing picture quality requires human capital, and the evolution of human capital depends on the usage of cameras and the timing of camera switching decisions. Consumers are forward looking and have rational expectations over the evolution of prices and human capital.

Consumer i in each month $t = 1, \ldots, T$ decides whether to purchase a new camera and whether to produce pictures. In each month, she first chooses whether to purchase a camera and, if so, which format (DSLR or point-and-shoot) and brand to buy. If she buys a new camera model, she immediately replaces the old one with no resale value. Part of her human capital stock will transfer to the new camera and the rest will be lost. Next, she decides whether to take pictures in this period. When she takes pictures, she stochastically learns about a new method and improves her human capital. At the end of the period, she derives utility from purchasing a camera, from the picture quality she produced, and from the disutility of spending money on new cameras.

Table 3. Decomposition of General and Product-Specific Learning Curves

	Baseline	Indiv. batch	Flex. switch cost	Flex. switch cost
Constant	4.183*** (0.060)	2.242*** (0.033)	4.216*** (0.060)	4.186*** (0.060)
Years since first picture	0.079*** (0.002)	0.065*** (0.002)	0.076*** (0.002)	0.081*** (0.002)
Years since first picture squared	–0.002*** (0.000)	–0.002*** (0.000)	–0.002*** (0.000)	–0.002*** (0.000)
Switched camera	–0.035*** (0.004)	–0.038*** (0.005)		
Months since switched camera	0.009*** (0.001)	0.010*** (0.001)		
Months since switched camera squared	–0.000*** (0.000)	–0.000*** (0.000)		
Switched camera within brand			–0.028*** (0.006)	
Months since switched within brand			0.007*** (0.001)	
Months since switched within brand squared			–0.000** (0.000)	
Switched camera across brands			–0.233*** (0.055)	
Months since switched across brands			0.058*** (0.008)	
Months since switched across brands squared			–0.003*** (0.000)	
Switched, PS to DSLR				–0.063*** (0.007)
Months since switched, PS to DSLR				0.009*** (0.002)
Months since switched, PS to DSLR, squared				–0.000** (0.000)
Switched, DSLR to PS				0.018 (0.011)
Months since switched, DSLR to PS				0.013*** (0.003)
Months since switched, DSLR to PS, squared				–0.001*** (0.000)
Switched, PS to PS				0.014* (0.007)
Months since switched, PS to PS				0.002 (0.002)
Months since switched, PS to PS, squared				–0.000 (0.000)
Switched, DSLR to DSLR				–0.051*** (0.007)
Months since switched, DSLR to DSLR				0.008*** (0.002)
Months since switched, DSLR to DSLR, squared				–0.000 (0.000)
Individual FEs	Yes	No	Yes	Yes
Individual-upload month FEs	No	Yes	No	No
Camera FEs	Yes	Yes	Yes	Yes
Time since joined Flickr	Yes	No	Yes	Yes

Table 3. (Continued)

	Baseline	Indiv. batch	Flex. switch cost	Flex. switch cost
Upload month FEs	Yes	No	Yes	Yes
Number of pictures posted	Yes	No	Yes	Yes
Number of pictures taken	Yes	Yes	Yes	Yes
Ordering within upload month	Yes	Yes	Yes	Yes
Tags	Yes	Yes	Yes	Yes
R^2	0.18	0.07	0.18	0.18
Observations	1,493,542	1,493,542	1,488,048	1,488,048

Notes. "Switched camera" refers to whether the individual has switched camera in the past 18 months, whereas "months since switched" takes values between 1 and 18. Indiv., Individual; Flex., flexible; PS, point-and-shoot; FEs, fixed effects.

Figure 4 illustrates the timing of actions and state transitions within a period t. Some of the notations will be introduced later.

5.2. Camera Choice and the Evolution of Cameras

In each period, the consumer makes decisions to purchase and to use cameras. I denote these decisions as $\boldsymbol{A}_{it} = (B_{it}, D_{it})$, where symbols A, B, and D stand for "action," "buy," and "do." The term B_{it} (buy) characterizes the purchase decision as a choice over a brand-format combination. I consider combinations of two formats (a point-and-shoot camera or a DSLR) and three brands (Canon, Nikon, and "other brands"), plus the option of not buying ($B_{it} = 0$), for a total of seven purchase options. I do not consider model choice because there are over 1,000 cameras, some with only subtle distinctions in observed characteristics. My dynamic discrete choice model cannot handle such dimensionality.

One state variable affected by camera choice is the camera brand format. Let $K_{it} = 1, \ldots, 6$ denote the brand format owned by consumer *i at the end of* period t.[18] If the consumer buys a camera, she replaces K_{it-1} with the new camera; that is,

$$K_{it} = \begin{cases} K_{it-1} & \text{if } B_{it} = 0, \\ B_{it} & \text{if } B_{it} > 0. \end{cases} \tag{5}$$

I do not consider resale or multihoming in cameras.[19]

Another state variable affected by the camera choice is the consumer human capital, H_{it}. Human capital evolution is the focus of this paper and will be discussed separately in Section 5.4.

5.3. Camera Usage and Production of Picture Quality

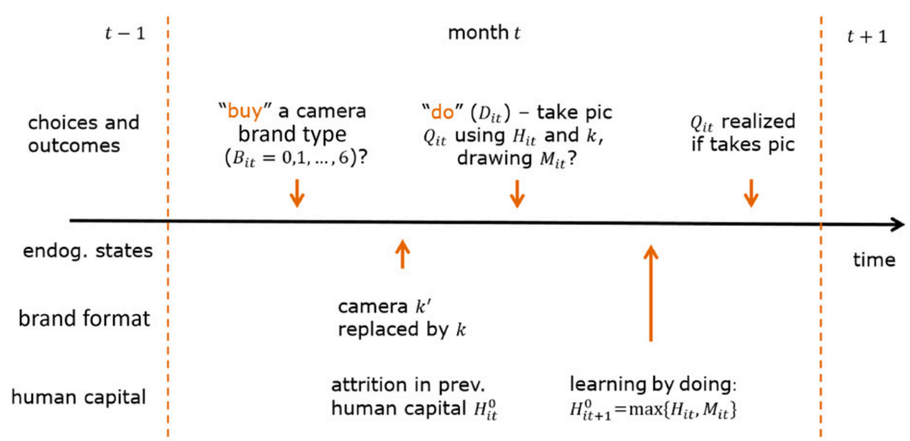
The binary variable D_{it} (do) denotes product usage decisions. After camera choice, the consumer decides whether she takes pictures ($D_{it} = 1$) or not ($D_{it} = 0$), using the latest camera K_{it}. If she takes pictures, she produces picture quality Q_{it}, from which she derives her consumption utility. To keep the model simple, I do not model the decision on the number of pictures taken. If I were to model this aspect, it would be necessary to also model the choice of which pictures to upload. This selection problem would be a significant extension of the current model and would require additional identifying assumptions.

