Learning by Doing and the Demand for Advanced Products: Online Appendix

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A Alternative specification of the structural model

A.1 General setup

I construct and estimate an alternative specification of the structural model in order to check for robustness of my results. In this alternative specification, the timing assumption follows Section 5.1, the evolution of endogenous camera stock follows 5.2, and the human capital transition process follows 5.4.

However, compared to the baseline model in Section 5, this alternative specificationhas three main differences : 1) characterization of technology evolution, 2) allowing for more parameters to be different across individuals, and 3) allowing for endogenous choice of the initial camera.

First, in the model, the production function of picture quality is specified as

$$Q_{it}\left(\bar{Q}_j, K_{it}, H_{it}\right) = q_i + \bar{Q}_j + \gamma_{\tilde{k}} \cdot H_{it} + \eta_{it}, \tag{1}$$

where the consumer produces picture quality using her human capital stock H_{it}, camera format

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$\tilde{k} = 1,4$, and technology $\bar{Q}_j$ that is specific to the camera model j. Technology $\bar{Q}_j$ now affects consumer picture quality and thus her camera choice, and therefore should be in the state space. I characterize technology evolution in detail in the next section.

Second, in the model, I assume that all individual-specific parameters follow a two-type distribution as is conventional in the literature, and the simplicity of the two-type model allows for additional heterogeneous parameters. I allow for heterogeneity in all parameters except for the return to human capital for a given camera format ($\gamma_{\tilde{k}}$) and the scale of η_{it}.[1] Notably, I allow for type-specific switching thecosts in human capital, now denoted as $s_{i,k'k}$.

Third, the baseline model assumes that the initial camera is given exogenously. Under the two-type heterogeneity, I can endogenize the initial camera choice and make it depend on type-specific preferences and learning speed, in a way similar to Hendel and Nevo (2006). Specifically, I compute the stationary distribution of camera formats given parameters of each consumer type, with human capital and technology fixed at their initial values.

A.2 Camera technology evolution

A camera model's role in creating picture quality can be measured by camera fixed effects in Equation (4). I project these fixed effects on observed camera characteristics and treat the projection, $\bar{Q}_j$, as an observable in the structural model. I discuss the measurement of $\bar{Q}_j$ in Sub-section A.4 at the end of this section.

If the consumer does not switch cameras, $\bar{Q}_j$ does not change and she takes its value deterministically into the next period. If the consumer switches to a new camera, I assume she does not know the exact technology level $\bar{Q}_j$ of the new model j, but rather forms rational expectations of its distribution,

$$\bar{Q}_j \sim \mathcal{N}\left(\bar{Q}_t^m, \sigma_q^2\right), \tag{2}$$

where the average market quality $\bar{Q}_t^m$ increases stochastically over time, but the variance σ_q^2 is a

[1] $\gamma_{\tilde{k}}$ should be common across individuals because the ability to use each camera should already be captured by human capital H_{it}.

constant. Further, market quality evolves in a Markov fashion,

$$\bar{Q}_t^m = \chi_0 + \chi_1 \bar{Q}_{t-1}^m + \omega_t. \tag{3}$$

As a result, technology of the camera the consumer holds at the beginning of a period, $\bar{Q}_j$, and the market technology frontier technology at the beginning of the period, $\bar{Q}_t^m$, are both state variables that the dynamic programming problem should condition on. In implementation, I discretize both the current camera and market frontier technology to 0.2-grid.

To note, there are two simplifying assumptions in my model of technology. First, I reduce dimensionality of technology by considering the Markov transition of the index $\bar{Q}_j$, rather than each individual characteristics. This step is similar to the idea in Melnikov (2013) because it is almost impossible to keep track of each characteristic (and also because technology is not the central focus of my paper).[2] Second, I assume that consumers draw $\bar{Q}_j$ after buying the camera j, because otherwise I would have to model choices over many (more than 1,000) camera models.

In alternative versions of this paper, I three notable alternative versions of technology and have always reached similar conclusions: 1) I do not model technology at all, which is the main specification of my paper, 2) I model Markov transition of camera resolution as the only relevant characteristic, 3) I model consumer utility as decreasing in the time since last adoption, which follows a renewal process similar to Rust (1987). None of these versions have suggested different qualitative conclusions. Therefore, I do not view camera technology as a vital part of the main point.

