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A New Look at Prices of Personal Computers, Tablets, and Cell Phones

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Introduction

Official price measures for high-tech devices indicate that rates of decline have slowed dramatically in recent years. These sluggish recent price trends for high-tech products are evident in figure 1, which plots price indexes from the NIPAs for computer investment as well as the official measure of producer prices of microprocessor units (MPUs). These slower rates of price decline have been taken as evidence that Moore's Law—the idea that the number of transistors on a semiconductor will double every couple of years—has slowed or come an end.[1] More broadly, taken at face value, these more sluggish rates of price decline imply, all else equal, a more restrained pace of innovation in the sectors producing these products.

However, questions have been raised about official price measures. Byrne, Oliner, and Sichel (2015) developed alternative measures of quality-adjusted prices for MPUs that have fallen much faster than official measures in recent years. Byrne and Corrado (2016) developed alternative price indexes for communications equipment that have been falling more rapidly than official measures of these prices. Also, Byrne (2015a) provides evidence that prices of data storage equipment have been falling faster than in official measures, and Byrne (2015b) highlights similar measurement issues for prices of special-purpose electronic equipment, which includes equipment employed in medical, military, and aerospace applications. Taken together, these studies raise the possibility of significant mismeasurement of prices for other high-tech devices. Accordingly, we believe that it is time for a new look at price measurement for a broader set of high-tech products.

[1] A recent *Economist* cover story and banner calling out "The End of Moore's Law" made this case, as did Robert Gordon's recent book on U.S. economic growth. See the *Economist* March 12th-18th, 2016, Technology Quarterly, pp. 3-14 and Gordon (2016), pp. 444-447.

This paper takes a step in that direction by developing new hedonic price indexes for personal computers, tablets, and cell phones. This set of platforms or devices range from mature products like PCs to newer tablets and cell phones. Some analysts have suggested that PCs are no longer the primary locus of innovation because people just do not need more powerful PCs.[2] We assess the evidence for that argument and also consider tablets and cell phones, which appear to be very much the locus of current innovation.

We investigate a second research question as well: Is it important to use actual performance measures (rather than just technical characteristics) in hedonic price regressions for PCs, tablets, and cell phones? Byrne, Oliner, and Sichel (2015) demonstrated that using performance measures is important for gauging price trends of microprocessors. However, this idea is not new, and decades ago researchers called for the inclusion of actual performance measures in hedonic price regressions rather than technical characteristics (see Triplett, 1989, and Berndt and Griliches, 1993). In addition, specifically in the context of computer power, Nordhaus (2007) noted that computational power often increased more rapidly than increases in chip density. This discrepancy highlights the value of using a broader performance measure that can capture performance improvements coming from advances other than just chip density or clock speed. For some products, such as communications equipment, end-user measures of performance have been relatively unavailable so there is little choice but to use

[2] See Gordon (2016), p. 447 for a discussion.

characteristics. For many computing products, however, performance measures are available, and this paper assesses their importance for hedonic regressions.[3]

[This version of the paper includes results for desktops as well as a first look at tablets and cell phones. We will include more complete results for tablets and cell phones as well as results for laptops in the next version.]

To consider price trends for personal computers, tablets, and cell phones, as well as the role of performance measures in gauging these trends, we assembled datasets from The NPD Group, Inc. (NPD) and International Data Corporation (IDC) on prices and characteristics of personal computers, tablets, and cell phones along with extensive data on performance measures for these devices.

Our results for personal computers build on a rich literature that has examined prices of PCs. Aizcorbe (2014) provides an extensive bibliography (pp. 99-101). In addition to papers cited there, we note work by Benkard and Bajari (2005), Holdway (2001), Erickson and Pakes (2011), and Diewert, Heravi, and Silver (2008).[4] The analysis that uses the most recent data of PC prices for the U.S. market, Aizcorbe and Pho (2005), extends only through 2003. We bring the story up to date and cover a period of some interest and debate. As noted above, official prices have slowed markedly, and we provide a check using outside data for this development. Further, we expand results to new platforms for which BLS' quality adjustment likely is incomplete. For tablets, we

[3] Chwelos (2000) studied desktop PC prices from 1990 to 1998 with a control for benchmark test scores and found that constant-quality prices fell at a similar rate to indexes estimated by Berndt and Rappaport (2003) without benchmarks; for laptops, however, the use of benchmark scores resulted in price indexes with substantially faster price declines. Getsova (2015) used the Berndt and Rappaport data and specifications to show that price trends for desktop computers were nearly identical from 1976-1999 when the regressions included clock speed as an explanatory variable and when they included a performance measure instead. Sun (2014) used performance measures in a study of microprocessors in laptops.
[4] For a survey, see Triplett (2006). Bureau of Labor Statistics (2011) provides an overview of procedures used in the Producer Price Index.

believe our results are among the first to document quality-adjusted price trends, which we show using both hedonic and matched-model indexes.[5]

Overall, our results suggest that, on a quality-adjusted basis, price declines of desktop PCs have indeed slowed. Hedonic indexes based on benchmark performance scores fall somewhat faster than those that omit this information, but both types of indexes indicate a shift to slower price declines. At the same time, prices for tablets have been falling rapidly as this platform has dramatically evolved and gained market share.