Specifically, picture quality is produced through a production function that combines the consumers' human capital stock H_{it} and camera format $\tilde{k} = 1, 4$:[20]

$$Q_{it}(K_{it}, H_{it}) = q_i + \gamma_{\tilde{k}} \cdot H_{it} + \eta_{it}. \tag{6}$$

In the above specification, H_{it} is the consumer's human capital stock at the point when she takes pictures.

Figure 4. (Color online) Timing of Decisions and Evolution of the State Variables



Note. Endog., endogenous; prev., previous.

Parameter $\gamma_{\tilde{k}}$ captures the returns to human capital that is specific to the camera format $\tilde{k}$; if the DSLR camera format is a complement to consumer human capital (as suggested by the evidence in Section 4.2.3), then $\gamma_{\tilde{k}}$ should be larger for DSLR cameras (denoted $\tilde{k}=4$) than for point-and-shoot cameras ($\tilde{k}=1$). The term q_i characterizes the consumer's time-invariant ability as some consumers consistently produce pictures with high quality. I normalize human capital $H_{it} \in [0,1]$ and normalize that each consumer starts with initial human capital 0. Therefore, human capital focuses only on "improvements" within the consumer. Finally, the error term η_{it} is independent and identically distributed logistic with scale σ_η and location 0.

One might expect other features of the camera to affect picture quality. In addition, the set of available features might change over time as technology progresses, which influences both consumer picture quality and consumer purchase decisions. In the online appendix, I present and estimate a full model with endogenous camera technology and find that the characterization of technology does not qualitatively affect my main results.[21] For simplicity, I do not incorporate technology evolution in the main body of this paper.

5.4. The Evolution of Consumer Human Capital

5.4.1. Switching Costs in Consumer Human Capital. Camera switching decisions affect the consumer's human capital stock. Denote the consumer human capital stock at the beginning of period t by H^0_{it}, and the human capital stock she uses to produce pictures by H_{it}, that is, after her camera switching decision. If she does not switch cameras, H_{it} is the same as H^0_{it}. If she switches to a new camera, some of her human capital is product specific and therefore becomes obsolete. Figure 3 documents that picture quality produced by newly adopted cameras is proportionally lower than picture quality produced by familiar cameras, suggesting that switching costs are proportional to human capital. Table 3 documents that switching costs depend on the brands and formats of the cameras the consumer switches between. Motivated by these findings, human capital transitions at the camera switching decision according to

$$H_{it} = \begin{cases} H^0_{it} & \text{if } B_{it} = 0, \\ (1 - s_{k'k}) \cdot H^0_{it} & \text{if } B_{it} > 0, \end{cases} \tag{7}$$

where $s_{k'k}$ are the proportional switching costs that depend on brand and format of both cameras. The proportional structure of switching costs implies that consumers with higher human capital are more locked into their existing cameras.

I further parameterize the switching costs in the following way. I assume that switching to any DSLR camera incurs a baseline switching cost. In addition, if the consumer trades up from a point-and-shoot camera, she incurs an additional switching cost, $s^{tradeup}$, in a multiplicative way. If the consumer switches brands when she buys a DSLR camera, she incurs additional switching costs s^{brand}. The consumer does not incur any switching costs if she purchases a point-and-shoot camera or does not buy any camera. All possible cases of switching costs can be summarized in the following way:

$$1 - s_{k'k} = \begin{cases} 1 & \text{do not buy DSLR}, \\ 1 - s^{baseline} & \text{within DSLR in the same brand}, \\ (1 - s^{baseline}) \cdot (1 - s^{tradeup}) & \text{PS to DSLR in the same brand}, \\ (1 - s^{baseline}) \cdot (1 - s^{brand}) & \text{within DSLR across brand}, \\ (1 - s^{baseline}) \cdot (1 - s^{tradeup}) \cdot (1 - s^{brand}) & \text{PS to DSLR across brand}. \end{cases} \tag{8}$$

I assume these switching costs are common across consumers. In the online appendix, I relax this assumption and present an alternative model with heterogeneous switching costs, and do not find much heterogeneity in these parameters.

5.4.2. Learning by Doing. Taking pictures might improve consumer human capital. I model consumer learning by doing as the discovery of good methods, that the consumer remembers and can use on future occasions. Each time the consumer takes pictures, she randomly experiments with a method by drawing it from an individual-specific distribution. If she finds a method that surpasses all the methods she learned in the past, she replaces her existing method with the new one. Human capital captures the consumer's memory of the best method she ever obtained, conditional on using the same camera. Although good methods that improve human capital arrive stochastically, on average, more experienced consumers are capable of producing better pictures.

To formalize this idea, I assume that potential methods M_{it} follow the distribution $\mathscr{F}$ of a logistic-transformed normal random variable:

$$M_{it} \sim \mathscr{F}(\mu_{i\tilde{k}}, \sigma^2); \tag{9}$$

that is, $M_{it} = \frac{\exp(X_{it})}{1+\exp(X_{it})}$ and $X_{it} \sim \mathcal{N}(\mu_{i\tilde{k}}, \sigma^2)$.[22] I allow the mean $\mu_{i\tilde{k}}$ to depend on the camera format, so DSLR users can potentially have a different learning speed compared with point-and-shoot users. I capture heterogeneity in learning speed through individual-specific $\mu_{i\tilde{k}}$, but keep σ^2 constant across individuals.

