Online Appendix : Data Construction and Supplementary Tables.

In this Appendix, we explain how our dummy variables for the various characteristics were constructed and we list various Tables for indexes which are described in the main text. The first eight subsections of this Appendix describe panel time dummy characteristics hedonic regressions as we introduce an additional explanatory characteristic one at a time. These regressions are unweighted Time Dummy Characteristics regressions of the type defined by (41) in the main text.

A.1 A Characteristics Hedonic Regression with Clock Speed as the Only Characteristic.

The price indexes P_A^t and P_{UV}^t make no adjustments for changes in the average quality of laptops over time. Let lnP denote the vector of dimension 2639 that consists of the logarithms of the monthly unit value prices of the subset of the 366 products that were sold in each month. We start our analysis by regressing the price vector lnP on the time dummy variables D_2, …, D_{24} and dummy variables for the clock speed of each laptop that was sold during the sample period.

The clock speeds range from 1.0 to 3.4 in increments of 0.1. Thus there are 25 possible clock speeds. Vectors of dummy variables of dimension 2639, D_{C1}, D_{C2}, …, D_{C25}, were generated using IF statements applied to the CLOCK variable.[1] The number of observations in each cell of clock speeds were as follows: 53, 280, 69, 18, 85, 51, 225, 0, 486, 104, 165, 201, 63, 186, 151, 31, 305, 12, 124, 10, 2, 10, 0, 4, 4. Thus D_{C8} and D_{C23} were vectors of zeros and there were no products that have clock speeds equal to 1.7 or 3.2. Also, several cells had very few members. Thus we reduced the number of cell speed categories from 25 to 7. We attempted to get approximately the same number of observations in each category except the highest cell speed category. New Groups 1 to 7 aggregated old groups 1-3, 4-8, 8-9, 10-12, 13-15, 16-18 and 19-25 respectively. Thus the new dummy variable vector D_{C1} equals the sum of the old vectors $D_{C1} + D_{C2} + D_{C3}$, the new D_{C2} equals the sum of the old vectors $D_{C4} + D_{C5} + D_{C6} + D_{C7} + D_{C8}$ and so on.

Our first hedonic regression regresses lnP on the time dummy variable vectors $D_2, D_3, \ldots, D_{24}$ and the 7 clock speed dummy variable vectors D_{C1}, D_{C2}, …, D_{C7}. The number of products that are in each of the 7 new clock speed cells are 402, 379, 486, 470, 400, 348 and 154. Since we have only one characteristic, our initial linear regression is the following one:

$$\text{(A1) } \ln P = \Sigma_{t=2}^{24}\, \rho_t D_t + \Sigma_{j=1}^{7}\, b_{Cj} D_{Cj} + e$$

where e is an error vector of dimension 2639.

We estimated the unknown parameters, ρ_2^*, ρ_3^*, …, ρ_{24}^*, b_{C1}^*, …, b_{C7}^* in the above linear regression model using ordinary least squares. The log of the likelihood function was – 1401.58 and the R^2 between the observed price vector and the predicted price vector was only 0.2984. If increased clock speed is valuable to purchasers, we would expect the estimated b_{Cj}^* coefficients to increase as j increases. For this regression, the estimates for b_{C1}^*, …, b_{C7}^* were –0.4213, 0.0669, 0.1498, –0.0050, 0.2606, 0.3253 and 0.4535. These coefficients increase monotonically except for b_{C4}^*, so overall, it seems that purchasers do value increased clock speed.[2]

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[1] Using SHAZAM, D_{C1}, D_{C2}, …, D_{C25} can be generated using the commands GENR DCL1=(CLOCK.EQ.1.0), GENR DCL2=(CLOCK.EQ.1.1), …, GENR DCL25=(CLOCK.EQ.3.4).

[2] Of course, these coefficients will change as we add other characteristics to the regression.

The estimated ρ_t^* are the logarithms of the price levels P^{t*} for t = 2,3,…,24 but we will not list the estimated price levels until we have entered all 8 of our characteristics listed in the data Appendix B into the regression.

Once the estimates for the b_{Cj} are available, we can calculate the logarithms of the appropriate quality adjustment factor α_{tn}^* that can be used to determine the quality of product n in month t. Denote the logarithm of α_{tn}^* by β_{tn}^* for t = 1,…,24 and $n \in S(t)$. Denote the vector of estimated quality adjustment factors (of dimension 2639) by β^*. It turns out that β^* can be calculated as follows:

(A2) $\beta^* = \Sigma_{j=1}^{7} b_{Cj}^* D_{Cj}$.

It is convenient to have a constant term in a linear regression: if this is the case, then the error terms must sum to zero across all observations. We can introduce a constant term into our regression model defined by (A1) as follows. First define ONE as a vector of ones of dimension 2639. Consider the following linear regression model:

(A3) $\ln P = \Sigma_{t=2}^{24} \rho_t D_t + b_0 ONE + \Sigma_{j=2}^{7} b_{Cj} D_{Cj} + e$

where e is an error vector of dimension 2639. Thus we have added a vector of ones as an independent variable in the new regression defined by (A3) and dropped the first clock speed dummy variable vector D_{C1} as an explanatory variable. Denote the ordinary least squares estimates for the parameters in (A3) by ρ_2^{**}, ρ_3^{**}, …, ρ_{24}^{**}, b_0^{**}, b_{C2}^{**}, …, b_{C7}^{**}. It turns out that $\rho_t^{**} = \rho_t^*$ for t = 2,3,…,24 and the following vector equation also holds:

(A4) $b_0^* ONE + \Sigma_{j=2}^{7} b_{Cj}^* D_{Cj} = \Sigma_{j=1}^{7} b_{Cj}^* D_{Cj}$.

