Data, Digitization, and Productivity

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Data and digital-based business platforms

- Digital transformation is affecting whole societies, and is a topic of interest in many disciplines
- In a digitizing economy, many economic activities are potentially driven by data.
- Data are becoming a key corporate asset, complemented with analytics, and organizations are
  - ✓ Investing heavily in digital platforms and data analysis
  - ✓ Demanding a workforce with skills in data science

Many claims in business and technology literature:

- Volume is growing > 50% per year
- “Data is the new oil”
- Digital transformation of business and societies: “You ain’t seen nothing yet”

Approach to the analysis of data in this paper

- Data refers to “big data”
- Set out the case for treating data and the knowledge gained from data analytics as a long-lived asset
  - ✓ Implies that firms need to invest to create data assets of value
  - ✓ Implies that asset provides services that contribute to production in an economy
- Data assets are nonrival (though excludable) goods
  - ✓ The impact of data needs to be analyzed with reference to its nonrivalry and excludability

Examples of Data Use
Rival
Product-level forecasting (e.g., Amazon)
A/B Internet testing and marketing (e.g., Google)
IoT factory systems (e.g., Siemens)
Targeted advertising on consumer content platforms
Fintech (e.g., algorithmic trading, digital lending, etc.)
Product-led growth strategies (e.g., Slack)
Customer lists/after sales services design
Nonrival
DaaS (Data as a Service) platforms (e.g., BDEX, Nielsen)
Financial records (FICO scores)
Vehicle records (CARFAX reports)
Personal medical records (across service providers)
Genomic and other public biomedical research data
Government statistics (economic, demographic, social)
Note: Classifications as rival or nonrival represent whether data is used primarily within single or multiple organizations.

Outline of paper

- Introduction: what we do in context of
  - ✓ Business strategy and technology literature
  - ✓ (Burgeoning) economic literature on data
- Data and investments in data: Concepts
  - ✓ Data value creation
  - ✓ Data capital ≅ Intangible capital
  - ✓ Data capital, growth, and innovation
    - – Data and relative intangible asset prices
- Data and investments in data: Measurement
  - ✓ Intangible investment: Just how much is data capital?
  - ✓ Measures for US, UK, and major EU countries
- Data capital and productivity: Empirical results and implications

Today's presentation:

Concepts and framework

New results on intangible asset prices

Labor productivity scenarios

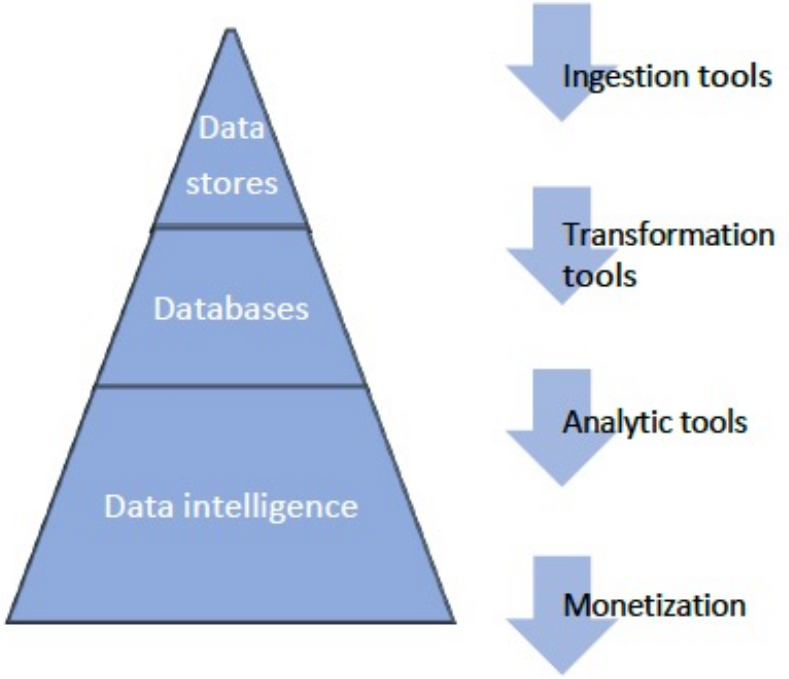
Under way. Preliminary empirical results for INTAN-Invest/EULEMS to be issued in December 2021.