A.3 Estimation results

Appendix Table 1 presents parameter estimates for the two-type model. I find that the parameter estimates are similar in sign and magnitude to the continuous-type model. First, at the mean human capital (now at $\bar{H}_{it}^0 = 0.7$) using a DSLR camera produces better pictures that account for 19.1% higher views.[3] Compared to the baseline continuous-type model, the returns to experience is esti-

[2] The difference to Melnikov (2013) is that I assume the camera fixed effects (projected on observables) is Markov while Melnikov assumes that continuation value is Markov.

[3] (0.625 - 0.352) * 0.7 = 0.191.

mated higher in the two-type model despite I now control for technology evolution. One explanation to this difference is that heterogeneity is treated in a much simpler way here and thus selection biases are not fully controlled for (Dubé et al., 2010).

Second, heterogeneity mainly occur in the initial quality q_i, learning speed μ_{i1} (but the additional learning speed using a DSLR camera, $\mu_{i4} - \mu_{i1}$, is similar), tastes to picture quality β_i and effort from picture-taking θ_i. In contrast, individual parameters are similar in the switching costs in human capital, price sensitivity α_i, and some of the choice intercepts. In fact, in past versions of this paper, I estimate different versions of the two-type dynamic discrete choice model and consistently find heterogeneity structures similar to Table 1. This heterogeneity structure guides my choice of the seven random coefficients in the continuous-type model.

In addition to that parameter estimates are similar between the two-type and continuous-type models, I also compute counterfactual simulations similar to the experiments in Section 7, and find results similar.

In summary, the baseline model has richer consumer heterogeneity in the focal set of parameters whereas the two-type model characterizes technology evolution. Despite such difference, the magnitude of the estimates are not far from each other. I choose to present the continuous-type specification because of its ability to capture rich heteorgeneity and thus selection, but the qualitative conclusion of this paper is invariant of this modeling choice.

A.4 Implementation detail: measurement of the technology index

I capture heterogeneity across cameras of the same brand and format by a state variable $\bar{Q}_j$, which is a projection of camera fixed effects (estimated in Equation (4)) on camera characteristics. I choose the set of characteristics that are similar across point-and-shoot and DSLR cameras produced in the same era, because the production function should capture the return to DSLR format ("advanced camera") in the coefficients γ_k. Within my data, I project camera characteristics on resolution (coded in a total of 8 dummies variables, of 0.5-megapixel grids) and year of introduction.

From a researcher's point of view, I estimate parameters $\psi_{1,r}$ and $\psi_{2,y}$, so as to infer $\bar{Q}_j$ from

Appendix Table A 1: Parameter estimates: the alternative version

Common parameters		Individual-specific production parameters			Preferences		
			Type I	Type II		Type I	Type II
productivity of P&S $\gamma_{P\&S}$	0.352*	quality intercept q_{i0}	0.224*	1.520*	utility to pic quality β_i	0.732*	0.175*
	(0.025)		(0.011)	(0.015)		(0.052)	(0.018)
productivity of DSLR γ_{DSLR}	0.625*	mean method, point-shoot μ_{i1}	-4.343*	-2.031*	utility/effort of usage θ_i	-0.003	1.307*
	(0.016)		(0.003)	(0.050)		(0.017)	(0.035)
scale of η_{it}	0.642*	mean method, DSLR μ_{i4}	-3.785*	-1.309*	log price sensitivity α_i	-2.118*	-1.956*
	(0.002)		(0.007)	(0.050)		(0.167)	(0.157)
Type I share	0.585*	std. dev. of method σ_i	2.168*	2.151*	buy point & shoot	-2.647*	-2.933*
	(0.000)		(0.000)	(0.003)		(0.083)	(0.092)
		switching cost: any camera	0.023*	0.025*	buy DSLR	0.341	0.051
			(0.000)	(0.004)		(0.317)	(0.298)
		switching cost: format	0.079*	0.120*	buy Canon	0.327*	-0.005
			(0.000)	(0.002)		(0.051)	(0.062)
		switching cost: brand	0.106*	0.117*	buy non-Canon	-0.102*	-0.405*
			(0.000)	(0.004)		(0.047)	(0.058)
					switch format	-0.475*	-0.231*
						(0.053)	(0.073)
					switch brand	-0.367*	-0.808*
						(0.041)	(0.050)

