Learning by Doing and the Demand for Advanced Products

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Abstract

In markets where product usage requires consumer skills, learning by doing – the evolution of these skills through using the product – plays an important role in shaping demand evolution in the long run. In this paper, I measure the returns to experience on a sample of users of digital cameras, via a measure of their picture quality. I then relate this measure to data on camera usage and switching, and estimate a dynamic demand model with learning by doing. I find that a 1-year increase in experience enhances a starting consumer’s camera-usage skills, which raises both her welfare by an amount equal to her lifetime spending on cameras, and her demand for advanced products in the same brand by 26%. Thus, not only is the provision of knowledge valued by the consumer, but it also increases her product demand. On the other hand, for some consumers, up to 26% of her experience is not transferable to products with different designs – in particular across brands. Hence, learning from using products in this category makes the consumer increasingly brand loyal.

Keywords: learning by doing, switching cost, dynamic programming, forward-looking behavior, digital camera market

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1 Introduction

“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,¹ Should you buy a DSLR or Point and Shoot Digital Camera?

“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,² Nikon vs. Canon

The two quotes above demonstrate a widely-held belief among practitioners – that novices and expert consumers demand products of different quality; and among the experts, their demand is specialized, and thus dependent on their previous experience. The role of consumer product experience is not unique to the digital camera industry. For products such as home electronics, sports equipment, entertainment, food and beverages,³ marketing practitioners have long realized the wide differences in the demand between novices and experts, and have targeted their different needs by developing portfolios of differentiated products.

Despite the importance of experience accumulation in consumer demand, the quantitative understanding of this is limited. This is because standard choice data alone confound the returns to experience with alternative explanations, such as changes in tastes or increases in awareness. In the context of choices of digital cameras, this paper utilizes a unique data-set that provides a measure

³Alba and Hutchinson (1987) are among the first to conceptualize the role of consumer product experience – “expertise”. In two experimental studies, Nam et al. (2012) and Clarkson et al. (2013) document the differences between expert and novice consumers, in their choices of, respectively, digital cameras and food/beverages. Albuquerque and Nevskaya (2012) model a consumer’s progressively higher tendency to play video games. Youn et al. (2008) document that beginner climbers tend to choose entry level climbing gears, and will later progress into advanced but specialized products.
of the returns to consumer experience, and quantifies its role in the demand for entry-level and advanced digital cameras. This allows for a better understanding of the long-run evolution of demand from entry-level to advanced products, and potentially, better quantitative marketing decisions.

In this paper, a consumer of digital cameras cares about her picture quality, which she learns to produce through the accumulation of experience. Hence, being able to measure the effect of experience on picture quality, and the effect of increasing picture quality on her demand for advanced products, is key to understanding the effect of experience on demand in this case. For this purpose, I collect individual panel data from pictures displayed on a photo-sharing website, Flickr.com. And I exploit the fact that pictures are sorted by the date of upload, and I compare the number of views among pictures that a consumer uploads at the same time. Since these pictures are displayed together and are likely to be viewed together, the differences in views are more likely to reflect picture quality differences. In addition, I observe variations in when and by which camera each picture was taken, within the same batch of upload, and hence can infer the causal effect of experience and equipment on the picture quality.

With up to 10 years of measurement of picture quality per individual, jointly with observations of camera usage and switching, the role of experience accumulation is evident even without a (structural) model. On the one hand, with their experience accumulating, consumers are capable of producing higher quality pictures. On the other hand, after a consumer switches cameras, she cannot immediately produce pictures of as high quality as she did with the previous one; and this gap is larger for consumers with more experience. This indicates that not only is the consumer obtaining general experience in photography, she is also accumulating specific knowledge about using the given product.

To quantify the role of experience on demand in this context, I then construct a structural model of a consumer’s demand for cameras and choices of product usage. In the model, the quality of the camera that the consumer owns is complemented by her ability to use it – her “human capital”, which improves with previous experience through learning by doing. Accumulation of experience thus changes the consumer’s relative importance of product quality and price, and spurs the demand for advanced products. However, part of the consumer’s experience is knowledge on operating a specific camera, and cannot be utilized after she switches to another one. The consumer thus faces

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4The latter is inferred from changes in the identity of the cameras.
a key tradeoff. On the one hand, learning by doing encourages her to *delay* switching to advanced products, since higher human capital brings higher immediate benefit for using the product. On the other hand, the longer she waits, the more effort she spends on learning non-transferable, camera-specific features; and because of this, the consumer would rather switch to advanced products *early*.

To ensure that alternative explanations are controlled for, I allow for differences across consumers, in their (time-invariant) preferences as well as the way that past history affects their current choices, which captures across-consumer differences in demand and demand evolution. In addition, the initial period differences, both in prior experience and in the choice of the first camera, are also captured by the model. Finally, I also model technology evolution, and the individual’s rational expectation on it.

Both the data and the structural estimates find substantial returns to experience in photography: on average, a consumer with 3 years of experience values her consumption utility with any given camera *more than twice* as much as when she just started photography. In addition, not all the experience gained is generalizable to other cameras: for example, for an average Canon compact camera user with 3 years of experience, only 2 years of her experience is applicable to a Nikon DSLR camera. So she faces a switching cost of 1 year of experience, should she switch to the latter. The switching cost is less pronounced if she would have switched within Canon, and hence, the lack of applicability of camera-specific knowledge across brands plays a crucial role in encouraging consumers to be brand loyal.

To my knowledge, this is the first paper to structurally quantify the role of accumulation in product usage experience on consumer demand. Although the empirical exercise focuses on choices between entry-level and advanced digital cameras, the insight from this paper can be applied to a broad range of industries, such as home electronics, sports equipment, entertainment, and other categories where usage of products requires consumer human capital. In studying consumer human capital evolution, this paper contributes to practical understanding of the evolution of consumer demand through product usage, as well as consumers’ gradual tendency to be locked in to products with similar characteristics – such as brands.

As the first contribution, this paper quantifies the returns to experience on consumers’ demand for advanced products. Experience accumulation increases a consumer’s payoff from product us-
age, which in turn increases her demand for advanced products. I find that 1 extra year of human
capital can increase a starting consumer’s demand for the advanced products in the same brand by
26%. This implies that the overall experience stock among consumers has a substantial influence
on the market demand for advanced products, and thus offers an explanation of the demand-driven
innovation hypothesis (Adner and Levinthal, 2001). Supply-side provision of consumer knowledge
– such as free product training, stimulating consumer content creation, or designing products that
are easy to use – can facilitate the evolution of demand via the increase in consumer human capital.
In addition, the consumer herself values the 1-year human capital increase by 405 dollars – which
is equivalent to her discounted total lifetime spending in the entire digital camera market. This
number is in line with casual observations of market price for a photography course, and implies
considerable consumer demand for supply-side provision of knowledge.

Part of the consumer experience is product-specific. As the second contribution, this paper
finds that an important barrier to knowledge transfer is the differences in product designs across
brands, which creates significant brand loyalty that accumulates through experience. As a con-
sumer’s product experience accumulates, she becomes less willing to switch to other brands. I
find that an experienced Canon compact camera user would have been twice as willing to upgrade
to Nikon DSLRs, if her experience were fully applicable to Nikon cameras. Conversely, because
switching across brands becomes increasingly costly over time, a consumer will tend to pick a
brand with favorable long-run characteristics, and attempt to stick to the brand in the future. This
can make products within a brand intertemporal complements – in the sense that a permanent price
drop can increase the sales of other products under the same brand.\(^5\) The mechanism for non-
transferable human capital is not well-known to the brand loyalty literature, and this paper thus
offers an alternative explanation to brand loyalty (Guadagni and Little, 1983; Dubé et al., 2010),
evolution of consumer brand preferences through experience accumulation (Erdem and Keane,
1996; Bronnenberg et al., 2012), and umbrella branding (Wernerfelt, 1988).

The remainder of the paper is structured as follows. Section 2 gives a brief review to the
literature related to this study. Section 3 describes the data collection process and how I define the
key variables – in particular, the identification strategy that allows us to measure picture quality.

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\(^5\) That is, even for mildly forward-looking consumers. The results are produced under an annual discount factor
of 0.54, in line with field estimates from consumer choice data, but far below the commonly used 0.95, which implies
the market interest rate.
Section 4 then presents model-free evidence that shows the importance of consumer learning by doing, and the role of switching cost. Given the evidence, Section 5 outlines an empirical model of experience evolution and consumer choices on purchasing and using cameras. Next, Section 6 presents and discusses parameter estimates, implied state evolution and price elasticities. Section 7 then discusses the managerial implications, and Section 8 concludes.

2 Related Literature

This paper can be positioned in the intersection of two literatures. On the one hand, my discussion of learning by doing draws from previous theoretical work on consumer human capital (Becker, 1965; Michael, 1973; Alba and Hutchinson, 1987; Jovanovic and Nyarko, 1996; Ratchford, 2001). Built from the framework in Becker (1965), Michael (1973) and Ratchford (2001) point out that consumer human capital determines their utility from product consumption. With different methodology, Alba and Hutchinson (1987) categorize the dimensions of consumer “expertise”, and point out its difference from a consumer’s information set. Jovanovic and Nyarko (1996) build a framework where non-forward-looking, Bayesian individuals update their knowledge on product usage from previous usage experience, and this increases their incentives to ascend to higher-quality products. Their framework is applied in Foster and Rosenzweig (1995) in their empirical study of increasing rural labor productivity and the choice of applying a new agricultural technology. Ratchford (2001) constructs a framework for consumer human capital, and points out its implication for life-cycle consumption, brand loyalty (in particular, related to its non-transferability) and the decisions to search. Built on this literature, this paper is the first empirical study using field data to study the effect of consumers’ human capital on their product replacement/upgrade decisions.

On the other hand, the consumer demand framework of this paper is derived from the literature on dynamic discrete choice of differentiated products, for example, Melnikov (2000), Song and Chintagunta (2003) and Gowrisankaran and Rysman (2012). In Melnikov (2000) and Song and Chintagunta (2003), since their interest focuses on first-time adoption decisions, they assume

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6 A previous version of this paper also uses the Jovanovic and Nyarko framework, i.e., to specify a Bayesian updating process for human capital accumulation – human capital as one minus the posterior variance. Applying to this context, their framework produces similar quantitative insights and a good model fit.
away repeated purchases, and hence greatly simplify computation. Gowrisankaran and Rysman (2012) allow for repeated purchases, but impose a dimensionality-reduction assumption on the state space, to ease the computational burden. In my paper, the focus is on re-purchase rather than first-time purchase decisions, and I need to consider endogenous product usage decisions and the corresponding outcome – in this case the picture quality. I also take into account dynamic optimization under differentiated product characteristics. Specifically, to maintain the key feature of evolving consumer human capital as well as accounting for other (high-dimensional) state variables, I impose a dimensionality-reduction assumption that is in spirit of Gowrisankaran and Rysman (2012), but does not require the extra layer in the fixed point algorithm.

The fact that consumer human capital is not perfectly transferable creates a switching cost. The general topic of switching cost relates to the empirical literature on the effect of switching costs on consumer decisions, in grocery shopping (Dubé et al., 2010), pharmaceutical products (Crawford and Shum, 2005), health care (Nosal, 2012), and many other categories. In this literature, there are various explanations to a consumer’s lack of willingness to transition across brands – hence “brand loyalty”. In this paper, I propose an alternative mechanism: that consumers are brand loyal because it is difficult for their experience to transfer across brands – possibly due to differences in designs. A similar explanation, “skill-based habits”, is proposed by Murray and Häubl (2005) in their experimental studies. In addition, I also demonstrate that this has dynamic implications especially for forward-looking consumers.

This paper is also related to the empirical literature on the effect of consumer learning. This literature (Erdem and Keane 1996; Erdem et al. 2005, among others) characterizes the effect of information of product attributes on consumer demand. In this framework, knowledge also endogenously evolves through past purchase experience, but the main effect of such knowledge is on consumers’ belief (i.e. their information sets), while in my model, experience is effective on consumers’ \textit{ex post} utility from product usage.\footnote{Empirically speaking, learning on product attributes tends to stop rather quickly,\footnote{For example, Dubé et al. (2010) do not find non-stationarity in the choice pattern for products that are not new to the market.} while in the case of learning by doing, I examine changes in consumer

\footnote{The difference also corresponds to the difference in “familiarity” and “expertise” in Alba and Hutchinson (1987). In Nelson (1970), the different explanations are two aspects of his categorization of experience goods: “After using ..., its price and quality can be combined to give us posterior estimates of the utility of its purchase.” [Nelson (1970), “Information and Consumer Behavior”, p.313].}
choice patterns over the course of up to 10 years.