This paper is organized as follows. Section 2 describes the data we use. Section 3 describes our approach to estimating hedonic price indexes for these products, while Section 4 provides our empirical results. Section 5 concludes.

1. Data

We collected and assembled a number of datasets to obtain comprehensive information on prices, characteristics, and performance measures for personal computers, tablets, and cell phones.

Prices and Characteristics for Personal Computers and Tablets

For desktops, laptops, and tablets, we employ monthly data on prices and technical characteristics from NPD for specific models spanning January 2007 to December 2014. These data cover PCs sold through a wide range of distribution channels, and NPD intends for the data to be nationally representative. We aggregate the observations to quarterly and annual averages to smooth through noise in the data. Revenue and units reported by major brick-and-mortar and online outlets by model, net

[5] The Bank of Japan currently employs hedonic adjustment for tablet computer prices in its Corporate Goods Price Index. See https://www.boj.or.jp/en/statistics/outline/exp/pi/cgpi_2010/hed2010f.pdf.

of returns, are used to calculate the average sale price.[6] The revenue data also allow us to construct revenue shares for use as weights in the regression analysis. The data include extensive information on features for each model, including memory, hard disk size, weight, dimensions, operating system, and the specific microprocessor in the device.

The dataset includes 55,803 distinct models of PCs, including 34,162 laptops, 19,378 desktops, and 2,263 tablets, with full data on characteristics for each of the models. On a quarterly basis, we have 138,130 observations on prices, while on an annual basis we have 63,411 prices.

Market Shares and Matched-model Price Changes for Personal Computers and Tablets

From 2007 to 2009, prior to the transformation of the tablet market by the introduction of the Apple iPad in April 2010, laptop PC sales accounted for about two-thirds of revenue in the NPD data, desktops for about one third, and tablets for a trivial share. Beginning in 2010, the tablet share rose rapidly. By 2014, tablets accounted for 15 percent of NPD sales revenue, while laptops and desktops accounted for 56 percent and 29 percent of revenue respectively.

To obtain an initial characterization of price declines for laptops, desktops, and tablets together, we constructed Fisher-weighted matched-model price indexes with the average quarterly price observations and revenues in the NPD data. The overall matched-model index fell 7.7 percent per year on average from 2007 to 2014, reflecting declines for desktops, laptops, and tablets of 6.2 percent, 7.6 percent, and 11.9 percent respectively. The relatively rapid price decline for tablets is consistent with the substitution toward tablets indicated by the increase in its revenue share noted above.

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[6] The NPD data do not cover direct purchases from a PC producer, such as sales of Dell units from the company's website. However, sales of Dell PCs at brick-and-mortar stores like Office Depot or at online stores like Amazon are included.

The key question considered in this paper is whether hedonic methods, which have the potential to control for quality change more completely than matched-model indices, deliver similar results.

Prices and Characteristics for Cell Phones

For cell phones, we use quarterly data provided by IDC for specific models of smartphones—cell phones with advanced operating systems capable of running a wide variety of programs—and average quarterly unit prices for 24 brands of "feature phones," which essentially are old-fashioned "non-smart" cell phones. Price observations correspond to prices for phones without an associated service contract, and sales volumes are derived from company public announcements and consumer survey responses. A wide range of model characteristics are observed, including memory, screen size, screen resolution, operating system, and processor speed. In addition to prices and characteristics, the IDC data include unit sales, and we use these figures to construct unit sales and revenue share weights. These data cover cell phones sold through a wide range of distribution channels, and IDC intends for the data to be nationally representative.

The cell phone data span 2007:Q1 to 2015:Q3 and include 716 distinct smartphone models. On a quarterly basis, we have 3,849 observations on smartphone prices and characteristics. For feature phones, we observe average selling prices for phones distinguished by vendor and technical characteristics, such as type of air interface (e.g. CDMA v. GSM), and generation of network (e.g. 2G v. 3G). These average prices provide 646 quarterly observations.

Market Shares and Matched-model Price Changes for Cell Phones

Market shares have shifted strongly toward smartphones away from feature phones. Between 2007 and 2014, the revenue share of smartphones rose from 22 percent to 97 percent of the market, almost fully displacing the less powerful feature phones.