Note: This table reports structural estimates. Asymptotic standard errors from numerical Hessian. *: significant at 95% confidence level. Log likelihood = -267600.

observed camera characteristics. Specifically, I estimate a flexible reduced form model of camera fixed effect on resolution (megapixel) and introductory year, to capture the contribution of different camera characteristics:

$$FE_j = \sum_{r=1}^{8} \psi_{1,r}\mathbf{1}\left(resolution_j = r\right) + \sum_{y=2005}^{2013} \psi_{2,y}\mathbf{1}\left(intro.year_j = y\right) + \varpi_{ijt}. \tag{4}$$

I then take the linear prediction as $\bar{Q}_j$.

B Transition probability of the state variables

B.1 Human capital

As explained in Section 5.5, human capital improves when the consumer decides to take pictures in a period, and discovers a better method. So if the consumer does not take pictures, human capital stays constant for a period. If she takes pictures, but does not discover a better method, human capital also stays equal to the previous period value. Therefore, following Equation (6), given picture taking, the conditional probability density function for the next period human capital to be equal to h, is

$$\begin{aligned}
\Pr\left(H_{ikt+1}=h|H_{ikt},D_{it}=1,B_{it}=0\right) &= 0\cdot\mathbf{1}\left(h<H_{ikt}\right)+ \\
&\quad \Pr\left(M_{it}\leq h\right)\cdot\mathbf{1}\left(h=H_{ikt}\right)+ \\
&\quad \phi\left(h/\sigma_i\right)\cdot\mathbf{1}\left(h>H_{ikt}\right),
\end{aligned} \tag{5}$$

where the first term indicates that human capital in $t+1$ cannot go below H_{ikt} if there was no camera switching. The second term indicates that if the method draw was "unlucky" and the consumer did not find a better method than the historical best, human capital will stay at H_{ikt}. The last term captures the distribution of improvement, where ϕ denotes the standard normal probability density function. One can rewrite this term into $\phi\left(h/\sigma_m|M_{it}>h\right)\cdot\Pr\left(M_{it}>h\right)$ given $h>H_{ikt}$. Here, it is clear that the density of improved human capital depends on whether the consumer could find a better method, and the conditional density of "better methods".

With camera switching from k' to k, human capital first takes a loss due to switching cost, and then undertakes Equation (5). That means, if signal exceeds $\left(1-s_{k'k}\right)H_{ik't}$ – which is the "left-over" human capital after switching – learning will happen. This implies

$$\begin{aligned}
\Pr\left(H_{ikt+1}=h|H_{ik't},D_t=1,B_{it}=k\right) &= \Pr\left(M_{it}\leq h\right)\cdot\mathbf{1}\left(h=\left(1-s_{k'k}\right)H_{ik't}\right)+ \\
&\quad \phi\left(h/\sigma_i\right)\cdot\mathbf{1}\left(h>\left(1-s_{k'k}\right)H_{ik't}\right).
\end{aligned} \tag{6}$$

Note that ϕ – the density of new method arrival – is unchanged. This highlights the assumption that human capital does not alter the underlying method distribution. However, the probability that human capital improves changes because the area $h>\left(1-s_{k'k}\right)H_{ik't}$ is now larger. Therefore, comparing terms between Equations (5) and (6), although the expected future human capital decreases as a result of switching cost, the expected learning rate increases. In particular, if the switching cost is large, this implication resembles the sharp drop in picture quality after camera switching, but the high learning speed that immediately follows.

B.2 Camera

Besides human capital, there are two terms that changes with a camera: the brand-format combination K_{it} (which I refer to as a "camera") and the characteristics-specific quality index $\bar{Q}_j$ (which I refer to as a "model"). I keep track of all possible current and future brand-format combinations. Therefore, the camera evolves deterministically.