After taking pictures in period t, the consumer reflects on the result and concludes a method M_{it}. If the method is better than her human capital—the best method she has used in the past—she replaces her human capital with the new method. If the new method does not surpass her human capital, she does not learn and carries the same human capital into the next period. Formally, human capital transition can be written as

$$H^0_{it+1} = \begin{cases} M_{it} & \text{if } D_t = 1 \text{ and } M_{it} > H_{it}, \\ H_{it} & \text{otherwise.} \end{cases} \tag{10}$$

Recall that the distinction between H^0_{it} and H_{it} is only due to the switching costs from new camera purchases.

There are two implications from this parameterization of human capital evolution. First, higher current human capital stock leads to higher expected picture quality next month. Second, the probability of human capital improvement, $\Pr(M_{it} > H_{it} | H_{it})$, is decreasing in the current human capital stock. This property implies decreasing marginal returns to learning, which is a common feature in many learning models such as the Bayesian learning model (Erdem and Keane 1996), the Bayesian learning by doing model (Jovanovic and Nyarko 1996), and the power law of production experience (Benkard 2000, Besanko et al. 2010).

5.5. State Space and Flow Utility

The consumer's decisions depend on the camera she owns at the beginning of period t, $K_{it-1} = k'$, which is the camera she holds at the end of period $t-1$. Her decisions also depend on human capital stock H^0_{it}. These two state variables are endogenous to the consumer's past decisions. Prices for each camera format, $P_{\tilde{k}t}$ for $\tilde{k} = 1, 4$, are two exogenous state variables that evolve independently from the consumer's decisions. I use $\boldsymbol{S}_{it} = (K_{it-1}, H_{it}, P_{1t}, P_{4t})$ for compactness of notation.

I now describe the flow utility. In each month, the consumer derives utility from purchasing a camera and from consuming the picture quality she produces. She derives disutility from the money she spends on new cameras and utility from the activity of picture taking. Formally, utility as a function of state $\boldsymbol{S}_{it}$ and actions $\boldsymbol{A}_{it} = (B_{it}, D_{it})$ is

$$\begin{aligned} u_i(\boldsymbol{A}_{it}, \boldsymbol{S}_{it}) + \varepsilon_{it}(\boldsymbol{A}_{it}) = {} & (\beta_i \cdot \mathbb{E}[Q_{it} | \boldsymbol{A}_{it}, \boldsymbol{S}_{it}] - \theta_i) \cdot \mathbf{1}(D_{it} = 1) \\ & + \sum_{k \neq 0} \alpha \log(P_{\tilde{k}t}) \cdot \mathbf{1}(B_{it} = k) \\ & + \sum_{k \neq 0} \lambda_{ik} + \lambda^{format} 1(\text{format}) \\ & + \lambda^{brand} 1(\text{brand}) + \varepsilon_{it}(\boldsymbol{A}_{it}). \end{aligned} \tag{11}$$

In the above specification, the first term characterizes the expected utility for producing picture quality Q_{it}, taking an expectation over the production function (6) and integrating out the error term η_{it}. The term β_i captures the tastes to picture quality. I allow it to be heterogeneous across individuals. Parameter θ_i captures the utility or effort of taking pictures other than enjoying picture quality; $\theta_i > 0$ would suggest that it takes effort to take pictures. The second term captures the disutility on price. I assume the consumer derives utility from log price, or that her utility responds to percentage rather than absolute changes in price.[23] The rest of the utility function characterizes immediate utility or disutility in buying a new camera (λ_{ik}, individual specific) and additional utility from switching camera formats and switching brands (λ^{format} and λ^{brand}). These additional inertia terms are not related to switching costs in consumer human capital.

5.6. Dynamic Programming

With rational expectations, the individual makes purchase and usage decisions every period by maximizing the sum of discounted flow utilities, or solving

$$\max_{\boldsymbol{A}_{i\tau}} \sum_{\tau \geq t} \delta^{\tau - t} \mathbb{E}[u_i(\boldsymbol{A}_{i\tau}, \boldsymbol{S}_{i\tau}) + \varepsilon_{i\tau}(\boldsymbol{A}_{i\tau}) | \boldsymbol{S}_{it}]. \tag{12}$$

Given stationarity assumptions on the function $u_i(\cdot, \cdot)$ (as in (11)) and transition process of $\boldsymbol{S}_{it} = (K_{it-1}, H_{it}, P_{1t}, P_{4t})$, this is a standard dynamic decision problem in spirit of Rust (1987) and others, where the consumer solves the equivalent static decision problem

$$\max_{\boldsymbol{A}_{it}} U_i(\boldsymbol{A}_{it}, \boldsymbol{S}_{it}) + \varepsilon_{it}(\boldsymbol{A}_{it}), \tag{13}$$

where the choice-specific value function $U_i(\boldsymbol{A}_{it}, \boldsymbol{S}_{it})$ is defined by the Bellman equation

$$U_i(\boldsymbol{A}, \boldsymbol{S}) = u_i(\boldsymbol{A}, \boldsymbol{S}) + \delta \cdot \mathbb{E}\left[\max_{\boldsymbol{A}'} U_i(\boldsymbol{A}', \boldsymbol{S}') | \boldsymbol{A}, \boldsymbol{S}\right]. \tag{14}$$

All state transition probabilities apply in the expectation operator in Equation (14).

There is one discrete state variable (camera stock) and three continuous state variables (human capital and log prices for both camera formats). I discretize $H_{it} \in [0, 1]$ evenly into 11 0.1 grids and log average prices into 0.2 grids. I check various degrees of discretization and find the results are not sensitive to it.

I assign a monthly discount factor of 0.975, the same discount factor as in Nair (2007) and Dubé et al. (2010b). Previous versions of this paper used monthly discount factors of 0.95 and 0.99 and produced similar results.

5.7. Heterogeneity

The structural model outlined so far allows for individual-specific parameters in their initial picture quality, learning speed, taste for picture quality, preference (or effort) for picture taking, and additional choice intercepts. Although it is common to characterize consumer heterogeneity by two-type discrete distributions, such characterization might not be sufficient to capture the heterogeneity in learning and product choice in my context.

My model assumes that individual-specific parameters are drawn from a multivariate normal distribution. Allowing for continuously distributed parameters imposes much higher computation burden, because the model needs to be solved for each draw and at each set of trial parameters. Therefore, as I set up the model, I limit my attention to seven parameters that are heterogeneous. These parameters are initial picture quality q_i, learning speed (using either camera format) μ_{i1}, taste for picture quality β_i, preference (or effort) for picture taking θ_i, and choice intercepts for buying a DSLR camera, a Canon camera, and a non-Canon camera.