Data value creation

- **Data stores** are raw records not yet cleaned, formatted, or transformed for analysis
- **Databases** consist of transformed raw data suitable for some form of data analytics or visualization
- **Data intelligence** reflects the further integration of data with advanced analytic tools

Distinguish types of data according to ”work done” to store, process, and analyze data for input to decision-making

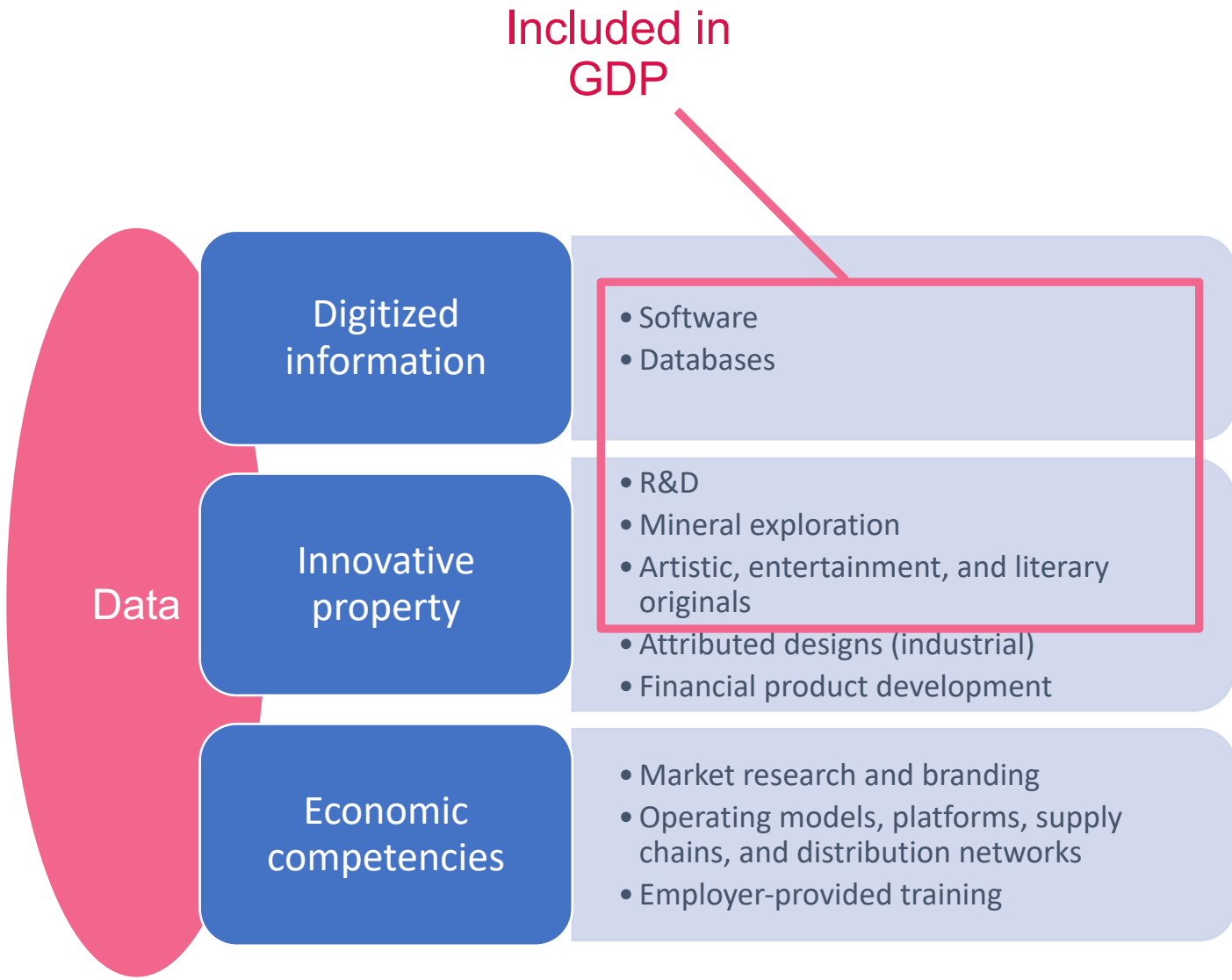
Figure 1. Data stack:
Data assets, digital tools, and monetization