3 Data

3.1 Collection

I extract picture level data from Flickr.com – a popular photo sharing website. Flickr started its business in 2000 by Ludicorp, and was acquired by Yahoo! in 2005. The data extraction was implemented between March 2012 and April 2013, until a major change in user-interface took place on Flickr. During the data collection period, pictures (including their detailed information) were publicly viewable, even without a user account.

Camera-recorded information is embedded in each picture, as Exif (exchangeable image file format) data. For the purpose of this paper, those data contain valuable information for camera identity, as well as the date of capture. To complement the Exif data, I also collect information on the date of upload, and the cumulative views and “favorite” votes from the upload till the data-extraction time. Figure 1 summarizes the information I get from each picture.

I collect data at two levels. At the picture level, I sort an individual’s pictures in order of upload dates, and collect the data once, from one in every five pictures. This gives me cross-sectional data on picture level information. At the individual level, I collect data on Flickr-summarized monthly picture-taking and uploading records, for each individual.

I also gather a cross-sectional data-set for camera characteristics, and a longitudinal auction price data-set. The camera characteristics data-set is compiled from the Flickr camera database, DPreview.com, and Cnet.com. In addition, Pixel-peeper.com summarized a long monthly price history for average Ebay auction prices per camera, from 2006 to 2013.

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9I did not re-visit a picture multiple times, because the time spent on collecting data from each picture is large.
Figure 1: Structure of picture-level data from Flickr

Note: This figure depicts the structure of my picture level data, extracted from Flickr.com. The vertical dashed line divides data that are originally recorded by the cameras (Exif data, embedded in each picture), and data that are originally recorded by Flickr. From the camera-recorded data, I collect the camera identity (in this example, Nikon D60) and capture date. From Flickr-recorded data, I collect the upload date, as well as the cumulative views and “favorite” votes from upload to data-extraction. This is done once per picture.
Table 1: Sample Selection Criteria

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taken by compact camera or DSLR</td>
<td>96.4</td>
</tr>
<tr>
<td>Exif data complete</td>
<td>89.6</td>
</tr>
<tr>
<td>Taken after year 2000</td>
<td>89.0</td>
</tr>
<tr>
<td>All above criteria</td>
<td>75.6</td>
</tr>
<tr>
<td>obs.</td>
<td>2777753</td>
</tr>
</tbody>
</table>

Notes: This table reports the sample selection criteria. On the picture level data, I drop the observations on pictures taken by camera formats other than compact camera or DSLR; or with Exif data that lack an indicator of camera model or date of capture; or taken no later than January 1, 2000. Altogether, this excludes 24.4% of the sample.

3.2 Sample selection and summary statistics

I focus on the “pro account” (paid account) users, who are able to upload many more pictures than the free account users.\(^\text{10}\) The free account users tend to upload few pictures even over many years. Hence, one might run into the risk of omitting certain camera-switching decisions. On the other hand, however, pro accounts are less representative for the entire market. This paper focuses on within-individual changes, and hence does not require data to be representative over demographics. However, the quantitative conclusions from the counterfactual experiments should not be over-generalized.

I collect data from all paid account users with a user-name no longer than 5 letters/digits. Focusing on shorter user-names gives me users with long histories on Flickr, and usually enables us to observe camera usage in long time spans.\(^\text{11}\) On the other hand, it is reasonable to assume that user-names are exogenous to the variables of interest. Sampling one in every 5 pictures gives me close to 2.8 million observations on the picture level. Among these data, I disregard the pictures taken by cell phones, film cameras, camcorders or digital media players, or those claimed to be taken prior to year 2000 (which is more likely to be a mistake in the camera date settings), or have incomplete Exif data (in particular when identities of the cameras or the picture taking time are missing). This excludes 24.4% of the picture data – as shown in Table 1.

Table 2 provides summary statistics for the user level data after sample selection. There are

\(^{10}\)Flickr offers either a free account – which is imposed a monthly upload capacity as well as a maximum-viewable-pictures restriction, or a “pro account” that costs $24.95 (as in 2012) annually.

\(^{11}\)The underlying assumption is that the naming strategy is orthogonal to preference and experience. On the other hand, the in-sample duration is not orthogonal to preferences – and hence I do not select on it.
Table 2: User Level Data Summary

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Stdev</th>
</tr>
</thead>
<tbody>
<tr>
<td>months since registered in Flickr</td>
<td>69</td>
<td>74</td>
<td>24</td>
</tr>
<tr>
<td>number of contacts at data extraction</td>
<td>94</td>
<td>20</td>
<td>292</td>
</tr>
<tr>
<td>total number of pictures</td>
<td>1691</td>
<td>981</td>
<td>1897</td>
</tr>
<tr>
<td>number of in-sample pictures</td>
<td>359</td>
<td>203</td>
<td>410</td>
</tr>
<tr>
<td>number of cameras ever used in-sample</td>
<td>4</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>max views per month, first 10 pic</td>
<td>7</td>
<td>1</td>
<td>57</td>
</tr>
<tr>
<td>max views per month, last 10 pic</td>
<td>20</td>
<td>4</td>
<td>193</td>
</tr>
<tr>
<td>price of the least expensive camera used</td>
<td>216</td>
<td>157</td>
<td>191</td>
</tr>
<tr>
<td>price of the most expensive camera used</td>
<td>1040</td>
<td>762</td>
<td>655</td>
</tr>
<tr>
<td>obs.</td>
<td>5499</td>
<td>5499</td>
<td>5499</td>
</tr>
</tbody>
</table>

Notes: The table reports summary statistics from the data. Mean, Median and StDev are the mean, median and standard deviation of the data, respectively. The number of contact is the number of other accounts, who are followed (subscribed) by the given user at the time of data extraction. The number of cameras ever used in-sample is the number of unique camera identities one observes from the user’s Exif data. Prices of the least and most expensive cameras are in 2005 US dollars.

Three interesting points to note. First, the median duration of observation for a user is beyond 6 years. This is a long enough period to observe the slow evolution of an individual’s photography knowledge. Second, among the 6 years in Flickr, the median user only subscribed to 20 other users. Compared to Facebook users, this shows that (this sample of) Flickr users are not social-network driven.\[^{12}\] Second, there is a considerable increase in the maximum views per unit time among pictures taken at the beginning of the sample, compared to those taken at the end of the sample; while the views have a larger spread towards the end of the sample. This suggests both an *increase* and a *divergence* in the number of views one’s pictures can attract.\[^{13}\] Third, the median individual has had 3 cameras throughout the 6 years’ in-sample period, while there is considerable dispersion in the prices of her camera: the real (Ebay auction) price of her most expensive camera is more than twice of the price of her least expensive camera.

\[^{12}\]As a comparison, the median Facebook user has 200 friends, by account of Aaron Smith (extracted in June, 2014, from http://www.pewresearch.org/fact-tank/2014/02/03/6-new-facts-about-facebook/).

\[^{13}\]Which might be due to changes in picture quality, or changes in the size of user base of Flickr.com.
3.3 Picture quality

In this section, I construct an index of picture quality, which will be later treated as data in the reduced form analysis and structural estimation. The basic idea is that a large amount of views of a picture might either suggest that it has high quality, or that a period of high popularity of Flickr coincided with the period when the picture was on display. I exploit the variation between the date of capture of a picture, and the date when it was uploaded. Holding the date of upload fixed, differences in views among the pictures should solely reflect differences in their quality – as we are effectively holding the flow of viewers to be the same. My sample consists of more than 158,000 user-months of upload combinations. Among those uploaded in the same month, the first picture was captured 4 months earlier, on average, than the last picture. This gives me ample variation in the capture dates to measure picture quality.

Formally, I model the cumulative number of views of picture $p$ captured by individual $i$, as the accumulation of an underlying viewer-flow process to the photographer $i$, $\text{flow}_{ipt}$, which is by itself multiplicative in the quality of the picture $q_{ip}$, the overall flow of viewers into Flickr.com $\phi_t$, and other observed characteristics of the picture that are not related to quality, $z_{ip}$ (e.g. the order that pictures are displayed might affect their views):

$$\text{views}_{ip} = \sum_{t_0 \leq t \leq t_1} \text{flow}_{ipt}$$

where

$$\text{flow}_{ipt} = \phi_t \exp(q_{ip} + z_{ip} \psi).$$

Omitting $i$ and $p$ subscripts, I denote $t_0$ and $t_1$ to be the calendar dates of upload and data extraction, respectively. Note that $t_0$ and $t_1$ are picture specific. The cumulative number of views is the summation of the viewer flow between these two dates. In the viewer flow specification, $q_{ip}$ is the (unobserved) quality of the picture, which is implicitly a function of user experience, camera, and an econometric error.\textsuperscript{14}

\textsuperscript{14}One might alternatively interpret this as a noisy measure of picture quality.
Take the log of Equation (1), we have

$$\log (\text{views}_{ip}) = \Phi_{0 \leq t \leq 1} i + z_{ip} \psi + q_{ip},$$

(2)

noting that $\Phi_{0 \leq t \leq 1} = \log (\sum_{t_0 \leq t \leq t_1} \phi_t)$ is a time-window-specific fixed effect, that captures the overall cumulative viewer arrival in the time window $[t_0, t_1]$, when the picture was on display.

To measure picture quality, I estimate Equation (2) by ordinary least squares, controlling for combinations of picture upload month and data extraction month ($\Phi_{0 \leq t \leq 1}$), as well as individual fixed effects (contained in $q_{ip}$). I also include the following control variables in $z_{ip}$: 1) the topic of the pictures, as captured by tag fixed effects, 2) the number of pictures uploaded in the same batch, 3) the order of the focal picture in the upload batch, and 4) months since a user was registered on Flickr (as a proxy of the accumulation of friends networks). All control variables are coded as dummies, allowing the specification to be as flexible as possible. I take the projected individual fixed effect plus the residual term, as a proxy of picture quality.$^{15}$

Table 3 summarizes the maximum picture quality $\hat{q}_{ip}$ in each picture-taking month, which characterizes the quality of pictures that an individual can produce. One can immediately spot the following patterns.

First, with accumulating years of experience, the individual can produce increasingly higher picture quality, up to a point where knowledge has been saturated, and the change in picture quality is statistically negligible. In other words, there is a clear pattern of learning with decreasing speed.

Second, using a small subsample with non-zero favorite-votes data,$^{16}$ one can cross-check whether the developed measure of picture quality is reasonable. I find that the correlation between maximum picture quality and maximum rating (if nonzero) is around 60%, which justifies that the maximum quality is a reasonable measure of the outcome of picture taking.$^{17}$

$^{15}$The reason I consider individual fixed effects as systematic across-individual difference in quality rather than other factors such as being popular on Flickr, is because we can trace every user to her starting point in Flickr, but not to her initial experience in photography. Therefore, it is much more plausible to think of heterogeneity in initial conditions as heterogeneity in skills. As a robustness check, leaving out the individual fixed effect does not qualitatively change the (reduced form and structural) estimates.

$^{16}$The share of individual-monthly observations where at least one picture has received at least one favorite vote is 15%.

$^{17}$As a side note, the mean quality has a poor correlation with the average rating: around 10%. 13
Table 3: Summary of the monthly highest inferred quality

<table>
<thead>
<tr>
<th>Years of Expr</th>
<th>Max Quality</th>
<th>Stdev</th>
<th>Max Favs</th>
<th>Corr. with Qual.</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 year</td>
<td>0.619</td>
<td>1.503</td>
<td>0.636</td>
<td>0.583</td>
<td>3704.000</td>
</tr>
<tr>
<td>1 year</td>
<td>1.537</td>
<td>1.747</td>
<td>0.938</td>
<td>0.625</td>
<td>2561.000</td>
</tr>
<tr>
<td>2 years</td>
<td>1.835</td>
<td>1.852</td>
<td>1.034</td>
<td>0.648</td>
<td>2788.000</td>
</tr>
<tr>
<td>3 years</td>
<td>2.054</td>
<td>1.832</td>
<td>1.073</td>
<td>0.628</td>
<td>3026.000</td>
</tr>
<tr>
<td>4 years</td>
<td>2.091</td>
<td>1.782</td>
<td>1.087</td>
<td>0.612</td>
<td>3240.000</td>
</tr>
<tr>
<td>5 years</td>
<td>2.045</td>
<td>1.731</td>
<td>1.064</td>
<td>0.600</td>
<td>3290.000</td>
</tr>
</tbody>
</table>

Notes: This table summarizes the individual-monthly maximum of the inferred picture quality (Section 3.3), which is treated as data in the subsequent analysis. Monthly maximum refers to quality of the best picture captured in the given month, by an individual. Years of experience is defined as number of years from the first in-sample picture to the current month of picture-taking. The first two columns summarize its mean and standard deviation. The third column presents average of the highest rating (“favorites”) one gets for pictures taken in the month, given that the highest rating is non-zero (15% of the individual-month data). The fourth column presents its correlation coefficient with the highest inferred quality. Finally, the fifth column shows number of observations on the individual-month of capture level.