The quality index stays constant if the camera, say j', does not change. If the consumer switches to a new camera j, she draws a new $\bar{Q}_j$ from an exogenously evolving distribution that depends only on calendar time of purchase. This pins down the distribution of $\bar{Q}_j$:

$$\Pr\left(\bar{Q}_j < q | B_{it} \neq 0, t\right) = \Phi\left(\frac{q - \bar{q}_t}{\sigma_q}\right) \tag{7}$$

where $\bar{q}_t$ and σ_q are parameters that are estimated in reduced form, and Φ denotes standard normal CDF.

B.3 Prices

I model log price evolution as first order Markov processes, separately for point-and-shoot and DSLR cameras. Specifically, for each format $\tilde{k} = 1, 4$, log prices follow:

$$\log\left(P_{\tilde{k}t+1}\right) = \kappa_{\tilde{k}0} + \kappa_{\tilde{k}1} \cdot \log\left(P_{\tilde{k}t}\right) + \varepsilon_{\tilde{k}t+1}. \tag{8}$$

An individual forms rational expectations on the price distributions next month. Because prices are discretized on a set of grid points, I compute the transition matrices $\Pi_{\tilde{k}}$ according to the estimates of above, with element $\pi_{\tilde{k},ij}$ as

$$\pi_{\tilde{k},ij} = \Pr\left(P_{\tilde{k}t+1} = p_j | P_{\tilde{k}t} = p_i\right) \tag{9}$$

where p_i, p_j are discrete grid points of price.

C Additional results

C.1 Stochastic growth in consumer human capital

Complementing the descriptive evidence in Section 4, I now explore how consumer human capital improves. In particular, I test between whether human capital improves through time or through picture-taking practices. The latter is an outcome of learning by doing, while the former would suggest that learning happens externally (or picture-taking actions have measurement error). To test between these explanations, I estimate the following specification for picture quality:

$$Q_{im} = \theta_0 + \theta_m \cdot m + \theta_q \cdot Q_{im-1} + \theta_t \cdot t_m + \theta_k \cdot SLR_{im} + \theta_i + \vartheta_{im} \tag{10}$$

where m is month in which the individual takes pictures, t_m is the calendar month of picture-taking month m, and Q_{im-1} is picture quality from the previous picture-taking month $m-1$. I also control for changes in equipment SLR_{im} and individual fixed effect θ_i.[4]

I estimate a first-differenced version of the above specification:

$$\Delta Q_{im} = \theta_m + \theta_q \cdot \Delta Q_{im-1} + \theta_t \cdot \Delta t_m + \theta_k \cdot \Delta SLR_{im} + \Delta \vartheta_{im}, \tag{11}$$

where I denote Δ as the first difference operator (between m and $m-1$). I instrument ΔQ_{im-1} by Q_{im-2}, because the term is correlated with first-differenced past error term $\Delta \vartheta_{im-1}$.[5] The results are presented in Table 2.

I find a positive carry-over effect from a change of picture quality in the most recent past to the change of picture quality in the current month. I do not find any evidence supporting that learning is deterministic (i.e. through the number of past camera usages) or learning is external (i.e. through a time trend). In column 3, I control for changes in all camera dummies and find that the serial correlation in Q_{im} is not due to changes in camera. In line with these findings, I adopt a structural

[4]Implicitly, I assume that the error term is serially uncorrelated and orthogonal to all right-hand side variables.

[5]This is because they have common component ϑ_{im-1}. We can instrument this by Q_{im-2} due to the assumption that ϑ_{im} is serially uncorrelated. See Arellano and Bond (1991) for details.

Appendix Table A 2: Reduced-form picture quality evolution

	D.quality	D.quality, t-1 (1st stg.)	D.quality
D.quality, t-1	0.096***		0.098***
	(0.008)		(0.009)
quality, t-2		-0.258***	
		(0.006)	
D.dslr	0.023	0.005	
	(0.024)	(0.018)	
D.time	-0.002	-0.004**	-0.003
	(0.002)	(0.001)	(0.002)
constant	0.005	0.107***	0.007*
	(0.003)	(0.007)	(0.003)
camera dummies	No	No	Yes