Note. The stack to the left depicts the stages of data asset value creation based on applying layers of tools shown on the right.

Data as an asset

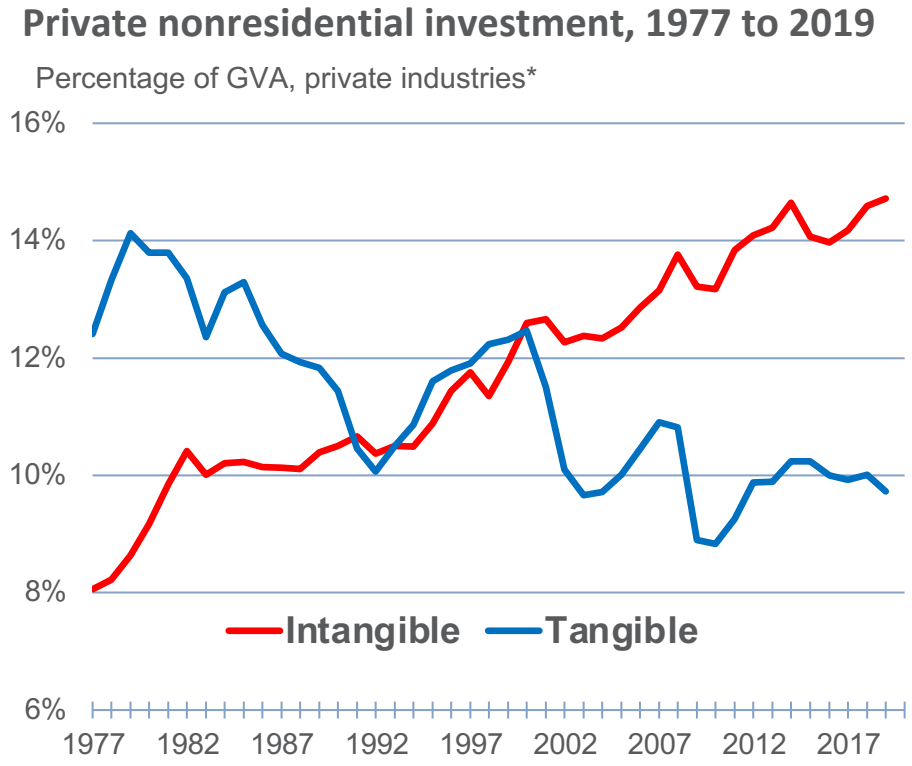
- Intangible investment includes
  - ✓ Most data assets **and**
  - ✓ Data tools and data analytics apps
- Only some intangibles are available from official national accounts
- Data measurement challenges:
  - ✓ Refining estimates of intangible investment
  - ✓ Disentangle data-driven components



Source: Corrado, Hulten, and Sichel (2005, 2009).