Thus the vector of log quality adjustment factors for the positive observed prices in the sample, β^* defined by (A2), is also equal to the following expression:

(A5) $\beta^* = b_0^* ONE + \Sigma_{j=2}^{7} b_{Cj}^* D_{Cj}$.

In the models which follow, we will add additional characteristics to the hedonic regression model defined by (A3) rather than adding addition explanatory variables to the model defined by (A1).

A.2 A Hedonic Regression that Added Memory Capacity as an Additional Characteristic.

We add memory capacity as another price determining characteristic of a laptop. There were only 3 sizes of memory capacity (the variable MEM in the Data Appendix B): 4096, 8192 and 16384. Construct dummy variable vectors of dimension 2639 for each value of MEM.[3] Denote these vectors as D_{M1}, D_{M2} and D_{M3}. The new log price time dummy characteristic hedonic regression is the following counterpart to (A3):

(A6) $\ln P = \Sigma_{t=2}^{24} \rho_t D_t + b_0 ONE + \Sigma_{j=2}^{7} b_{Cj} D_{Cj} + \Sigma_{j=2}^{3} b_{Mj} D_{Mj} + e$.

[3] Using SHAZAM, the commands to create these dummy variable vectors D are: GENR DM1=(MEM.EQ.4096) ; GENR DM2=(MEM.EQ.8192) and GENR DM3=(MEM.EQ.16384). The number of products in each of these 3 cells are 620, 1710 and 309.

The log of the likelihood function was – 648.937, a gain of 752.64 log likelihood points for adding 2 new memory size parameters. The R^2 between the observed price vector and the predicted price vector was 0.6034. If increased memory capacity is valuable to purchasers, we would expect the estimated b_{Mj}^* coefficients to increase as j increases. For this regression, the estimates for b_{M2}^* and b_{M3}^* were .5493 and 0.9789. This regression indicates that purchasers do value increased memory capacity and are willing to pay a higher price for a laptop with greater memory capacity, other characteristics being held constant.

A.3 A Hedonic Regression that Added Screen Size as an Additional Characteristic.

There were 10 different screen sizes (in units of 10 inches) in our sample of laptop observations. This variable is listed as SIZE in Appendix B. The 10 screen sizes in our sample were: 1.16, 1.2, 1.25, 1.33, 1.4, 1.54, 1.56, 1.6, 1.61 and 1.73. The usual commands were used to generate 10 dummy variables for this characteristic. However, for the screen sizes 1.2, 1.56 and 1.61, we had only 12, 14 and 35 observations in our sample for these three sizes. Thus we combined the dummy variable for size 1.2 with the dummy variable for 1.16,[4] combined the dummy variable for size 1.56 with size 1.54 and combined the dummy variables for sizes 1.6 and 1.61. Denote the resulting 7 dummy variables of dimension 2639 by D_{S1}, D_{S2}, …, D_{S7}. The number of observations in each of the 7 screen size cells was 98, 154, 810, 257, 1106, 114, 100.

The new log price Time Dummy Characteristics hedonic regression is the following counterpart to (A6):

(A7) $\ln P = \Sigma_{t=2}^{24} \rho_t D_t + b_0 ONE + \Sigma_{j=2}^{7} b_{Cj} D_{Cj} + \Sigma_{j=2}^{3} b_{Mj} D_{Mj} + \Sigma_{j=2}^{7} b_{Sj} D_{Sj} + e.$

The log of the likelihood function was – 202.270, a gain of 446.667 log likelihood points for adding 6 new screen size parameters. The R^2 between the observed price vector and the predicted price vector was 0.7173. If increased screen size is valuable to purchasers, we would expect the estimated b_{Sj}^* coefficients to increase as j increases. For this regression, the estimates for b_{S2}^*-b_{S7}^* were 0.73371, 0.59447, 0.22923, 0.34524, 0.74190 and 0.68987. This regression indicates that purchasers prefer small and large screen sizes over intermediate screen sizes for laptops.

A.4 A Hedonic Regression that Added Pixels as an Additional Characteristic.

There were 10 different numbers of pixels in our sample of laptop observations. A larger number of pixels per unit of screen size will lead to clearer images on the screen and this may be utility increasing for purchasers. The pixel variable is listed as PIX in the Appendix B. There were 10 different PIX sizes in our sample. The 10 sizes (in transformed units of measurement) were: 1.049, 1.246, 1.296, 2.074, 3.318, 4.096, 5.184, 5.530, 5.898 and 8.294. The number of observations having these pixel sizes were as follows: 324, 4, 2, 1769, 5, 400, 14, 3, 79 and 39. The usual commands were used to generate the 10 pixel dummy variables, D_{P1}-D_{P10}. However, the number of observations in pixel groups 2, 3, 5, 7 and 8 were 14 or less so these groups of observations need to be combined with other categories. We ended up with 5 pixel groups: the new group 1 combined groups 1, 2 and 3; old group 4 became the new group 2, old groups 5 and 6 were combined to give us the new group 3, old groups 7, 8 and 9 were combined to be the new group

[4] GENR DS1=(SIZE.GE.1.16).AND.(SIZE.LE.1.20) is the SHAZAM command to construct the combined dummy variable.

4 and the old group 10 became the new group 5. Denote the new pixel dummy variable vectors as D_{P1}-D_{P5}. The number of observations in each of these new pixel cells was 330, 1769, 405, 96, 39.

