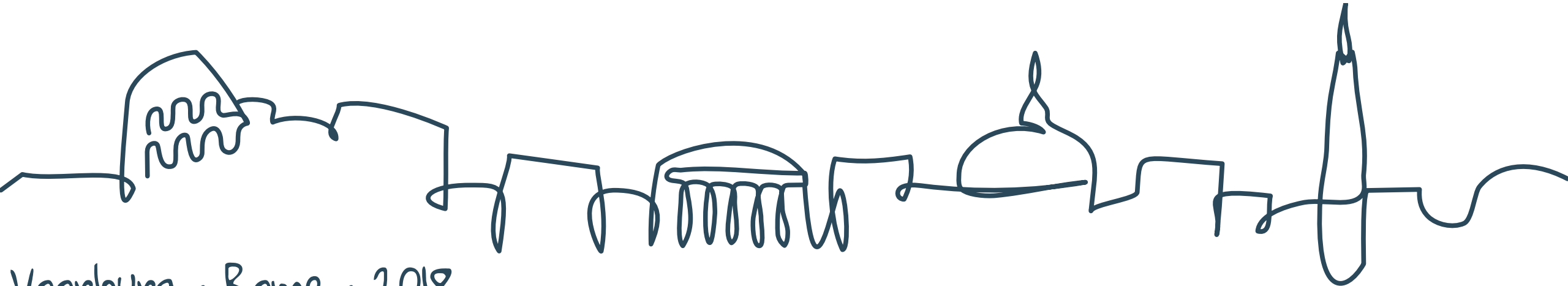# Accounting for Quality Change with Alternative Data Sources: A National Accounting Perspective

**Ana Aizcorbe**

Bureau of Economic Analysis -- US

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# BEA's price index initiative

① Our most carefully-watched statistic is real GDP growth, whose calculation requires deflators to strip out the influence of inflation from the changes in nominal spending that we calculate.

② While the estimate of what inflation was TODAY is extremely important, many of our constituents also care about trends so that any measurement problems in the historical data also matter to us.

③ We have embarked on a multi-year project to assess any potential problems in the deflators that we use in the national accounts.

④ In addition to reviewing any existing studies, the project involves seeking out new data sources that could potentially be used to construct price indexes both over history (to refine our trends) as well as going forward.

⑤ We are collaborating closely with our colleagues at the Bureau of Labor Statistics, who are committed to exploring new data sources and how those sources might be used to improve measurement going forward; we are focusing on the historical indexes.

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**Ana Aizcorbe**

Bureau of Economic Analysis -- US

# This talk will address three broad questions

① How do national accountants think about quality change?

② What are the data requirements for constructing historical price indexes?

③ What kinds of alternative data sources have we used to construct historical indexes and what have we learned from these experiences?

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Bureau of Economic Analysis -- US

# National Accountants wish to decompose changes in spending into price and quantity (volume) components

- We would like any changes in prices that arise from changes in quality to be counted as a change in "quantity," not a change in price.

- We do not think in terms of "cost of living indexes." Instead, our concept is "constant-quality indexes."

  - Even when we use CPI indexes (which some interpret as cost of living indexes), we do not interpret them that way.

**Crude decomposition:**

| CHANGE IN SPENDING (or REVENUES, or COST) | = CHANGE IN AVERAGE PRICE | + CHANGE IN QUANTITY |

**Accounting for Quality:**

| CHANGE IN AVERAGE PRICE | = CHANGE IN "CONSTANT-QUALITY" PRICES | + CHANGE IN "QUALITY" |

**Better decomposition:**

| CHANGE IN SPENDING | = CHANGE IN "CONSTANT-QUALITY" PRICES | + CHANGE IN QUANTITY + CHANGE IN "QUALITY" |

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# There are two methods that can be used for these decompositions

① Indirect method: Matched-Model Indexes

Assume that differences in prices at a point in time

reflect differences in the quality of goods.

① Direct method: Hedonic techniques

Explicitly model how quality affects price.

Let's focus on matched model methods today.