As an initial look at price trends, we constructed Fisher-weighted matched-model price indexes for both types of cell phones. The index for feature phones fell 21 percent per year on average from 2007 to 2015, while the index for smartphones declined at an average rate of 8 percent. Splitting the 2007-2015 period in half, the price declines accelerated for both types of cell phones, in contrast to the pattern for desktop PCs. For smartphones, the average annual rate of price decline increased from 4 percent over 2007-2011 to 11 percent over 2011-2015; for feature phones, the average rate of decline quickened from 10 percent to 32 percent across the two periods. We consider below whether hedonic indexes that exploit the characteristics information in the IDC data produce similar results.[7]

Benchmark Performance Measures for Personal Computers

As noted above, Byrne, Oliner, and Sichel (2015) emphasized the importance of using actual measures of performance in hedonic regressions for microprocessors rather than relying on technical characteristics such as clock speed. For PCs, we use performance measures for the included CPU from Passmark, supplemented by the scores from the Standard Performance Evaluation Corporation (SPEC) that Byrne, Oliner, and Sichel (2015) used. We matched these scores by model to the NPD data.

[7] Byrne and Corrado (2015) produced a quality-adjusted price index based on transaction prices for used cell phones in recent years. An updated version of their index, used in the Federal Reserve Board's industrial production index, fell 20 percent per year on average from 2007 to 2014. Based on their results, and observation of technical improvements, we suspect the matched-model results for smartphones understate the true rate of constant-quality price decline.

SPEC is a widely-cited non-profit corporation that establishes performance benchmark tests for computing equipment and publishes test results submitted by member organizations.[8] These scores are based on a suite of tasks designed to reflect the needs of computer users. We used the benchmark suites SPEC® CPU2006 and SPEC® CPU2000. The SPEC scores we use from CPU2000 are an average of 26 tests, while the score we use from CPU2006 are an average of 29 tests.[9] These tests are designed to capture the types of tasks performed by actual users and are scaled so that higher scores indicate better performance.

Passmark provides scores on the performance of a PC's microprocessor, based on an average of eight different tests.[10] These tests are designed to fully exploit multiple cores and threads available on a PC. They also are scaled so that higher scores indicate stronger performance.

Perhaps not surprisingly, the SPEC and Passmark scores are highly correlated with each other, with a correlation coefficient of 0.95. SPEC and Passmark cover somewhat different sets of models. Rather than using both scores (and reducing our sample size) or running separate regressions on different samples, we use the SPEC scores to impute Passmark scores for models for which we have a SPEC score but not a Passmark score. We do this imputation for about one-quarter of the observations in our quarterly sample.[11] Given the high correlation between SPEC and Passmark, we are comfortable using these imputed values.

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[8] The description of SPEC scores is taken directly from Byrne, Oliner, and Sichel (2015).

[9] See https://www.spec.org/benchmarks.html#cpu for a description of SPEC scores. Also, see Appendix A in Byrne, Oliner, and Sichel (2015).

[10] See https://www.passmark.com/ for a description of Passmark CPU scores.

[11] The imputed Passmark scores are the fitted values from a regression of Passmark scores on SPEC scores and a constant for observations with both scores.

Benchmark Performance Measures for Tablets

We matched the price and characteristics data for these devices to Passmark performance scores (SPEC has not evaluated the chips used in tablets or smartphones.) Passmark provides several scores for tablets, including a CPU benchmark similar to the one above for desktops and laptops, as well as scores for memory access, disk access, two-dimensional graphics, and three-dimensional graphics.

We also matched to performance scores from Geekbench, another provider of benchmarks for tablets and phones.[12] Geekbench scores are based on an average of 22 tests, each run in single-core and multi-core mode. The individual tests on which the Geekbench score is based cover processor performance (as with SPEC and Passmark) and also battery performance. They too are scaled so that higher scores indicate better performance. [We will use the Geekbench scores in the next version of the paper as a robustness check and to get better coverage of chips designed by ARM.]

Benchmark Performance Measures for Cell Phones [For next version.]

3. Procedures for Hedonic Price Indexes[13]

To fix ideas, we first describe a dummy-variable hedonic specification:

$$\ln(P_{i,t}) = \alpha + \sum_k \beta_k X_{k,i,t} + \delta_t D_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where $P_{i,t}$ is the price of a device i in period t, $X_{k,i,t}$ is the value of characteristic k for device i in period t (measured in logs or levels, as appropriate), $D_{i,t\in Y}$ is a time dummy

[12] See https://browser.primatelabs.com/ios-benchmarks and https://browser.primatelabs.com/android-benchmarks for a description of Geekbench scores.

[13] This section draws heavily from Byrne, Oliner, and Sichel (2015), including language taken directly from that paper.

variable (fixed effect) that equals 1 if device i is observed in period t and zero otherwise, and $\varepsilon_{i,t}$ is an error term.