The new log price time dummy characteristic hedonic regression is the following counterpart to (A7):

(A8) $\ln P = \Sigma_{t=2}^{24} \rho_t D_t + b_0 ONE + \Sigma_{j=2}^{7} b_{Cj} D_{Cj} + \Sigma_{j=2}^{3} b_{Mj} D_{Mj} + \Sigma_{j=2}^{7} b_{Sj} D_{Sj} + \Sigma_{j=2}^{5} b_{Pj} D_{Pj} + e.$

The log of the likelihood function for the hedonic regression defined by (A8) was – 71.1313, a gain of 131.139 log likelihood points for adding 4 new pixel number parameters. The R^2 between the observed price vector and the predicted price vector was 0.7440. If an increased number of pixels is valuable to purchasers, we would expect the estimated b_{Pj}^* coefficients to increase as j increases. For this regression, the estimates for b_{P2}^*-b_{P5}^* were 0.19750, 0.21889, 0.56884 and 0.69244. Thus the coefficients for the pixel dummy variables increase monotonically, indicating that purchasers are willing to pay more for an increase in screen clarity.

A.5 A Hedonic Regression that Added HDMI as an Additional Characteristic.

The dummy variable that indicates the presence of HDMI in the laptop has already been generated and is listed in Appendix B as the column vector HDMI. Denote this column vector as D_{H2} in the following hedonic regression which adds D_{H2} to the other regressor columns in (A8):

(A9) $\ln P = \Sigma_{t=2}^{24} \rho_t D_t + b_0 ONE + \Sigma_{j=2}^{7} b_{Cj} D_{Cj} + \Sigma_{j=2}^{3} b_{Mj} D_{Mj} + \Sigma_{j=2}^{7} b_{Sj} D_{Sj} + \Sigma_{j=2}^{5} b_{Pj} D_{Pj} + b_{H2} D_{H2} + e.$

The log of the likelihood function for the hedonic regression defined by (A9) was 49.499, a gain of 120.631 log likelihood points for adding 1 new HDMI parameter. The R^2 between the observed price vector and the predicted price vector was 0.7764 which is a material increase over the R^2 of the previous model which was equal to 0.7440. If having HDMI capability in the laptop is valuable to purchasers, we would expect the estimated b_{H2}^* coefficient to be positive. Our estimated coefficient b_{H2}^* was equal to 0.36041 which is a positive number and hence, the presence of HDMI in the laptop increases utility.

A.6 A Hedonic Regression that Added Brand as an Additional Characteristic.

There are 11 brands in our sample. In Appendix B the variable BRAND takes on values from 1 to 12 but there are no brands that correspond to the number 2 in our sample for the 24 months in the years 2021 and 2022. Here are the numbers of observations in each of the 12 BRAND categories: 4, 0, 3,101, 6, 235, 107, 389, 489, 439, 327, 479. We calculated the sample wide average price for each brand and re-ordered the brands according to their average prices with the lowest average price brands listed first and the highest average brand listed last. After re-ordering (and dropping old brand 2), the new brand ordering from 1-11 consists of the following initial brands: 7, 6, 5, 9, 1, 12, 8, 4, 11, 10, 3. The number of observations in each new BRAND category are as follows: 107, 235, 66, 489, 4, 479, 389, 101, 327, 439, 3. Construct the 11 vectors of dummy variables for the 11 new brand categories and denote these vectors of dimension 2639 by D_{B1}-D_{B11}.

Add the column vectors D_{B2}-D_{B11} to the other regressor columns in (A9) in order to obtain the following hedonic regression model:

(A10) $\ln P = \Sigma_{t=2}^{24} \rho_t D_t + b_0 ONE + \Sigma_{j=2}^{7} b_{Cj} D_{Cj} + \Sigma_{j=2}^{3} b_{Mj} D_{Mj} + \Sigma_{j=2}^{7} b_{Sj} D_{Sj} + \Sigma_{j=2}^{5} b_{Pj} D_{Pj} + b_{H2} D_{H2}$

$+ \Sigma_{j=2}^{11} b_{Bj}D_{Bj} + e.$

The log of the likelihood function for the hedonic regression defined by (A10) was 754.295, a huge gain of 704.796 log likelihood points for adding 10 new brand parameters. The R^2 between the observed price vector and the predicted price vector was 0.8631 which is a very big increase over the R^2 of the previous model which was equal to 0.7764. The estimated brand coefficients b_{B2}^*- b_{B11}^* are as follows: – 0.1014, 0.1366, 0.0975, 0.1201, 0.5048, 0.4136, 0.1469, 0.4743, 0.2880, 0.6401. Thus there is a general tendency for the marginal utility of a more expensive brand to be higher than the marginal utility of a cheaper brand.

A.7 A Hedonic Regression that Added the Type of Central Processing Unit as an Additional Characteristic.

There are 10 types of Central Processing Units (CPUs) in our sample. Here are the numbers of observations in each of the 10 CPU categories: 245, 702, 766, 39, 66, 87, 255, 11, 462, 6. Construct the 10 vectors of dummy variables for the 10 CPU categories and denote these vectors of dimension 2639 by D_{U1}-D_{U10}.

Add the terms $\Sigma_{j=2}^{10} b_{Uj}D_{Uj}$ in order to obtain the new hedonic regression model. The log of the likelihood function for the new hedonic regression model was 1012.80, a large gain of 258.505 log likelihood points for adding 9 new CPU parameters. The R^2 between the observed price vector and the predicted price vector was 0.8874, which is an increase over the R^2 of the previous model which was equal to 0.8631.

A.8 A Hedonic Regression that Added Laptop Weight as an Additional Characteristic.