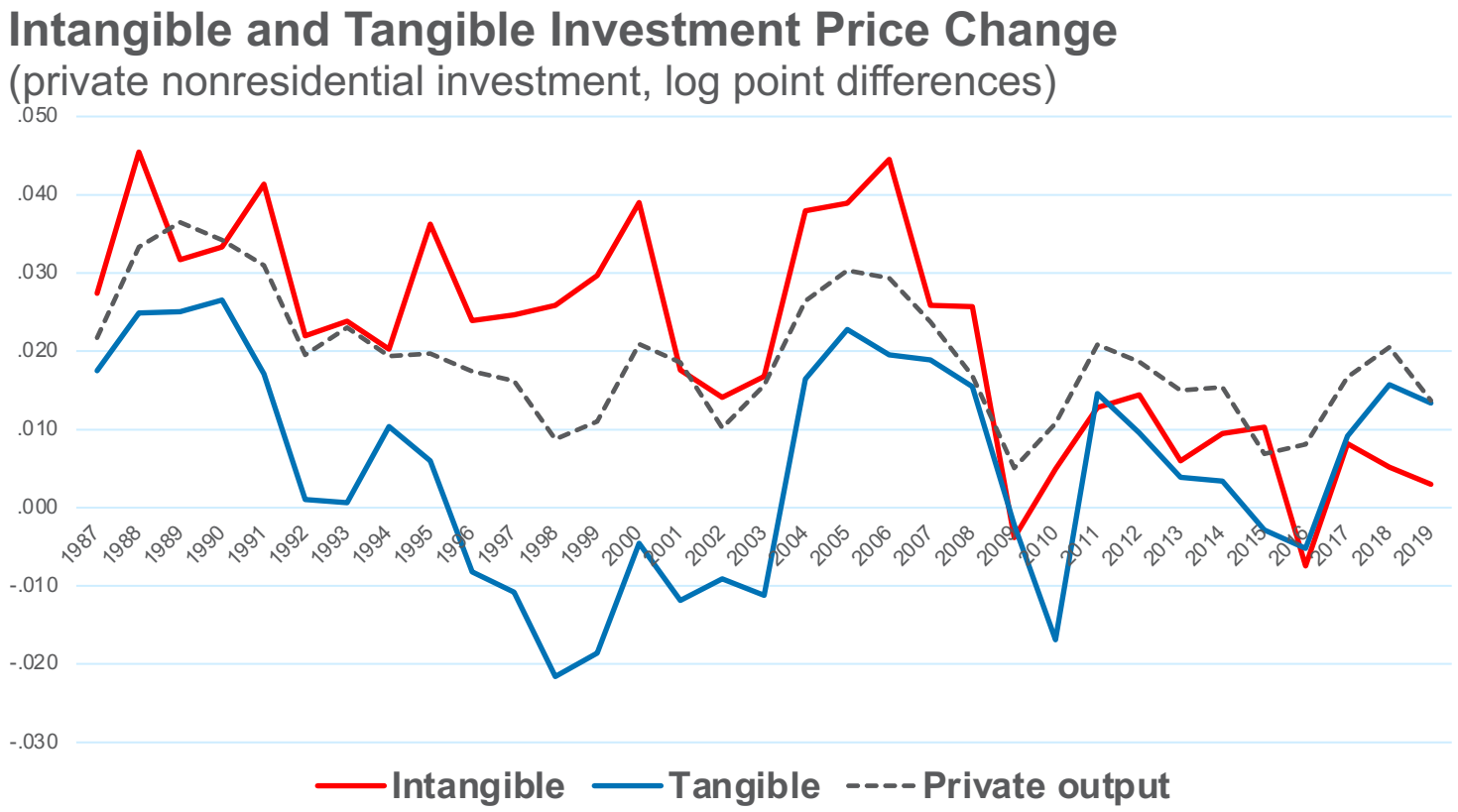
Data-driven innovation and intangibles

- The use of data to create new intelligence is viewed as an “innovation in the method of innovation”
  - ✓ Modern data use fosters faster, more efficient experimentation and feedback in computer-controlled production processes, R&D, marketing research, and business strategy and operating model development.
- This improved “productivity” of resources devoted innovation activities, i.e., intangibles, suggests that their unit cost falls
  - ✓ Implies drop in relative prices for intangible assets



Source: Unpublished update to Corrado and Hulten (2010).
Note: Private industries gross value added is not adjusted to include intangibles.

