# Education Intensity and the Sources of, and Prospects for, U.S. Economic Growth

Dale Jorgenson

Harvard University

Mun Ho

Harvard University

Jon Samuels

U.S. Bureau of Economic Analysis<sup>1</sup>

#### Abstract

We identify a new mechanism whereby education impacts economic growth: industry educational intensity. We define educational intensity as the share of an industry's workforce with a college degree and above and use this new classification to build estimates of the sources of U.S. economic growth from the bottom up across industries. We find that that since 1995, the contribution of education intensive industries to aggregate value added growth exceeds that of non-education intensive industries and that this difference was driven by larger contributions of capital, labour, and TFP growth in these industries. The shift toward educationally intensive industries has not been enough to revive aggregate labour productivity and GDP growth over the medium term; we find that growth over the next ten years will be restrained by slower growth in capital and labour quality.

In previous accounting of the sources of economic growth, improvements in the educational attainment of the workforce manifest as increases in labour quality. The basic economic mechanism is that more educated workers are more productive

than workers with lower levels of education attainment and this difference in marginal productivities is reflected in their relative wages. Using this basic setup, growth accounting can identify the contribution of improvements in education to growth. For

<sup>1</sup> Dale Jorgenson is Samuel W. Morris University Professor at Harvard University. Mun Ho is Visiting Scholar for Harvard China Project on Economy, Energy and Environment. Jon Samuels is Research Economist at the U.S. Bureau of Economic Analysis. The views expressed are solely those of the authors and not necessarily those of the Bureau of Economic Analysis or the U.S. Department of Commerce. We thank the Andrew Sharpe, Michael Christian, and Cindy Cunningham for helpful comments. Emails: djorgens@fas.harvard.edu; munho@seas.harvard.edu and Jon.Samuels@bea.gov.



example, Jorgenson, Ho, and Stiroh (2005) found that increases in educational attainment accounted for approximately 10 per cent of U.S. GDP growth between 1948 and 2002, and about 15 per cent of labour productivity growth.

This approach to including labour quality in accounting for the sources of aggregate growth is widely used, for example, in the various country studies in Jorgenson, Fukao and Timmer (2016). In this article we examine the impact of education on aggregate growth and productivity from a new dimension: educational intensity of industries. We define educational intensity for each industry based on the composition of workers within the industry. This allows us to first associate economic growth at the industry level with the educational characteristics of the work force, and then link educational intensity with aggregate U.S. growth and productivity. Our approach within the KLEMS framework allows us to decompose the sources of economic growth between industries that are education intensive and those that are not.

There is a large literature examining the role of information technology and intellectual capital in productivity growth at the industry level (Biagi, 2013) but little discussion of the link between these capital inputs and characteristics of the workers. Here we

examine the relationship between the share of educated workers in an industry and its productivity growth and use of information technology, and whether education intensity is related to intensity of research and development.

An important motivation for focusing on industry educational intensity is that prospects for labour quality growth due to continued improvement in educational attainment are weak. Jorgenson, Ho, and Samuels (2019) have estimated that labour quality growth is likely to contribute only 0.12 percentage points per year to growth, less than half of the contribution it made between 1990 and 2015. By focusing on educational intensity of industries, we are able to examine the impact of shifts toward industries that are educational intensive and assess the impacts of this on the prospects for growth.

Another motivation for classifying industries by educational intensity is that education is related to employment probability and the distribution of employment across industries. Labour force participation (or employed share of population) are important for future economic growth. Less educated workers are generally less likely to be employed than workers with more education. Furthermore, it has been established in previous work that the 2008 financial crisis

and Great Recession affected less educated workers disproportionately as they suffered much higher rates of unemployment.

However, there is less discussion about the differences of impacts at the industry level, and no discussion of whether industries that are education intensive provided some insulation for workers with less education. If all industries had the same educational intensity, then shifts of workers out of and into the labour market would have a proportional impact on economic growth. But, because educational intensity differs across industries and because the dynamics of highly educated worker differs from less educated workers, it is important to account for industry education intensity and educational attainment in 1) analyzing the sources of U.S. economic growth, and 2) assessing the prospects for growth going forward.

We take on these two tasks in turn. In the first part of the article, we present new results on the role of industry educational intensity in economic growth. To do this, we develop a set of growth accounts that identifies the 63 industries in the U.S. National Accounts and classifies them according to their intensity of use of highly educated workers. We find that a disproportionate share of the high TFP growth industries are in the education intensive group. As part of

this TFP calculation, we extend the U.S. growth accounts in Jorgenson *et al.* (2017) to cover the postwar period 1947-2015.