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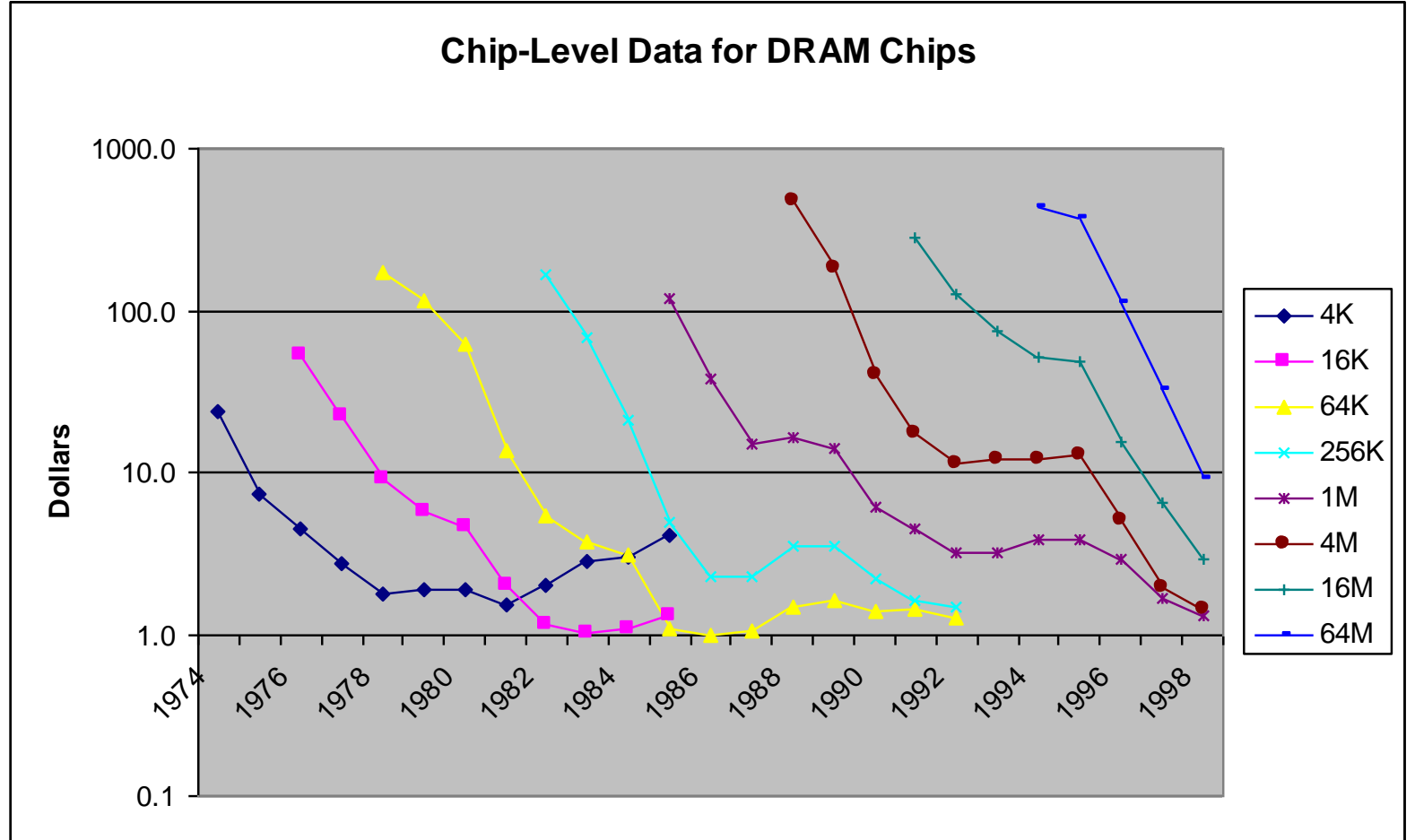
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# How does the matched model method account for quality change?

These price curves for DRAM chips show that prices of new (better) chips typically sell at a higher price than the older (lower quality) chips.

○ These price curves are typical for many IT durable goods like computers and many types of consumer electronic products.

○ Lets use this as an example to illustrate how the matched-model method accounts for quality change

**Chip-Level Data for DRAM Chips**

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# How does the matched model method account for quality change?

- In this simple example, the change in the average price from t=0 to t=2 is $P_{2,2} / P_{1,0}$

- Assume that these price contours are for goods that are identical. That is, the attributes of chip 1 do not change from t=0 to t=1 and similarly for chip 2.

- If so, then price changes over the life of the chip are constant-quality price changes:
$( P_{2,2} / P_{2,1} )$ and $( P_{1,1} / P_{1,0} )$

- And, the gap in the prices of the new and old chip at t=1 is the market's valuation of the quality improvement in the new chip:
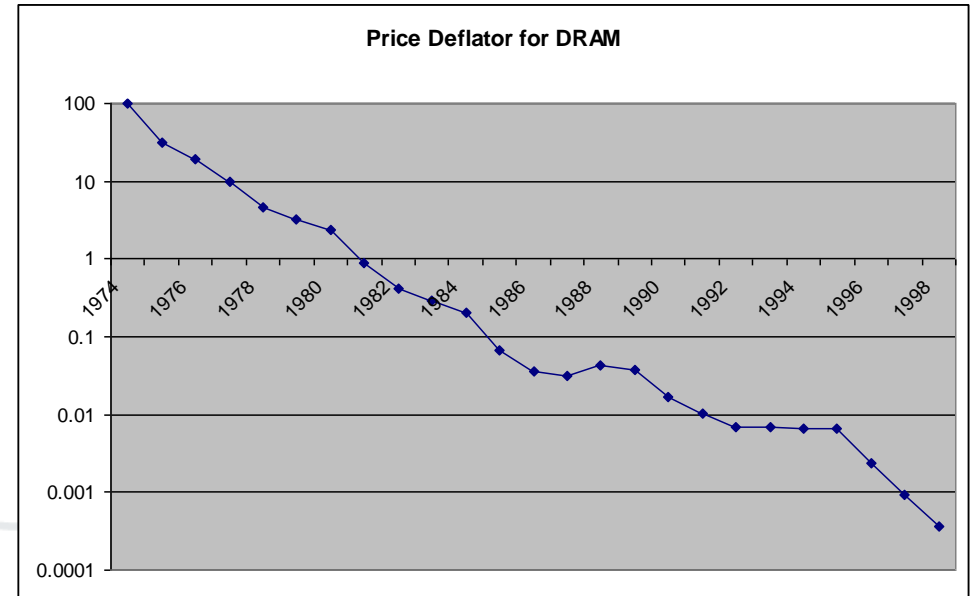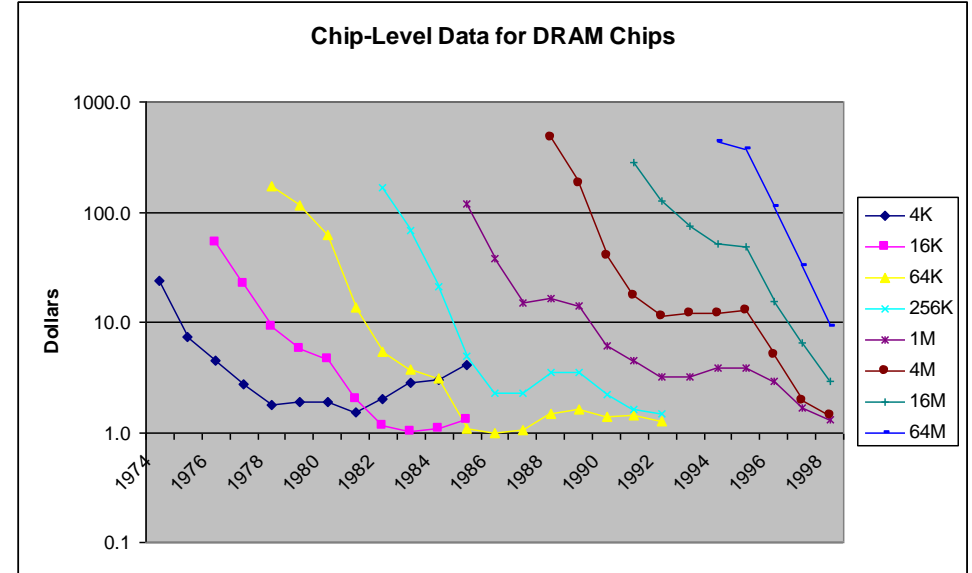$( P_{2,1} / P_{1,1} )$