Price deflator for intangible assets shows a marked disinflationary trend



- A newly calibrated price index for intangible investment in the United States that incorporates (a) a new price index for investments in brand and the marketing subcomponent of organizational capital, and (b) an IT services price for the computer consulting services subcomponent of organizational capital.
- Intangible asset price change trends down noticeably with time, reflecting (a) increased shares of capitalized IT services and software, whose prices fall relatively rapidly, as well as (b) substantially smaller price change for investments in brand and marketing after 2005.
- The brand and marketing deflator includes both internet and traditional paid media costs, as well as content creation and production costs (purchased and in-house).
- The media costs component of this price index is based on eight BLS input cost producer price indexes and industry sources on the composition of media spend by type, including internet ads (PC and mobile). Production costs are based on the gross output price index for the NAICS 5418 industry.

Source: Corrado, Carol (2021). "Measuring Intangible Capital and Productivity: Implications for Growth and Productivity" The Brookings Hutchins Center Productivity Initiative working paper.

Contribution of data capital to productivity growth

- Long-term growth promoting potential of data capital depends on the extent to which their volume rises more rapidly than their relative price falls (i.e., that the input shares continue to rise)
- Ultimately this is an empirical question about the degree of substitutability between data/AI and human efforts.
- Apart from spillovers (to be discussed in a moment), the impacts of data capital on labor productivity growth can be calibrated using estimates of two effects determined by input cost shares and relative prices:
  - ✓ Use effect (capital deepening)
  - ✓ Production effect (tfp)
- This approach has been a mainstay of productivity analysis with IT capital.

But data capital is rather different ….

- Table reports scenarios for the contribution of data capital to labor productivity growth
- Potential contribution of data capital to labor productivity exhibits a wide range
  - ✓ Synergies among data capital efficiency and an economy's breadth of use and capability for digital transformation
  - ✓ Data capital tends to be domestically produced (much production occurs within firms and international trade in data assets remains limited), so impact on labor productivity is "doubly" important.
- Underscores importance of getting the asset prices/asset services price right.

Table 3. Long-term Scenarios: Contribution of data capital to annual labor productivity growth (percentage points)

	Productivity advantage (relative asset price growth differential)	
Adoption (digital capability)	Narrow edge 1 percentage point	Large edge 5 percentage points
Broad use (and net exporter of data services)	0.25	1.26
10 percent capital income share		
11 percent production share		
Limited use (and net importer of data services)	0.12	0.58
5 percent capital income share		
4.5 percent production share		