3.4 Camera ownership

I next infer camera ownership from the Exif data behind each picture. As previously mentioned, the camera identity is embedded in the picture’s Exif data. I then assume that, for a given individual, whenever one observes a new camera capturing its first in-sample picture, I assume that the previous camera has been replaced.

For 75% of all individual-camera combinations, I never observe an old camera taking pictures after the arrival of a new camera. For the remaining 25%, although the earlier cameras still take pictures, the majority of the pictures are taken by the most recent cameras acquired. To document this, Figure 2 presents the joint probability of the number of cameras that are still active (i.e. cameras that would take pictures later than this date), and the occasions that the newest cameras taking most pictures. Overall, there are few cases when the latest camera is not the most active one.
Figure 2: Joint probability of the number of cameras owned, and whether the latest camera takes the most pictures (x-axis: # cameras)

Note: This figure shows the joint probability of the number of cameras owned at a given time, and the incidence that most pictures are taken by the latest camera. A camera is owned at a point in time if I observe at least one picture taken before that, and at least one picture taken afterward. By construction, a camera takes all pictures if it is the only “owned” camera – as represented by the dark bar at x axis = 1. When more than one camera is present, I find that in most occasions, the last camera still takes most pictures.

3.5 Computing price indices

For digital cameras, as other consumer electronics, prices vary a lot among retailers, fluctuate over short periods of time, and display large differences across first- and second-hand markets. I cannot observe the actual prices that the consumers observe. Instead, I observe the monthly average Ebay auction price for each camera model. This price data are averaged across first and secondary markets. Especially for older camera models, it better represents the prices the consumers face compared to a retailer’s list price.

With this data, I first deflate prices to 2005 US dollars. Then, separately for both camera formats, I take the weighted average of the prices of all available cameras in a given month, by their market shares in the Ebay auction data.\textsuperscript{18,19} Since the data only ranges from 2006 onward, I interpolate the missing values before 2006, by taking a log-linear fit against time, plus a simulated

\textsuperscript{18}That is, the number of auctions for a given camera model, as a percentage of the total number of auctions in the sample.

\textsuperscript{19}In this version, I do not consider other camera characteristics such as resolution. In robustness-check versions when this was considered, I use the same method to compute resolution indices.
regression error.\textsuperscript{20}

4 Reduced form evidence

4.1 Overview

This section first presents descriptive evidence on an average individual’s increasing tendency to use advanced cameras, even when \textit{calendar} time effects are controlled for. Then, I present the following reduced-form evidence that point to consumer learning by doing: 1) complementarity between a consumer’s experience and her usage of an advanced product; 2) the imperfect transferability of consumer experience upon camera switching; and 3) the long-run evolution of picture quality, and the increasing attrition of knowledge if the consumer switches cameras.

4.2 Increasing tendency to using the advanced products

I first screen out individuals who I observe for less than 5 years, and only look at the remainder of the sample in their first 5 years. This avoids selective attrition – in this case, that the individuals with lower ability to generate picture quality might systematically drop out earlier. With this screening criterion, we have the same set of individuals in every time period for the reduced form evidence.

I first present evidence that suggests an increasing tendency to use advanced products, as one’s experience in photography grows. To pin down experience effects, I control for the role of technology and other sources of calendar-time effects, by estimating a linear probability model with the choice of camera format on the left-hand side, and experience dummies and calendar time dummies on the right-hand side:

\[
\text{Format}_{it} = \alpha_i + \sum_{t=1}^{60} \beta_{expr,t} (expr_{it} = t) + \sum_{y=2001}^{2013} \beta_{year,y} (year_{it} = y) + \epsilon_{it}.
\] (3)

Essentially, controlling for the calendar time effects allows us to compare within a given point in

\textsuperscript{20}Separately for each format, I regress log price index on a linear time trend, and interpolate the missing value using the linear prediction plus a simulated prediction error. The R-squared for the linear regression are around 0.7 for both formats. Keane and Wolpin (1994) use this method to interpolate missing data in their value function calculations.
Figure 3: Product-format choice and user experience (selected sample)

Notes: This figure depicts the changes in the choice of product format (DSLR vs compact camera), given a user’s years of experience – defined as the number of years since one’s first in-sample picture. It also depicts (part of) the 90% confidence intervals. To control for selective attrition, I choose the subset of individuals whom I observe for no less than 5 years, and only focus on their first 5 years of data. To control for advances in technology (and other calendar-time effects), I estimate a linear probability model in Equation (3), and present the estimated $\hat{\alpha}_i + \hat{\beta}_{\text{expr},t}$ as the calendar-time-detrended estimates in camera usage choice.

The resulting tendency to use DSLR cameras – calendar-time de-trended – is shown in Figure 3. Despite the large confidence interval (which might be due to the amount of control variables and fixed effects), I find that having 5 years of photography experience raises one’s tendency to use an advanced camera by 10%. This suggests that experienced consumers are more likely to choose advanced products, given a constant technology level.

4.3 Complementarity between advanced cameras and human capital

The next 3 pieces of evidence picture an explanation to the increasing shares for advanced products. As the second piece of evidence, I show that there is complementarity between using an advanced product (i.e. a DSLR) and having rich experience in picture taking, in producing high-quality pictures. To show this, I take the within-individual-month difference between the highest picture
Figure 4: Complementarity between experience and advanced products (selected sample)

Notes: This figure shows complementarity between experience and advanced cameras, in the sense of increasing each others’ productivity in generating maximum monthly picture quality. Within individual-month, I take the difference between monthly highest picture qualities generated by DSLR and compact cameras, for those who used both in the month (6.9% of the individual-month observations). This is the “gain from DSLR” measure in the Y axis. The solid line is local polynomial fit against experience, while dashed lines are 95% confidence intervals. To eliminate selective attrition, I limit the sample to consumers we observe for more than 5 years.

quality generated by a DSLR camera and a compact camera – for a small subsample of individuals using both formats in a given month. This measure, “gain from DSLR”, is defined in 6.9% of all individual-month observations.

Plotted against experience, Figure 4 find that a starting consumer does not find that using a DSLR contributes to her ability to produce high-quality pictures. This quickly changes when she gains the first year of experience, as the consumer now finds a 0.2-unit difference in picture quality, between using a DSLR and a compact camera. This provides within-individual evidence on the complementarity between knowledge and product quality. Also note that the difference starts slightly above zero, which indicates that even new consumers do not find a DSLR camera generating lower picture quality than a compact camera.

Alternative between-individual evidence, presented in Appendix Figure 12, is qualitatively similar.
4.4 Changes of picture quality at camera-switch

Thirdly, I present evidence for the imperfect transferability of consumers’ knowledge on camera usage – or human capital, across different cameras. To do so, I normalize the date of camera-switching to be period 0, and look at the highest quality an individual produces in a given month, around the time when she switches products. Figure 5 shows that there is an immediate drop in picture quality at switching. The drop in picture quality indicates that not all the knowledge from the previous product is transferred to the new camera.

Note that the highest picture quality drops despite that the individual produces more pictures immediately after switching – which would have generated higher picture quality if there were no human capital attrition. Also note that the pattern is robust (besides being noisier) when conditioning on the direction of camera switching, as presented in Appendix Figure 11.

In addition, after the camera switch, the picture quality quickly goes up in the first 3-4 months, and it further gradually increases to a higher level in 1.5 years after the switch. This suggests that at the instance of camera switching, the individual loses both explicit knowledge on camera operations (e.g. menu and button layout), as well as implicit knowledge on camera usage (e.g. how to best circumvent a certain product limitation). While the first can be quickly learned in a month or two, the second can only be learned with long experience with the new camera.

4.5 Evolution of picture quality and switching cost

Finally, in separate panels, Figure 6 presents the evolution of consumers’ monthly maximum picture quality, and the decrease in quality when using a new camera, conditional on her experience. In the left panel, monthly maximum picture quality increases sharply at early experience levels, and gradually stops increasing from year 3 onwards. This shows that consumer learning by doing enhances their human capital on camera usage, but the learning speed is lower when one already processes knowledge. The figure can be plotted separately for compact camera and DSLR users. Shown in Appendix Figure 12, the concave trend persists, while DSLRs produce significantly better picture quality than compact cameras.

In the right panel, I contrast the maximum picture quality produced by consumers who have used their cameras for more than 3 months, and those who have been with their camera for no
Figure 5: Quality of best pictures around camera switching

Notes: This figure depicts the changes in maximum picture quality, around the period when an individual switches cameras. We focus on the years before and after a consumer switches her camera at year 0. With the left vertical axis, the dark line (and dashed lines as its 95% confidence interval) depicts the maximum picture quality that the consumer can produce, using her old camera until year -1/12, and new camera from year 0. The dash-dot gray line depicts the number of pictures that the consumer takes in each month. Both lines are local polynomial estimates with bandwidth 1.
Figure 6: Quality of best pictures over photographic experience

Notes: Left panel: monthly highest picture quality for a given individual, against (general) experience in years. Right panel: the difference between monthly highest picture quality produced by individuals who are using cameras that have been purchased more than 3 months ago, and those by individuals who are using cameras purchased more recently, plotted against years of experience. For both panels, the solid circles are mean values across individuals, while brackets are 95% confidence intervals. To eliminate selective attrition, I limit the sample to consumers we observe for more than 5 years.

more than 3 months. Users of new cameras systematically generate lower picture quality than users who are familiar with theirs, which agrees with the drop in picture quality at switching, in Figure 5.\textsuperscript{21} In addition, when plotted against years of (general) experience,\textsuperscript{22} I find that at the start of the sample, the picture quality generated by an inexperienced consumer shows no statistically significant difference between new cameras, and cameras that the consumer is familiar with. On the other hand, for those with longer (general) experience, the switching cost is significant and increasingly important. This suggests that as the consumer learns, a share of the incoming knowledge is product-specific – the accumulation of which generates the increasing switching cost profile.

\textsuperscript{21}The picture quality generated by new cameras, and cameras that the consumers are familiar with, can be found in Appendix Figure 13.

\textsuperscript{22}This is defined as the duration between the production of the first in-sample picture, and the current month of picture taking.
5 Structural Model

5.1 Overview

This section presents the structural empirical model. Whereas the model on durable good purchase with learning by doing is general, it will be presented in the context of digital camera markets for concreteness. A bare-bone version of the model with numerical results will be presented in Section B in the Appendix, to highlight the key properties of a demand model with (general and specific) learning by doing.

In the model, I jointly characterize a consumer’s decisions to purchase digital cameras, and her decisions to use the product. Combining a camera and the stock of experience – or “human capital” – produces pictures that generate consumption utility,\(^{23}\) and at the same time, contributes to the consumer’s human capital stock. Therefore, past usage decisions build up consumer human capital, and hence future utility. With rational expectations and a non-zero discount factor, the consumer makes camera replacement and usage decisions, taking into account the consequences of her decisions on her future human capital stock.

5.2 Decisions on camera replacement and usage

Consumer \(i\) in each period \(t = 1, \ldots, T\) decides whether to purchase a new camera, and in the case of purchase, which format and brand to buy. If the consumer buys a new camera, she replaces the old one with no resale value. Afterward, she decides whether or not to take pictures in this period, and if she does so, she derives utility from the highest picture quality generated by her camera and her stock of human capital.

I denote the decision as \(A_{it} = (B_{it}, D_{it})\), where symbols A, B, and D stand for “action”, “buy” and “do”, respectively. The discrete variable \(B_{it} > 0\) denotes the choice of buying a new camera, in which case the consumer chooses among combinations of one of the two formats (a compact camera or a DSLR) and one of the three brands (Canon, Nikon and “other brands”). In the case of no purchase, I denote \(B_{it} = 0\).