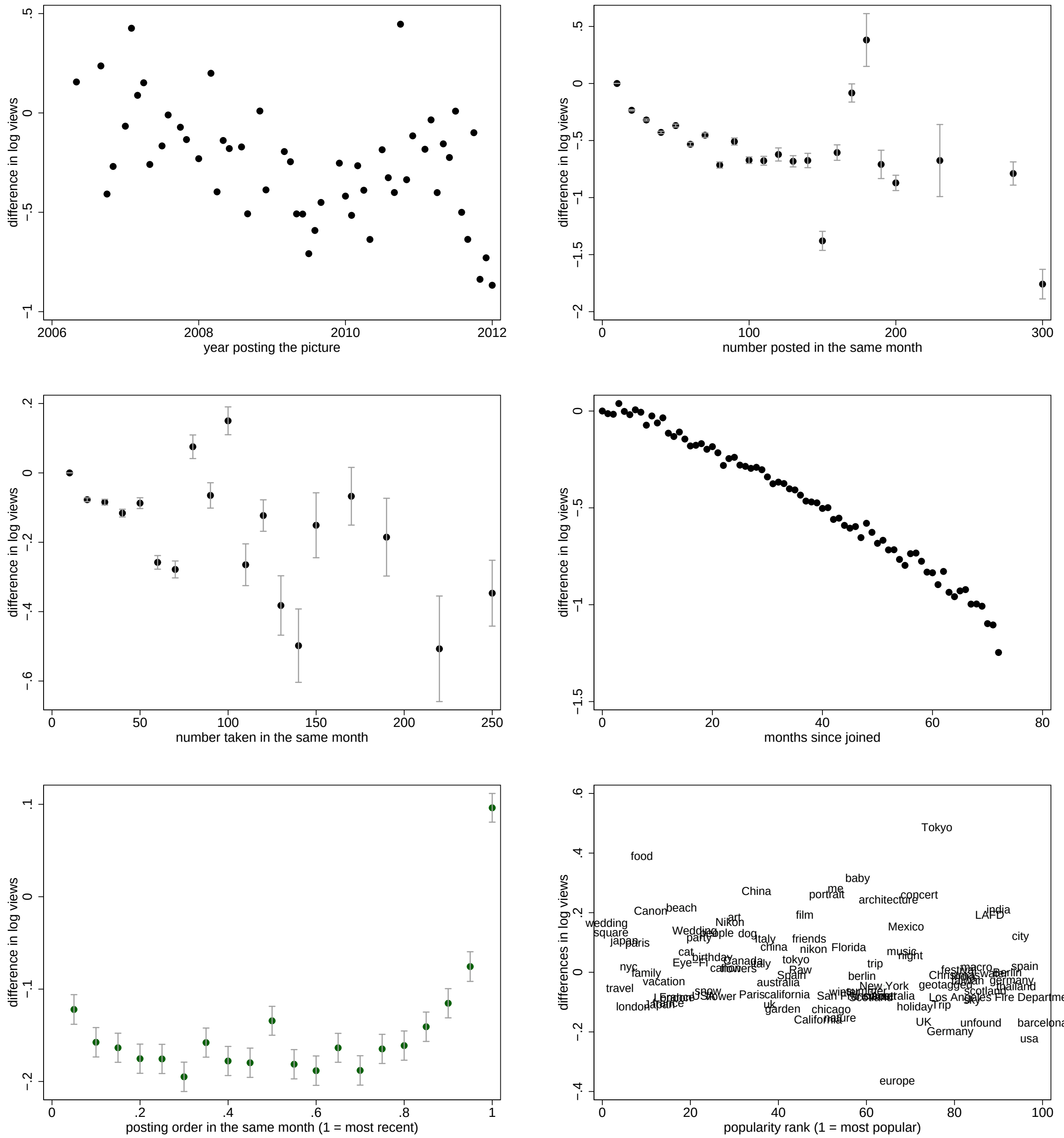
Note: This table presents Arellano-Bond estimates for Equation (11). "D" denotes Δ, or the first difference operator. The second column presents first stage estimates. Standard errors are heteroskedasticity robust and clustered by individual.

model of stochastic learning. [6]

C.2 Additional tables and figures

This section collects additional tables and figures referred to in the main text. Table 3 presents camera transition matrix in the data. Table 4 presents estimates of the exogenous state transition process. Figure 1 summarizes estimates of the control variables in Equation (4). Figure 2 presents evidence of consumer switching costs in human capital under alternative measures. Figure 3 shows differences in picture quality from DSLR and point-and-shoot cameras, within individual-year. Figure 4 shows changes in the number of pictures produced around the point when the consumer switches cameras. Table 5 shows additional results to the counterfactual simulations.