As I present the model, I assume the following parameters are homogeneous: switching costs in human capital, the price coefficient, the standard deviation of new methods, the difference in learning speed between DSLR and point-and-shoot cameras (i.e., $\mu_{i4} - \mu_{i1}$), choice intercepts for point-and-shoot cameras, and consumer inertia in switching format and brand. One might wonder whether there is important heterogeneity among these parameters. I estimate a two-type heterogeneity model on all parameters (online appendix, Section A) and find that consumer heterogeneity in the above-mentioned seven parameters is the most important.

5.8. Computation and Estimation

I estimate the model using simulated maximum likelihood. I take 100 × 7 numbers from the Halton sequence, denoted by ν_ι for $\iota = 1, \ldots, 100$, to mimic 100 draws of a seven-by-one standard normal random vector. The random coefficient vector for "type" ι is the mean coefficient plus the deviation term:[24]

$$\Theta_\iota = \bar{\Theta} + \Sigma^{1/2}\nu_\iota, \tag{15}$$

where $\Sigma^{1/2}$ denotes the square-root of the covariance matrix Σ, here assumed to be diagonal.[25]

Given a consumer type ι, I fully solve the model through Bellman Equation (14). Next, I compute the likelihood function for individual time (as a function of the individual-specific parameters Θ_ι) as

$$\begin{aligned} l_{it|\iota} &= g_\eta\left(Q_{it} - (q_i + \gamma_{\tilde{k}} \cdot H_{it})\right)^{\mathbf{1}(D_{it}=1)} \\ &\quad \cdot \prod_a \left(\frac{\exp\left(U_i(\boldsymbol{a}, \boldsymbol{S}_{it})\right)}{\sum_{a'} \exp\left(U_i(\boldsymbol{a}', \boldsymbol{S}_{it})\right)}\right)^{\mathbf{1}(A_{it}=a)}. \end{aligned} \tag{16}$$

The first part of the likelihood is the density of the prediction error for picture quality, that is, the difference between observed quality Q_{it} and the model-predicted one from the human capital equation. The second part is the standard logit model likelihood function. The steps of solving the Bellman equation and computing the likelihood are repeated for all 100 Θ_ι draws. Finally, for each individual i across all periods, I average the individual likelihood $\prod_t l_{it|\iota}$ across all 100 types to obtain the likelihood of observing i's picture quality and choices:

$$L_i = \frac{1}{100}\sum_{\iota=1}^{100}\left(\prod_t l_{it|\iota}\right). \tag{17}$$

I simultaneously estimate the mean coefficients $\bar{\Theta}$ and the diagonal variance matrix Σ by maximizing the sum of log likelihood across individuals.

The computational burden is nontrivial in this dynamic model. I use a PC graphical processing unit to compute the contraction mapping in (14). For a given type ι, the contraction mapping takes about 1 second at the specified state space, and evaluation of the likelihood for each type takes 1.5 seconds in total (including time spent for the contraction mapping). There seems to be some scale economy across types: it takes 74 seconds to evaluate the likelihood once for 100 types.

5.9. Identification

I now discuss identification of the structural model, given implied picture quality, choices of picture taking and camera purchase, and other observed state variables as data.

On the one hand, the consumer production function is identified because product usage and switching affect picture quality in a way that is directly observed in data. Specifically, with normalization of initial human capital $H_{i1} = 0$, the production function intercept q_i is identified by the initial period observed picture quality. In addition, with the normalization that $H_{it} \leq 1$, camera format effect $\gamma_{\tilde{k}}$ is identified by comparing differences in the stationary picture quality across camera formats. Finally, learning speed (and the heterogeneity in learning speed) and switching costs are identified through changes in picture quality as results of camera usage and switching, respectively.

In the above argument, because product usage and switching decisions are not random, they must be captured by a (discrete choice) model with exclusion restrictions to separately identify them. Here, prices do not directly affect the production of picture quality and will affect it only through choices of camera usage and purchase. Using prices as the key excluded variable requires that prices are measured well; in Section 3.5, I provide descriptive statistics showing that my eBay price data are reasonable measures of prices.

On the other hand, within a consumer, variations in her picture quality (from the now-identified production function) lead to changes in her product choices. This correlation identifies her preferences for picture quality,

β_i. For example, if the consumer's picture quality steadily increases over time but I do not see a trend in her camera choice (factored in the changes of prices), my model will conclude the consumer does not care about picture quality, and thus β_i will be indistinguishable from zero. Conversely, if changes in the expected picture quality are aligned with the consumer's product choice changes, the model will conclude that β_i is positive.

In contrast to this within-consumer identification argument, some consumers persistently produce high picture quality, and some consumers persistently tend to choose DSLR cameras or tend to use their cameras more often. These across-consumer heterogeneities are captured by the heterogeneity in initial quality q_i, preferences for taking pictures θ_i, and other preference parameters λ_i.

Finally, my identification strategy relies on two implicit assumptions. First, I assume that consumers have rational expectations about state (camera, human capital, and price) transitions. Second, as shown by Magnac and Thesmar (2002), I cannot identify the discount factor δ without imposing further exclusion restrictions. I set δ at a value conventional in the literature.

6. Estimation Results

6.1. State Transition Processes

I first estimate exogenous state transition processes for prices (separately for each format). For prices of both point-and-shoot and DSLR cameras, I find the simple first-order Markov process explains 83%–89% of variations in the data. These measures of fit suggest the simple model capture the data sufficiently well.[26] My structural model assumes consumers hold rational expectations on prices according to these estimates.

6.2. Structural Parameter Estimates

6.2.1. Production Function. I apply the model to the estimation sample obtained from Section 3.2.2, consisting of 4,110 individuals. Table 4 presents all parameter estimates of the baseline structural model.

The production function parameters (common across all consumer types) suggest that using a DSLR camera produces higher picture quality conditional on human capital. As the model estimates, the average beginning-of-period human capital stock is $\bar{H}^0_{it} = 0.25$. At this average, DSLR cameras will produce pictures that are 12.0% more popular because of higher quality.[27] This return to DSLR is lower than documented in Section 4.2.3, which suggests a selection bias that arises from consumers with higher human capital (or learning speed) choosing DSLR cameras.