\(^{23}\)I follow the terminology in Michael (1973) and Foster and Rosenzweig (1995). Alternative terminology include “know-how” (Besanko et al., 2010), and “expertise” in Alba and Hutchinson (1987). I also use the term “knowledge” interchangeably with human capital, and this is not to be confused with information.
State variable $K_{it} = 1, \ldots, 6$ denotes the identity – the brand-format combination – of the camera that the individual owns at the end of period $t$. If a camera is purchased, the consumer replaces the previous camera that she owned with the new one, i.e.

$$K_{it} = \begin{cases} 
K_{it-1} & \text{if } B_{it} = 0 \\
B_{it} & \text{if } B_{it} > 0.
\end{cases} \quad (4)$$

I do not consider resale, or multiple camera ownership.

The binary variable $D_{it}$ denotes the decision of whether to take pictures ($D_{it} = 1$) or not ($D_{it} = 0$), using the latest camera $K_{it}$, i.e. after the replacement decision. If she decides to use the camera, she incurs a cost of effort $e_i$, which summarizes the dis-utility or utility from taking pictures in a period. Also, she takes one draw that determines the realization of the highest picture quality – denoted $Q_{ikt}$ – from which she derives her consumption utility.

To keep the model simple, I do not model the decision on the number of pictures to take. Modeling this aspect will also necessitate modeling of picture selection and upload decisions, which are not central to the core mechanism.

The timing of consumer decisions and evolution of the state variables are graphically presented in Figure 7.

### 5.3 Learning by doing

Learning by doing is reflected by the accumulation of the stock of human capital, or the productive knowledge that the consumer has on her camera. I model human capital accumulation through pictures taking, in a way that is similar to the labor/firm learning by doing literature (Besanko et al., 2010, 2014; Shaw and Lazear, 2008; Levitt et al., 2013). Human capital $H_{ikt}$ on camera $k$ accumulates by one unit at the end of the period, whenever the consumer has taken pictures.

$$H_{ikt+1} = H_{ikt} + D_{it}. \quad (5)$$
Figure 7: Timing of decisions and evolution of the state variables

Notes: The figure presents the timing assumptions of consumer decisions and state evolution, in a given period.

As normalization, the individual has 1 unit of initial human capital at the start of the sample:\footnote{I normalize it to 1 so that the productivity of picture quality is increasing in the shape parameter $\kappa$, introduced in Equation (8). Heterogeneity in the initial experience is captured by individual-specific intercept in Equation (7).}

\[ H_{t1} = 1. \]

5.4 Switching cost

Human capital is product specific, and hence cannot be fully transferred to other cameras. For example, knowledge on menu layouts of one camera cannot be fully applied to the others. Hence, there is attrition on consumer human capital when she switches from camera $k$ to $k'$. Specifically, motivated by Figure 6, I impose that the switching cost is \emph{proportional} to the current human capital stock:

\[ H_{ikt} - H_{ik't} = s_{ikk'} \cdot H_{ikt}, \quad (6) \]

where the switching cost $s_{ikk'}$ is set to be symmetric in $k$ and $k'$. Further restrictions will be imposed on $s_{ikk'}$ to reduce the number of parameters to be estimated.
5.5 Production function

The individual derives utility from the quality of the best picture she produces. This is the output of a production function of the “physical capital quality” – a common function $f$ of the brand-format combination of the current camera – and an individual-specific, concave function of the human capital stock, $g_i$. Formally,

$$Q_{ikt}(K_{it}, Y_{it}, H_{ikt}) = q_i + f(K_{it}, Y_{it}) \cdot g_i(H_{ikt}) + \eta_{ikt} \quad (7)$$

and

$$f(K_{it}, Y_{it}) = \sum_{k=1}^{6} \gamma_k 1(K_{it} = k) + Y_{it},$$

where $Y_{it} = \sum_{y=2001}^{2013} \phi_y 1(year_k = y)$ is the year-of-introduction effect of camera model $k$ on picture quality, and I name it “technology index”. Given the separable structure, $\gamma_k$ captures time-invariant camera format effect, whereas $\phi_y$ captures the time effect, or a general trend of technology, in the quality of pictures. Overall, the function $f(K_{it}, Y_{it})$ captures the camera specific returns to human capital stock.

On the other hand, I restrict

$$g_i(H_{ikt}) = H_{ikt}^{\kappa_i} \quad (8)$$

where $\kappa_i \in (0, 1)$ dictates the concavity of picture quality with respect to the human capital stock.

In the previous version of this paper, I presented a model with a non-parametric learning curve, which generates qualitatively the same results.

Finally, $\eta_{ikt}$ is an independent and identically distributed (IID) econometric error, that captures non-systematic variation in the maximum picture quality.

5.6 Utility

In the model, the consumer derives per-period utility from 1) consuming the quality of the best picture she made in this period, 2) effort spent taking pictures, 3) her expenditure on buying new

---

25 The $i,t$ subscript in $Y_{it}$ captures the identity of the camera model (beyond the brand-format combination).

26 An alternative way to capture the effect of technology is to introduce observed characteristics – the most popular one being camera resolution. This is implemented in earlier versions, and I found that resolution has little explanatory power on the measured picture quality.
cameras, and 4) the immediate satisfaction from buying new cameras. Considering these four aspects, and denote I model the utility function as

\[ \bar{u}_{iat} = u_{ia}(K_{it-1}, Y_{it}, H_{ik't}, P_{k't}) + \varepsilon_{iat} \]

\[ = (\alpha_i \cdot E[Z_{ikt}|K_{it}, Y_{it}, H_{ik't}] + e_i) \cdot 1(D_{it} = 1) + \sum_{k' \neq 0} (\beta_{i1} P_{k't} + \beta_{i2} P_{k't}^2) \cdot 1(B_{it} = k') + \sum \sum \lambda_{i,k,k'} 1(B_{it} = k', C_{it-1} = k) + \varepsilon_{iat}. \]

where, following notational conventions in the above section, I denote \( k' \) as the realization of \( K_{it} \), and \( k \) as that of \( K_{it-1} \). These four sources of utility are explained below.

1) At the time when making decisions, the individual derives linear utility from the expected picture quality, since the idiosyncratic shock on the maximum picture quality, \( \eta_{ikt} \), is not yet realized at the point of decision. I allow the marginal utility on picture quality to be heterogeneous across individuals. Denote it \( \alpha_i \).

2) The consumer takes pictures in some periods but not in others. I allow for a “utility of effort” – parameter \( e_i \) – to incur whenever pictures are taken in a given period. This captures the (dis-)utility from taking pictures, if one were to generate zero quality.

3) To control for systematic variation in the camera purchase decisions that are not explained by the evolution of human capital, I consider the conventional price effects. Specifically, I impose quadratic dis-utility from price spent, when the individual purchases camera \( k' \) (i.e., \( B_{it} = k' > 0 \)). In this case where price dispersions are large, the quadratic functional form captures that marginal dis-utilities from spending an extra dollar might be different on a 80-dollar compact camera, and on a 800-dollar DSLR.\(^{27}\)

4) To account for other variation in the choice patterns, I allow for immediate utility impacts from purchasing new cameras, which can be history-dependent. Further restrictions are placed in Section 5.10.

\(^{27}\)A linear specification will not fundamentally change estimates of the other parameters, but will predict very different elasticities for DSLRs and for compact cameras, while a natural log specification will overly flatten the utility profile, within common price range for DSLRs.
5.7 State space and transitions of the state variables

I denote the state variables as \( S_{it} = (K_{it-1}, Y_{it}, H_{ikt}, P_t) \). Here, \( K_{it-1} \) is the brand-format combination of the camera at the beginning of the period. \( Y_{it} = (Y_{it-1}, \tilde{Y}_t) \) – the “technology index” – summarizes the technology level of the previous camera \( (Y_{it-1}) \) as well as the current market “state-of-the-art” technology \( (\tilde{Y}_t) \). \( H_{ikt} \) is consumer human capital with respect to the camera \( K_{it-1} = k \) at the beginning of the period. And finally, \( P_t \) is a vector of price indices for all brand-format combinations on the market at time \( t \).

The transition processes for camera brand-format \( K_{it-1} \) and human capital \( H_{ikt} \) are characterized by the camera replacement Equation (4) and the human capital transition Equations (learning by doing (5) and switching cost (6)).

Finally, I assume that individual decisions do not affect the market equilibrium prices and the market technology level. The individuals are price takers, who rationally expect an exogenous price-index transition matrix

\[
\Pi_{pp'} = \Pr (p_{kt} = p' | p_{kt-1} = p).
\]

In addition, I assume that the “personal” technology \( Y_{it} \) stays constant if an individual does not make a purchase. If she does, however, she expects the technology of the new camera to immediately jump to the market technology level. On the other hand, the market technology index \( \tilde{Y}_t \) follows an exogenous Markov process on its own. Specifically,

\[
Y_{it} = \begin{cases} 
\tilde{Y}_t & \text{if } B_{it} \neq 0 \\
Y_{it-1} & \text{if } B_{it} = 0.
\end{cases}
\]

and

\[
\tilde{Y}_t = \chi_0 + \chi_1 \tilde{Y}_{t-1} + \omega_t.
\]

The Markov assumption on the market technology follows the ideas in Gowrisankaran and Rysman (2012) and Hendel and Nevo (2006),\(^{28}\) in the follow sense. On the one hand, it is a di-

\(^{28}\)Gowrisankaran and Rysman (2012) assume that the discounted sum of future utility is Markov, while Hendel and Nevo (2006) assume that a part of the individual flow utility is Markov.
mensionality reduction assumption, so that in computing the optimal decision rules, the researcher does not have to keep track of each of all the picture quality-relevant state variables, but rather, a sufficient statistic of them. On the other hand, the assumption conjectures that the individual does not know exactly what technology level she is going to get in the next period, but her Markov belief is on average correct.

5.8 Dynamic programming

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

$$\max_a \sum_{\tau \geq t} \delta^{\tau-t} \mathbb{E}_t [u_{ia}(S_{iat}) + \epsilon_{iat}].$$

Given stationarity assumptions on the function $u_{ia}(\cdot)$ (as in (9)) and transition process of $P_t$, this is a standard dynamic decision problem in spirit of Rust (1987) and others, where the consumer solves the equivalent static decision problem

$$\max_a U_{ia}(S_{iat}) + \epsilon_{iat}$$

where the choice-specific value function $U_{ia}(S_{iat})$ is defined by the Bellman equation

$$U_{ia}(S) = u_{ia}(S) + \delta \cdot \mathbb{E} \left[ \max_a U_{ia}(S') | S, a \right].$$  \hspace{1cm} (12)

5.9 Identification

Section 3.3 discussed identification of picture quality, from cross-sectional data of picture taking and posting dates, and their cumulative views. With exogenous variation in the picture-taking dates, within pictures that are posted at the same time, one can separately identify the popularity of the Flickr website and of each individual photographer, from the quality of their pictures. Table 3 documents that the inferred picture quality follows “intuitive” patterns, in the sense that it is well correlated with the ratings data, for a small subsample of pictures with nonzero ratings. Appendix A performs robustness checks for when the upload decisions are selective.
Next, I treat each individual’s monthly maximum picture quality as data, and separately identify the evolution of picture quality, and individuals’ utility from picture quality and other market characteristics. The production function and the evolution of human capital is identified by the observed evolution of picture quality, as a function of the previous period quality, initial picture quality, identity of the camera, and the camera usage and switching decisions. With panel data, systematic variations across individuals detect heterogeneity in the evolution of human capital, while the production function parameters are the same across consumers. Of course, this is achieved by controlling for endogenous camera usage and switching decisions, which are modeled in the dynamic discrete choice problem and jointly estimated.

Identification of the dynamic discrete choice model, treating picture quality as a state variable with known evolution, is achieved under standard conditions as in Magnac and Thesmar (2002) and Kasahara and Shimotsu (2009).

5.10 Implementation

5.10.1 Production function parameters

In the production function, I assume that the returns to human capital, \( \gamma_k \), are the same for the same format of cameras. This reduces the computation burden of estimation. As a robustness check, relaxing this restriction does not introduce noticeable differences among \( \gamma_k's \) between brands.