**Chart 1. Simple Example of Quality Measurement**
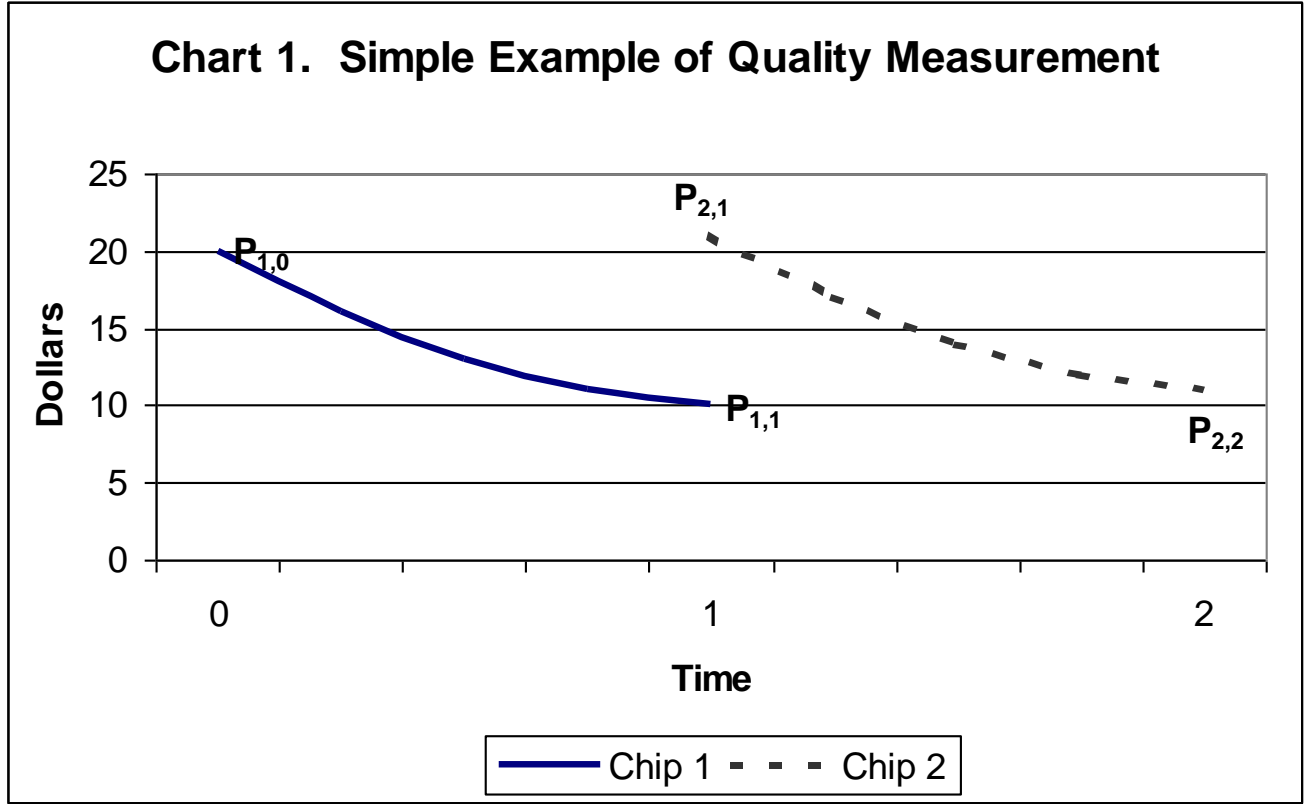


$$P_{2,2} / P_{1,0} = ( P_{2,2} / P_{2,1} )( P_{2,1} / P_{1,1} )( P_{1,1} / P_{1,0} )$$

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# Accounting for quality yields declining C-Q prices.

○ Once you strip out the estimate of "quality," the price index falls rapidly.

○ The increase in DRAM revenues over this period is more than explained by increases in quality-adjusted quantities.

NOTE: This technique cannot be applied in all cases (e.g., Housing, custom software) because of the custom nature of the goods.

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Chip-Level Data for DRAM Chips


Price Deflator for DRAM

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# How one defines the good to be priced is critical.

① We would like changes in spending resulting from shifts to lower priced grocery stores (like Costco in the US) to be reflected as a change in price, not quantity (if the quality of the goods is the same).

   ① If the BLS prices these items separately (as if they are different goods) and we use the resulting index to deflate spending at grocery stores, these shifts will be recorded as changes in quantity.

② Similarly, we would like changes in spending resulting from shifts to generic drugs that are identical in content from their branded counterparts to be recorded as a change in price, not quantity.

③ The issue also arises when revenues received by doctors drop because patients are shifting to less-generous insurance plans that pay doctors less for identical services.

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# What are the data requirements for constructing matched model indexes?

① The data must be granular enough that one can track prices of identical things over time.