6.2.2. Initial Picture Quality and Learning Speed. The standard deviation of μ_{i1} shows sizable learning rate heterogeneity across consumers. Figure 5 illustrates how this parameter translates to divergence in human capital across consumers over time. I track the path of human capital distribution for two draws of μ_{i1} at, respectively, the 25th and 75th percentiles. The two draws represent two distinct types of consumers, who diverge in their path of human capital evolution: in three years, the faster learner has a mean human capital stock at 0.351, much higher compared with the slower learner at 0.072.

6.2.3. Price Sensitivity. The (log) price sensitivities show that consumers dislike paying for high-priced

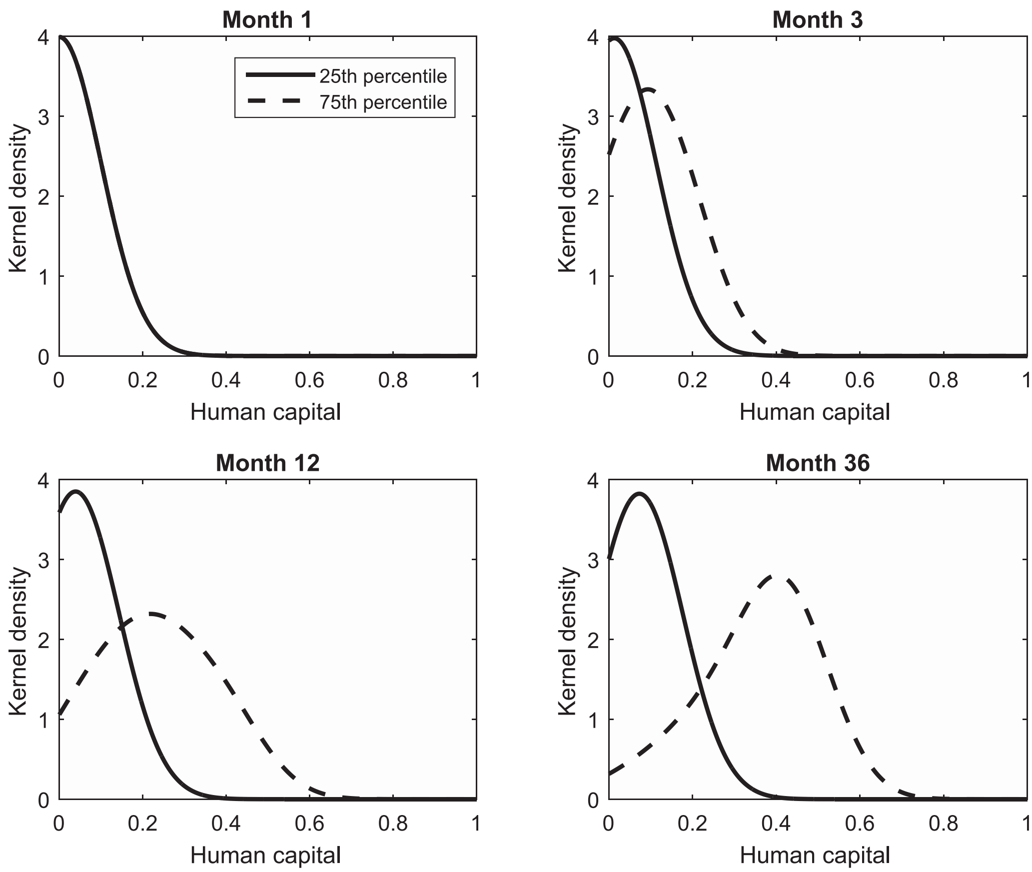
Table 4. Parameter Estimates: Main Specification

	Mean	St. dev.
Productivity of PS, γ_{PS}	0.419* (0.043)	
Productivity of DSLR, γ_{DSLR}	0.897* (0.035)	
Quality intercept, q_i	0.970* (0.017)	1.124* (0.008)
Mean method, μ_{i1}	−3.354* (0.000)	1.531* (0.001)
Different method from DSLR, $\mu_{i4} - \mu_{i1}$	0.183* (0.000)	
Std. dev. of method, σ	0.928* (0.000)	
Switching cost: any camera, $s^{baseline}$	0.023* (0.000)	
Switching cost: format, $s^{tradeup}$	0.087* (0.000)	
Switching cost: brand, s^{brand}	0.105* (0.000)	
Scale of η_{it}	0.519* (0.002)	
Utility to pic quality, β_i	0.500* (0.011)	0.135* (0.014)
Utility/effort of usage, θ_i	0.556* (0.033)	1.510* (0.007)
log *Price sensitivity*, α	−1.872* (0.098)	
Buy point-and-shoot, λ^{PS}	−3.018* (0.055)	
Buy DSLR, λ_i^{DSLR}	−0.283 (0.184)	0.158* (0.040)
Buy Canon, λ_i^{Canon}	0.094* (0.038)	0.154* (0.051)
Buy non-Canon, $\lambda_i^{nonCanon}$	−0.311* (0.036)	0.144* (0.055)
Switch format, λ^{format}	−0.427* (0.040)	
Switch brand, λ^{brand}	−0.600* (0.032)	

Notes. This table reports structural estimates for the continuous-type version. The log likelihood = −241,640. Asymptotic standard errors are from a numerical Hessian.

*Significant at the 95% confidence level.

Figure 5. Predicted Evolution of Human Capital



Notes. The four panels present four cross sections of predicted human capital distributions, separately for consumers at the 25th and 75th percentiles of learning rate. Kernel density estimators have a bandwidth of 0.15.

products. Implied own elasticities are about –1.83 from a one-month change in the average price of a camera format.

6.2.4. Switching Costs. The switching cost estimates shown confirm my descriptive evidence on the lack of human capital transferability. For example, switching to a camera in the same format/brand costs 2.3% of human capital depending on the segment. Likewise, trading up to a DSLR camera in the same brand costs 10.8%, and trading up to a DSLR from a different brand costs 20.2%.[28] I do not estimate switching cost heterogeneity, but use the two-type model to confirm that switching costs in human capital are similar across segments (online appendix, Section A). Recall that these switching costs do not capture all consumer inertia.