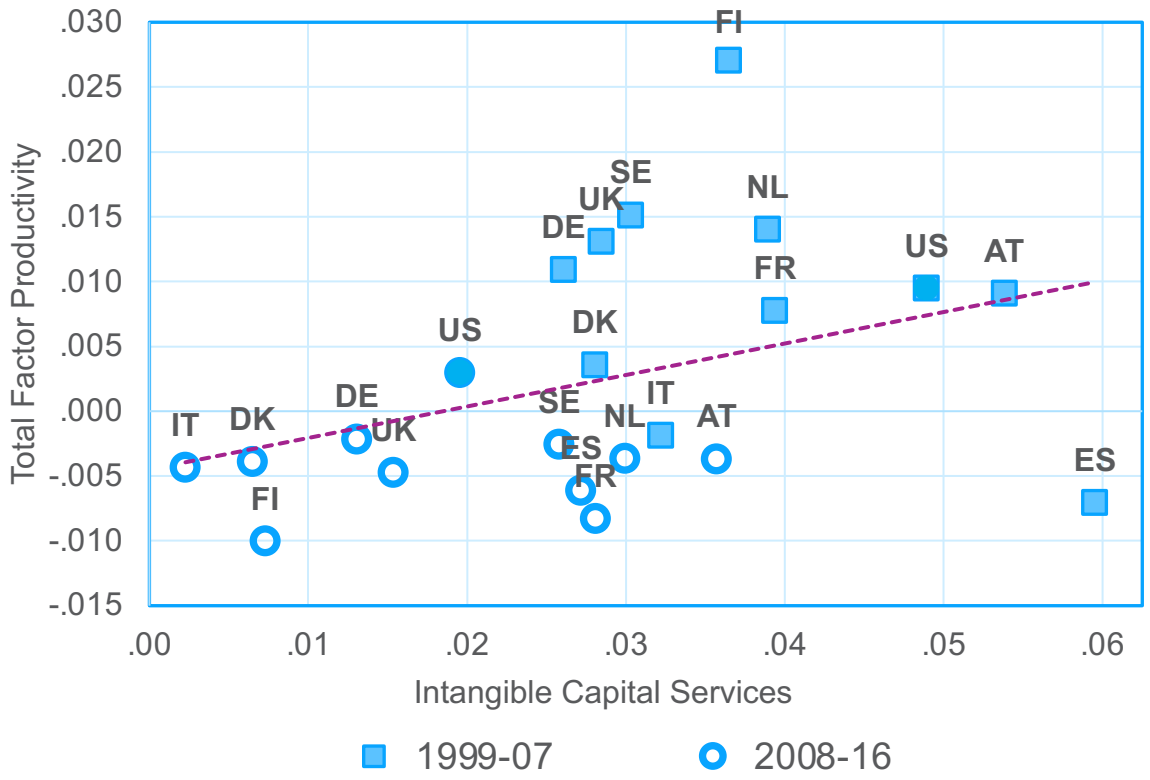
Note: Contributions include the sum of the use and production effects of data capital.

The calculations are based on the steady-state solution to a two-sector model that consists of a data capital producing sector and all other goods and services. In this simple model, the contribution of the data sector to labor productivity equals the sum of the use effect, $^{v^D}/_{v^L}\ (-\dot{p})$ plus the production effect, $\omega^D(-\dot{p})$, where v^D and v^L are the income shares of data capital and labor, ω^D is the production share of data investments, and $(-\dot{p})$ is the relative productivity of data measured as the rate of decline in the relative price of data assets (sign reversed). The calculations in the table assume labor's share of total income, v^L, equals .7. For a derivation, see Oulton (2012) or Byrne and Corrado (2017).

How might data capital impacts be amplified due to spillovers?

- Intangible framework includes a spillover channel due to nonrival character of the assets
  - ✓ Implies (aggregate) increasing returns
  - ✓ Existing literature finds the contribution of intangible capital input is amplified by 20 percent
- Effects need to be reconsidered with growing importance of data capital
  - ✓ Tendency for data assets to be held as trade secrets, policies that restrict uses of personal data (diminished effect?)
  - ✓ Greater importance of open-source software (larger effect?)

Nonrivalry and productivity spillovers to intangible capital



Source: Update of Corrado, Haskel, and Jona-Lasinio, "Knowledge Spillovers, ICT, and Productivity Growth" Oxford Bulletin of Economics and Statistics 79:4 (August 2017), 592-618.