We then modify our previously published projection model (Jorgenson, Ho, Samuels, 2019) to explicitly account for industry educational inten-The projection here is based sity. on the following: (i) employmentpopulation ratios that account for age and educational attainment, (ii) industry TFP growth that accounts for educational intensity, (iii) capital quality growth, and (iv) an extrapolation of the trend shift to industries that are intensive in educated workers. We also include a projection of labour quality growth, which continues to be low in comparison to our historical estimates.

The article proceeds as follows: in Section 1, we implement our educational intensity measure and calculate its impact on the industry level sources of growth. In Section 2, we relate industry educational intensity to information technology, research and development intensity, and industry TFP growth while in Section 3 we relate education to participation in the labour market. The relationship between education and employment participation is important for evaluating the prospects for economic growth, and we take up medium term projections of growth in Section 4. Section 5 concludes.

## Educational Intensity at the Industry Level and the Source of Growth

Our first objective is to introduce a classification of industry-level educational intensity to analyze the sources of economic growth. The starting point is the latest available industry accounts from the BEA which include measures of output and capital, labour and intermediate inputs for 65 industries covering 1998-2015.<sup>2</sup> To this, we add historical data for the same series from Jorgenson, Ho, and Samuels (2019). We then aggregate over the industries in the manner described in Jorgenson, Ho and Stiroh (2005, Chapter 8), which yields our basic information on the industrylevel sources of growth.

One of our main contributions in this article is to group industries in this dataset into those that are intensive in relatively highly educated workers and other industries. Table 1 gives the share of workers with BA, or higher degrees, out of all workers in each industry in 2007, on the eve of the Great Recession. We also give a measure of the relative size of the industries by showing the share

of all workers going to each industry. The share of highly educated workers ranges from 8.0 per cent in truck transportation to 68.2 per cent in computer systems and 68.5 per cent in securities.

The national average share is 30.7 per cent and we divide the industries into two groups. The educationally intensive (or skill intensive) group consists of those industries with a share larger than the national average. The other industries are allocated to the non-educationally intensive group. The categories are listed in the column marked "skill intensive." The last two columns give indices of IT-intensity and R&D intensity (described below).

While our industry classification of education intensity is based on a single year of data (in part to allow for a tractable classification of industries), we note that education intensity has shifted significantly over time and all industries have become more intensive in the use of college educated labour between 1947 and 2015. In 1947, the median share across industries of total labour compensation paid to workers with a BA degree and above was 0.09, so that workers without a college degree earned more than 90 percent of total labour compensation at

<sup>2</sup> The methods and the data sources of our industry growth accounts is given in detail in Jorgenson  $et\ al.$  (2005).



