Valuing Data as a New Asset Type

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Big Data is Raising Big Questions

The most valuable firms in the world today are valued largely for their data.

Raises a whole agenda of questions, theoretical and empirical, that touch on every aspect of finance:

- Data is a new asset class. Is it over-valued? (asset pricing)
- Do data-intensive firms have valuations that are realistic? (corporate fin)
- Are large troves of data an entry barrier for new firms? (entrepreneurship) What does market power look like if digital services are "free"?

Our industrial-era economic tools need updating for the modern data economy.

Outline

This talk: How do we start on this agenda?
It begins with measuring the amount and value of firms' data.

- What do we mean by data?
- Data economy mechanics
  - A by-product of transactions
  - Buying and selling data
  - Depreciating data
- Measuring and valuing data: 6 approaches
  - Cost
  - Value function estimation
  - Complementary inputs
  - Choice covariance
  - Revenue
  - Intangibles approach
- Conclude: Where next?

What do we mean by data?

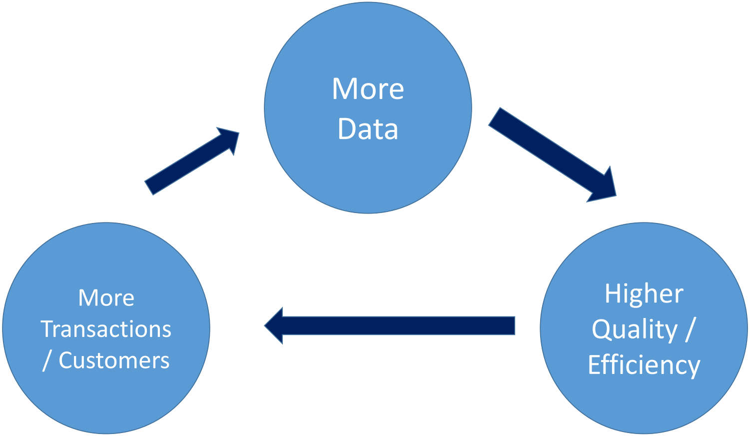
- Data is digitized information
- Data of interest is big data:
  Often generated by economic activity: search history, traffic patterns, purchases...
  Used for forecasting.
- Data is distinct from tech, patents, and learning-by-doing.
  - Ideas/ technologies: procedures or concepts. Data may be an input.
  - Learning by doing: Human capital, owned by workers. Not tradeable.

How data is generated and accumulated?

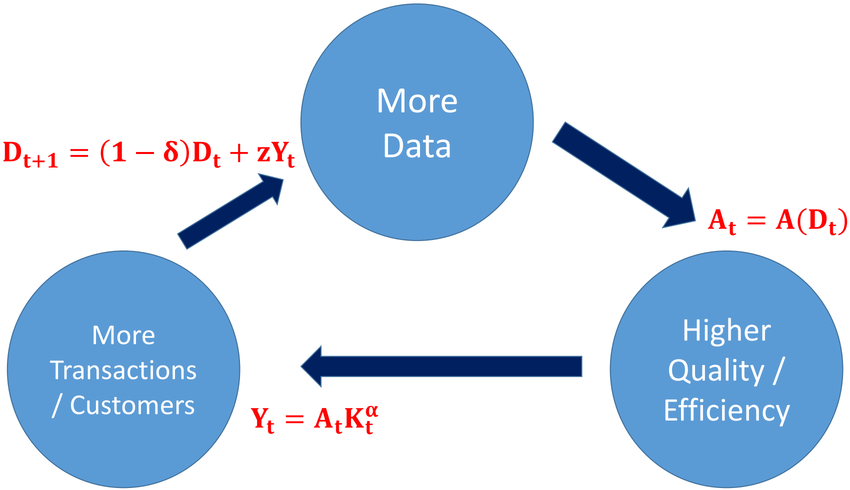
Most big data firms use is transactions, browsing/search history, GPS location, etc.

"It's free, but they sell your information."

A Data Feedback Loop



A Data Feedback Loop



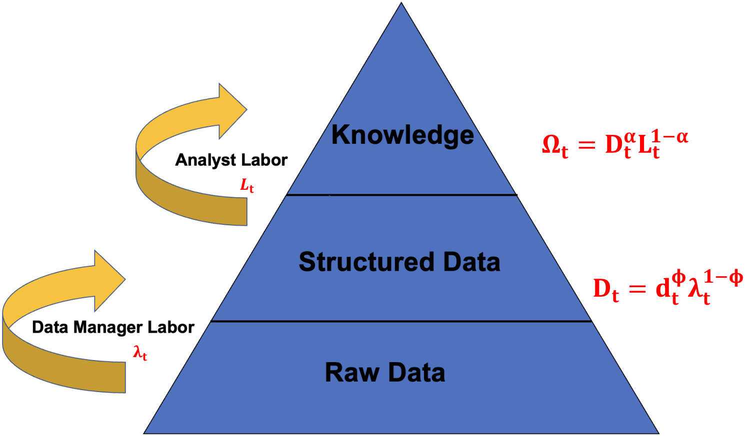
Data-fueled monopolies? (Farboodi, Veldkamp '22, Begenau-F-V '18)

What is Higher Quality? How Does Data Create Value for Firms?