  ① Scanner data is typically available at the SKU (barcode) level. If one thinks that the relevant attributes of the good are the same for all goods with the same barcode, then this is granular enough.

  ② On the other hand, model-level data for automobiles (like the data from JDPOWER) is typically not sufficiently granular. The data are at the nameplate level (Hyundai sedan) and do not allow one to control for different options like sunroof, special tires, leather seats, etc. that affect price.

② High-frequency (e.g., monthly) data is better than lower frequency data (e.g., annual)

③ It is always better to obtain transaction-level data rather than data that have been aggregated by a data vendor.

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# What kinds of datasets has the BEA used to construct historical price indexes?

**"Big Data" where you do your own collection**

○ Ex:  web scraping, Survey Monkey

○ Because you do it yourself, you know exactly what you are getting.

**Purchase data from with potential imputations and adjustments from a data vendor**

○ Ex:  IDC and Gartner (for IT goods), Nielsen and NPD Scanner data

**Poor documentation makes it difficult to know exactly what the data are until you have it in hand:
NEED FOR PILOT STUDIES**

**Traditional surveys From statistical agencies**

○ Ex:  Current Population Survey, Survey of Consumer Finances

○ Careful documentation is available to inform you of what the data contain and how they were collected (i.e., sampling).

○ Data collection is informed by statistical science and includes survey weights that may be used to obtain unbiased estimates for the population of interest.

**Are the data representative?**

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# The remainder of this talk will draw on pilot studies in four areas to illustrate the challenges in using these data

① Medical care services

② Custom software

③ Medical Equipment

④ Cloud computing

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# *MEDICAL CARE SERVICES*

① **Data source:** Companies that process claims for insurance companies sell the data to data vendors who then license the data to customers like the BEA. The data were procedure-level data with procedure codes and diagnoses for each service provided; an enrollment file provides demographic information on the patient.

② **Documentation:** Only documentation was a data dictionary that explained how the variables were defined: price, diagnoses, etc. No information was provided about exactly where the data came from: was it one large insurance company, or many? What kind of insurance company?

③ **Validation study**: We compared the time-series and cross-sectional properties of these data to those from government surveys to assess the validity of the data.

④ **Lesson learned:** representativeness is important for this sector. This is in stark contrast to the vendor's claim that "we have so many observations that you don't need to worry about the usual statistical properties"

⑤ **Outcome of pilot study:** We found an alternative (more expensive) source of claims data from MarketScan, a firm that has a staff of statisticians that conduct post-stratification reweighting to introduce representativeness to the data. BEA is using those data in its health account. https://truvenhealth.com/markets/life-sciences/products/data-tools/marketscan-databases

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- We formed a monthly time series of spending using all spending reported on the claims

- The time series:

  - Looked like a step function, with jumps every January

  - Had a trajectory much faster than that seen in other data.

- The vendor explained that their business grew over time. Each year, they would add claims from new health plans to their dataset.

- No documentation on how spending might have varied across plans.

- We had similar issues with ride-level data for UBER and transaction-level data from credit cards.

**Schematic: Total revenues received by providers as calculated from the raw claims data**



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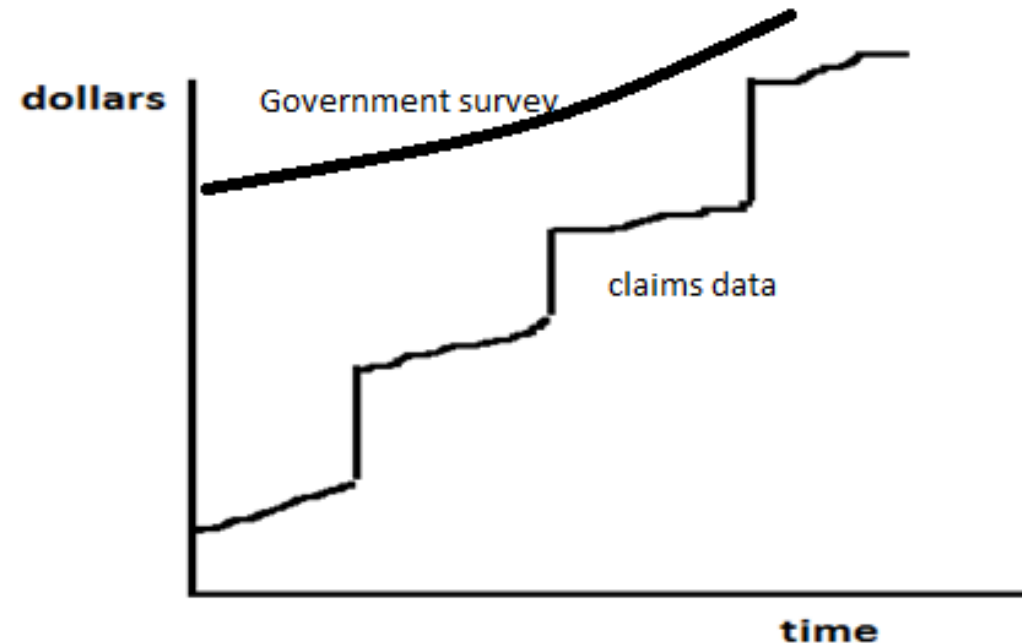
# Issue #2:  Vendor withheld some of the claims

① **We compared the percentage of enrollees that  received care:**

② The percentage of enrollees that submitted a claim (i.e., got health care) in the raw claims data was about 60%.

③ The comparable statistic from a national survey administered by the Census Bureau (MEPS) was substantially higher:  80%

④ Vendor explained that although they gave us a file with all the enrollees, they did not provide us with claims for all of the enrollees:  they removed claims for patients that looked invalid to them (they never provided very precise explanation for what the criteria for removal was).