[6] The symmetric structure here also implies quality-destroying knowledge further destroys future human capital. I cannot ensure that this is not a relic of the linear structure (and cannot estimate general a dynamic nonlinear panel data model), and thus do not take this into account in the structural model.



Appendix Figure A 1: Estimates of control variables in Equation (4)

Notes: These 6 figures report estimates of the control variables $\Phi_{t_0 t_1}$ and z_{ip}, from Eq. (4). In the first panel, I report the effect of upload time (t_0) as the average of the display window effect, $\Phi_{t_0 t_1}$, given t_0 across t_1. In the last panel, horizontal axis is the relative populartiy of the top 100 tags.

Appendix Table A 3: Conditional choice frequencies

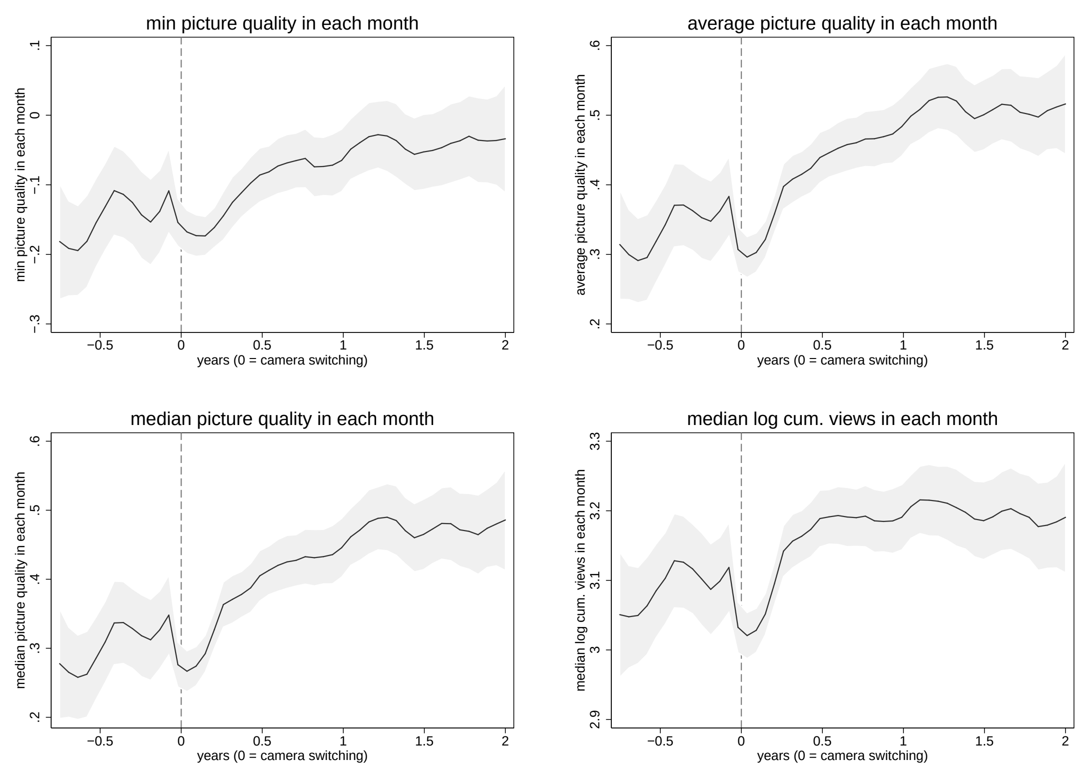
	No purchase	Buy: Canon PS	Nikon PS	other PS	Canon DSLR	Nikon DSLR	Other DSLR
Own: Canon PS	46716	541	68	318	510	308	41
Nikon PS	8887	87	28	88	68	85	12
other PS	41282	424	102	587	484	385	123
Canon DSLR	61756	371	58	278	833	301	46
Nikon DSLR	46166	253	75	198	305	625	32
Other DSLR	7593	26	7	48	33	37	73

Notes: Monthly transition frequencies between camera brand-formats. Rows: brand-format owned at the beginning of a month; columns: brand-format choice in the month, allowing for the choice of no purchase.