A potential shortcoming of equation 1, highlighted by Pakes (2003) and Erickson and Pakes (2011), is that the coefficients on the characteristic or performance variables are constrained to remain constant over the full sample period. One response to that concern is to run a cross-section regression for every time period and then to use results from those regressions to build up a price index.[14] Such an approach is appealing because it provides maximum flexibility for estimated coefficients to change over time and allows the results to be used in price index formulas. Byrne, Oliner, and Sichel (2015) judged that their sample of Intel microprocessors was too small to run reliable cross-section hedonic regressions for every quarter. As a compromise, that paper estimated adjacent-year hedonic regressions, and we do the same here to place the results on the same conceptual basis.[15] [The next version of this paper will consider several alternative specifications, including annual imputation hedonics and adjacent-quarter regressions.]

Specifically, we estimate the following regression for each two-year overlapping period:

$$\ln\left(P_{i,t}\right) = \alpha + \sum_k \beta_k X_{k,i,t} + \delta D_2 + \varepsilon_{i,t} \qquad (2)$$

where $P_{i,t}$ is the price of device i in year t. We measure $P_{i,t}$ as the annual average of the quarterly prices of device i within the year. The dummy variable D_2 equals 1 if the price observation is in the second year of the two-year overlapping period and 0 otherwise. To construct a price index from this sequence of regressions, we spliced together the percent

[14] See Aizcorbe's (2014) discussion and the references there.
[15] See Triplett (2006) for a discussion of adjacent-period hedonic regressions.

changes implied by the estimated coefficients on the D_2 variables. All of the reported results are bias-adjusted to account for the transformation from log prices to a non-log price index.[16]

For the explanatory variables in $X_{k,i,t}$, we include a set of technical characteristics as well as performance measures. For desktop PCs, the technical characteristics include clock speed of the MPU in the computer, the amount of random access memory (RAM), the size of the hard disk, and thermal design power. These variables all enter the regression as natural logs. We also include fixed effects for the PC's brand, its operating system, type of graphics processor, whether it is an all-in-one model, whether it has a small footprint, whether the PC shares memory between the main processor and the graphics processor, and whether it is marketed to commercial users (as compared with household users). Finally, as noted above, we measure benchmark performance for desktop PCs with the Passmark CPU benchmark measure, which is imputed from SPEC scores for models with missing Passmark data.

The explanatory variables for tablets include processor clock speed, amount of flash memory, weight of the device, screen quality in number of pixels, and screen size (diagonal), all of which enter as logs. For Apple tablets, we also include five Passmark performance measures, including benchmarks for CPU, memory, disk, two-dimensional graphics, and three-dimensional graphics. As described below, we run separate hedonic regressions for each brand we consider so we do not include brand fixed effects.

[16] Because the exponential function is nonlinear, the translation from the natural log of prices to price levels requires an adjustment in order to be unbiased. We apply the standard adjustment based on the estimated variance of the regression error; see Aizcorbe (2014) for details. This adjustment had very little effect on estimated price trends over our sample.

The hedonic regressions for PCs and tablets presented in this paper use revenue share weights based on the NPD data. In particular, we follow the weighting procedure described in Diewert, Heravi, and Silver (2008). For each of our adjacent-year regressions, we use the revenue shares for each model in each year. To be precise, consider a particular model—call it model A—that appears in both years. For the observation on model A in the first year of the adjacent-year regression, we use model A's revenue share in the first year out of total revenue in that year for all models included in the regression, while the observation on model A in the second year is weighted by its share of total revenue for all models in the regression in that year.

4. Results

Desktop Personal Computers

Results from our hedonic regressions for desktop personal computers are shown in Table 1. These figures are based on adjacent-year estimates of equation 2 with revenue share weights. We estimate the regressions first with technical characteristics alone and then add benchmark performance to gauge the effect of including the performance measure. As reported in table 1, the adjacent-year regressions over the full 2007-2014 sample period have, on average, more than 8,000 observations. Coefficients for all of these adjacent-year regressions are reported in table 2. Key results are described below.

Measures of performance increase much more rapidly over our sample than do the clock speeds of the MPU in a PC. Over the period 2007-2014, clock speed rose at an average annual rate of 3.6 percent, from 2.4 GHz to 3.1 GHz (not shown in table 1), while the measure of MPU performance from Passmark increased at an annual rate of

21.8 percent. Not surprisingly, this matches the pattern of results for MPUs in Byrne, Oliner, and Sichel (2015).

Measures of performance do a better job of explaining prices than do the clock speeds. As can be seen by comparing lines 3 and 4 in table 1, adding a measure of performance to the explanatory variables generates a higher R^2 than when performance is excluded (0.52 versus 0.59 over 2007-2014). This pattern holds across the 2007-2010 and 2010-2014 periods as well.

Based on these results (as well as a strong prior belief that performance measures are the variables that should, ideally, be included in hedonic regressions), our preferred specification (line 4) includes the performance measure as well as a full set of technical characteristics including clock speed. While there is always a risk of over-interpreting the coefficients in hedonic regressions, it is interesting that the coefficient on the benchmark performance measure is positive, large, and significant in every adjacent-year regression (averaging 0.47 across all of the adjacent-year regressions, as shown in table 2). At the same time, in the regression with only technical characteristics, the coefficient on clock speed is positive and significant in just four out of seven of the adjacent-year regressions, and the coefficient is significantly negative in the other three regressions.