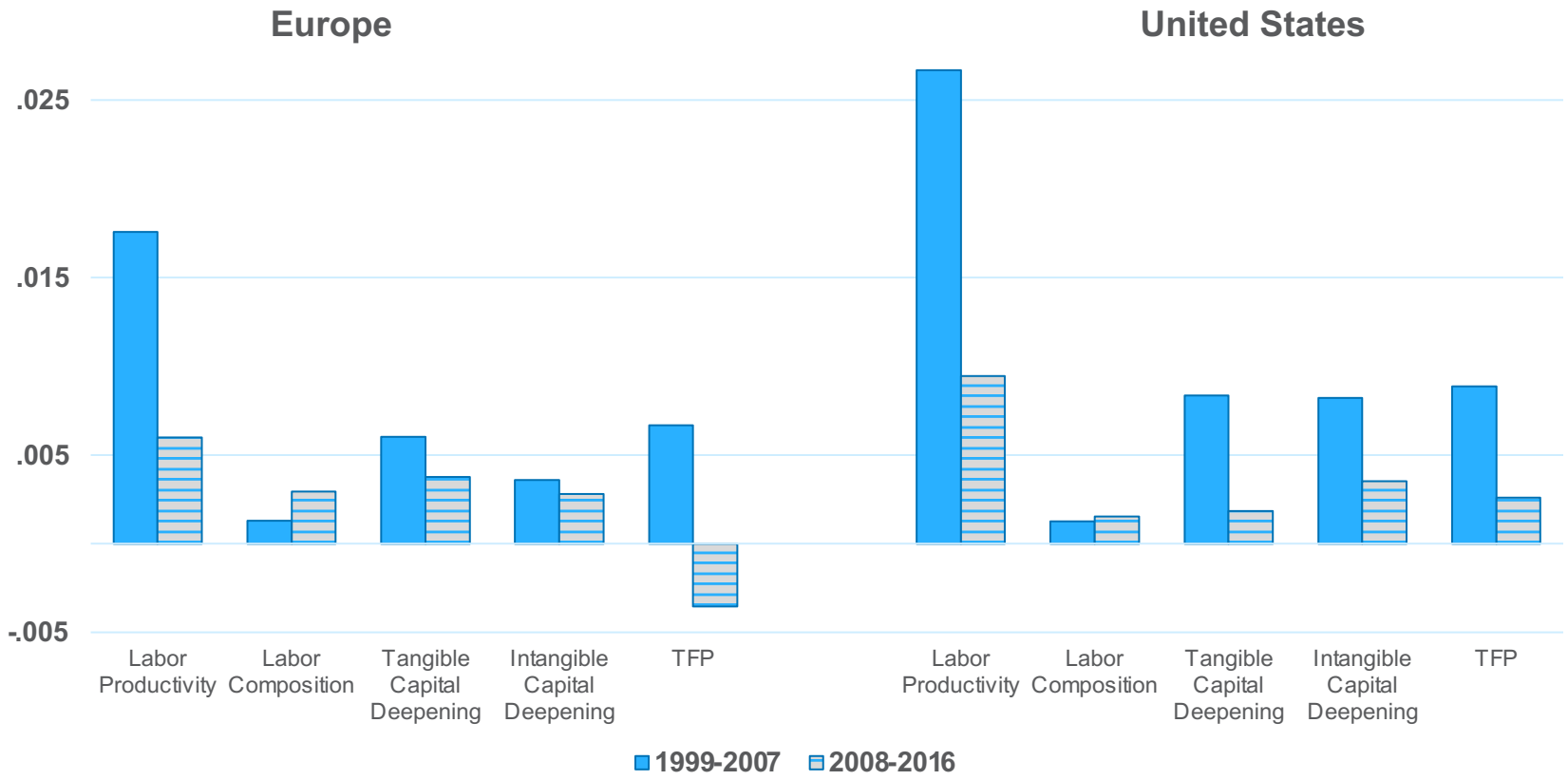
Thank you.

Back ups follow.