We defined 7 weight dummy variables, D_{W1}-D_{W7} by choosing the following break points for laptop weights: 1.0, 1.3, 1.6, 1.9, 2.1 and 2.3. The D_{W1} cell consisted of laptops that weighed less than 1 kilo, the D_{W2} cell consisted of laptops that were in the interval $1 \leq \text{WEIGHT} < 1.3$, ,,, , the D_{W6} cell consisted of laptops that were in the interval $2.1 \leq \text{WEIGHT} < 2.3$ and the D_{W7} cell consisted of laptops that satisfied the inequality $\text{WEIGHT} \geq 2.3$. The number of laptops in each of these cells was as follows: 417, 408, 477, 311, 297, 466, 263.

Add the column vectors D_{W2}-D_{W7} to the right hand side of the previous regression in order to obtain the following hedonic regression model:

$$\text{(A11)}\ \ln P = \Sigma_{t=2}^{24} \rho_t D_t + b_0 ONE + \Sigma_{j=2}^{7} b_{Cj} D_{Cj} + \Sigma_{j=2}^{3} b_{Mj}D_{Mj} + \Sigma_{j=2}^{7} b_{Sj}D_{Sj} + \Sigma_{j=2}^{5} b_{Pj}D_{Pj} + b_{H2}D_{H2}$$
$$+ \Sigma_{j=2}^{11} b_{Bj}D_{Bj} + \Sigma_{j=2}^{10} b_{Uj}D_{Uj} + \Sigma_{j=2}^{7} b_{Wj}D_{Wj} + e.$$

The log of the likelihood function for the hedonic regression defined by (A11) was 1074.86, an increase of 62.06 over the previous log likelihood for adding 6 additional parameters. The R^2 between the observed price vector and the predicted price vector was 0.8926 which is a substantial increase over the R^2 of the previous model which was equal to 0.8631. The estimated weight coefficients b_{W2}^*- b_{W7}^* are as follows: 0.0765, 0.0018, -0.2094, -0.2447, -0.1852 and -0.2378. Thus a lighter laptop has on average a slightly positive price premium but the price premium becomes negative (and approximately constant) for laptops that weigh more that 1.6 kilos.

The estimated coefficients on the time dummy variables in this regression are ρ_2^*, ρ_3^*, …, ρ_{24}^*. Define $\rho_1^* \equiv 0$ and the estimated period t price levels $\pi_t^* \equiv \exp[\rho_t^*]$ for t = 1,2,…,24. Define the month t *Time Dummy*

Characteristics Price Index, $P_{TDC}{}^t \equiv \pi_t{}^*$ for t = 1,…,24. This index is listed in Table A2 in the following subsection.

A.9 The Weighted Time Dummy Characteristics Hedonic Regression Model.

The price indexes defined in sections A.1-A.8 can be constructed by using information on product prices and the amounts of the various characteristics of each product. If in addition, information on quantities sold or purchased during each month in scope is available, then Weighted Time Dummy Characteristics price indexes defined by equations (49) in section 3 can be constructed.

Recall that the expenditure share that corresponds to purchased product n in month t is defined as $s_{tn} = p_{tn}q_{tn}/\Sigma_{j\in S(t)}\, p_{tj}q_{tj}$ for t = 1,…,24 and $n\in S(t)$. To obtain the weighted counterpart to the hedonic regression model defined by (A11) above, we just form a share vector of dimension 2639 that corresponds to the $\ln p_{tn}$ that appear in (A11) and then form a new vector of dimension 2639 that consists of the positive square roots of each s_{tn}. Call this vector of square roots SS. Now multiply both sides of (A11) by SS to obtain a new linear regression model which again provides estimates for the unknown parameters that appear in (A11). The R^2 for this new weighted regression model turned out to be 0.9152 which is substantially higher than the R^2 for the counterpart unweighted model which was 0.8926.

The parameter estimates for this weighted hedonic regression model are listed in Table A1. This is our preferred regression from all of the regression models that have been presented thus far.

Table A1: Parameter Estimates for the Weighted Time Dummy Characteristics Hedonic Regression

Coef	Estimate	Std. Error	t-stat	Coef	Estimate	Std. Error	t-stat
$b_0{}^*$	-1.146	0.038	-29.950	$b_{S4}{}^*$	0.374	0.031	12.000
$r_2{}^*$	-0.001	0.016	-0.053	$b_{S5}{}^*$	0.547	0.044	12.490
$r_3{}^*$	0.018	0.016	1.154	$b_{S6}{}^*$	0.727	0.050	14.630
$r_4{}^*$	0.024	0.016	1.517	$b_{S7}{}^*$	0.733	0.047	15.650
$r_5{}^*$	0.019	0.016	1.191	$b_{P2}{}^*$	0.001	0.018	0.046
$r_6{}^*$	0.004	0.016	0.255	$b_{P3}{}^*$	0.215	0.043	4.944
$r_7{}^*$	-0.026	0.016	-1.607	$b_{P4}{}^*$	0.362	0.055	6.600
$r_8{}^*$	-0.028	0.016	-1.713	$b_{P5}{}^*$	0.266	0.033	8.143
$r_9{}^*$	-0.038	0.016	-2.323	$b_{H2}{}^*$	0.296	0.019	15.460
$r_{10}{}^*$	-0.032	0.016	-1.972	$b_{B2}{}^*$	-0.191	0.025	-7.688
$r_{11}{}^*$	-0.060	0.016	-3.650	$b_{B3}{}^*$	0.083	0.033	2.485
$r_{12}{}^*$	-0.089	0.016	-5.433	$b_{B4}{}^*$	-0.032	0.022	-1.429
$r_{13}{}^*$	-0.101	0.016	-6.165	$b_{B5}{}^*$	0.007	0.133	0.050
$r_{14}{}^*$	-0.109	0.017	-6.592	$b_{B6}{}^*$	0.319	0.022	14.320