In our preferred specification, the average pace of price decline over 2007-2014 is 8.8 percent. This rate of price decline is more rapid than that generated by a matched-model index calculated on the NPD data over the full 2007-2014 period. Nonetheless, this pace of decline is rather modest by historical standards. For the period 1976-1999, Berndt and Rappaport (2001) estimated that desktop PC prices fell at an average annual rate of 27 percent (see Table 1, Panel A of their paper).

Given that performance (as measured by the Passmark CPU benchmark) increased at an average annual rate of over 20 percent over this period and technical characteristics generally improved as well, our results suggest that buyers were not placing tremendous value on that improved performance.

While rates of price decline are relatively modest by historical standards, average prices fall faster when the performance variable is included as an explanatory variable than when it is omitted. A comparison of lines 3 and 4 indicates that the price indexes generated when performance is included fall, on average, 3 percentage points faster than those generated when performance is omitted. In earlier periods, performance and clock speed were interchangeable in hedonic regressions for desktop PCs. Getsova (2015) replicated the results in Berndt and Rappaport (2001) and showed that implied rates of price decline were nearly identical if the clock speed variable included in Berndt and Rappaport's specification was replaced by a composite performance measure from SPEC.

This pattern is what we expected to see given our prior that performance measures are important for correctly specifying hedonic regressions. That said, the difference between specifications with and without performance as an explanatory variable is not that large. This outcome might seem surprising given that Byrne, Oliner, and Sichel (2015) found that average price declines for MPUs in desktop PCs in recent years were about 20 percentage points faster when a performance measure was included in the hedonic regression than when clock speed was included. One might think that, if using performance measures rather than clock speed makes such a difference for chips, then using performance might also make a big difference when gauging quality change for PCs. Indeed, that was our prior.

But, on reflection, perhaps our results for desktop PCs are not so surprising given the cost share of MPUs in a personal computer. On average, that share is about 15 percent. Accordingly, if the inclusion of a performance variable generates a 20 percentage point faster average rate of price decline for MPUs, and the MPU makes up about 15 percent of the cost of a PC, then that faster decline in the cost of MPUs would, all else equal, generate about a 3 percentage point faster decline in the price of desktop PCs (=0.15 x 20). This figure is right in line with our results for PCs. Of course, many other factors affect the price of PCs, but this back-of-the-envelope calculation suggests that the magnitude of faster declines generated by using performance measures is in a reasonable ballpark.

Laptop Computers [Next version of paper.]

Tablets

Tablets became ubiquitous with the introduction of the iPad in 2010, but tablets for specialized commercial uses were in the market before 2010 and since then Apple has had plenty of competition for iPads. Accordingly, we focus separately on tablets made by Apple, its primary competitors in the consumer (and also commercial) market, and tablets made explicitly for specialized commercial applications (such as in health care).

To illustrate the evolution of these markets, table 3 shows revenue shares in the NPD data for different brands of tablets. Prior to 2010, the market largely consisted of tablets produced by Motion Computing, a maker of tablets for specialized commercial applications. Since 2010, iPads exploded in the consumer (and also in some commercial) markets, and several companies introduced competitors to the iPad. As of 2014, Apple, Samsung and Microsoft together accounted for 82 percent of the market.

Our results for tablets are based on the same adjacent-year regression specification as for desktop PCs (equation 2 shown above). We regress log prices on different combinations of the Passmark performance measures and technical characteristics (including the clock speed of the MPU in the tablet) as described in section 3. For this version of the paper, we present results for Apple iPads, tablets produced by Samsung and Microsoft that compete directly with the iPad, and tablets produced by Motion Computing for the specialized commercial market. Table 4A shows results for the consumer segment, while table 4B reports results for specialized commercial tablets. Key results are described below.

For Apple tablets, performance has increased more rapidly than clock speed. Clock speed for Apple tablets increased 9.9 percent per year on average from 2010 to 2014, while the composite performance score from Passmark increased 22.0 percent per year.

Using actual performance measures slightly improves the fit of hedonic regressions for Apple tablets. As reported on lines 2 and 3 of table 4A, the R^2 rises a little when we include the five Passmark performance measures in the regression for Apple tablets.[17] In terms of price trends, prices fall about 2 percentage points faster on average when the Passmark performance measures are included than when just technical characteristics (including clock speed) are used. Just as for desktop PCs, the use of performance measures matters for Apple tablets, though the effect is not dramatic. Given our strong

[17] In some of the adjacent-year regressions, some of the performance measures are omitted due to collinearity.

priors that using performance measures is important, our preferred specification is the one using performance measures in line 3.