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# Issue #3: The data were not very representative

○ The claims data oversample enrollees in the South region

○ The rates of obesity are substantially higher in the South than in other regions

○ Because spending for obese patients is higher than for non-obese patients, total spending per patient calculated from the raw claims data is significantly higher than estimated in the MEPS.

○ Important lesson: one must assess the representativeness of the sample and make any corrections using post-stratification reweighting or other methods from the literature on survey non-response

Table 1. Population Levels and Distributions for the Commercial Population and Unweighted MarketScan Data

|  | | Commercial Population | | Unweighted MarketScan | |
|---|---|---|---|---|---|
|  | | 2003 | 2007 | 2003 | 2007 |
| of Enrollees (millions) | | 180.6 | 182.5 | 7.0 | 13.1 |
| **Gender** | | | | | |
|  | Male | 49.5% | 49.6% | 47.9% | 48.5% |
|  | Female | 50.5% | 50.4% | 52.1% | 51.5% |
| **Age** | | | | | |
|  | 0 to 17 | 27.3% | 26.3% | 25.3% | 26.4% |
|  | 18 to 24 | 9.6% | 9.6% | 7.8% | 7.6% |
|  | 25 to 34 | 14.5% | 14.7% | 12.1% | 11.9% |
|  | 35 to 54 | 36.3% | 35.6% | 38.3% | 37.6% |
|  | 55 and over | 12.2% | 13.8% | 16.6% | 16.5% |
|  | Mean Age | 32.3 | 32.9 | 34.5 | 34.1 |
| **Region** | | | | | |
|  | NE | 19.3% | 18.9% | 11.5% | 12.0% |
|  | MW | 24.4% | 23.7% | 29.4% | 24.3% |
|  | S | 34.0% | 34.3% | 45.5% | 48.0% |
|  | W | 22.3% | 23.1% | 13.7% | 15.7% |

Notes: Commercial population estimates are taken from the CPS estimates of the commercially insured population, while unweighted MarketScan estimates are enrollee counts from the MarketScan data for individuals in non-capitated plans with drug benefits that are enrolled for the entire year.

# Outcome

**We obtained the MarketScan data and used it to create a "health account' that includes price indexes defined using cost per episode of care.**

Within the satellite account, there are two different sets of disease-based statistics. One version uses data from the Medical Expenditure Panel Survey, the only nationally representative survey that contains detailed expenditure information by disease. BEA calls this the "MEPS Account." Because of its relatively small sample size, the MEPS Account produces more volatile estimates across years. To address this issue, we also produce the "Blended Account," which blends together data from multiple sources, including large claims databases that cover millions of enrollees and billions of claims.

Looking at spending by disease is a first step toward BEA's goal of developing an account that allows better assessment of value in health care spending. BEA continues to conduct research to expand and improve its health statistics.

https://www.bea.gov/national/health_care_satellite_account.htm

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# *CUSTOM SOFTWARE SERVICES (QP)*

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① **Data source:**  Consulting company created metrics for the size of custom projects and gave us part of their data to assess its potential usefulness for purposes of constructing price indexes.  These were contract-level data with prices and attributes of the projects.

② **Documentation:**  They did not provide formal documentation.  We held a series of conference calls with them where we had the  opportunity to ask questions before purchasing the data.

③ **Validation:**  We did not find an alternative source with which to validate the data.  In particular, other sources had information on projects, their size, industry etc. but no information on the price of the project.  We picked through the data looking for any anomalies and found several.

④ **Lesson learned**:  We have something very specific in mind when we think "data."  While we had expected to see data collected in the course of their consulting contracts, we found that many of the key variables (like wages, which figure into the calculation of price) were assumed.  These "data" are best viewed as the reflection of judgmental assumptions made by industry experts.

⑤ **Outcome of pilot study:**  We were not comfortable using any of the price indexes that we calculated.
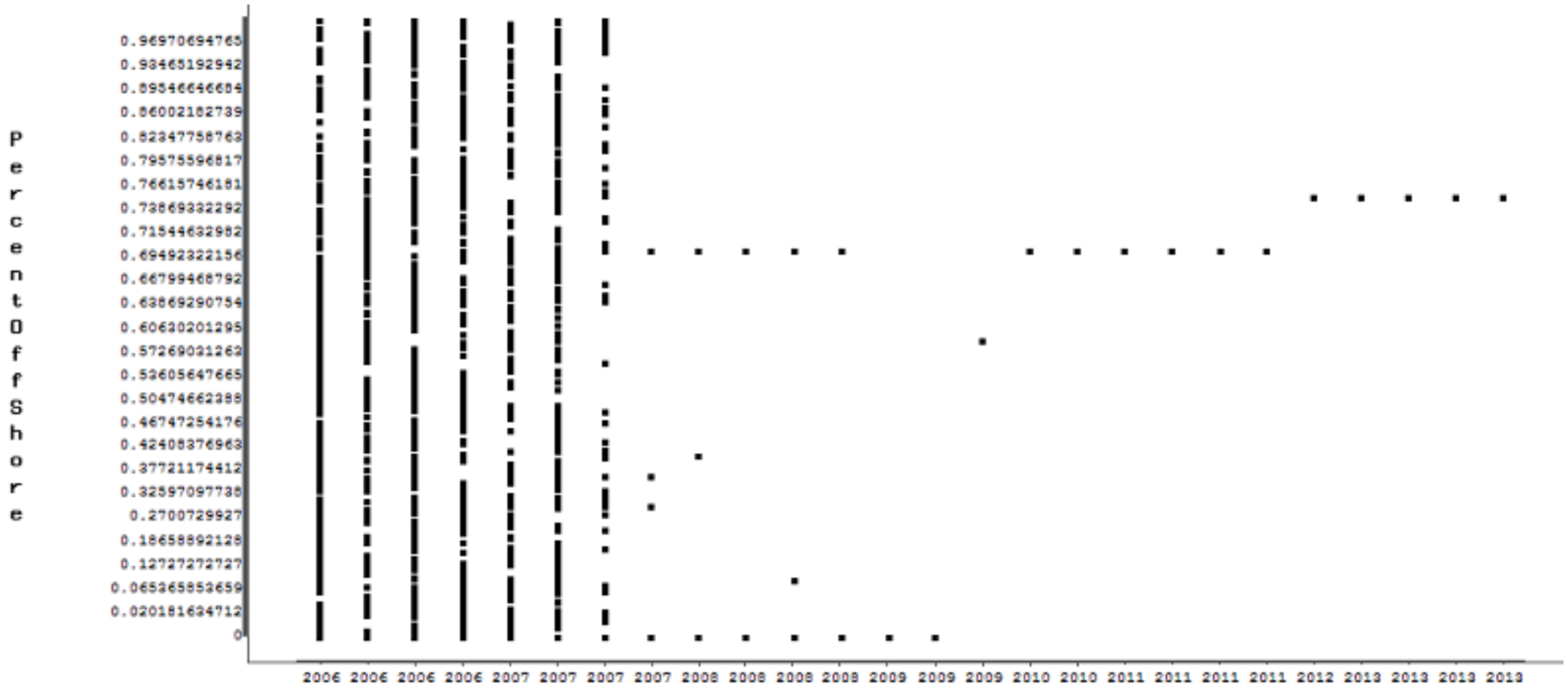
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# The data contained anomalies that were hard to ignore