r_{15}^*	-0.103	0.017	-6.178	**b_{B7}^***	0.240	0.023	10.350
r_{16}^*	-0.083	0.017	-4.942	**b_{B8}^***	0.010	0.029	0.356
r_{17}^*	-0.092	0.017	-5.438	**b_{B9}^***	0.310	0.024	12.710
r_{18}^*	-0.098	0.017	-5.778	**b_{B10}^***	0.190	0.032	5.940
r_{19}^*	-0.096	0.017	-5.630	**b_{B11}^***	0.838	0.143	5.857
r_{20}^*	-0.115	0.017	-6.809	**b_{U2}^***	0.202	0.012	16.470
r_{21}^*	-0.122	0.017	-7.208	**b_{U3}^***	0.149	0.015	9.831
r_{22}^*	-0.116	0.017	-6.825	**b_{U4}^***	0.445	0.030	14.710
r_{23}^*	-0.098	0.017	-5.752	**b_{U5}^***	-0.184	0.024	-7.660
r_{24}^*	-0.080	0.017	-4.681	**b_{U6}^***	0.043	0.026	1.622
b_{C2}^*	0.076	0.015	5.039	**b_{U7}^***	0.213	0.015	14.500
b_{C3}^*	0.239	0.017	14.230	**b_{U8}^***	0.212	0.074	2.854
b_{C4}^*	0.177	0.017	10.670	**b_{U9}^***	-0.113	0.019	-5.923
b_{C5}^*	0.206	0.017	11.950	**b_{U10}^***	-0.160	0.127	-1.258
b_{C6}^*	0.341	0.021	16.410	**b_{W2}^***	0.083	0.019	4.417
b_{C7}^*	0.293	0.021	14.090	**b_{W3}^***	0.063	0.021	3.073
b_{M2}^*	0.093	0.014	6.509	**b_{W4}^***	-0.137	0.039	-3.536
b_{M3}^*	0.399	0.019	20.810	**b_{W5}^***	-0.102	0.039	-2.603
b_{S2}^*	0.476	0.034	14.110	**b_{W6}^***	-0.142	0.040	-3.577
b_{S3}^*	0.598	0.032	18.880	**b_{W7}^***	-0.154	0.039	-3.944

There are 68 parameters in this regression model with 2571 degrees of freedom for the error terms. It can be seen that the clock speed parameters b_{Cj}^* increase with respect to j up to a point and then basically level off; the memory capacity parameters b_{M2}^* and b_{M3}^* are monotonically increasing; the screen size parameters b_{Sj}^* are roughly increasing; the pixel parameters b_{Pj}^* are monotonically increasing (except for b_{P5}^*); the HDMI parameter b_{H2}^* is positive which indicates that the availability of HDMI is valued by purchasers and the brand parameters b_{Bj}^* are weakly increasing so that the higher price brands are mostly preferred by purchasers. With respect to weight, it appears that lighter models are preferred up to a point and then weight does not seem to matter much.

The estimated coefficients on the time dummy variables in this regression are ρ_2^*, ρ_3^*, …, ρ_{24}^*. Define $\rho_1^* \equiv 0$ and the estimated period t price levels $\pi_t^* \equiv \exp[\rho_t^*]$ for t = 1,2,…,24. Define the month t *Weighted Time Dummy Characteristics Price Index*, $P_{WTDC}^t \equiv \pi_t^*$ for t = 1,…,24. This index is listed in Table A2 (and plotted in Chart 1 in the main text) and it is our a priori preferred index thus far. The corresponding unweighted (or equally weighted) Time Dummy Characteristics Price Index P_{TDC}^t is also listed in Table A2 along with the simple average laptop price indexes P_A^t and P_{UV}^t defined in section 4 of the main text.

Table A2: Weighted and Unweighted Time Dummy Characteristics Price Indexes

Month t	P_{WTDC}^t	P_{TDC}^t	P_A^t	P_{UV}^t
1	1.00000	1.00000	1.00000	1.00000
2	0.99916	1.03434	1.03525	0.99703
3	1.01864	1.04148	1.03503	1.00972
4	1.02478	1.03703	1.02127	0.99538
5	1.01945	1.07987	1.06279	1.02001
6	1.00416	1.07009	1.06571	1.00173
7	0.97411	1.01789	1.02721	0.98386
8	0.97240	1.01430	1.02049	0.97422
9	0.96258	1.00193	1.01082	0.95086
10	0.96811	1.02021	1.03594	0.99085
11	0.94176	0.99361	1.01327	0.94737
12	0.91440	0.94729	0.94941	0.87888
13	0.90354	0.97001	0.90281	0.84358
14	0.89693	0.95736	0.91423	0.84563
15	0.90243	0.94297	0.89907	0.84560
16	0.92074	0.95474	0.93198	0.85366
17	0.91236	0.95019	0.89127	0.80235
18	0.90691	0.94800	0.86620	0.79067
19	0.90880	0.95120	0.85147	0.79919
20	0.89099	0.93186	0.83124	0.79319
21	0.88478	0.93140	0.84793	0.77090
22	0.89057	0.93760	0.90356	0.85345
23	0.90642	0.95243	0.85940	0.84609
24	0.92290	0.93462	0.89247	0.87814
Mean	0.94362	0.98418	0.95287	0.90302

A.10 Supplementary Tables for Sections 4-7

Table A3: Sample Wide and Adjacent Period Weighted and Unweighted Characteristics Price Indexes.