Table 1: Skill Intensity by Industry, 2007

		Industry share of workers (%)	Workers with BA+(%)	Skill intensive	IT category	R&D Intensity
1	Farms	1.01	14.9			0
2	Forestry, fishing, and related	0.4	13.8			0
3	Oil and gas extraction	0.1	38.1	Yes		0.009
4	Mining, except oil and gas	0.15	11.9			0.012
5	Support activities for mining	0.2	25.3			0.011
6	Utilities	0.36	26.7			0.003
7	Construction	6.32	11.0			0.013
8	Wood products	0.35	9.7		Using	0.026
9	Nonmetallic mineral products	0.33	15.1			0.082
10	Primary metals	0.3	15.3			0.042
11	Fabricated metal products	1.03	12.7			0.095
12	Machinery	0.78	21.1			0.27
13	Computer and electronic products	0.83	46.4	Yes	Producing	0.477
14	Electrical equipment	0.28	25.1			0.34
15	Motor vehicles and parts	0.65	21.2			0.401
16	Other transportation equipment	0.47	37.3	Yes	Using	0.388
17	Furniture and related products	0.37	12.7		Using	0.091
18	Miscellaneous manufacturing	0.46	26.8		Using	0.404
19	Food, beverage and tobacco	1.11	16.0			0.072
20	Textile mills and textile product	0.23	12.0			0.049 0.094
21 22	Apparel and leather products	0.18	15.2			
23	Paper products Printing and support activities	0.3 0.43	17.4 19.7		Using	0.12 0.106
24	Petroleum and coal products	0.08	30.9	Yes	Using	0.100
25	Chemical products	0.56	42.6	Yes		0.512
26	Plastics and rubber products	0.49	14.7	165		0.132
27	Wholesale trade	4.05	29.6		Using	0.132
28	Retail trade	10.83	16.9		Using	0.009
29	Air transportation	0.32	35.5	Yes	Using	0.009
30	Rail transportation	0.13	12.1	100	008	0.004
31	Water transportation	0.04	28.9		Using	0.008
32	Truck transportation	1.14	8.0		0	0.005
33	Transit, ground passenger transp.	0.32	14.6			0.005
34	Pipeline transportation	0.03	29.9		Using	0.006
35	Other transportation activities	0.83	17.9		Using	0.005
36	Warehousing and storage	0.44	11.3		_	0.004
37	Publishing, ex. internet (incl software)	0.65	55.9	Yes	Using	0.089
38	Motion picture and sound recording	0.29	45.3	Yes		0.001
39	Broadcasting, telecommunications	0.92	38.8	Yes	Using	0.032
40	Data proc, internet pub., info. svc	0.22	56.4	Yes	Producing	0.13
41	Fed Res banks, credit intermediation	1.91	37.8	Yes	Using	0.005
42	Securities, comm contracts, inv.	0.63	68.5	Yes	Using	0.019
43	Insurance carriers	1.59	43.9	Yes	Using	0.014
44	Funds, trusts, financial vehicles	0.06	67.5	Yes		0
45	Real estate	1.3	37.8	Yes		0
46	Rental and leasing services	0.45	22.7		Using	0
47	Legal services	0.91	62.1	Yes	Using	0
48	Computer systems design, services	0.99	68.2	Yes	Producing	0.276
49	Misc. prof., scientific, tech sves	3.89	61.5	Yes	Using	0.25
50	Management of companies	1.21	52.6	Yes	Using	0.009
51	Administrative and support vcs	5.77	19.6		Using	0
52	Waste management	0.25	10.2	V	II	0.01
53	Educational services	2.09	62.1	Yes	Using	0.085
54	Ambulatory health care services	3.83	41.9	Yes	Using	0.034
55 56	Hospitals, Nursing, resid care Social assistance	4.89 1.94	33.3 29.9	Yes	Using Using	0.031 0.008
50 57	Performing arts, spectator sports	0.58	47.3	Yes	Osing	0.008
57 58	Amusements, gambling, recreation	0.98	19.9	109		0.005
59	Accommodation Accommodation	1.24	16.6			0.009
60	Food services and drinking places	6.42	9.2			0.009
61	Other services, ex. government	5.19	22.9		Using	0.055
62	Federal government	3.31	32.3	Yes	Using	0.424
63	State and local government	12.61	19.6	- 00	208	0.026
	All industry average	100.00	30.7			0.020
	urce: Authors' calculations.					

Source: Authors' calculations.



the median industry. By 2015, this median share of labour compensation paid to BA and above workers had increased to about 0.44, demonstrating the seismic shift in educational intensity across all industries.

This broad increase demonstrates an important point in considering the prospects for economic growth going forward: the overall educational attainment distribution of workers is distinct from the relative intensity in which industries use different types of workers. In forming our industry classifications, we base our analysis on the latter concept (relative intensity) so that we can identify shifts in the economic contributions of industries that are relatively intensive in the use of educated workers.

We start by presenting the contributions to aggregate value added of the educationally intensive (EI) and non-educationally intensive (NEI) groups in Chart 1. The contribution of an industry is its growth rate of value-added, multiplied by its share of total value-added (GDP).<sup>3</sup> The sum over all industries in the educationally intensive (EI) group is given by the dark bars in Chart 1 while the light bars gives the non-educationally intensive (NEI) group.

We divide the post-war period into

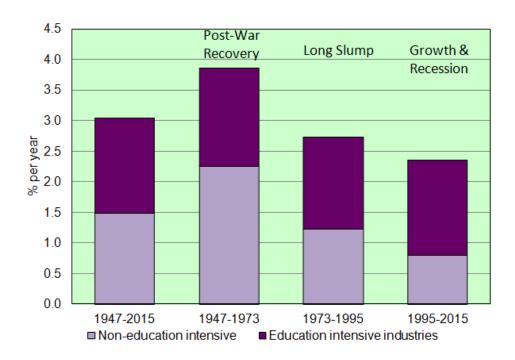
three eras, reflecting the well-known break points in productivity growth—the Post-War Recovery, 1947-73, the Long Slump, 1973-1995, and Growth and Recession, 1995-2015. The last era is further sub-divided among the Investment Boom, 1995-00, Jobless Growth, 2000-07, and the Great Recession, 2007-15. Over the entire 1947-2015 period the two groups made almost the same contribution to aggregate value-added.