5.10.2 Switching cost

To further parameterize the switching cost \( s_{ikk'} \), I allow it to vary across the cases when the consumer switches within the same format of products, or across formats, or across brands. I assume that switching across formats incurs no smaller switching cost than within a format; and similarly, switching across brands incurs no smaller cost than within a brand. To impose these assumptions, I specify the following structure for the switching cost across formats and across brands:

\[
1 - s_{ikk'} = \left(1 - s_{baseline}^i\right) \cdot \left(1 - s_{format}^i\right) \cdot \left(1 - s_{brand}^i\right)
\]
where $s_i^{format}$ and $s_i^{brand}$ symbolize the across-format and across-brand switching cost, taking value 0 when the individual switches within format or brand, respectively.\(^{29}\)

### 5.10.3 Choice intercepts and other explanations of state dependence

The utility function in (9) gives a very general specification of choice state dependence and choice-specific intercepts, that does not depend on the potential picture quality one generates. In implementation, I restrict the utility specification to a more parsimonious structure, which is characterized by 5 parameters:

$$
\lambda_{DSLR}(B_i^t \geq 4) + \lambda_{Canon}(B_i^t = 1, 4) + \lambda_{Nikon}(B_i^t = 2, 5)
$$

$$
+ \lambda_{FormatSwitch}(format_i^t \neq format_{i-1}) + \lambda_{BrandSwitch}(brand_i^t \neq brand_{i-1})
$$

where $\lambda_{DSLR}$ captures the immediate utility of purchasing a DSLR camera (relative to a compact camera),\(^{30}\) $\lambda_{Canon}$ and $\lambda_{Nikon}$ capture the immediate utility of purchasing specific brands, while $\lambda_{FormatSwitch}$ and $\lambda_{BrandSwitch}$ capture format- and brand- switching effects (in additional to the switching cost in human capital).

### 5.10.4 Heterogeneity

To capture heterogeneity in the preferences and the human capital formation processes, I assume that there exists a finite-mixture of permanent individual heterogeneity, both in the utility function and in the evolution of human capital. That is, I allow individuals to have different initial picture quality, different learning speeds, different switching costs, and different utility parameters. To implement this, I normalize the initial human capital to $H_{i1} = 1$. At the same time, I allow the production function intercepts $q_i$, shape parameter $\kappa_i$, as well as the switching cost $s_{ikk'}$, to be heterogeneous across individuals. On the other hand, I impose that the production function (7) is homogeneous across individuals. The parameters to estimate are a vector of production function\(^{30}\)

\(^{29}\)For example, from a Canon compact camera, switching to another Canon compact camera costs $1 - (1 - s_i^{baseline})$; switching to a Nikon compact camera costs $1 - (1 - s_i^{baseline}) \cdot (1 - s_i^{brand})$; switching to a Canon DSLR costs $1 - (1 - s_i^{baseline}) \cdot (1 - s_i^{format})$; and finally, switching to a Nikon DSLR costs $1 - (1 - s_i^{baseline}) \cdot (1 - s_i^{format}) \cdot (1 - s_i^{brand})$.

\(^{30}\)I cannot estimate a separate compact camera utility because the two brand coefficients almost capture the entire market, so a $\lambda_{Compact}$ and $\lambda_{DSLR}$ together will produce close-to-perfect colinearity with the brand parameters.
coefficients \((\gamma_k, \sigma^2\eta)\), as well as a vector of heterogeneous utility and human capital evolution parameters \((\alpha_m, \beta_m, \epsilon_m, q_m, \kappa_m, s_m)\), where \(m = 1, 2\) to represent parameters for one of the two segments.

5.10.5 Initial conditions

Heterogeneity in the prior-to-sample experience is characterized by the heterogeneous production function intercept \(q_m\).

Choices of the initial cameras are endogenous to preference heterogeneity. To endogenize the initial cameras, I compute the stationary distribution of camera formats based on the observables in the first period, as in Hendel and Nevo (2006).\(^{31}\)

5.10.6 Dimensionality reduction

Dimensionality reduction follows Equation (10), where I impose that the index function of year dummies – which summarizes the role of yearly technology on the evolution of picture quality – follows a linear transformation at the point of camera switching. This in spirit follows Gowrisankaran and Rysman (2012), who assume that the value function is a Markov index function.

Different from their work, however, I can compute the index \(Y_{it}\) given parameters \(\phi_y\) – as it is an explicit function of the primitives – and hence avoid the extra fixed point loop in Gowrisankaran and Rysman (2012). Therefore, the algorithm in estimation does not deviate from the classical Nested Fixed Point algorithm in Rust (1987).

5.10.7 Discount factor

Finally, I give all consumers a discount factor of 0.95 monthly. The discount factor implies that the consumers will discount away 70% of the value of a camera in two years, which I find intuitive. This also implies an annual discount factor of 0.54, which is lower than the field-data estimates by

\(^{31}\)Alternatively, one could model the initial brand-format distributions. I only model the initial camera format distributions because, monthly choice probability being close to zero, the brand-format choice probability matrix is more likely to be singular at some parameter values.
Table 4: Production function estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return to human capital - all compacts</td>
<td>2.30</td>
<td>0.26</td>
</tr>
<tr>
<td>- all DSLRs</td>
<td>2.62</td>
<td>0.20</td>
</tr>
<tr>
<td>Year of intro - 2008</td>
<td>-0.29</td>
<td>0.01</td>
</tr>
<tr>
<td>- 2009</td>
<td>-0.31</td>
<td>0.04</td>
</tr>
<tr>
<td>- 2010</td>
<td>-0.23</td>
<td>0.07</td>
</tr>
<tr>
<td>- 2011 or later</td>
<td>0.12</td>
<td>0.07</td>
</tr>
<tr>
<td>Scale of error term ($\sigma_v$)</td>
<td>0.68</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Note: This table reports structural estimates for the production function. Year dummies before 2008 is restricted to zero because of potential collinearity with the individual-specific constant. Bootstrap standard errors are reported, which are computed from estimates of 20 random samples with replacement.

Dubé et al. (2009) (0.7), but higher than the estimates for the non-durable goods case in Yao et al. (2012).  

6 Estimation results

6.1 Production function

Table 4 shows that the returns to experience is 13.9% higher, when using a DSLR camera – which qualitatively confirms the pattern shown in Appendix Figure 12. This shows that an advanced camera is a strong complement to consumer human capital (and vice versa). However, quantitatively, the model finds that a DSLR camera does not produce as high the picture quality as the descriptive evidence, because of the endogenous camera choices made by individuals of different experience.

6.2 Initial picture quality

I estimate the constant term in the production function, $q_i$, separately for each type of consumers. I interpret them to be the initial picture quality prior to registering on Flickr. Among other parameters, Table 5 presents estimates of $q_i$, which is $-2.88$ for the first type, and $-0.96$ for the second. This indicates a small part of the sample (34%) registered their Flickr accounts (i.e., enters the

32 The discount factor in Yao et al. (2012) is close to zero annually, but is reasonable in their context of mobile phone contracts, since it requires a much shorter-term thinking on the consumer side.
Table 5: Utility, learning and switching cost estimates

<table>
<thead>
<tr>
<th></th>
<th>&quot;novices&quot;</th>
<th>s.e.</th>
<th>&quot;experts&quot;</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility: pref to quality ($\alpha_i$)</td>
<td>1.92</td>
<td>0.26</td>
<td>1.28</td>
<td>0.27</td>
</tr>
<tr>
<td>- effort ($e_i$)</td>
<td>0.01</td>
<td>0.11</td>
<td>-0.88</td>
<td>0.61</td>
</tr>
<tr>
<td>- expenditure ($\beta_{1i}$)</td>
<td>-1.34</td>
<td>0.31</td>
<td>-1.34</td>
<td>0.29</td>
</tr>
<tr>
<td>- expenditure squared ($\beta_{2i}$)</td>
<td>0.06</td>
<td>0.02</td>
<td>0.08</td>
<td>0.02</td>
</tr>
<tr>
<td>- preference to DSLR ($\lambda_{DSLR}$)</td>
<td>3.81</td>
<td>1.42</td>
<td>3.19</td>
<td>1.19</td>
</tr>
<tr>
<td>- preference to Canon ($\lambda_{Canon}$)</td>
<td>-1.35</td>
<td>0.20</td>
<td>-1.57</td>
<td>0.28</td>
</tr>
<tr>
<td>- preference to Nikon ($\lambda_{Nikon}$)</td>
<td>-1.31</td>
<td>0.23</td>
<td>-1.67</td>
<td>0.17</td>
</tr>
<tr>
<td>- switching formats ($\lambda_{FormatSwitch}$)</td>
<td>-0.50</td>
<td>0.19</td>
<td>-0.75</td>
<td>0.22</td>
</tr>
<tr>
<td>- switching brands ($\lambda_{BrandSwitch}$)</td>
<td>-1.82</td>
<td>0.22</td>
<td>-2.46</td>
<td>0.15</td>
</tr>
<tr>
<td>Initial picture quality ($q_i$)</td>
<td>-2.88</td>
<td>0.24</td>
<td>-0.96</td>
<td>0.34</td>
</tr>
<tr>
<td>Shape parameter ($\kappa_i$)</td>
<td>0.08</td>
<td>0.02</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td>Switching cost: baseline ($s_{baseline,i}$)</td>
<td>0.06</td>
<td>0.03</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>- additional from across formats ($s_{format,i}$)</td>
<td>0.07</td>
<td>0.02</td>
<td>0.10</td>
<td>0.03</td>
</tr>
<tr>
<td>- additional from across brands ($s_{brand,i}$)</td>
<td>0.07</td>
<td>0.03</td>
<td>0.11</td>
<td>0.02</td>
</tr>
<tr>
<td>Type probability</td>
<td>0.66</td>
<td>0.09</td>
<td>0.34</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Note: This table reports structural estimates for the rest of the parameters. Bootstrap standard errors are reported, which are computed from estimates of 20 random samples with replacement.

sample) with considerably more photography experience compared to the rest. For this reason, I denote this smaller segment the “experts”, and the rest the “novices”. Also, note that the across-consumer difference is much larger than the average within-consumer evolution of picture quality, the latter shown in Figure 6.

### 6.3 Learning by doing

Table 5 also presents estimates for the returns to learning and the switching cost. The shape parameter $\kappa_i$ determines the importance of consumer human capital in shaping her picture quality, i.e. the returns to learning. Also, the same parameter captures her learning speed, or the marginal increase in knowledge from each time she takes pictures. From the estimates, I find that $\kappa_i$ is far below 1, which is strong evidence for decreasing returns to experience. In addition, the returns to learning implied by the shape parameter is different across segments, and I find that for the novice consumers, additional experience gained in the sample plays a much larger role, than that of the experts. This indicates that those with lower initial knowledge stocks learn faster – consistent with the decreasing marginal returns from learning.
Given the parameter estimates, Figure 8 presents the evolution of consumers’ (maximum) picture quality in monetary value, conditional on the experience in photography.\(^{33}\) Given the consumer type and the camera format, the figure clearly shows learning by doing with decreasing speed. Quantitatively, the first year of experience increases the value of a novice’s picture quality by a monetary value of $60. This is to say, for a novice consumer, she now values the picture-taking activity in a month by 60 US dollars more. By the end of year 5, this value is further increased to $120. On the other hand, the contribution of experience for an expert consumer is much lower, due to the lower returns to learning \((\kappa)\). The first year of experience increases picture quality by $30, while the first 5 years increases it by $50.\(^{34}\)

The returns to experience found here seem small at the first glance – especially compared to the price differences between entry level and advanced digital cameras. However, note that the accumulation of human capital is persistent, and hence, the utility gains from learning hence go far into the future.

Comparable estimates include Shaw and Lazear (2008), who find that the output of production workers increases by 53\% in their first 8 months on the job.

### 6.4 Non-transferable human capital and the switching cost

As mentioned in Section 5.10, I allow switching costs to be specific to within/across formats and brands, imposing that the across-format or brand switching cost is no smaller than the within-format or brand counterpart.

It is natural to expect that previous knowledge is less applicable if a user switches to a camera of a different format, e.g. from a compact camera to a DSLR – as the handling and operation of the product is very different, despite general principles of photography still apply. Moreover, I also find that across-brand switching is an important source of switching cost. This implies that there are vast differences in product design across different brands – such as brand-specific menu and button layouts.