○ For each variable in the dataset, we did scatter plots of the contract-level information over time. The plots that follow use a variable on the percent of work done offshore and the log of programmers' wages in the data to illustrate these anomalies.

○ Observations in the earlier period seemed valid to us and displayed a wide spread of values, like one would expect to see.

○ In later years, however, the spread narrowed substantially:

   ○ In the offshoring variable, the spread went from 0-100% in the earlier data to moslty three values:  0%, 10%, 30%, 70%, and 75%.  It looked more like a guess than an actual calculation of offshoring revenue to total revenue for each project.

   ○ Similarly for wages, where it looked as if they switch from wages reported for each project to using an industry-level wage for programmers.

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# Issue #1:  They call this «data»?

**Scatter plot of percent offshore activity over time**

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# Issue #1 again:  What happened in 2009?

### Scatter plot of ln(wage) over time

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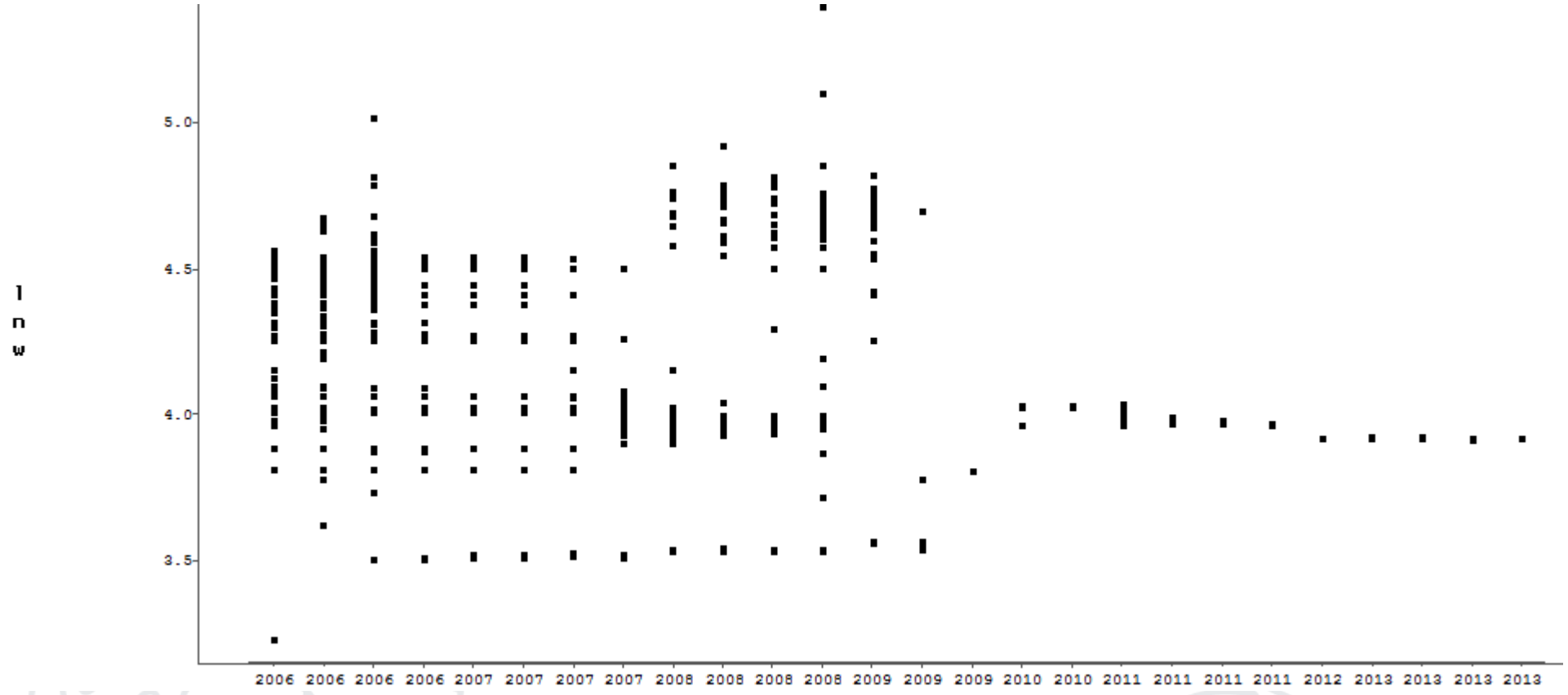
# Outcome