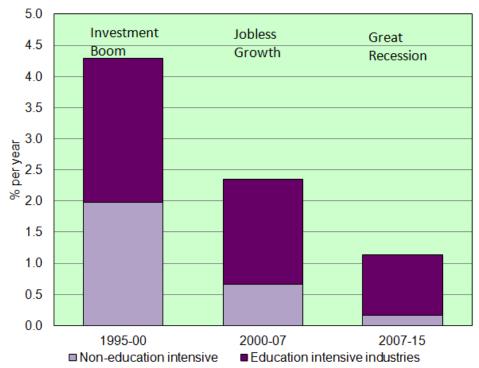
The educationally intensive (EI) group was smaller during the period 1947-1973, but dominated after that. In the Growth and Recession period, the EI group contributed 1.6 percentage points, compared to 0.8 points for the NEI group. bottom half of Chart 1 shows the dramatic change between these two groups. During the Investment Boom they contributed about equally (2.3) versus 2.0 percentage points). the Jobless Growth period the EI group contributed 1.69 versus 0.67 points and during the Great Recession (2007-15) the EI group contributed 0.98 versus 0.16 points. Many NEI sectors had negative growth in valueadded, including furniture and related products, apparel and leather and allied products, textile mills and textile product mills, paper products,

<sup>3</sup> We use a production possibility frontier method to aggregate over the value-added of each industry (Jorgenson, Ho and Stiroh (2008, equation 8.21).



Chart 1: Contributions of Education Intensive and Non-education Intensive Groups to Value Added Growth, 1947-2015





Source: Author's calculations.

Sources of Growth for education intensive and non-education intensive

2.5

2

4

1.5

0.5

1995-00

2000-07

2007-15

Education intensive

Non-Education intensive

Non-college Labor

TFP

Chart 2: Sources of Growth of Education Intensive and Non-education Intensive Industries, 1995-2015

Source: Author's calculations.

and construction. Most of these were manufacturing industries (excluding computers and electronic products).

We next discuss the sources of growth for the EI and NEI groups. Chart 2 gives the contributions of capital, college-labour, non-college labour and TFP to their growth for the three sub-periods of the Growth and Recession era (1995-2015). The sources of growth are constructed from the bottom up across industries, that is, the contributions of capital, labour, and TFP of each detailed industry are summed up using "Domar weights." The use of Domar weights (industry j's value added share of GDP divided by the value

added share of gross output in j) in aggregation is described in Jorgenson, Ho and Stiroh (2005, eq. 8.33).

First, we see that the growth of value-added in the EI group (total height of the bars in Chart 2) is higher in all three sub-periods. Second, college labour contributed positively to both groups after 2000, but noncollege labour contributed negatively. This came after the Investment Boom of 1995-2000 when non-college labour grew rapidly, especially in the NEI group. The college labour contribution to value-added growth is a higher share in the EI group for all three subperiods. During the Great Recession and Recovery (2007-15) the collegelabour share reached 34 per cent in the EI group, compared to the average 25 per cent share for the whole economy during the entire 1995-2015 period.

Third, the TFP contribution is significantly different between the EI and NEI groups. During the Investment Boom TFP growth was high and contributed more than 17 per cent to value-added growth in both groups. During the Jobless Growth period TFP growth remained strong in the El group, rising to a contribution to growth of 27 per cent. In the NEI group TFP growth remained positive and contributed about 16 per cent to growth. However, in the Great Recession period (2007-2015) TFP growth was positive in EI (a 28 per cent contribution) but negative in the NEI group.

Chart 3 shows the U.S. productivity record in another way by giving the decomposition of aggregate TFP growth into the sum over industry TFP growth, reallocation of capital and reallocation of labour.<sup>4</sup> Reallocations capture the aggregate effects of movement of factor inputs across industries. Aggregate TFP growth reaches a peak of 0.84 per cent per year during the Investment Boom, remains high at 0.65 per cent dur-

ing Jobless Growth, but crashes to 0.11 per cent after the Financial Crisis. During the Jobless Growth period the EI group contributed 0.46 percentage points to the 0.65 per cent total change, while the NEI group contributed 0.11 points and reallocation effects contributed 0.08 points. During the 2007-2015 period, the EI group contributed 0.27 points to the 0.11 per cent while NEI contributed -0.14 points.