Table 5 also presents the switching cost estimates, separately for each segment. I find that for...

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\(^{33}\)Due to the vast differences in the initial conditions, I present the increases in the monetary value of picture quality, relative to the first period.

\(^{34}\)In the model-free evidence section, the left panel of Figure 6 predicts faster increase in the picture quality, because changes in the camera format are not controlled for.
Figure 8: Evolution in the monetary value of picture quality

Notes: The solid lines depict the evolution of the individuals’ monthly highest picture quality, in monetary values, conditional on the years of experience. The dashed lines represent the monetary values of the instantaneous drop of picture quality, at an across-brand, within-format camera switch. These are plotted separately for the novice and the expert segments, only for consumers who use a DSLR. One can calculate the values for compact camera users by multiplying $\gamma_{\text{compact}} / \gamma_{\text{dslr}} = 0.88$. 
a current “novice” consumer using a Canon compact camera, switching to another Canon compact camera costs 6% of her human capital, while switching to a Nikon compact camera costs 13%. If she decides to upgrade to a DSLR camera, switching to a Canon DSLR costs 13% of her human capital, and 19% for switching to a Nikon DSLR. For an “expert” consumer, the additional knowledge she gains in sample is much more product specific; and for her, switching from a Canon compact camera to a Nikon DSLR costs 26%.

The dashed curves in Figure 8 show the picture quality after a counterfactual, within-format and across-brand switch (e.g. from a Canon DSLR to a Nikon one), in terms of monetary value – which demonstrates the extent of the switching cost. Although the model for switching cost is restrictive, the predicted, proportional switching cost patterns closely resembles the model-free patterns in Figure 6, or in Appendix Figures 13.

6.5 Other utility parameters

Between segments, the utility parameters from consuming picture quality and from purchasing cameras are different. A consumer from the novice segment derives slightly higher utility from consuming a unit of picture quality, yet much smaller dis-utility taking pictures. The dis-utility term, called “effort”, rationalizes that a consumer does not take pictures every period. It also represents how costly it is for each type of consumers to obtain an additional unit of human capital. Despite the higher “effort” for the expert segment, their low returns to learning and high initial quality results in a flatter picture-taking decision and camera-demand decision profiles, compared to the novice segment.

The nonlinear price effects show that, for a one-dollar price change, the individuals are much more sensitive at the lower price range. For the two segments, they become insensitive to price changes at 1,100 and 840 dollars, respectively. This covers all the observed compact camera prices, and 98% of the average monthly DSLR prices. Hence, the model generates downward-sloping demand.

The instantaneous utility parameters from camera purchase and brand switching – that are unrelated to picture quality – show that there is considerably positive utility from purchasing a DSLR camera. This might represent the utility from using the advanced camera features from
Table 6: Average short-run elasticities

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>No purchase</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Canon Compact</td>
<td>-1.8530</td>
<td>0.0105</td>
<td>0.0102</td>
<td>0.0103</td>
<td>0.0101</td>
<td>0.0101</td>
<td>0.0101</td>
</tr>
<tr>
<td>(2) Nikon Compact</td>
<td>0.0062</td>
<td>-1.8667</td>
<td>0.0059</td>
<td>0.0058</td>
<td>0.0059</td>
<td>0.0057</td>
<td>0.0056</td>
</tr>
<tr>
<td>(3) Other Compact</td>
<td>0.0050</td>
<td>0.0051</td>
<td>-1.8642</td>
<td>0.0050</td>
<td>0.0051</td>
<td>0.0051</td>
<td>0.0049</td>
</tr>
<tr>
<td>(4) Canon DSLR</td>
<td>0.2032</td>
<td>0.2213</td>
<td>0.2070</td>
<td>-3.5078</td>
<td>0.2124</td>
<td>0.2063</td>
<td>0.2047</td>
</tr>
<tr>
<td>(5) Nikon DSLR</td>
<td>0.0979</td>
<td>0.1012</td>
<td>0.0990</td>
<td>0.1001</td>
<td>-3.7606</td>
<td>0.1014</td>
<td>0.0962</td>
</tr>
<tr>
<td>(6) Other DSLR</td>
<td>0.1517</td>
<td>0.1603</td>
<td>0.1574</td>
<td>0.1581</td>
<td>0.1657</td>
<td>-3.6410</td>
<td>0.1506</td>
</tr>
</tbody>
</table>

Note: This table reports short-run elasticities. I compute elasticities by first calculating the implied choice probabilities for each type of consumer, and then the counterfactual choice probabilities when prices for a given brand-format in a row are temporarily reduced by 10% for the given month. Then, elasticities are computed from the averaged choice probabilities. For example, the first row, second column reads: a 10% temporary decrease in the price of Canon compact cameras decreases the demand for Nikon compact camera by 0.105%.

these cameras, or simply from status effects of using the DSLRs, and rationalizes the tendency to upgrade despite at a low human capital level. Finally, the utility parameters on brand-switching and format-switching are conventionally negative, and captures alternative explanations to state dependence that are unrelated to learning by doing.

6.6 Implied short-run price elasticities

To verify whether the model produces conventional price effects, I simulate price elasticities from an instantaneous 10% price decrease for a given brand-format, which is not expected to last beyond the given month. I calculate the implied choice probabilities for each type of consumers, with or without the price change, and weight average the choice probabilities to compute the implied demand. The price elasticities are then computed from the percentage changes in demand, as responses to the 10% decrease in the prices.

Shown in Table 6, I find that the short-run price elasticities are conventional, as in other empirical demand estimation literature in the digital camera industry (Song and Chintagunta, 2003; Gowrisankaran and Rysman, 2012). For example, a 10% decrease in the prices for Canon DSLRs increases the product’s current-period demand by 35%. Most of the additional demand comes from the consumers who would otherwise not purchase in this period (the “no purchase” category).\(^{35}\)

\(^{35}\)On average, the “no purchase” alternative has a baseline market share of 95%.
7 Counterfactual Experiments

7.1 Overview

With the parameter estimates, this section investigates 3 managerial implications. The first, and perhaps most straightforward, implication is that consumer experience increases their tendency to purchase advanced products. I find that for starting consumers, a 1-year increase in their human capital raises the sales of the advanced cameras in the same brand by 26%. Secondly, since experience accumulation leads to higher utility from product usage, consumers directly demand the provision of experience. I find that, for a 1-year increase in human capital, an average starting consumer is willing to pay $405 one-off, which is close to her expected discounted lifetime expenditure on digital cameras. Finally, since the imperfect transferability is most apparent in across-brand switching, the switching cost in knowledge creates brand loyalty, making across-brand switching increasing costly.

7.2 Learning by doing and sales of advanced products

Product usage becomes more enjoyable, when consumers are equipped with more experience on the current products. An increase in the consumer human capital raises her valuation on the complementary product features – especially those in the advanced products – and downplays the importance of price. In this experiment, I simulate the effect on sales, when consumers are given 1 extra year of experience, that can be fully applied to all brand-format of cameras. The results are presented in Table 7, in the format of relative changes in demand.

I find that, for Canon compact camera users who are in the sample for a year, a 1-year human capital shock increases their demand for Canon DSLR cameras by 26%, and Nikon DSLRs by 35%. The higher percentage increase for Nikon is due to the low base choice probabilities. At the same time, it also increases the sales of compact cameras – by 21% and 28%, respectively. This indicates that having a higher level of photography human capital complements the demand for digital cameras, so that an individual will be more likely to upgrade her entry-level product to an advanced one, or simply repurchase the same camera format to stay with the current technology.

For more experienced consumers, the effects are smaller or are negative. This is the result of
Table 7: Sales counterfactuals for Canon compact camera users

<table>
<thead>
<tr>
<th></th>
<th>Canon compact</th>
<th>Nikon compact</th>
<th>Canon DSLR</th>
<th>Nikon DSLR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 year from start</td>
<td>1.2124</td>
<td>1.2816</td>
<td>1.2588</td>
<td>1.3549</td>
</tr>
<tr>
<td>2 years</td>
<td>1.0402</td>
<td>1.1257</td>
<td>1.1270</td>
<td>1.1378</td>
</tr>
<tr>
<td>3 years</td>
<td>0.9322</td>
<td>1.0443</td>
<td>1.0867</td>
<td>0.9487</td>
</tr>
<tr>
<td>4 years</td>
<td>0.8936</td>
<td>1.0302</td>
<td>1.0655</td>
<td>0.8912</td>
</tr>
<tr>
<td>5 years</td>
<td>0.9160</td>
<td>1.0277</td>
<td>1.0502</td>
<td>0.9022</td>
</tr>
</tbody>
</table>

Note: This table reports percentage changes in sales for consumers with different amount of experience, who are, in the counterfactual experiment, given 12 months of additional human capital. For example, the first number reads: for consumers who are in the sample for 1 year, increasing their human capital by 1 year increases their purchase probability of Canon compact cameras by 21.24%, relative to the benchmark value.

the decreasing learning speed and the increasing switching cost.

7.3 The demand for experience

Having a larger human capital stock not only changes demand, but the direct impact on product-usage utility also increases welfare (Michael, 1973). Hence, there is a direct demand for usage experience that the supply side can provide. In the context of digital cameras, examples of such include free product training,\(^\text{36}\) photo contests (to incentivize product usage), and so forth.

In the second counterfactual experiment, I measure the size of such demand, by the utility-equivalent monetary amount to a 1-year increase in experience. Specifically, I calculate the amount of a fixed monthly subsidy, which provides the same expected sum of current and future utility as a 1-year increase in the consumer’s human capital. Formally, for consumer \(i\) at time \(t\), I find \(EV_i\) charged under any choice (including the outside option \(B_{it} = 0\), which had zero expenditure), such that

\[
\mathbb{E}_{it} \left[ \max_a U_{ia} (S_{it}; P_{k't}, \mathbf{1}(B_{it} \neq 0) - EV_i, H_{it}) \right] - \mathbb{E}_{it} \left[ \max_a U_{ia} (S_{it}; P_{k't}, \mathbf{1}(B_{it} \neq 0), H_{it} + \Delta H) \right] = 0,
\]

where \(P_{k't} \mathbf{1}(B_{it} \neq 0) - EV_i\) characterizes expenditure after subsidy \(EV_i\) while \(H_{it} + \Delta H\) is the human capital after the increase in experience (\(\Delta H = 12\) months). Finally, I present the discounted sum of the fixed monthly payment, at \(\delta = 0.95\).

\(^{36}\)For example, in India, Vietnam and potentially some other countries, Canon provides free short-lectures for users who just purchased their DSLRs.
Table 8: Valuation for additional 1 year of experience

<table>
<thead>
<tr>
<th></th>
<th>WTP: novice</th>
<th>WTP: expert</th>
<th>WTP: average</th>
<th>monthly expenditure</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 year from start</td>
<td>447.4989</td>
<td>325.3024</td>
<td>405.9334</td>
<td>332.8261</td>
</tr>
<tr>
<td>2 years</td>
<td>354.9264</td>
<td>181.1099</td>
<td>295.8021</td>
<td>382.8253</td>
</tr>
<tr>
<td>3 years</td>
<td>236.3609</td>
<td>119.8353</td>
<td>196.7243</td>
<td>426.4285</td>
</tr>
<tr>
<td>4 years</td>
<td>181.7395</td>
<td>91.5023</td>
<td>151.0450</td>
<td>444.2696</td>
</tr>
<tr>
<td>5 years</td>
<td>161.2669</td>
<td>82.4507</td>
<td>134.4573</td>
<td>464.0309</td>
</tr>
</tbody>
</table>

Note: This table reports, for consumers in different segments and with different levels of experience, the amount of compensation that is welfare-equivalent to a counterfactual increase in human capital by 12 months. I compute the amount of a fixed monthly subsidy, that is equivalent of this policy change – in the sense that it equates the expected sum of future utility for the consumer. I then take discounted sum of this stream of subsidy. For example, the first number reads: for consumers with 1 year of experience, her valuation of the 1-year extra human capital is measured as the utility-equivalent one-off tax at 447 dollars. The last column reports the expected discounted lifetime expenditure for consumers with the corresponding experience (without the extra human capital). This number is provided as a benchmark to understand the magnitude of consumer valuation of knowledge.