**BEA introduced a productivity adjustment in the 2018 comprehensive update**

" [T]he price indexes for both custom and own-account software will reflect, for the first time, an explicit adjustment to account for changes in productivity. Currently, these price indexes are estimated using a weighted average of the BEA prepackaged software price index and a BEA input-cost index that is based on BLS data on wage rates for computer programmers and systems analysts and on intermediate input costs associated with the production of software. The prepackaged software price reflects actual market prices and therefore reflects implicit changes in productivity, but the input-cost index does not. BEA will implement an explicit productivity adjustment to the input-cost index, beginning with 1997. The adjustment will be based on research conducted by BEA using reports from academic, commercial, and public sources.

https://www.bea.gov/scb/2018/04-april/0418-preview-2018-comprehensive-nipa-update.htm

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# *MEDICAL EQUIPMENT (ECRI)*

① **Data source:** Nonprofit organization that provides information on recalls and other developments related to medical equipment in exchange for information on the contract the provider used to purchase equipment. Government providers are excluded because they use prices that are pre-negotiated by the GSA.

② **Documentation:** They did not provide formal documentation. They gave us access to the website that providers use to report the data and did our own data dictionary based on what we learned there. We also held a series of conference calls with them where we had the opportunity to ask questions before purchasing the data.

③ **Validation:** We purchased data on imaging equipment to convince ourselves that the data would be useful. When we purchased the rest of it, we were able to assess: 1) the extent of their coverage (using data from the national accounts), and 2) how long it took them to show data for new models.

④ **Lesson learned:** Overall, we view these data as reliable and the vendor was very accessible to answer our questions.

⑤ **Outcome of pilot study:** Price indexes for two types of medical equipment were introduced into the 2018 Comprehensive Update.

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# Issue #1:
# Coverage of ECRI data on Medical Equipment

o We had difficulty constructing a concordance between 1700 ECRI categories (e.g., CTSCAN, electric beds) and 6-digit NAICS codes:

> 33451011 Medical diagnostic equipment
> 33451012 Medical therapy equipment
> 33451013 Other electromedical equipment
> 334517 Irradiation apparatus manufacturing

o For imaging equipment, matching the ECRI items was fairly straightforward.
  - Even so, it was not clear where to place components, for example, workstations and software used to interpret the images

o We did not have sufficient expertise in the types of equipment covered in the other two NAICS codes. We will make a second attempt over the coming year.

o To hold down costs, we did not purchase all of the categories that ECRI had available and may have missed important spending.

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o Given our current concordances, coverage was too thin for 33451012 Medical therapy equipment

o Coverage for 33451013 Other electromedical equipment looked fine but we were not confident about the way we matched up the categories.

o Note: use of the matched model index (mm) required contracts with only one type of equipment; so not all contracts could be used.

| 2016 | 33451011 | 33451012 | 33451013 | 33451017 |
|---|---|---|---|---|
| BEA estimate of domestic use | $ 4,228,158,091 | $ 12,689,706,385 | $ 1,604,222,853 | $ 4,596,210,193 |
| ECRI data (Justin) | $ 965,390,244 | $ 546,032,988 | $ 491,674,431 | $ 1,418,148,898 |
| percent of domestic use | 22.8% | 4.3% | 30.6% | 30.9% |
| ECRI data purchased by BEA | $ 773,666,001 | $ 301,064,810 | $ 459,574,752 | $ 1,308,684,235 |
| percent of all ECRI data | 80.1% | 55.1% | 93.5% | 92.3% |
| ECRI data used for mm index | $ 285,894,588 | $ 96,336,483 | $ 161,751,346 | $ 693,596,614 |
| pct of ECRI data purchased | 37.0% | 32.0% | 35.2% | 53.0% |
| pct of all ECRI data available | 29.6% | 17.6% | 32.9% | 48.9% |
| Percent of domestic use | 6.8% | 0.8% | 10.1% | 15.1% |

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# Outcome

**BEA introduced price indexes for two categories of medical equipment in the 2018 comprehensive update**

"Beginning with 2002, BEA will introduce newly developed annual estimates of quality-adjusted prices for components of electro-medical equipment, including magnetic resonance imaging equipment, ultrasound scanning devices, and CT-scan machinery. These types of medical equipment embody rapid rates of product innovation that can present challenges when using standard matched-model techniques. These new price indexes were developed by BEA using data from the ECRI Institute on purchases of medical equipment by health care providers. The new annual price indexes better account for product quality change than the previously used price indexes, which were based on monthly PPIs and monthly international price indexes (IPIs) from BLS. The improved prices indexes will be used to deflate annual private fixed investment and exports and imports of electro-medical equipment. The previously used PPIs and IPIs will be used in conjunction with the newly developed annual indexes to estimate the higher frequency quarterly prices."

https://www.bea.gov/scb/2018/04-april/0418-preview-2018-comprehensive-nipa-update.htm

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# CLOUD SERVICES (451)

① **Data source:** Consulting company that produces its own "cloud price index" https://451research.com/services/price-indexing-benchmarking/cloud-price-index We have contracted with Dan Sichel (who has done price index work in this area) to assess the potential usefulness of the 451 price index for us at the BEA.

② **Documentation:** There is some documentation, but part of what Dan Sichel wants to do is to pin down exactly where their index comes from and to assess whether 451 has additional information that can be used to improve the index.

③ **Validation:** We will compare the 451 indexes to those found in recent academic studies. https://repository.wellesley.edu/thesiscollection/386/ http://www.nber.org/chapters/c13899

④ **Outcome of pilot study:** Stay tuned….