In our preferred specification, prices of Apple tablets fall at an average rate of 10.6 percent from 2010-2014. Over this period, average prices (with no quality adjustment) drop at an average rate of 7.5 percent, and the quality adjustment pulled that rate of price decline down to 10.6 percent.

At this point, we have not yet collected enough performance measures for tablets produced by non-Apple manufacturers to be able to assess the potential importance of using performance measures. Accordingly, the hedonic price regressions for Samsung, Microsoft, and Motion Computing include technical characteristics (including clock speed) but do not include performance measures.

Among competitors to Apple, quality adjusted prices of Samsung tablets (for 2012-2014) and Microsoft tablets (for 2013-2014) fall at average rates of 26.2 percent and 24.3 percent, respectively. These price declines are quite substantial and raise the possibility that Samsung and Microsoft, after introducing new products to compete with Apple, cut prices aggressively to gain market share (which they did as seen in table 3). For the adjacent-year regressions on which these price trends are based, those for Samsung products fit extremely well with an average R^2 of 0.97. The adjacent-year regressions for Microsoft tablets did not fit as well, with an average R^2 of 0.39

In the specialized commercial market, quality adjusted prices of Motion Computing tablets were essentially flat over the period 2007-2010, and then fell at a modest 1.8 percent average rate over 2010-2014 (table 4B). These specialized markets are quite distinct from the consumer market (though Apple, Samsung, and Microsoft are all trying to sell their tablets into these specialized markets). We suspect that the less intense competition in these specialized markets could have lead to less pressure to innovate and, more generally, less downward pressure on prices.

Overall, the results for tablets indicate significant price declines for Apple iPads and very rapid price declines for tablets produced by Samsung and Microsoft that compete with Apple. In the market for specialized commercial tablets, quality-adjusted prices for Motion Computing tablets have been flat to modestly moving down.

Mobile Phones

As noted above, we constructed Fisher-weighted matched-model price indexes for both types of cell phones. As shown in table 5, the index for feature phones (non smartphones) fell 21 percent per year on average from 2007 to 2015, while the index for Apple and non-Apple smartphones declined at an average rate of 8 percent. Splitting the 2007-2015 period in half, the price declines accelerated for both types of cell phones, in contrast to the pattern for desktop PCs. For smartphones, the average annual rate of price decline increased from 4 percent over 2007-2011 to 11 percent over 2011-2015; for feature phones, the average rate of decline quickened from 10 percent to 32 percent across the two periods.

We will include hedonic indexes for cell phones in the next version of the paper.

5. Conclusion

Our hedonic results indicate that prices for desktop PCs have been falling quite slowly since 2010 and more slowly than in earlier periods, but concurrently prices for tablets have been declining rapidly as this platform has dramatically evolved and gained market share. These price trends are consistent with the idea that PCs have become a mature technology that has not been changing particularly rapidly in recent years. Yet, tablets, which are a new platform and very much the locus of innovation, have seen quite rapid price declines in recent years according to our hedonic regressions. In addition, matched-model indexes for smartphones and feature phones show notably rapid price declines with faster declines in recent years. The next version of the paper will add hedonic estimates for cell phones and will bring laptops into the analysis. An assessment of potential biases in official price measures for computing equipment and cell phones will be possible after we have completed this further analysis.

On our second research question about the role of performance measures, we find for both PCs and tablets that hedonic regressions that include performance measures generate price declines that are more rapid than when performance measures are excluded. That being said, the difference in price trends from the inclusion or not of performance measures is not nearly so dramatic as in the case of MPUs documented by Byrne, Oliner, and Sichel (2015). However, this difference between MPUs and PCs in the effect of using performance measures is in a reasonable range given that MPUs account for a modest share of the value of a PC.

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Table 1
Personal Computers: Price Indexes for Desktops
Average Annual Percent Change, 2007-2014

	2007-14			2007-10			2010-14		
	percent change	R^2	Average # observations	percent change	R^2	Average # observations	percent change	R^2	Average # observations
1. Average price	-2.0			-5.5			0.6		
2. Matched-model, NPD Data	-6.2			-7.6			-5.1		
3. Technical characteristics	-5.7	0.52	8,660	-14.1	0.63	6,457	0.7	0.43	10,312
4. Performance and technical characteristics	-8.8	0.59	8,658	-15.4	0.67	6,455	-3.9	0.52	10,311

Notes: Price indexes are generated from adjacent-year regressions with revenue-share weights. The performance variable is the Passmark CPU Benchmark. All estimates are bias adjusted to account for the translation from log price to a price index. The reported R^2 is the average across each of the adjacent-year regressions. Percent changes are measured as differences in log levels.