In summary, there are substantial differences between the two groups of industries. The differences in both output and TFP growth performance widened during the Great Recession and the current recovery. Next, we relate educational intensity to previous work on information technology and research and development (R&D), and then we incorporate this information into our outlook for medium term economic growth.

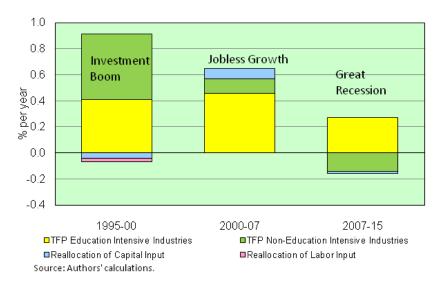
## Skill Intensity, IT-intensity, R&D Intensity and Industry TFP Growth

We now turn to a discussion of the input characteristics at the industry level to display the relationship between educational intensity, R&D, and TFP growth. There are many

International Productivity Monitor

<sup>4</sup> The decomposition is explained in Jorgenson, Ho and Stiroh (2005) equation 8.34. The contribution of TFP from an industry group to aggregate TFP is the Domar-weighted sum of the TFP growth in each of the member industries.

Chart 3: Contribution of Industry Groups to Aggregate Productivity Growth, 1995-2015



models that link human capital, productivity and growth (e.g. Stokey, 2018). Corrado, Hulten and Sichel (2009) is one of the earlier estimates of the role R&D. They find that intangible capital (excluding software) contributed 0.57 points of the 3.09 per cent annual growth in non-farm business labour productivity during 1995-2003. In our earlier accounting of growth (Jorgenson et al. 2016) we distinguished IT-capital, R&D capital and other capital, and estimated that R&D capital contribution as modest: about 0.12 percentage points of the 2.37 per cent annual growth rate of GDP (including the non-business sector) during 1995-2012 compared to 0.64 points for IT-capital and 0.53 points for other capital. The R&D contribution is slightly bigger over

the 1947-73 period when it was 0.26 points of the 3.73 per cent aggregate growth rate.

To give a more detailed portrait of the role of R&D we provide the intensity of R&D capital for each industry in 2007 in the last column in Table 1.<sup>5</sup> We plot the relation between R&D intensity and share of BA+ for these 63 industries in Chart 4. More than half the industries have R&D intensity smaller than 0.02, but there is no simple monotonic relation between skill-intensity and R&D shares. The correlation coefficient between them is 0.19 for the whole set of 63 industries.

In another accounting for US growth in Jorgenson *et al.* (2007) and Jorgenson *et al.* (2017) we divided the U.S. industries into three groups—IT-

<sup>5</sup> The intensity of R&D capital is defined in Jorgenson et al. (2016).



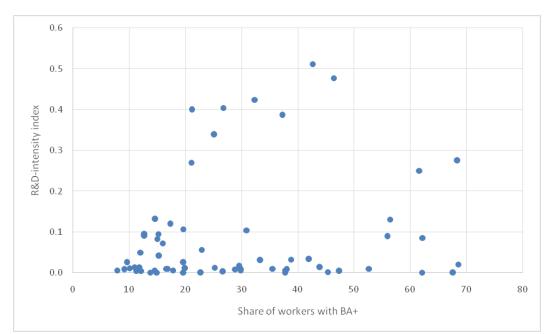


Chart 4: R&D Intensity versus Education-Intensity in 63 U.S. Industries, 2007

Source: Authors' Calculations

producing, IT-using (relatively IT intensive) and Non-IT (relatively non-IT intensive)—and showed how the tiny IT-producing sector with less than 4 per cent of total value added contributed more than half of aggregate TFP growth during 2000-2007, and essentially all of aggregate TFP growth after the Financial Crisis (2007-2015).<sup>6</sup>

The IT-producing group and many of the IT-intensive sectors are also intensive users of highly educated workers. In the "IT category" column of Table 1 we indicate which industries are IT-producing, IT-using and Non-IT based on their inputs in 2005. All

the IT-producing industries are skillintensive (computers, data processing, computer systems design), but are relatively small. The industries with many well-educated workers include banks, professional services, education, health services, hospitals and the federal government. The relation between IT-intensity and skillintensity is plotted in Chart 5 which shows a much stronger correlation (0.62) than that between R&D and skill-intensity. This industry level relation should inform the literature on skill-biased technical change and polarization of labour markets<sup>7</sup> (e.g. Acemoglu and Autor 2010, Michaels,

<sup>7</sup> Our industry database includes wages by education attainment and other demographic characteristics for each industry and year.