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# 451 Research Price Indexes



Figure 8: Selected Global Cloud Service Benchmark Shifts, Q3 2016 to Q3 2017

Source: 451 Research, 2017

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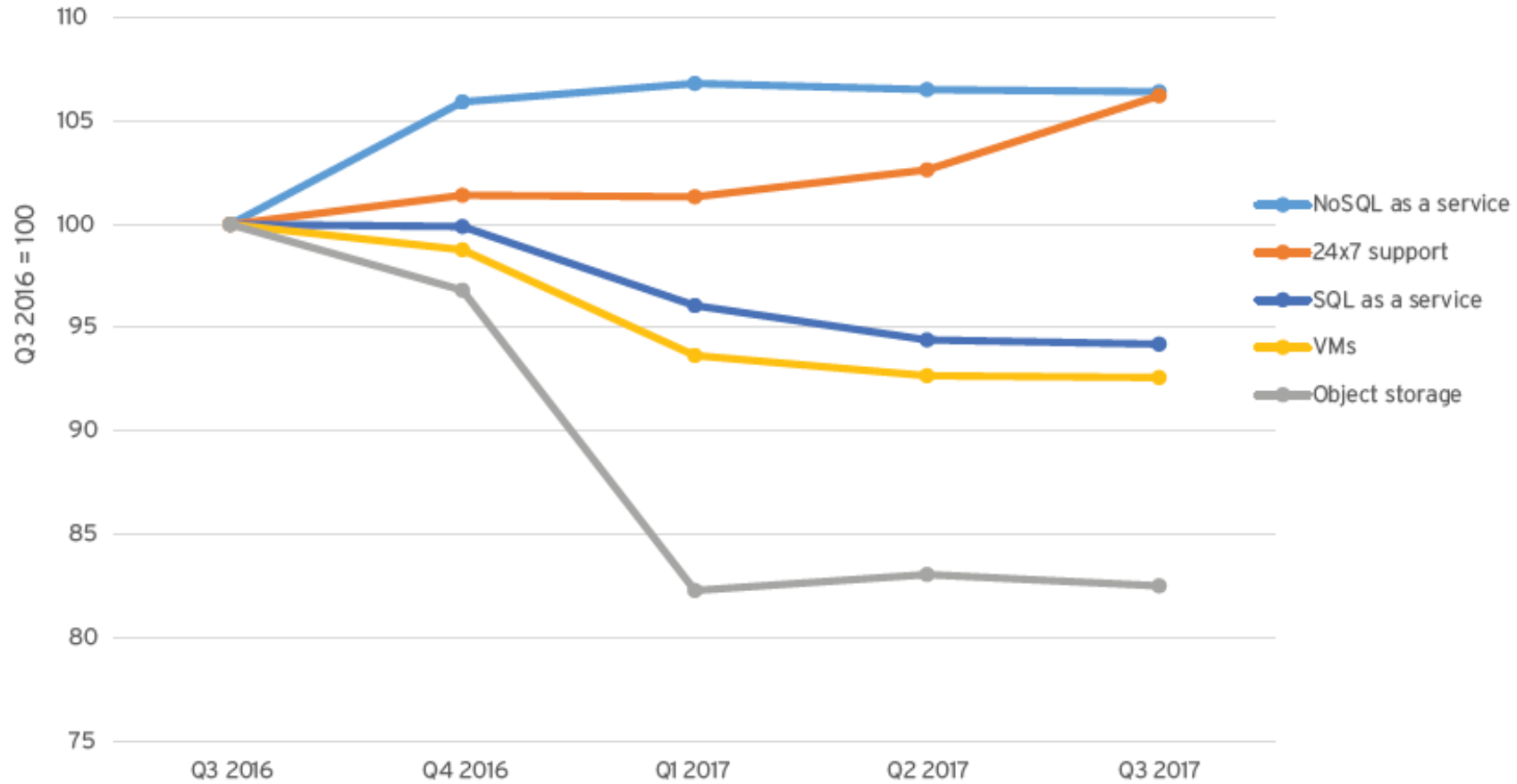
# Pilot study has just started....

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# Summary: It is important to ask ALL the questions

**Data vendors do not understand the sophistication with which statistical agencies approach data.**

**Because they don't understand our needs, they typically don't offer the relevant information until you ask them.....**

- Where do the data come from? How were the data obtained? Have you always obtained it this way?

- Did you give us all the data, or did you leave some out? Why did you exclude any observations? Did you exclude outliers?

- Get a list of their «categories» to assess the coverage and any problems with building concordances.

- For each variable, obtain:

  - A precise definition: what do you mean by «price»? How do you handle any returns (negative prices?), discounts, rebates?

  - Descriptive statistics, including frequency counts of missing observations. Note: most datasets have missing values for some variables.

    - We bought data on used prices for equipment to calculate depreciation rates and the year of introduction (critical for calculating depreciation) was missing in most of the observations.

  - Details on any adjustments made

    - Dollars and quantities reported in the NPD scanner data are adjusted to match industry totals.

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# Other data sources that we are studying for price index purposes

① **Residential communication services**

   ① Survey data from JDPOWER beginning in 2006 on wireless and wireline services to households
https://www.jdpower.com/business/press-releases/jd-power-2017-full-service-smartphone-satisfaction-study

   ② List prices for wireless services from whistleout.com, a firm that provides all prices for wireless plans at a point in time.  They provide us with a snapshot once a month. https://www.whistleout.com/

   ③ List prices for wireline services from Telogical: http://www.telogicalsystems.com/residential-wireline/ :

② **UBER**

   ① Data from SLICE, a company that obtains permission to access your email and uses receipts sent to you via email to form a transaction-level dataset of UBER rides (obvious selection issues here) https://www.slice.com/

**Ana Aizcorbe**

Bureau of Economic Analysis -- US

# Thank you!

Ana.Aizcorbe@bea.gov