6.3. Model Fit

I examine whether the model can simultaneously fit the following three patterns: (1) the evolution of the consumer's picture quality over time, (2) the impact on her picture quality at the instance of camera switching, and (3) her camera purchase and usage probabilities over time. These are presented graphically in Figure 6. These figures show the model can keep track of both the evolution of picture quality over experience and the evolution of camera purchase and usage. In addition, the model can capture short-run impacts and recovery of picture quality after switching to a different camera.

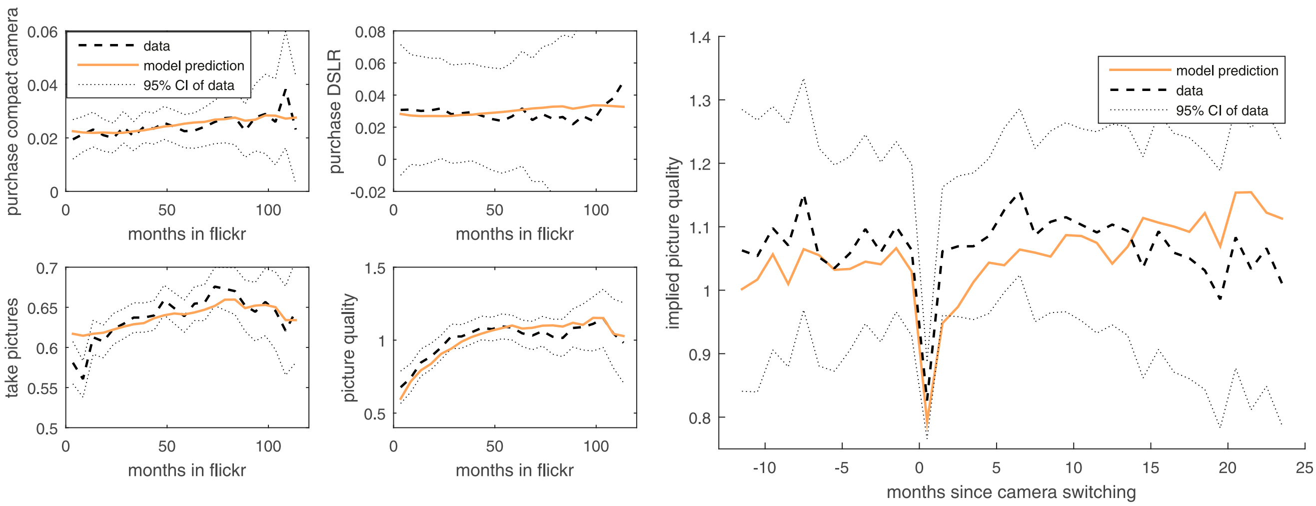
7. Human Capital and the Demand for Advanced Products

7.1. Counterfactual Question and Setup

What is the impact of human capital on firm revenue and product diffusion, especially for advanced products that require skills for use at their full potential? To answer this question, I conduct two groups of counterfactual experiments, changing the consumer learning process and simulating the paths of product adoption and usage—and thus firm revenue. I do not model the supply side; therefore, the discussion around how switching costs affect equilibrium prices is beyond the scope of this paper.[29]

I simulate paths of consumer purchase and usage decisions at my model estimates. Specifically, this simulation focuses on a set of 4,110 hypothetical consumers, who have the same heterogeneity distribution

Figure 6. (Color Online) Model Fit



Notes. The left panels show model predicted and observed data over time. The four panels show choice probabilities of compact cameras and DSLRs (top panels), picture taking (bottom left), and picture quality (bottom right). The right panel shows observed and predicted picture quality before and after switching.

as my estimates and start at the same initial conditions as in my sample (i.e., the same distribution of initial cameras and facing the same initial prices). Month by month, each of these consumers decides whether to buy a new camera and whether to use their camera. Their human capital and camera ownership evolve as an outcome of these decisions. I repeat this simulation step for seven years. This exercise gives me adoption paths and firm revenue according to my model estimates. I calculate standard errors of model prediction by parametric bootstrapping: I randomly draw 50 sets of parameter estimates from the asymptotic distribution and simulate the baseline diffusion path under each draw.

I calculate expected firm revenue from DSLR sales in the baseline and each of the counterfactual scenarios. Because prices do not change in my counterfactual experiments, the results on firm revenue are equivalent to those on purchase quantities. I discuss the counterfactual experiments and results in Sections 7.2 and 7.3.

7.2. No Learning

In the first group of experiments, I quantify the impact of consumer human capital on product diffusion and firm revenue. To do so, I fix human capital at zero and simulate the adoption paths without learning by doing at all. Note that the consumer can still produce and consume picture quality, and still has the same production function intercept q_i (which might be interpreted as her human capital accumulated prior to the sample). Also note that prices still evolve according to the model estimates, so that over time consumers might still purchase more advanced products because of the lower prices. The difference between this “no learning” counterfactual and my baseline estimates is interpreted as the impact of learning by doing on diffusion and revenue of advanced products.