Intangible is capital a driver of growth, especially in the US

Decompositions of growth in labor productivity in market sector industries

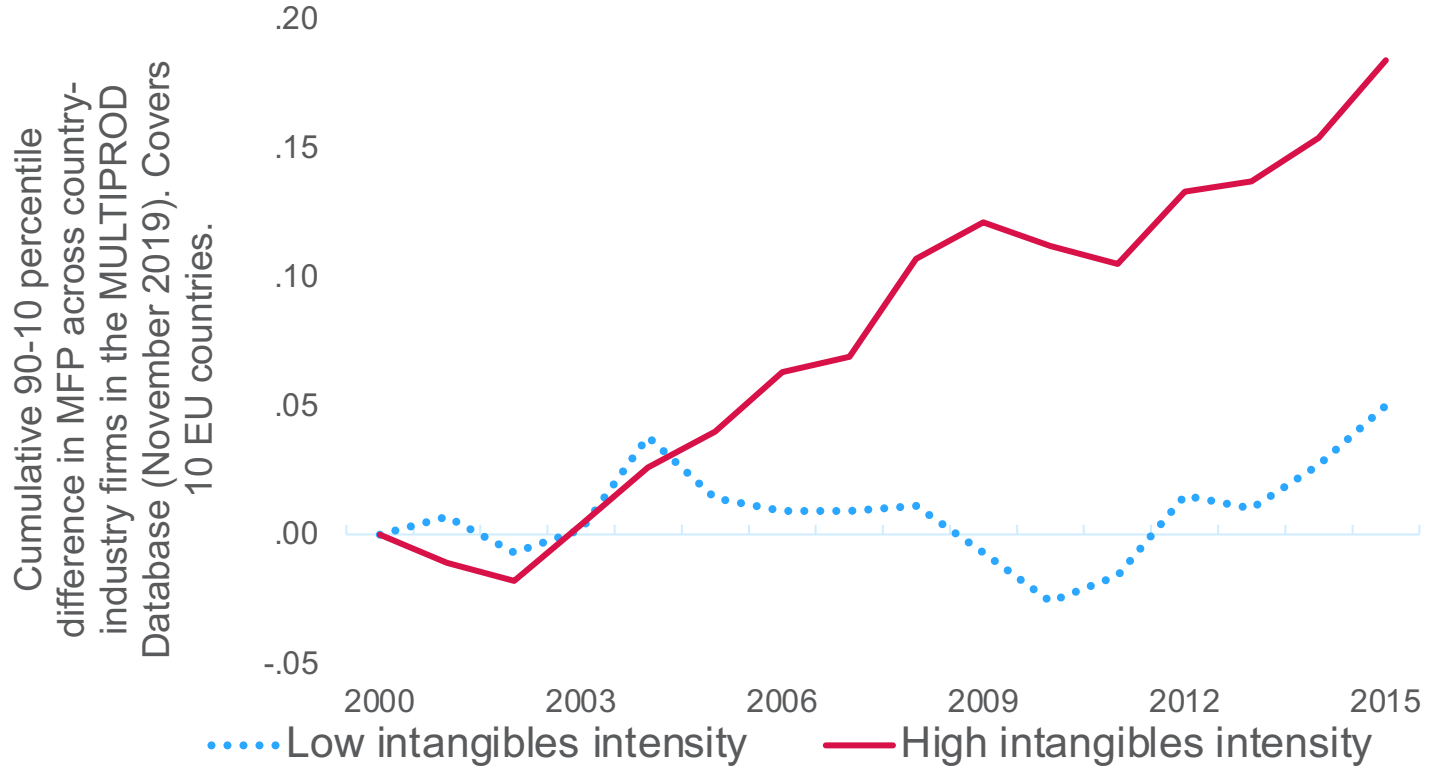
Natural log differences



Source: Corrado, Haskell, Iommi, and Jona-Lasinio (2019). Europe consists of 12 , mostly Western, European countries.
Note: Market sector is slightly narrower than the business sector used by the BLS in its productivity estimates.

Intangible investment a factor behind growth in productivity dispersion at the firm level

Evolution of firm-level productivity dispersion by intangible intensity of industry in a regression framework, after controls*



** Classification of industries according to intangibles intensity based on INTAN-Invest data.*
Source: Preliminary results from Corrado, Criscuolo, Haskel, Himbert, and Jona-Lasino (2021)