<sup>6</sup> Non-IT industries use some information technology but are relatively less intensive of their use in IT. IT-intensity is given by the ratio of IT input to total capital plus IT intermediate input, where IT input is the sum of IT capital and IT intermediates (details in Jorgenson, Ho, Samuels, 2016, eq. 1).

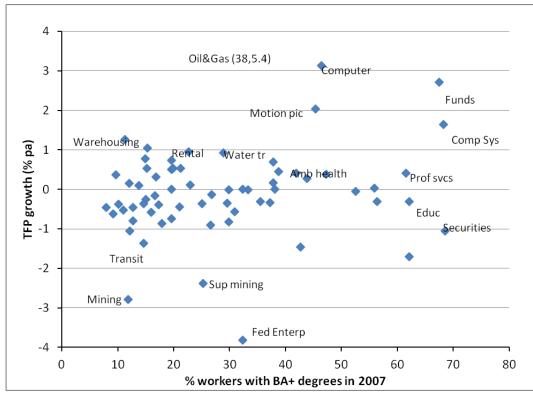
1.0 0.9 • 0.8 0.7 IT-intensity index 0.6 0.5 0.4 0.3 0.2 0.1 0.0 70 0 10 20 50 80 40 Share of workers with BA+

Chart 5: IT-Intensity versus Education-Intensity in 63 U.S. Industries, 2007

Source: Authors' Calculations

4

Chart 6: TFP Growth (2007-15) versus Skill Intensity by Industry and Linear Trend



Source: Authors' Calculations



Natraj, van Reenen 2014).

From our updated industry growth accounts for 1947-2015 we derive the growth rate of total factor productivity (TFP) in a manner described in detail in Jorgenson, Ho and Stiroh (2005). This allows us to discuss the correlates of TFP growth at the industry level and can inform the discussion of endogenous growth of technology and skills. We first have Chart 6 where we plot industry TFP growth during the Great Recession and Recovery period (2007-2015) versus the skill intensity given in Table 1 (oil and gas is a outlier with a TFP growth of 5.4 per cent and left out of the plot). The positive but weak relation between them is clear (the correlation coefficient is 0.21). The high skill intensity industries such as computer systems, funds, computer manufacturing, and professional services have high TFP growth rates. The low skill intensity industries such as mining (excluding oil and gas), transit and ground passenger transportation, rail transportation, and fabricated metal products have large negative TFP growth rates. There are some service industries with high skill intensities but low TFP growth—securities, education, legal services and data processing and information services.

These are sectors with well-known difficulties in measurement.

Chart 5 shows that IT-intensive industries tend to be more skill intensive, and we just noted that TFP growth is very weakly related to skill-intensity.<sup>8</sup> Turning now to R&D capital and TFP, the scatterplot in Chart 7 shows that TFP growth over the 2007-2015 period is not strongly correlated with the R&D capital intensity in 2007 (correlation of 0.11). A plot of TFP growth over 1995-2015 shows an even weaker correlation.

#### **Education and Employment**

At the outset, we noted that the traditional mechanism in sources of growth analysis that drives the contribution of education to economic growth is increases in labour qual-The previous sections of this ity. article have demonstrated that education attainment matters not only as an input to production, but that the output and productivity of industries that are relatively more intensive in educated workers differs considerably from the NEI industries. This implies, that as employment participation (employment-population ratio) recovers from the large fall dur-

<sup>8</sup> Jorgenson, Ho and Samuels (2016: Chart 5) have a scatterplot like Chart 6 showing a weak correlation between IT-intensity and TFP growth for 1995-2012.



4.0 3.0 2.0 1.0 TFP growth rate 0.0 -1.0 -2.0 -3.0 -4.0 0.1 0.5 0.6 0.0 0.2 0.3 0.4 R&D intensity in 2007

Chart 7: TFP Growth (2007-15) and R&D Intensity for 63 US Industries

Source: Authors' Calculations

ing the Great Recession, the impact on industries depends on the skill mix of the workers returning to work. To fix ideas, suppose that as a result of the recession there was a 10 per cent reduction of workers without a college degree. As these workers return to work, the industries most impacted would most likely be NEI industries. Furthermore, this would impact the aggregate share of output of the EI versus the NEI industries that we take as an input into our projection model below.