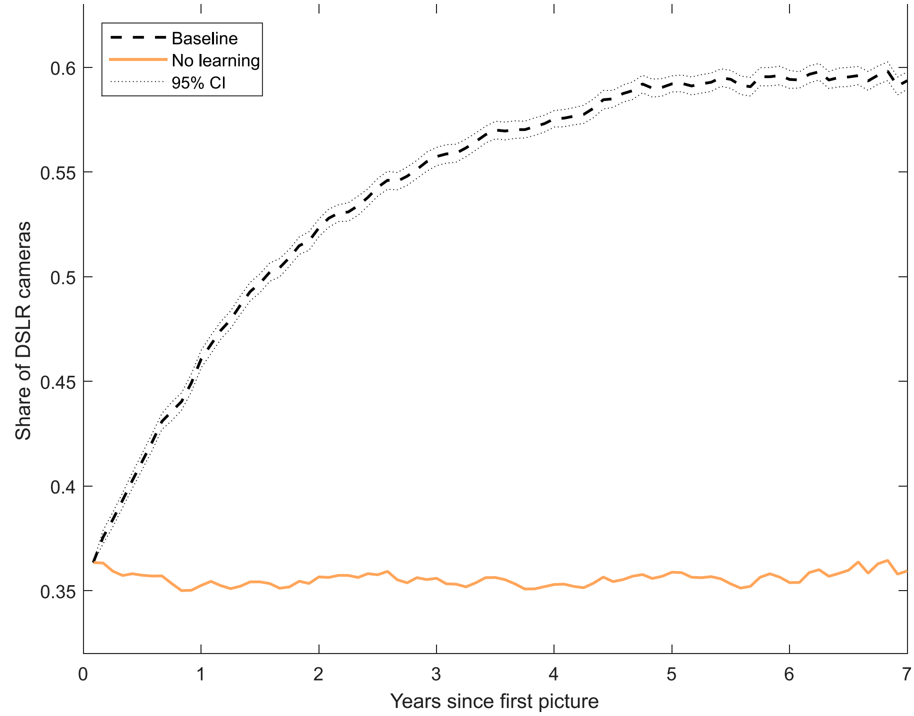
Figure 7 shows the simulated shares of consumers using DSLR cameras over time, under model estimates and under this counterfactual scenario. If there were no learning at all (within the sample), consumers would be less likely to adopt a DSLR camera given the lower return. My simulation shows that the five-year adoption rate (share of DSLR cameras) is 0.360, which barely changed from the initial condition and is 39% lower relative to the baseline shares (0.594).

I next examine the impact of learning by doing on sales and revenue. Table 5 presents the net present value (NPV) of DSLR revenue under various counterfactual scenarios, which is calculated as the sum of seven years of revenue at an annual firm discount factor of 0.95.[30] From a revenue perspective, the expected NPV of seven-year revenue is \$985 per customer, or \$302 (23%) lower than the baseline results. Learning by doing explains a large share of the choices of, and revenue from, advanced products.

7.3. Decomposition of Consumer Switching Costs

In the second group of experiments, I investigate the impact of consumer switching costs (in human capital) on firm revenue. My estimates show that consumer switching costs depend on product format and brand, so it is plausible that improving product design—in particular, the ease of use for advanced products or the interoperability across brands—can increase demand. To further investigate this aspect, I simulate firm revenue from DSLR cameras under the following four scenarios: (1) turning off all switching costs in human capital;

Figure 7. (Color online) Diffusion of DSLRs Without Learning by Doing



Notes. Simulated shares of DSLR cameras from a panel of 4,110 consumers for a duration of seven years. Each household starts with their initial camera and the price they initially faced as in the data. The dashed line shows baseline diffusion with 95% confidence intervals. The solid line shows the counterfactual diffusion path without consumer learning by doing.

(2) turning off format-switching costs, that is, $s^{tradeup} = 0$; (3) turning off brand-switching costs, that is, $s^{brand} = 0$; and (4) turning off both the brand-switching costs in human capital and the brand-switching inertia in utility, that is, $s^{brand} = 0$ and $\lambda^{brand} = 0$.

In this section, I focus on the results of scenario 3 because s^{brand} captures most of the effects of human capital transferability. Scenario 4 is presented to contrast the magnitude of switching costs in human capital against conventional measures of consumer inertia (Dubé et al. 2010a). In Table A5 in the online appendix, I present the results of all the counterfactual experiments, including results measured by year-by-year revenue changes.

Table 5. NPV of DSLR Revenue in Counterfactual Scenarios

	NPV of DSLR revenue
Baseline	1,286
No learning	985
No brand-switching cost	1,384
No brand-switching cost and inertia	1,929

Notes. The tables reports the simulated discounted sum of revenue from DSLR sales at a firm discount factor of 0.95, calculated from my simulation of adoption decisions of a panel of 4,110 households for a duration of seven years. The four rows correspond to (1) the baseline, (2) when consumers do not learn by doing at all, (3) when there is no brand-switching cost in human capital, and (4) when there is no brand-switching cost in both human capital and utility term for brand switching (i.e., the new brand coefficient is zero).

I find that revenue (which is driven by quantity given fixed prices) increases when consumers face lower switching costs in human capital because they now purchase new products at a higher frequency. In particular, I find that most of the effects come from the elimination of brand-switching costs in human capital (as opposed to format-switching costs): this is a counterfactual world where all brands of DSLR cameras follow exactly the same design, and therefore consumers who switch across brands do not incur more losses in human capital than they do within a brand. My simulation result suggests that consumer purchase more frequently, leading to an 8% increase in DSLR revenue, from \$1,286 to \$1,384.

It is also interesting to compare the magnitude of switching costs driven by brand-specific human capital (which this paper focuses on) versus alternative sources of brand-switching costs, such as inertia (Dubé et al. 2010a) or accumulation of lenses or other accessories (Hartmann and Nair 2010, Huang 2018). In this paper, all alternative sources of brand-switching costs are simplified to the brand-switching coefficient in the consumer utility function. The last row of Table 5 reports DSLR revenue when the brand-switching costs in human capital (s^{brand}) and brand-switching inertia (λ^{brand}) are both turned off. I find that eliminating both s^{brand} and λ^{brand} increases revenue by \$643. Comparatively, eliminating s^{brand} will grow revenue by \$97, which is 15% of the total effect.[31] Therefore, although there are many sources of consumer switching costs, switching costs in consumer human capital—arising from different product designs for different brands—is an important one. Making more similar products will considerably increase demand for both firms because consumers will find it easier to switch between products, therefore purchasing more. However, there might be important pricing implications related to this counterfactual scenario, which are beyond the scope of this paper.

8. Concluding Remarks

This paper uses publically available data to measure the evolution of human capital and the extent to which it affects consumer product adoption decisions. As the consumer learns by using digital cameras, she becomes proficient in using advanced product features and thus has higher willingness to pay for advanced digital cameras in general. However, she also accumulates human capital that is specific to a specific brand or format of products and is not transferable to other products. In these cases, she also displays increasing loyalty to the product she owns.