Table 8 presents the results, separately for consumers from different segments, with different experience levels. I find that across segments, the valuations for additional experience are comparable. This is because although the expert segment has lower returns to experience in the production function, it is also more costly for them to obtain experience on their own, because of the higher $e_i$. On the other hand, the less experienced consumers value the additional human capital much higher than the experienced consumers, due to the decreasing marginal returns to learning. An average starting consumer values the additional experience by $405, which is even higher than their discounted expected lifetime expenditure in the digital camera product category. As a comparison, the tuition fee for a one-month New York Institute of Photography online course is $50, yielding a discounted sum of $460 for a year.\(^{37}\) For the more experienced consumers, the valuation decreases due to decreasing returns to experience – down to $134, or 29\% of the consumer’s expected lifetime expenditure.

### 7.4 Product specific experience and brand loyalty

The final two experiments focus on the effect of non-transferable consumer human capital, where the across-brand component plays a major role. For example, switching from a Canon compact

\(^{37}\)Information from http://www.nyip.edu/courses/professional-photography in September 2014.
camera to a Nikon DSLR costs 17% of a novice consumer’s human capital stock, or 26% of an expert’s. Switching within the same brand would have costs the two consumers 13% or 17% of their human capital stock, respectively. This difference between within- and across-brand switching cost incentivizes the consumer to stick to a particular brand, and the effect is accentuated when experience with the brand further accumulates. As a result, not only would a consumer avoid brand switching *ex post*, in fear of losing part of the already accumulated experience, but they also tend to avoid brand switching *ex ante*, by planning their brand choice ahead in accordance with the expected long-run product characteristics. These two aspects are shown in two counterfactual experiments.

To demonstrate that experience accumulation can cause the consumer to be locked in, I simulate counterfactual choice probabilities when the brand-switching cost component in human capital is removed. Table 9 presents, for consumers who are currently using Canon compact cameras, the *relative* changes in choice probabilities for both entry-level and advanced products the under this counterfactual scenario. I condition on that the consumers are currently using Canon compact cameras, to better see the differences across formats and brands.

I find that for consumers with more experience, switching costs are more and more salient in changing their choice profiles. For consumers with 5 years of experience, the sales of Nikon DSLR cameras and Canon compact cameras increases by 28% and 25%, respectively. This naturally comes from the increasing nature of switching cost in the consumer knowledge stock. From the table, those who will switch to DSLRs at some point are more willing to switch to Nikon DSLRs, while those who decides to stick to the compact cameras (due to preference as well initial human capital heterogeneity), decides to increase their shares of expenditure on Canon. The second point seems counter-intuitive, but comes from the high across-brand switching dis-utility which is still present. Hence, with higher potential human capital (due to the switching cost decrease), some consumers will increase their purchase probability into compact cameras, but will do so within brand.

Appendix Table 3 shows the results of another experiment, where I keep the switching costs as estimated, but eliminate the brand-switching *dis-utility*, in the fifth row of Table 5. This can be interpreted as “other switching costs” that are unrelated to consumption of picture quality. I find that elimination of brand-switching dis-utility *increases* the purchase probabilities of Nikon
### Table 9: Choice probability changes without switching cost, Canon compact camera users

<table>
<thead>
<tr>
<th></th>
<th>Canon compact</th>
<th>Nikon compact</th>
<th>Canon DSLR</th>
<th>Nikon DSLR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 year from start</td>
<td>0.0027</td>
<td>0.0040</td>
<td>0.0023</td>
<td>0.0039</td>
</tr>
<tr>
<td>2 years</td>
<td>0.0088</td>
<td>0.0111</td>
<td>0.0060</td>
<td>0.0148</td>
</tr>
<tr>
<td>3 years</td>
<td>0.0647</td>
<td>0.0069</td>
<td>0.0180</td>
<td>0.0599</td>
</tr>
<tr>
<td>4 years</td>
<td>0.1484</td>
<td>0.0119</td>
<td>0.0284</td>
<td>0.1613</td>
</tr>
<tr>
<td>5 years</td>
<td>0.2542</td>
<td>0.0312</td>
<td>0.0363</td>
<td>0.2813</td>
</tr>
</tbody>
</table>

**Note:** This table reports counterfactual changes in the predicted choice probabilities when all switching costs in human capital transition are eliminated. The changes are reported as relative to the benchmark model estimates, averaged across all consumers in the sample, conditional on their level of experience. For example, the first number reads: the demand for Canon compact cameras will increase by 0.27%, when all switching costs in human capital transition are eliminated.

DSLR cameras by up to 9 times. Even though this seems to be a much larger effect, it is not clear whether the parameters we estimated are truly causality (versus merely heterogeneity in the brand preferences).

On the other hand, expectations of consumer switching costs also lead to pre-planning on brand choice, in the sense that because choices of brand can become increasingly costly over time, consumers put great importance on the long-run expected product characteristics, when making their brand choices. In my final counterfactual experiment, I show that consumers instantaneously switch to the brand with more attractive permanent prices. In fact, the effect is large even for consumers who are not very forward-looking, as in the structural analysis, they have a discount rate that is drastically higher than the market interest rate.\(^{38}\)

In Table 10, I simulate price elasticities from a known, permanent 10% price decrease – the only difference from Table 6 is that the price changes are permanent and the consumers rationally expect this.\(^{39}\) Most notably, the table shows that, in face of a permanent price change in one of the DSLRs, many consumers will instantaneously switch to the compact cameras in the same brand. This is because within-brand switching costs are much lower than across-brand switching costs, hence making knowledge acquired from using the previous product much more valuable if the consumer sticks with the same brand. As a result, when Nikon DSLRs are permanently cheaper, a Canon user who is not prepared to purchase a DSLR right away, might decide to purchase a Nikon

---

\(^{38}\)I assume a discount factor of 0.95 monthly, or equivalently, 0.54 annually.

\(^{39}\)I only report elasticities for Canon and Nikon products for the ease of reading, while the complete table can be found at Appendix Table 2.
Table 10: Average long-run elasticities for Canon and Nikon products

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Canon Compact</td>
<td>-1.9383</td>
<td>0.0288</td>
<td>0.0268</td>
<td>0.0417</td>
</tr>
<tr>
<td>(2) Nikon Compact</td>
<td>0.0126</td>
<td>-1.9628</td>
<td>0.0245</td>
<td>0.0093</td>
</tr>
<tr>
<td>(4) Canon DSLR</td>
<td>-1.6431</td>
<td>0.8915</td>
<td>-3.9841</td>
<td>1.1946</td>
</tr>
<tr>
<td>(5) Nikon DSLR</td>
<td>0.3735</td>
<td>-2.3449</td>
<td>0.7000</td>
<td>-4.8753</td>
</tr>
</tbody>
</table>

Note: This table reports long-run elasticities, computed from demand responses to permanent price changes of 10% for a given brand-format of camera. For example, the first row, second column reads: a foreseeable, permanent 10% price decrease for Canon compact cameras decreases the demand for Nikon compact cameras, by 0.427%. Only Canon and Nikon products are included for the ease of reading, while the complete table can be found at Appendix Table 2.

compact camera. In doing so, her further-acquired knowledge can be transferred within Nikon, with lower attrition. Analogous arguments hold for Nikon users in this situation. This explains that, intertemporally, products within a brand can be strong intertemporal complements.

8 Concluding Remarks

This paper quantifies the importance of consumer learning by doing – i.e. accumulation of product-specific human capital through usage – on their demand for advanced products. In the context with entry-level and advanced digital cameras, I measure the returns to consumer experience, via looking at how a homogenous set of viewers receive a consumer’s pictures, taken at different points in time. On the one hand, experience leads to higher utility from product usage (in this case, via higher picture quality). Thus, not only is the provision of knowledge valued by the consumer, but it also increases her demand for advanced products. I find that for a beginner, increasing her human capital by 1 year results in a 26% higher demand for within-brand product upgrades. On the other hand, I find that up to 26% of a consumer’s product experience is not fully transferable, and this discourages product switching – in particular between brands where product-design differences are greater. As a result, more experienced consumers display greater brand loyalty; and knowing so, even mildly forward-looking consumers consider products across brands to be much more substitutable in the long run, than those within a brand.

The model of consumer learning by doing that is proposed in this paper has great generalizability in home electronics, sports equipment, entertainment, and other categories that require
consumer skills to use the products. From a managerial point of view, understanding the evolution of consumer knowledge not only helps understand the evolution of their demand – in particular the migration from entry level to more advanced products, but it also helps understand their tendency to be locked in to products that are similarly designed as their previous ones. Further, because usage experience is desirable on its own, there is demand for supply-side provision of consumer knowledge, such as the firm offering training services, competitions in user content creation, or simply designing products that are easy to use. From the manager’s perspective, whether such actions are profitable depends not only on the returns to experience, but also on how widely-applicable the product knowledge is.

The empirical exercise in this paper is done on a relatively small sample, which might be non-representative; however, the difficulty of measuring the returns to experience limits the usage of more standard market share data, used in Song and Chintagunta (2003), Gowrisankaran and Rysman (2012), among others. This is related to the general difficulty of identifying the source of state dependence from choice data alone (Ching et al., 2013), which is beyond the scope of this paper.
References


Yao, Song, Carl F Mela, Jeongwen Chiang and Yuxin Chen (2012), ‘Determining consumers’
discount rates with field studies’, *Journal of Marketing Research* **49**(6), 822–841.

Youn, N., I. Song and D. MacLachlan (2008), ‘A multi-category approach to modeling consumer
preference evolution: The case of sporting goods’.
Appendices

A Returns to experience in photography

A.1 Overview

This section estimates the returns to experience in photography in reduced form, where the model is flexible enough to allow for deviations from the assumptions used to infer picture quality, in Section 3.3. Hence, this section also serves as a robustness check for the picture quality measure.

A.2 Specifications

I first further assume quadratic specification of picture quality $q_{ip}$ from Equation (2):

$$q_{ip} = \theta_1 x_{ip} + \theta_2 x_{ip}^2 + \sum cam_{it} + q_{i0} + \eta_{it}$$

which is a quadratic on experience $x_{ip}$, plus a set of camera fixed effects, individual fixed effect $q_{i0}$, and a error term $\eta_{it}$. I then regress

$$\log(views_{ip}) = \sum_{t_0,t_1} \Phi_{t_0 t_1} + z_{ip} \psi + \theta_1 x_{ip} + \theta_2 x_{ip}^2 + \sum cam_{it} + q_{i0} + \eta_{it}$$

and the parameters $\theta_1$ and $\theta_2$ capture the returns to experience. Note that this specification shares essentially the assumption I use to infer picture quality, other than the additional quadratic functional form on experience, and the separability in camera dummies.

There are, however, two potential concerns to the assumptions to Equation (2). First, the flow of viewers could interact with experience, resulting in heterogeneous display-window effect. In other words, $\Phi_{t_0 t_1}$ might be individual specific. The second concern is associated with the timing of upload, i.e. the user might strategically choose the time to upload a picture based on its quality. Both arguments point to the heterogeneity of the display window dummies.

With this in mind, I also estimate the returns to experience on a more-flexible specification. Although this cannot be used to infer picture quality, it serves as an robustness check. Specifically,
Appendix Table 1: Returns to experience in photography

<table>
<thead>
<tr>
<th></th>
<th>individual fixed effect</th>
<th>individual-display window fixed effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>experience (100 months)</td>
<td>0.641***</td>
<td>0.546***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>experience sq (0000s)</td>
<td>-0.139***</td>
<td>-0.116***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>camera dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>topic dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>upload order</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>display window</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>months since joined Flickr</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>number of pics uploaded</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Rsq.</td>
<td>0.112</td>
<td>0.006</td>
</tr>
<tr>
<td>obs.</td>
<td>1557232</td>
<td>1560224</td>
</tr>
</tbody>
</table>

Note: This table provides reduced form estimates of the returns to experience in photography. The dependent variable is log of cumulative number of views, per picture level. The first column corresponds to Equation (13), where we infer the returns to experience using within-individual variation, but adding covariates to control for aggregate calendar time trend in Flickr. The second column reports estimates using within-individual-upload-time variations, based on the specification in Equation (14). Measured in picture quality, the first specification estimates a 3-year return to experience of 21.3%, or an annualized 6.7%; the second specification estimates a 3-year return of 18.2% – annualized to 5.8%. Within-effect R-squared are provided.