Table 2
Desktop Personal Computers
Summary of Coefficient Estimates for Revenue-Weighted Adjacent-Year Regressions
(coefficients in bold are statistically significant at the 5% level)

Technical Characteristics Only	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
speed	**0.49**	**0.54**	**0.67**	**0.50**	**-0.23**	**-0.37**	**-0.44**
RAM	**0.31**	**0.28**	**0.31**	**0.36**	**0.34**	**0.26**	**0.22**
disk size	**0.05**	0.00	**-0.05**	**-0.19**	**-0.18**	**-0.10**	**-0.16**
power	**-0.52**	0.04	**0.15**	**0.21**	**0.36**	**0.28**	**0.39**
all-in-one	**0.33**	**0.55**	**0.50**	**0.36**	**0.32**	**0.36**	**0.44**
small	0.09	0.14	0.17	0.17	0.13	0.09	**0.13**
vendors (# significant of 6)	2.00	3.00	3.00	4.00	3.00	3.00	5.00
OS (# significant of 19)	2.00	8.00	9.00	3.00	6.00	8.00	6.00
graphics processor (# sig. of 10)	2.00	3.00	6.00	4.00	6.00	3.00	2.00
shared memory	**-0.36**	**-0.30**	**0.30**	**0.36**	**0.36**	**-0.38**	**-0.13**
commercial	**0.16**	**0.12**	**0.07**	0.03	0.06	0.07	**0.09**
Tech Characteristics & Performance	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
benchmark	**0.32**	**0.60**	**0.51**	**0.37**	**0.38**	**0.53**	**0.60**
speed	**0.38**	**0.00**	**0.16**	**0.44**	-0.15	**-0.36**	**-0.30**
RAM	**0.22**	**0.16**	**0.23**	**0.29**	**0.23**	**0.06**	**0.05**
disk size	0.03	-0.02	**-0.08**	**-0.23**	**-0.23**	**-0.15**	**-0.20**
power	**-0.54**	**-0.31**	**-0.24**	**-0.13**	0.00	**-0.13**	**-0.08**
all-in-one	**0.37**	**0.63**	**0.50**	**0.38**	**0.36**	**0.40**	**0.44**
small	**0.09**	**0.13**	**0.16**	**0.14**	**0.11**	**0.08**	**0.10**
vendors (# significant of 6)	3	4	6	4	3	1	6
OS (# significant of 19)	2	6	6	4	2	10	6
graphics processor (# sig. of 10)	0	4	8	7	4	1	2
shared memory	**-0.32**	**-0.17**	**-0.17**	**-0.23**	**-0.11**	0.08	**0.12**
commercial	0.12	**0.10**	**0.07**	-0.01	-0.03	-0.05	-0.02

Table 3
Tablet Revenue Shares by Brand
(Percent)

	2007	2008	2009	2010	2011	2012	2013	2014
Apple	0	0	0	84	70	70	52	35
Samsung	0	0	0	0	4	11	15	12
Microsoft	0	0	0	0	0	0	12	35
Motion Computing	67	91	90	12	4	5	3	2
Other	33	9	10	4	23	14	17	16
Total tablets	100	100	100	100	100	100	100	100

Table 4A
Consumer Tablets: Price Indexes for Apple, Samsung, and Microsoft
Average Annual Percent Change, 2010-2014

	Apple			Samsung			Microsoft		
	Percent change, 2010-14	R^2	**Average # observations**	**Percent change, 2011-2014**	R^2	**Average # observations**	**Percent change, 2013-14**	R^2	**Average # observations**
1. Average price	-7.5			-20.5			31.0		
2. Clock speed and other technical characteristics	-8.4	.77	438	-26.2	.97	178	-24.3	.39	77
3. Performance and technical characteristics (except clock speed)	-10.6	.79	438						

Notes: The performance controls for Apple are Passmark performance scores for CPU, memory, disk access, 2D graphics, and 3D graphics. All estimates are bias adjusted to account for the translation from log price to a price index. The reported R^2 is averaged across each of the adjacent-year regressions.

Table 4B
Specialized Commercial Tablets: Price Indexes for Motion Computing
Average Annual Percent Change, 2007-2014