In this paper, I directly measure consumer human capital by comparing the number of views between different pictures, uploaded at a given point in time. These pictures are likely shown to the same set of viewers, so the differences in views can be considered as differences in picture quality given a rich set of controls. Pictures captured by an experienced consumer generally have better quality, but those captured with a camera new to the consumer are of worse quality. These findings indicate that some parts of consumer human capital are general, whereas some parts are specific to a product. Next, I estimate a dynamic structural model to quantify the impact of human capital on consumers' product usage and replacement decisions. Within my sample, if consumers could not learn at all, the adoption rate for advanced products would have been 39% lower, and firm revenue would have been 23% lower driven by sales volume. In addition, if advanced cameras had the same design across brands, consumers would find it easier to get used to a product from a different brand, leading to 8% higher firm revenue from more frequent switching.

One limitation is that my paper addresses only the impact of human capital on consumer demand. Quantifying the impact of learning by doing on equilibrium prices and product design is beyond the scope of this paper but is an interesting direction for future work. In addition, one might expect that the digital camera industry is not the only industry in which consumer human capital plays an important role. In categories such as consumer electronics, cookware, sports equipment, and video games there is anecdotal evidence suggesting that consumer skills evolve, and those with different skills sort into different products. In these contexts, managers should try to measure the role of consumer human capital and quantify its implications for their marketing strategies.

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Endnotes

[1] See http://digital-photography-school.com/should-you-buy-a-dslr-or-point-and-shoot-digital-camera (retrieved March 2014).

[2] See http://www.kenrockwell.com/tech/nikon-vs-canon.htm (retrieved March 2014).

[3] I perform this exercise controlling for photographer fixed effects and upload-time fixed effects as well as observables that reflect alternative explanations, such as the subject of a picture. I also provide several robustness checks to my measure of picture quality.

[4] Information about these examples come from, in the above order, https://www.pcmag.com/news/353337/how-to-take-a-free-apple-product-workshop, https://www.barnesandnoble.com/b/summer-reading-for-kids/_/N-2mir, and https://www.surlatable.com/category/cat2211278/.

[5] As an anecdotal example, user "kip leong" posts on the Digital Photography Review forum (June 24, 2008, https://www.dpreview.com/forums/thread/2355580) about zoom direction:

> I was surprised to learn that with some makers you turn the zoom ring clockwise to zoom in, and with other makers counterclockwise.…When I tried out a Canon it was the opposite of what I was used to, and it felt strange. This has narrowed down my buying choices.

[6] There was an option to set photos as "private," in which case they will be accessible only to a selected set of users. I do not observe private photos in my data set.

[7] Source: Wikipedia archives, available at https://en.wikipedia.org/w/index.php?title=Flickr&oldid=592158468.

[8] By my experiments on the website, the view counts even if the viewer does not have an account. Also, repeated clicks on a picture (presumably by the same cookie) will not increase the views.

[9] One alternative way is to randomly sample from a set of accounts. However, Flickr does not list existing accounts, and individually verifying whether each possible account name exists is a nontrivial task.

[10] The in-sample duration is not orthogonal to preferences and choices, and hence I do not condition on users with long in-sample durations.

[11] For example, by the account of Smith (2014), the median Facebook user has 200 friends.

[12] For example, Figure A2 in the online appendix reproduces the pattern in Figure 3.

[13] See http://www.infotrends.com/public/Content/INFOSTATS/Articles/2008/10.28.2008.html.

[14] I use a log-linear fit against time, plus a simulated prediction error with the same variance as in the sample. The R^2 values for the linear regression are around 0.7 for both formats.

[15] Figure A3 in the online appendix shows the difference by year.

[16] This number is calculated from $-0.033 + 0.008 \cdot 1 - 0.000 \cdot 1^2$.

[17] If I do so, picture quality residuals q_{ip} will have different normalizations in different batches and therefore cannot be compared across batches. Therefore, although I can control for $\Phi_{i,t_{p0},t_{p1}}$ when estimating the average learning rate, I cannot control for these fixed effects and infer individual picture quality.

[18] I fix $K_{it} = 1, 2, 3$ as point-and-shoot cameras of Canon, Nikon, and other brands, and $K_{it} = 4, 5, 6$ as DSLRs of these brands.

[19] As discussed in Section 3.4, I observe few cases of possible multihoming. Thus, I abstract from multihoming as it will greatly complicate computation. Also, I do not observe resell, or whether the consumer purchases from the new or used goods markets. Therefore, I do not model these decisions.

[20] Occasionally, I use $\tilde{k} = 1$ as the realized point-and-shoot format (for a given camera) and $\tilde{k} = 4$ as the DSLR format.

[21] The robustness of my results comes from the observation that camera characteristics such as resolution do not have a large impact on my measure of picture quality. This observation is not surprising because my measure of picture quality relies on viewers clicking on the thumbnails, which are small and do not contain much detail.

[22] I use the logistic transformation to maintain the normalization that $H_{it} \in [0, 1]$.

[23] This choice of functional form is because of the gap between point-and-shoot and DSLR camera prices: using a linear-utility specification will give the same qualitative result, but the price elasticities for DSLR cameras will be mechanically larger in magnitude.

[24] With an abuse of notation, I later use Θ_i and $\bar{\Theta}$ as if they contain all random and nonrandom coefficients.

[25] More generally, if Σ has off-diagonal elements that are nonzero, one should replace $\Sigma^{1/2}$ with the Cholesky decomposition of Σ. In other versions, I try to estimate some off-diagonal elements but find that the estimates are not statistically significant and robust. My intuitive explanation of this result is that the purchase occasions are scarce, and therefore the data to identify the covariance structure in heterogeneity are thin.

[26] Table A4 of the online appendix shows full results of the state transition estimates. These include prices and technology evolution. The latter is used only in the alternative model specification in Section A of the online appendix.

[27] Picture quality is increased by $(0.897 - 0.419) * 0.25 = 0.120$. Recall that my measure of picture quality is derived from log number of views. Thus, 0.120 increase in the picture quality measure is interpreted as 12.0% increase in views driven by picture quality.

[28] Take $1 - (1 - 0.023)*(1 - 0.087)*(1 - 0.105)$ to arrive at 0.202.

[29] On the question of how switching costs affect prices, see Dubé et al. (2009) on consumer packaged goods, and Chintagunta et al. (2018) and Huang (2018) on tied goods.

[30] I also examine the impact on point-and-shoot camera revenue, but the effect there is much smaller.

[31] This number is calculated from $(1384 - 1286)/(1929 - 1286) = 0.1522$.

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