I allow for interactions of individual heterogeneity and the display-window effects, resulting in individual-display-time dummies $\Phi_{i,t_0,t_1}$. Equation (13) now becomes:

$$\log (views_{ip}) = \tilde{z}_{ip} \psi + \theta_1 x_{ip} + \theta_2 x_{ip}^2 + \sum cam_{it} + \tilde{\Phi}_{i,t_0,t_1} + \tilde{\eta}_it,$$

(14)

where $\tilde{\Phi}_{i,t_0,t_1}$ now captures a combined effect of baseline picture quality $q_{i0}$ and individual-specific flow of viewers. We can regress (13) controlling for individual-batch fixed effects.

A.3 Estimates

The first column in Table (1) presents the estimation results from Equation (13). I find that the returns to experience is positive within sample period, with a decreasing marginal return. This is consistent with the learning curve measures in Shaw and Lazear (2008), Besanko et al. (2010), Levitt et al. (2013), among others. Quantitatively, the annual return to experience in the first 3 years amounts to an increase in picture quality, such that it generates 6.7% more views.
I further check the sensitivity of this result to potential endogeneity problems, as discussed. Shown in Column 2, the robust learning speed estimates are not economically different from the benchmark estimates – hence, the inferred learning curve economically robust to the potential concern of endogeneity.

B  A simple illustrative model

B.1 Model

This section provides a simple illustrative model to highlight the core mechanism. Assume that the individual derives utility from the camera quality $\gamma_k, \ k = h, l$ with $\gamma_h > \gamma_l$, and the human capital $H_{it}$, which evolves exogenously as in $H_{it+1} = H_{it} + 1$. Further, camera quality and human capital enter multiplicatively into the utility, hence they are complements.

The individual starts at technology $l$, and makes a one-shot upgrade decision, $D_{it} = 0, 1$, at the financial cost of $\beta \cdot P$, as well as a proportional human capital cost $s$. Once upgraded, she cannot turn back (and it is not rational of her to do so).

Finally, there is a random utility shock $\epsilon_{idt}, \ d = 0, 1$, conditional on the decision. We can summarize the assumptions by the utility function

$$ u_{it} = \gamma_h H_{it} - \beta P \cdot 1 (D_{it} = 1) + \epsilon_{idt}. $$

B.2 Static case

If the individual is myopic, her choice probability is

$$ \Pr(D_{it} = 1) = \mathbb{F} (\gamma_h (1-s) H_{it} - \gamma_l H_{it} - \beta \cdot P) 
= \mathbb{F} ((\gamma_h - \gamma_l) H_{it} - s\gamma_h H_{it} - \beta \cdot P) $$

where $\mathbb{F}$ is the CDF of $\Delta \epsilon$. Clearly, if

$$ (\gamma_h - \gamma_l) H_{it} - s\gamma_h H_{it} > 0 $$

51
\[
\frac{\gamma_h}{\gamma_l} > (1 - s)^{-1}
\]
then the upgrade probability profile should be increasing in \( H \). In words, when the consumer is myopic, if the instantaneous gain in technology outweighs a function of the loss in skills, then the individual tends to upgrade late due to future human capital growth.

### B.3 Dynamic case: numerical results

When the individual maximizes the discounted sum of future utility flow, the analytical problem becomes more complicated, due to the value function being hardly tractable. Instead, I provide numerical results, which demonstrates that qualitatively the same property holds as in the static case.

I set \( \gamma_h = 1.1, \gamma_l = 1, P = 12 \), and compare the resulting choice probability profiles when the consumer is myopic (\( \delta = 0 \)), or \( \delta = 0.95 \), given that there is no switching cost (\( s = 0 \)), or \( s = 0.3 \). To make choice probabilities comparable across static/dynamic cases, I set \( \beta = 0.2 \) in the static case, and \( \beta = 3 \) in the dynamic case.

Figure 9 shows the results. The two figures in Panel A confirms the previous analysis: when switching cost is large, upgrade probabilities will be decreasing in human capital. However, compared with Panel B, which shows the results of a dynamic model, there are two conclusions to be drawn:

(1) Choice probabilities still can be decreasing in human capital at high switching costs – and the qualitative take-away from the illustrative model holds in the dynamic case;

(2) However, when forward looking, the consumers are able to “shift” the upgrade timing, and upgrade earlier due to the lower switching cost. In the dynamic case (Panel B, compared to Panel A), the area below the choice probability profiles – i.e. the fraction of population using an advanced camera – is much less sensitive to the increase in switching cost.
Figure 9: Numerical choice probability in various cases

Notes: The four figures are numerical choice probabilities along consumer experience, given different parameter settings. Panel A depicts choice probabilities under a static model, with or without switching cost; while panel B depicts that of a dynamic model.
C An alternative model of household production

One can derive an alternative structural model where an advanced product is more complicated than an entry-level product, and hence, using it requires more effort. Here, the role of consumer human capital reduces such effort cost, and allows one to spend more effort into picture taking. On the other hand, switching to a different product makes some of the human capital obsolete, which increases the effort cost required to use the new product.

This section shows that such a model generates similar predictions to our benchmark model. First, assume that expected picture quality is produced by the camera technology specific to camera $k$, $\Gamma_k$, and some consumer effort, $E_{it}$:

$$\mathbb{E}[Q_{ikt}] = \Gamma_k \cdot E_{it}$$

but spending effort incurs a cost, specific to the current camera, and dependent on the current human capital:

$$c_k(H_{it}) \cdot (E_{it})^\sigma$$

with $c_k(H_{it}) > 0$ and $\sigma > 1$. This is to say, it is always possible to produce the best picture, but for a consumer with low human capital level, producing high quality picture might not be rational. In addition, the marginal cost of producing additional picture quality is increasing.

The consumer maximizes the net utility from consuming the picture quality net of the cost. In other words, she solves

$$\max_{E_{it}} \alpha \Gamma_k \cdot E_{it} - c_k(H_{it}) \cdot (E_{it})^\sigma$$

where again, $\alpha$ is the marginal utility from consuming the picture quality.

$$\alpha \Gamma_k - c_k(H_{it}) \cdot \sigma (E_{it}^*)^{\sigma-1} = 0,$$

or

$$E_{it}^* = \left(\sigma^{-1} \alpha \Gamma_k (c_k(H_{it}))^{-1}\right)^{\frac{1}{\sigma-1}}$$
Substitute \( E_{it}^* \) into the production function, and assume that

\[
c_k(H_{it}) = c_{0k}/H_{it},
\]

and we can see the similarity to the benchmark model:

\[
E[Q_{ikt}]|E_{it}^* = \Gamma_k \cdot \left(\sigma^{-1} \alpha \Gamma_k (c_k(H_{it}))^{-1}\right)^{\frac{1}{\sigma-1}}
\]

\[
= \sigma^{-\frac{1}{\sigma-1}} \alpha \Gamma_k \frac{1}{\sigma-1} c_k(H_{it})^{\frac{1}{\sigma-1}}
\]

\[
= \sigma^{-\frac{1}{\sigma-1}} \alpha \Gamma_k \frac{1}{\sigma-1} c_{0k}^{\frac{1}{\sigma-1}} H_{it}^{\frac{1}{\sigma-1}}.
\]

If one imposes that \( \kappa = \frac{1}{\sigma-1} \) and

\[
\gamma_k = \sigma^{-\frac{1}{\sigma-1}} \alpha \Gamma_k \frac{1}{\sigma-1} c_{0k}^{\frac{1}{\sigma-1}} + \kappa
\]

then we have a similar specification to the benchmark model.

However, note that the interpretation is not completely the same. Here, \( \kappa \) retains a similar interpretation – as a parameter that governs the returns to human capital. However, \( \gamma_k \) becomes an index of the returns to camera format, and a ratio that captures the tradeoff between spending effort and consuming high-quality pictures.

## D Model fit

This section examines the in-sample model fit of the purchase probabilities as well as picture quality, in comparison with the data, separately by each segment. To do this, I first compute the posterior type probability, and segment the raw data when the posterior probability of an individual being in one type is greater than 0.9. Then, I plot the time trend in raw data and purchase probability by type, together with the model predicted average quality and purchase probability.

Figure 10 shows that the model fits both purchase and picture quality data well – in that the model fit almost always lies in the 95% confidence interval of the sample average. For the novice
type, the model slightly over-predicts picture quality around year 4-6; and for the experts, the model under-predicts quality around year 2-3. As for choice probabilities, the model over-predicts the purchase probability of a DSLR around year 6-8.

Figure 10: Model fit: purchase probabilities and picture quality

Notes: These figures present in-sample fit for the baseline structural model, for picture quality and purchase probability of a DSLR, separately for both types.
E  Additional Figures and Tables

Figure 11: Switching cost controlling for camera formats

Notes: These figures present monthly maximum picture quality for each individual, before and after camera switching, conditional on the camera formats before and after. For detailed notes, see Figure 5.
Figure 12: Quality of best picture, conditional on camera format

Notes: These two figures present monthly maximum picture quality for each individual, against years of experience, conditional on usage of a given format of camera. For detailed notes, see Figure 5.

Figure 13: Quality of best picture from new and familiar cameras

Notes: These two figures present monthly maximum picture quality for each individual, separately by the format of cameras, and by whether the camera has been in use for more than 3 months. For detailed notes, see Figure 5.
Appendix Table 3: Choice probability changes without brand-switching *dis-utility*, Canon compact camera users

<table>
<thead>
<tr>
<th></th>
<th>Canon compact</th>
<th>Nikon compact</th>
<th>Canon DSLR</th>
<th>Nikon DSLR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 year from start</td>
<td>-0.1317</td>
<td>5.8351</td>
<td>0.4944</td>
<td>10.0064</td>
</tr>
<tr>
<td>2 years</td>
<td>-0.1599</td>
<td>5.2690</td>
<td>0.3815</td>
<td>8.6193</td>
</tr>
<tr>
<td>3 years</td>
<td>-0.1400</td>
<td>5.0750</td>
<td>0.3550</td>
<td>8.1983</td>
</tr>
<tr>
<td>4 years</td>
<td>-0.1108</td>
<td>4.9377</td>
<td>0.3605</td>
<td>8.3414</td>
</tr>
<tr>
<td>5 years</td>
<td>-0.0649</td>
<td>4.8322</td>
<td>0.3575</td>
<td>8.8907</td>
</tr>
</tbody>
</table>

*Note:* This table reports counterfactual changes in the predicted choice probabilities when the brand switching dis-utility term is set to zero. The changes are reported as relative to the benchmark model estimates, averaged across all consumers in the sample, conditional on their level of experience. For example, the first number reads: the demand for Canon compact cameras will *decrease* by 19.47%, when the brand-switching dis-utility is eliminated.

Appendix Table 2: Average long-run elasticities (complete table)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>No purchase</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Canon Compact</td>
<td>-1.9383</td>
<td>0.0288</td>
<td>-0.0059</td>
<td>0.0268</td>
<td>0.0417</td>
<td>0.0404</td>
<td>0.0028</td>
</tr>
<tr>
<td>(2) Nikon Compact</td>
<td>0.0126</td>
<td>-1.9628</td>
<td>-0.0232</td>
<td>0.0245</td>
<td>0.0093</td>
<td>0.0226</td>
<td>0.0017</td>
</tr>
<tr>
<td>(3) Other Compact</td>
<td>-0.0027</td>
<td>-0.0033</td>
<td>-1.9165</td>
<td>0.0186</td>
<td>0.0187</td>
<td>0.0167</td>
<td>0.0015</td>
</tr>
<tr>
<td>(4) Canon DSLR</td>
<td>-1.6431</td>
<td>0.8915</td>
<td>0.2713</td>
<td>-3.9841</td>
<td>1.1946</td>
<td>0.9689</td>
<td>0.0775</td>
</tr>
<tr>
<td>(5) Nikon DSLR</td>
<td>0.3735</td>
<td>-2.3449</td>
<td>-0.2718</td>
<td>0.7000</td>
<td>-4.8753</td>
<td>0.4822</td>
<td>0.0527</td>
</tr>
<tr>
<td>(6) Other DSLR</td>
<td>-0.0728</td>
<td>-0.0825</td>
<td>-1.0620</td>
<td>0.4714</td>
<td>0.4955</td>
<td>-3.5842</td>
<td>0.0633</td>
</tr>
</tbody>
</table>

*Note:* This table reports long-run elasticities, computed from demand responses to permanent price changes of 10% for a given brand-format of camera. For example, the first row, second column reads: a foreseeable, permanent 10% price decrease for Canon compact cameras *decreases* the demand for Nikon compact cameras, by 0.427%.