- Raises current profits: Choose better products, inventory, transportation, advertise to better customers.
- Creates market power
  - Firms with more data can grow bigger, exert monopoly power.
  - Is data an entry barrier?
- Reduces risk
  - Data is information. Information resolves uncertainty (risk).
  - Finance tools here are crucial.
  - This could be big: Risk compensation is 2x expected return.

Accumulating Data: Raw Data, Structured Data and Knowledge

Maybe labor is an input into useable data?



Accumulating Data: Buying it

- Indirect and direct data sales
  - Just like financial information can be monetized through analyst reports (direct) or the services of a managed fund (indirect).
  - Google could sell you names and zip codes of people who bought iPads (direct, structured).
    Or, they can place ads for you, using their information (indirect, knowledge).

- Data is (imperfectly?) non-rival: You can sell it and keep it.
  - But does sold data lose value? How much?
  - Losing some of the data you sell is like a negative bid-ask spread.
    Seller loses less than buyer gains. (as in Farboodi, Veldkamp '22)

$$\text{data}_{t+1} = (1-\delta)\text{data}_t + \underbrace{\gamma_t}_{\textit{data purchases}} - \underbrace{\iota|\gamma_t|\mathbb{1}_{\gamma<0}}_{\textit{loss from data sales}}$$

How does data depreciate?

- A key question for valuation.
- Ex: Data to forecast an AR(1): $\theta_{t+1} = \rho\theta_t + \epsilon_{t+1}, \quad \epsilon_{t+1} \sim N(0, \sigma_\epsilon^2)$.
- Precision: $V[\theta_t|\mathcal{I}_t]^{-1} := \Omega_t$. Call this a "stock of knowledge."
- Prior variance of tomorrow's state: $V[\theta_{t+1}|\mathcal{I}_t] = \rho^2\Omega_t^{-1} + \sigma_\epsilon^2$.
- If data forecasts θ_{t+1}, then a data point is: $s_t = \theta_{t+1} + e_{st}$.
- Bayes law for normals says: $t+1$ precision Ω_{t+1} is prior precision plus precision of n_s data points $n_s\sigma_s^{-2}$.

$$\Omega_{t+1} = \underbrace{(\rho^2\Omega_t^{-1} + \sigma_\epsilon^2)^{-1}}_{depreciated\ t\ data} + \underbrace{n_s\sigma_s^{-2}}_{new\ data\ inflows}$$

  Similar to $k_{t+1} = (1-\delta)k_t + i_t$, where $\delta = 1 - (\rho^2 + \sigma_\epsilon^2\Omega_t)^{-1}$.

- Data depreciates faster when it's abundant Ω_t and the environment has volatile innovations σ_ϵ^2.

Measuring and Valuing Data

Six Approaches to Measuring Data

1. Cost accounting
2. Complementary inputs
3. Value functions
4. Revenue
5. Choice covariance
6. Intangibles approach

Measurement Approach 1: Cost Accounting

- A book value approach to valuing assets is to cumulate the sum of costly investments.
  Why not add up data costs?

- Most data is a by-product of some other economic transaction.
  There was no explicit cost for it.

- Maybe customers are paid for data.
  Data is bartered for goods/ services.
  But that shows up as a discount in the price of the good.

- This may work well if we can impute the discount or if most of a firm's data sets are purchased.

Measurement Approach 2: Complementary Inputs

- Knowledge is produced using structured data and "analyst" labor:

$$K_{it} = \Psi_t \psi_i D_{it}^{\alpha} L_{it}^{1-\alpha}, \tag{1}$$

- New structured data is added to the existing stock of structured data with "data management" labor. Depreciates at rate δ:

$$D_{i,t+1} = (1-\delta) D_{it} + \lambda_{it}^{1-\phi} \tag{2}$$

- Estimate data stock from hiring and wages of each.
  What amount of data would make employing L_{it}, λ_{it} workers at wages w_{Lt}, $w_{\lambda t}$ optimal? (Abis-Veldkamp '21)

- Another observable complementary input: IT capital
  (Bresnahan, Brynjolfsson '02)