To examine whether changes in employment status are related to education we compare employment population ratios by gender, age group, and educational attainment. A substantial literature has discussed the ex-

tent and causes of the falling trend in labour force participation rates (LFPR) since the peak in 2000. Earlier studies of the LFPR, such as Kudlyak (2013) and Toossi (2013), took into account the differences among age and gender groups but did not consider the education dimension. Aaronson, Hu et al (2014), Aaronson, Cajner et al. (2014), Jorgenson et al. (2017), Montes (2018) and Abraham and Kearney (2018) included the effects of the sharper drop in participation rates among the less educated workers during the Great Recession.

The strand of papers focused on the LFPR, or employment-population ratios, does not make an explicit link between them and effective labour input. There are at least two possi-

ble ways in which they are related. The first is that the differential rise in participation rates among different age and education groups leads to a change in labour quality. For example, population aging lowers the aggregate participation rate (and thus effective labour input) by increasing the population weights of older age groups with lower participation rates. The second is that industries with their differing gender-age-education composition of workers could respond differently to an increase in the relative supply of highly educated workers. As we document in Charts 6 and 7. industries have wide range of TFP growth so that uneven recoveries of the LFPR's could affect the growth of aggregate TFP.

Projections by the Congressional Budget Office (CBO, 2018) take the total number of workers from LFPR models and use this directly in an aggregate output function. The Social Security Administration (SSA, 2018) assumes an aggregate labour productivity growth rate independent of the labour force projections. The only studies that explicitly recognize the implications of different LFPR's for labour quality are Bosler, Daly, Fer-

nald and Hobijn (2017) and Jorgenson, et al. (2017).

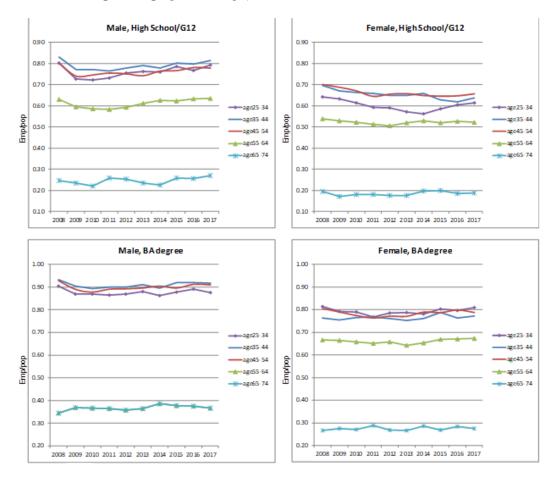
Before projecting the employmentpopulation trends for the mediumterm, we first describe the large differences in levels and trends for the various demographic groups in Chart 8.9Comparing the male rates in the left-hand graphs with the female rates on the right, we see that there is a gap of 10 percentage points or The largest gap is during the peak fertility age. Across the age groups for the college-educated men and women, the differences in employment-participation (EP) rates within the 25-54 age group are small. For women with only high school education, the EP rate for the 25-34 age group is significantly lower than that for the 35-54 group. For prime-age (25-54) men, those with BA's have EP rates around 90 per cent, while those with High School diplomas have rates less than 80 per cent. Prime-age women with BA's have rates around 75-80 per cent compared to the High School group rates around 60-70 per cent.<sup>10</sup> The employment-population ratio for the 65-75 age group is significantly lower than the 55-64 group. Thus, the aging of the workforce

<sup>10</sup> We do not present the data for those with less than high school since they are quite similar to those with high school, and those with MA+ degrees are somewhat similar to those with BAs.



<sup>9</sup> These ratios are tabulated from the Annual Social and Economic (ASEC) files in the Current Population Survey. In recent years the ASEC has a sample size of about 180,000 persons. The employment-population ratio is defined as the ratio of workers to total population, whereas the LFPR also includes the unemployed in the numerator.

Chart 8: Employment-Population Ratios after the Financial Crisis; Differences among Demographic Groups, 2008-2017



Source: Authors' Calculations

would lead to lower employment, and slower growth of labour input, ceteris paribus.

The period covered in Chart 8, 2008-2017, shows the impact of the Great Recession and the slow recovery of participation rates. We note the following features of these trends. For men in the 25-54 age group, for all education levels, the EP ratios have not recovered to the pre-crisis levels in 2007. For men aged 55-64, the ratio recovered to or exceeded the 2007 levels. For all age groups of women with high school education the EP ra-

tios have not recovered. For women with BA degrees, the EP ratios have largely recovered, and in the 55-64 age group, exceeded the 2007 level.