Month t	P_{WATDC}^t	P_{ATDC}^t	P_{WTDC}^t	P_{TDC}^t	P_A^t	P_{UV}^t
1	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
2	0.99941	1.02634	0.99916	1.03434	1.03525	0.99703
3	1.00664	1.03071	1.01864	1.04148	1.03503	1.00972
4	1.01001	1.02115	1.02478	1.03703	1.02127	0.99538
5	1.00707	1.03854	1.01945	1.07987	1.06279	1.02001
6	0.99525	1.02985	1.00416	1.07009	1.06571	1.00173
7	0.97186	0.98912	0.97411	1.01789	1.02721	0.98386
8	0.95958	0.98052	0.97240	1.01430	1.02049	0.97422
9	0.95255	0.96487	0.96258	1.00193	1.01082	0.95086
10	0.94933	0.97181	0.96811	1.02021	1.03594	0.99085
11	0.92949	0.94535	0.94176	0.99361	1.01327	0.94737
12	0.89945	0.91290	0.91440	0.94729	0.94941	0.87888

13	0.87509	0.91105	0.90354	0.97001	0.90281	0.84358
14	0.86282	0.89739	0.89693	0.95736	0.91423	0.84563
15	0.85110	0.88380	0.90243	0.94297	0.89907	0.84560
16	0.86220	0.89100	0.92074	0.95474	0.93198	0.85366
17	0.85740	0.88438	0.91236	0.95019	0.89127	0.80235
18	0.84617	0.87346	0.90691	0.94800	0.86620	0.79067
19	0.84141	0.86878	0.90880	0.95120	0.85147	0.79919
20	0.82485	0.84900	0.89099	0.93186	0.83124	0.79319
21	0.81818	0.84705	0.88478	0.93140	0.84793	0.77090
22	0.80652	0.84479	0.89057	0.93760	0.90356	0.85345
23	0.79541	0.84252	0.90642	0.95243	0.85940	0.84609
24	0.78797	0.83106	0.92290	0.93462	0.89247	0.87814
Mean	0.90457	0.93064	0.94362	0.98418	0.95287	0.90302

Table A4: Sample Wide and Adjacent Period Weighted and Unweighted Time Product Dummy Price Indexes

Month t	P_{WAPN}^t	P_{WATPD}^t	P_{APN}^t	P_{WAPN}^t	P_A^t	P_{UV}^t	P_{IWTPD}^t	P_{WTPD}^t
1	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
2	0.99418	0.99358	0.98360	0.98781	1.03525	0.99703	0.98800	0.98828
3	0.98545	0.98526	0.97430	0.98084	1.03503	1.00972	0.98203	0.98205
4	0.98051	0.98456	0.95867	0.96681	1.02127	0.99538	0.98006	0.98006
5	0.97207	0.97476	0.94051	0.94903	1.06279	1.02001	0.96867	0.96878
6	0.96116	0.96444	0.92312	0.93115	1.06571	1.00173	0.95101	0.95087
7	0.94694	0.94422	0.90168	0.90729	1.02721	0.98386	0.92232	0.92250
8	0.92992	0.93034	0.87603	0.88649	1.02049	0.97422	0.91792	0.91801
9	0.91529	0.91971	0.85586	0.86908	1.01082	0.95086	0.90975	0.90983
10	0.91368	0.91611	0.85387	0.86254	1.03594	0.99085	0.90303	0.90323
11	0.87873	0.89088	0.81698	0.83488	1.01327	0.94737	0.87834	0.87881
12	0.85354	0.85948	0.78665	0.80071	0.94941	0.87888	0.85132	0.85129
13	0.81652	0.82589	0.76148	0.77569	0.90281	0.84358	0.83257	0.83276
14	0.80553	0.81473	0.74738	0.76387	0.91423	0.84563	0.82512	0.82554
15	0.78508	0.79577	0.73124	0.74871	0.89907	0.84560	0.81357	0.81431
16	0.78568	0.79492	0.73239	0.74716	0.93198	0.85366	0.82289	0.82328
17	0.77720	0.78726	0.71871	0.73419	0.89127	0.80235	0.82014	0.82048
18	0.76806	0.77805	0.70662	0.72286	0.86620	0.79067	0.80959	0.81037
19	0.75559	0.76665	0.69273	0.70844	0.85147	0.79919	0.80882	0.80906
20	0.73834	0.75214	0.67681	0.69445	0.83124	0.79319	0.79788	0.79830
21	0.73080	0.74318	0.67221	0.68464	0.84793	0.77090	0.78764	0.78818
22	0.71954	0.73369	0.66130	0.67542	0.90356	0.85345	0.78436	0.78460
23	0.70053	0.71498	0.64524	0.66085	0.85940	0.84609	0.76800	0.76781
24	0.67717	0.69385	0.63138	0.64587	0.89247	0.87814	0.74489	0.74478
Mean	0.84965	0.85685	0.80203	0.81412	0.95287	0.90301	0.86950	0.86972