Measurement Approach 3: Value Function Approach

- The same tools macro uses to value capital work for data, with an adjusted law of accumulation.

$$V(\text{data}_t) = max_{K,L} A(\text{data}_t) K_t^{\alpha} L_t^{1-\alpha} - wL_t - rK_t + \beta V(\text{data}_{t+1})$$

- Pair with a theory of data inflows:
  - By-product of transactions
  - Data purchases / sales
  - Using labor to process raw data

- The state law of motion is the depreciation equation:

$$data_{t+1} = \underbrace{(\rho^2 data_t^{-1} + \sigma_\epsilon^2)^{-1}}_{depreciated\ \ data} + \underbrace{n_s \sigma_s^{-2}}_{new\ \ data\ \ inflows}$$

VALUE FUNCTION ESTIMATION RESULTS ABIS, VELDKAMP '22

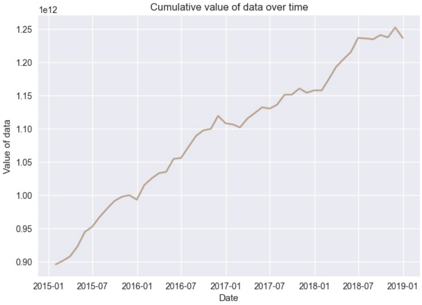


FIGURE: Estimated Value of the Aggregate Stock of Data, used for financial analysis, in hundreds of billions of current U.S. dollars, 2015-2018.

Data value is growing for 3 reasons:

1. Firms manage more data.
2. More analysis workers make each data point more valuable.
3. Firms are becoming more productive at using AI.

Measurement Approach 4: Revenue Approach

- The value of data is the pdv of the revenue it generates
- How to isolate data revenue from other revenue?
- Young, data-intensive firms may operate at a loss.
- This is doable. But you need a clear idea of how data generates revenue. A model is essential to compute counter-factuals with more/less data. (Manela, Kadan '21; Davila, Parlatore '21; Cong, Xie, Zhang '21)
- Problem: Data has different values to different agents (a private value asset)

Next: an example of valuing data as a private value asset, using a revenue approach.

Revenue Valution and Data's Private Value

- Suppose data is used to purchase a portfolio of risky assets.
- Value of data in $\mathcal{I}_{it}$ from an equilibrium with heterogeneous M-V investors, correlated information and learning from noisy prices:

$$\begin{aligned}\text{Value of data}_i \approx \; & \frac{\rho_i}{2}\mathbb{E}R_{t+1}{}'(\mathbb{V}\left[R_{t+1} \mid \mathcal{I}_{it}\right]^{-1} - \mathbb{V}R_{t+1}^{-1})\mathbb{E}R_{t+1} \\ & + \frac{\rho}{2}\mathrm{Tr}\left[\mathbb{V}R_{t+1} \cdot \mathbb{V}\left[R_{t+1} \mid \mathcal{I}_{it}\right]^{-1} - I\right]\end{aligned}$$

- One can estimate the conditional variances with return data, using forecasting regressions (sufficient statistics).
- Finding: The same data is worth $\$10 - \$1.2m$, depending on the investor's wealth, investment style, price impact or trading frequency.
  (Farboodi, Singal, Veldkamp, Venkateswaran, 2022)

Measurement Approach 5: Choice Covariance

- Data allows agents to make better choices (matching and signals)
- Better choices means actions q_t that covary with payoffs r_t.

$$E[q_t r_t] = E[q_t]E[r_t] + cov(q_t, r_t)$$

- Agents cannot achieve high covariance without information.
- Measure the covariance.
  Ex: Portfolio alpha, firm vs product markups (Eeckhout-Veldkamp '22) , or a customer click-conversion rate.

Measurement Approach 6: Intangibles Approach

- Typical intangible valuation uses book-to-market values.
  Crouzet-Eberly '20, Peters-Taylor '17
  Why not do this for data?

- Intangibles include: Branding, patents, organizational capital, ...
  e.g., Belo, Gala, Salomao, Vittorino '21, Eisfeldt-Papanikolaou '13, '14

  Data may contribute to each, but is not the same.

- How to tease apart the value of data from these other intangibles in market value?

- Presumes that equity market participants know how to value data.

Conclusions

- Data is one of the most important and highly-valued assets in the modern economy.
  Also one of the hardest to observe, measure and put a price on.
- Different approaches needed for different situations.
- Theory and measurement need to work together here.
- Next steps:
  - Explore data supply: data markets, platforms, data ownership
  - Demand estimates and supply $\rightarrow$ equilibrium prices.
    Valuation, fluctuations, data risk premia.
  - I.O. of data markets: pricing, competition, entry
- Many important open questions to tackle.
  Join us in exploring the data economy!