Appendix Table A 4: Exogenous state transition processes

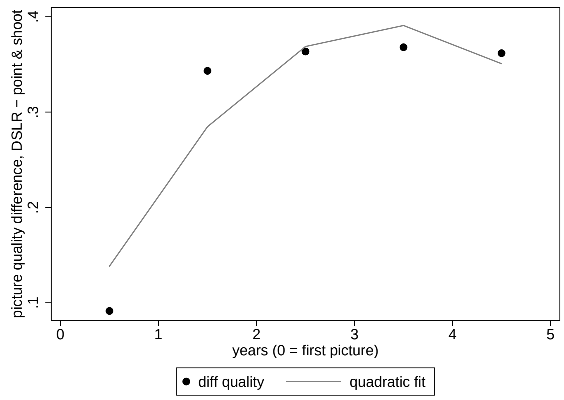
	logprice (PS)	logprice (DSLR)	market tech index
lagged dependent variable	0.887***	0.945***	0.933***
	(0.051)	(0.042)	(0.083)
constant	0.545*	0.351	-0.016
	(0.251)	(0.269)	(0.022)
Rsq.	0.83	0.89	0.57
RSS	0.18	0.13	0.04
obs.	62	64	96

Note: Estimates of log price and market technology transition processes. RSS is residual sum of squares.



Appendix Figure A 2: Switching cost under alternative measures of quality

Notes: Robustness check of changes in alternative measures of picture quality around camera switching. Top right to bottom left: minimum, mean and median of the picture quality distribution. Lower right: raw data of log views (without any controls).



Appendix Figure A 3: Picture quality difference between camera format

Notes: Within-individual-year differences in picture quality, between DSLR and point-and-shoot camera.

Appendix Table A 5: DSLR revenue by year, under all counterfactual scenarios

	baseline	no learning	no transferable learning	no brand-swit. cost	no format-swit. cost	no swit. cost	no brand-swit. cost and inertia
year 1	213	136	191	218	211	216	295
year 2	207	150	159	220	208	223	304
year 3	199	156	149	216	202	219	300
year 4	207	164	149	226	209	230	316
year 5	223	182	164	244	225	250	342
year 6	217	177	152	237	220	244	340
year 7	232	190	169	254	235	262	357
NPV DSLR revenue	1286	985	979	1384	1297	1407	1929

Note: Counterfactual annual revenue from DSLR sales, from my simulation of adoption decisions of a panel of 4,110 households for a duration of 7 years. Column 1 presents the baseline. Column 2-7 are counterfactual revenue when: 1) consumers do not learn by doing at all, 2) consumers learn about one camera but knowledge does not transfer to other cameras, 3) there is no brand-switching cost in human capital, 4) no format-switching cost, 5) no switching cost in human capital at all, and 6) no brand-switching cost in both human capital and utility term (i.e. the new brand coefficient is zero). Last row presents discounted sum of seven-year revenue at firm discount factor of 0.95.

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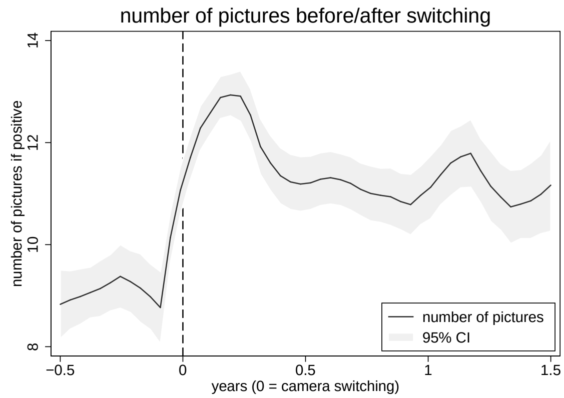

Appendix Figure A 4: Number of pictures before/after camera switching

Notes: This figure presents the number of pictures an individual produces, around the time of camera switching. This is conditional on these pictures eventually being uploaded to Flickr.

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