Table A5: Predicted Share Measures of Relative Price Similarity for 24 Months

r	Δ(r,1)	Δ(r,2)	Δ(r,3)	Δ(r,4)	Δ(r,5)	Δ(r,6)	Δ(r,7)	Δ(r,8)	Δ(r,9)	Δ(r,10)	Δ(r,11)	Δ(r,12)
1	0.000	0.010	0.009	0.017	0.031	0.049	0.051	0.051	0.072	0.064	0.088	0.101
2	0.010	0.000	0.001	0.009	0.015	0.026	0.027	0.033	0.041	0.045	0.055	0.055
3	0.009	0.001	0.000	0.005	0.006	0.012	0.016	0.017	0.023	0.024	0.032	0.034
4	0.017	0.009	0.005	0.000	0.012	0.015	0.021	0.020	0.027	0.027	0.041	0.046
5	0.031	0.015	0.006	0.012	0.000	0.001	0.008	0.003	0.007	0.007	0.017	0.022
6	0.049	0.026	0.012	0.015	0.001	0.000	0.008	0.003	0.007	0.006	0.016	0.021
7	0.051	0.027	0.016	0.021	0.008	0.008	0.000	0.005	0.004	0.006	0.007	0.008
8	0.051	0.033	0.017	0.020	0.003	0.003	0.005	0.000	0.000	0.001	0.001	0.001
9	0.072	0.041	0.023	0.027	0.007	0.007	0.004	0.000	0.000	0.001	0.000	0.001
10	0.064	0.045	0.024	0.027	0.007	0.006	0.006	0.001	0.001	0.000	0.001	0.004
11	0.088	0.055	0.032	0.041	0.017	0.016	0.007	0.001	0.000	0.001	0.000	0.000
12	0.101	0.055	0.034	0.046	0.022	0.021	0.008	0.001	0.001	0.004	0.000	0.000
13	0.140	0.083	0.050	0.050	0.029	0.028	0.024	0.016	0.014	0.017	0.013	0.013
14	0.141	0.094	0.057	0.055	0.035	0.034	0.032	0.022	0.024	0.023	0.019	0.018
15	0.149	0.101	0.062	0.057	0.041	0.040	0.037	0.027	0.030	0.029	0.024	0.024
16	0.178	0.116	0.080	0.077	0.051	0.048	0.046	0.035	0.037	0.037	0.032	0.034
17	0.300	0.236	0.148	0.129	0.093	0.087	0.093	0.076	0.076	0.078	0.074	0.086
18	0.380	0.299	0.172	0.144	0.085	0.077	0.083	0.067	0.069	0.067	0.068	0.082
19	0.394	0.343	0.284	0.255	0.155	0.155	0.158	0.138	0.139	0.141	0.134	0.143
20	0.608	0.507	0.326	0.253	0.173	0.166	0.172	0.153	0.153	0.154	0.157	0.185
21	0.589	0.501	0.284	0.223	0.155	0.147	0.185	0.166	0.166	0.168	0.171	0.196
22	0.850	0.671	0.445	0.380	0.232	0.222	0.246	0.247	0.244	0.246	0.246	0.290
23	0.865	0.657	0.491	0.457	0.363	0.373	0.427	0.406	0.406	0.410	0.417	0.463
24	1.013	0.856	0.613	0.459	0.318	0.307	0.354	0.261	0.263	0.261	0.282	0.325

r	Δ(r,13)	Δ(r,14)	Δ(r,15)	Δ(r,16)	Δ(r,17)	Δ(r,18)	Δ(r,19)	Δ(r,20)	Δ(r,21)	Δ(r,22)	Δ(r,23)	Δ(r,24)
1	0.140	0.141	0.149	0.178	0.300	0.380	0.394	0.608	0.589	0.850	0.865	1.013
2	0.083	0.094	0.101	0.116	0.236	0.299	0.343	0.507	0.501	0.671	0.657	0.856
3	0.050	0.057	0.062	0.080	0.148	0.172	0.284	0.326	0.284	0.445	0.491	0.613
4	0.050	0.055	0.057	0.077	0.129	0.144	0.255	0.253	0.223	0.380	0.457	0.459
5	0.029	0.035	0.041	0.051	0.093	0.085	0.155	0.173	0.155	0.232	0.363	0.318
6	0.028	0.034	0.040	0.048	0.087	0.077	0.155	0.166	0.147	0.222	0.373	0.307
7	0.024	0.032	0.037	0.046	0.093	0.083	0.158	0.172	0.185	0.246	0.427	0.354
8	0.016	0.022	0.027	0.035	0.076	0.067	0.138	0.153	0.166	0.247	0.406	0.261
9	0.014	0.024	0.030	0.037	0.076	0.069	0.139	0.153	0.166	0.244	0.406	0.263
10	0.017	0.023	0.029	0.037	0.078	0.067	0.141	0.154	0.168	0.246	0.410	0.261
11	0.013	0.019	0.024	0.032	0.074	0.068	0.134	0.157	0.171	0.246	0.417	0.282
12	0.013	0.018	0.024	0.034	0.086	0.082	0.143	0.185	0.196	0.290	0.463	0.325
13	0.000	0.004	0.003	0.006	0.018	0.023	0.036	0.038	0.044	0.084	0.102	0.094
14	0.004	0.000	0.001	0.003	0.011	0.017	0.025	0.025	0.030	0.066	0.077	0.076

15	0.003	0.001	0.000	0.000	0.004	0.007	0.011	0.010	0.015	0.049	0.055	0.057
16	0.006	0.003	0.000	0.000	0.001	0.004	0.004	0.005	0.006	0.041	0.043	0.046
17	0.018	0.011	0.004	0.001	0.000	0.002	0.003	0.003	0.004	0.039	0.041	0.044
18	0.023	0.017	0.007	0.004	0.002	0.000	0.001	0.003	0.002	0.036	0.036	0.040
19	0.036	0.025	0.011	0.004	0.003	0.001	0.000	0.001	0.001	0.035	0.033	0.037
20	0.038	0.025	0.010	0.005	0.003	0.003	0.001	0.000	0.001	0.034	0.034	0.037
21	0.044	0.030	0.015	0.006	0.004	0.002	0.001	0.001	0.000	0.033	0.031	0.036
22	0.084	0.066	0.049	0.041	0.039	0.036	0.035	0.034	0.033	0.000	0.001	0.004
23	0.102	0.077	0.055	0.043	0.041	0.036	0.033	0.034	0.031	0.001	0.000	0.001
24	0.094	0.076	0.057	0.046	0.044	0.040	0.037	0.037	0.036	0.004	0.001	0.000