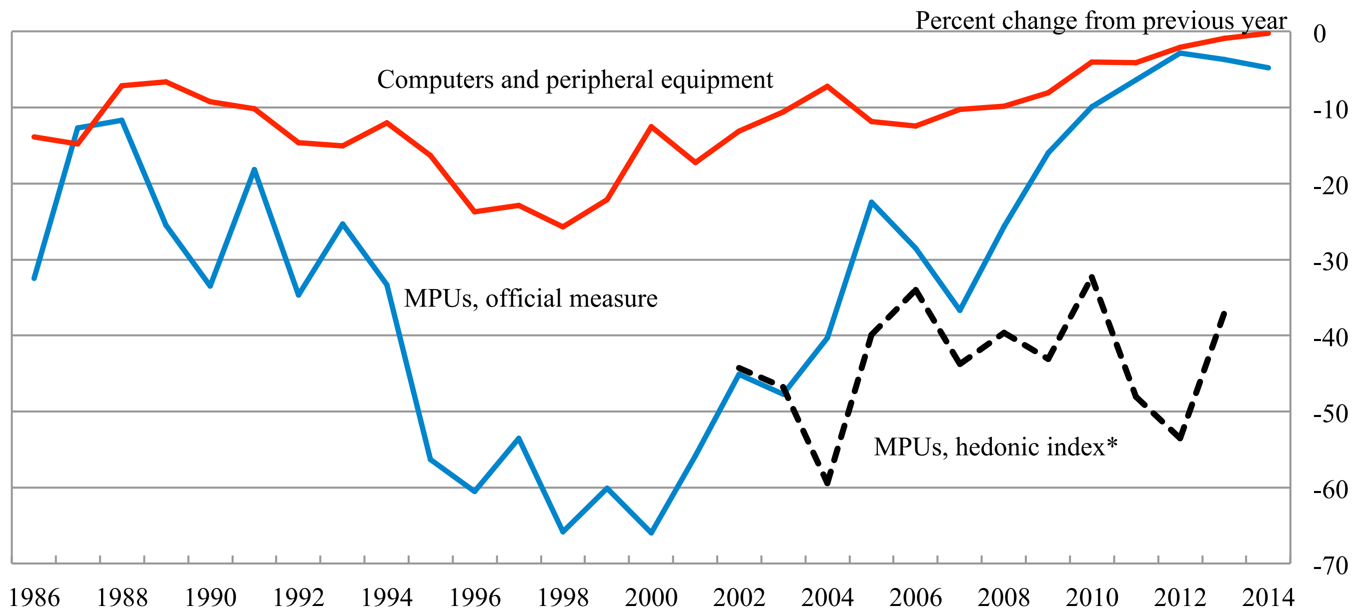
	Motion Computing			
	2007-2010		**2010-2014**	
	Percent change	R^2	**Percent change**	R^2
1. Average price	2.1		1.0	
2. Clock speed and other technical characteristics	.1	.32	-1.8	.66

Notes: All estimates are bias adjusted to account for the translation from log price to a price index. The reported R^2 is the adjusted measure averaged across each of the adjacent-year regressions.

Table 5
Cell Phones: Price Indexes
Average Annual Percent Change, 2007-2015

	Apple	Other smartphones	Non-smartphone	Total
1. Byrne & Corrado (matched model)				-20.0
2. Matched-model (this sample)	-7.3	-10.1	-20.9	-12.1
3. Speed and other technical characteristics				
4. Performance and technical characteristics (except speed)				

Figure 1
Price Indexes for Computers and Microprocessors



*Plotted as a 2-year moving average to smooth annual variation.
Sources. Computers and peripheral equipment, Bureau of Economic Analysis (NIPA table 5.3.4); MPUs, official measure, Byrne, Oliner, and Sichel (2015), using data from Grimm (1998, table 12) for 1986-92, Federal Reserve Board for 1993-97, and Bureau of Labor Statistics for 1998-2014; MPUs, hedonic index: Byrne, Oliner, and Sichel (2015).

Table A1. Desktop Price Indexes

Percent changes (log diffs)	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Matched-Model		-11.3%	-10.2%	-1.3%	-5.3%	-5.9%	-5.9%	-3.2%
Hedonic								
Tech Characteristics, No Benchmark		-19.6%	-26.7%	3.9%	-8.7%	0.6%	10.6%	0.1%
With Benchmark		-21.9%	-28.2%	3.9%	-11.5%	-3.9%	2.3%	-2.4%
Index levels								
Matched-Model	100.0	89.4	80.7	79.7	75.6	71.2	67.1	65.0
Hedonic								
Tech Characteristics, No Benchmark	100.0	82.2	62.9	65.5	60.0	60.4	67.2	67.2
With Benchmark	100.0	80.3	60.6	63.0	56.2	54.0	55.3	54.0

Note. Percent changes are differences in log levels.

Table A2. Tablet Price Indexes

	2007	2008	2009	2010	2011	2012	2013	2014
Hedonic, percent changes								
Apple, No Benchmark					-9.7%	-15.4%	-6.6%	-1.9%
Apple, With Benchmark					-9.7%	-16.6%	-7.7%	-8.4%
Samsung					-67.3%	-17.7%	-12.7%	-7.0%
Microsoft							-38.4%	-10.2%
Motion Computing		-8.1%	0.6%	7.9%	-0.3%	-2.6%	0.6%	-5.0%
Hedonic, Index levels								
Apple, No Benchmark				100.0	90.8	77.8	72.9	71.5
Apple, With Benchmark				100.0	90.8	76.9	71.2	65.5
Samsung					100.0	83.8	73.8	68.8
Microsoft							100.0	90.3
Motion Computing	100.0	92.2	92.8	100.4	100.1	97.5	98.1	93.3

Note. Percent changes are differences in log levels.