Table A5 can be used to construct the relative price similarity linked Predicted Share Price index, P_S^t, for t = 1,…,24. We set $P_S^1 = 1$. When comparing the prices of month 2 to the prices of previous months, there is only one possible comparison in our window of data so that we must compare p^2 to p^1. We use the matched model Fisher index $P_F(1,2)$ defined by (64) to define the similarity linked month 2 index. Thus $P_S^2 \equiv P_F(1,2)$. Now look at the column in Table A5 that has the heading $\Delta(r,3)$. Look at the first 2 entries in this column. We have $\Delta(1,3) = 0.0088$ and $\Delta(2,3) = 0.0007$. Since $\Delta(2,3)$ is smaller than $\Delta(1,3)$, we link month 3 to month 2 using the matched model Fisher index $P_F(2,3)$. Thus $P_S^3 \equiv P_S^2\, P_F(2,3)$. Now look at the column in Table A5 that has the heading $\Delta(r,4)$. Look at the first 3 entries in this column. We have $\Delta(1,4) = 0.0170$, $\Delta(2,4) = 0.0092$ and $\Delta(3,4) = 0.0046$. Since $\Delta(3,4)$ is the smallest of these 3 measures, we link month 4 to month 3 using the matched model Fisher index $P_F(3,4)$. Thus $P_S^4 \equiv P_S^3\, P_F(3,4)$. This procedure can be continued until we look down the column that has the heading $\Delta(r,24)$. The smallest measure of relative price similarity in the first 23 rows of this column is the entry for row 23 which has measure 0.0013. Thus we link month 24 to month 23 using the matched model Fisher index $P_F(23,24)$ which leads to the following definition for $P_S^{24} \equiv P_S^{23}\, P_F(23,24)$.[5]

The relative price Predicted Share Similarity Linked indexes P_S^t are listed in Table A6 below. We also list the chained maximum overlap Laspeyres, Paasche and Fisher indexes, P_{LCH}^t, P_{PCH}^t and P_{FCH}^t in Table A6. Finally, for comparison purposes, Table A6 lists our "best" hedonic price index from the previous sections, the Weighted Adjacent Period Time Product Dummy Index, P_{WATPD}^t, as well as the GEKS Index, P_{GEKS}^t and the Rolling Window GEKS with a Mean Splice using a window length equal to six months, P_{RWGEKS}^t. See Chart 4 for plots of the indexes listed in Table A6.

Table A6: The Predicted Share Similarity Linked Price Index and Other Comparison Price Indexes

Month t	P_S^t	P_{FCH}^t	P_{LCH}^t	P_{PCH}^t	P_{WATPD}^t	P_{WTPD}^t	P_{GEKS}^t	P_{RWGEKS}^t
1	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
2	0.99299	0.99299	0.99499	0.99099	0.99358	0.98828	0.98986	0.98805
3	0.98452	0.98452	0.98509	0.98395	0.98526	0.98205	1.00538	0.98295
4	0.98264	0.98264	0.98278	0.98250	0.98456	0.98006	1.01613	0.98220

[5] The entire set of bilateral matched model Fisher links is as follows: 2-1; 3-2; 4-3; 5-3*; 6-5; 7-6; 8-6*; 9-8; 10-9; 11-9*; 12-11; 13-12; 14-13; 15-14; 16-15; 17-16; 18-17; 19-18; 20-19; 21-20; 22-21; 23-22; 24-23. Note that there are only 3 bilateral links that are not chain links. Thus the similarity linked indexes for our data are likely to be close to the corresponding chained maximum overlap Fisher index.

5	0.97885	0.97249	0.97035	0.97463	0.97476	0.96878	0.99408	0.97832
6	0.96824	0.96195	0.95918	0.96472	0.96444	0.95087	0.98436	0.96645
7	0.94753	0.94137	0.93918	0.94357	0.94422	0.92250	0.95372	0.93796
8	0.93457	0.92689	0.92393	0.92986	0.93034	0.91801	0.94561	0.92793
9	0.92543	0.91782	0.91232	0.92335	0.91971	0.90983	0.93319	0.91697
10	0.92600	0.91838	0.90527	0.93168	0.91611	0.90323	0.93046	0.91910
11	0.89409	0.88924	0.87157	0.90727	0.89088	0.87881	0.90590	0.88811
12	0.86152	0.85685	0.84120	0.87279	0.85948	0.85129	0.87977	0.85596
13	0.82820	0.82371	0.81147	0.83614	0.82589	0.83276	0.85910	0.82232
14	0.81744	0.81301	0.80318	0.82295	0.81473	0.82554	0.85337	0.81562
15	0.79826	0.79394	0.78350	0.80451	0.79577	0.81431	0.83577	0.79723
16	0.79677	0.79245	0.78126	0.80379	0.79492	0.82328	0.84143	0.80033
17	0.78900	0.78472	0.77346	0.79615	0.78726	0.82048	0.84598	0.79806
18	0.77988	0.77565	0.76547	0.78596	0.77805	0.81037	0.82439	0.77913
19	0.76847	0.76431	0.75526	0.77346	0.76665	0.80906	0.84084	0.77302
20	0.75289	0.74881	0.74032	0.75740	0.75214	0.79830	0.84836	0.75935
21	0.74342	0.73938	0.73260	0.74623	0.74318	0.78818	0.83608	0.75324
22	0.73398	0.73000	0.72431	0.73573	0.73369	0.78460	0.83460	0.74573
23	0.71536	0.71148	0.70730	0.71569	0.71498	0.76781	0.79399	0.72752
24	0.69346	0.68970	0.68948	0.68993	0.69385	0.74478	0.75979	0.71031
Mean	0.85890	0.85468	0.84806	0.86139	0.85685	0.86972	0.89634	0.85941