These results demonstrate the importance of education in mediumterm prospects for returning to employment from non-employment. Because we do not have a model of how trends in employment-population will evolve, in the medium term projection below we fix employment-population ratios by demographic groups at their 2017 levels.<sup>11</sup> But we do take into account (as discussed below) that as less educated workers return to the workforce this may impact the distribution of economic output between education intensive and other industries.

#### **Medium Term Projections**

Medium term projections of economic growth are essential components of policy analysis and public program planning. The Congressional Budget Office is an important source of carefully considered outlooks for the U.S. economy (CBO, 2018), including an analysis of labour force participation trends. The BLS and Federal Reserve provide projections of LFPR and output growth, e.g. Toossi (2013), Lacey  $et \ al.$  (2017) and Aaronson, et al. (2014). The Social Security Administration (2018) also considers labour supply and productivity issues but over a much longer horizon.

Projections of the GDP use methods ranging from projections from growth accounts to Solow-type growth models. Here we present a method of projecting medium term growth that takes into account labour quality, capital quality and

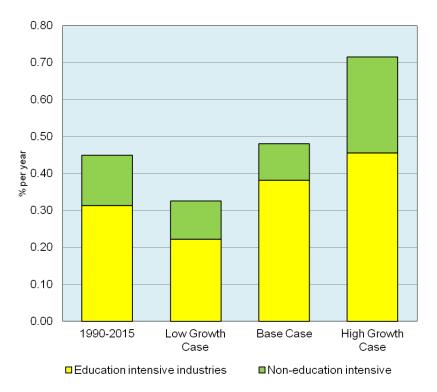
TFP growth. This method is described in detail in Jorgenson, Ho and Stiroh (2008) and Jorgenson, Ho, and Samuels (2019, eq. 1A.5). We first express labour productivity growth (output per hour worked) as a function of capital quality growth, labour quality growth, TFP growth and an adjustment for the share of reproducible capital in total capital. That equation is derived under the longrun assumption that output growth equals capital growth. Output growth is then the sum of labour productivity and hours growth.

We present three alternative projections for U.S. economic growth for the period 2017-2027 in Table 2: Base Case, Low Growth, and High Growth. This enables us to give some historical bounds on the uncertainty in projections of the growth of capital quality and TFP growth, and the share of output accounted for by industries intensive in highly educated workers. We present the three alternative projections in Charts 9, 10 and 11 where we also give historical data for 1990-2015 for comparison.

We use the following assumptions for all three projections. The capital share in value added and the share of reproducible capital in total cap-

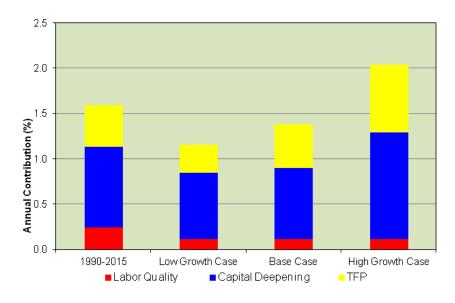
<sup>11</sup> The trends in the EP ratios may have structural and cyclical components. For example, enrollment rates may affect the EP ratio, and enrollment rates may have risen during the Great Recession as a cyclical response to weakness in the labour market. The continued recovery may reduce enrollment rates and thus impact EP ratios and labour quality in ways that we have not accounted for.

Chart 9: Contribution of Industry Groups to Aggregate TFP Growth, 2017-2027



Source: Authors' Calculations

Chart 10: Range of Labour Productivity Projections, 2017-2027



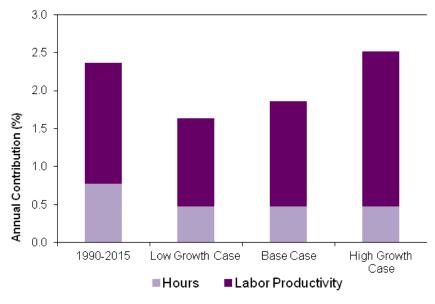
Source: Authors' Calculations

Table 2: Output and Labour Productivity Projections, Total Economy

		Projections 2017-2027		
	1990-2015	Low	Medium	High
			Projections	
Value Added Growth	2.37	1.64	1.86	2.52
ALP Growth	1.59	1.16	1.38	2.04
Effective Capital Stock	2.19	1.24	1.41	1.91
	Comm		non Assumptions	
Hours Growth	0.77	0.47	0.47	0.47
Labour Quality Growth	0.43	0.21	0.21	0.21
Capital Share	0.424	0.436	0.436	0.436
Reproducible Capital Stock Share	0.668	0.757	0.757	0.757
		Altern	Alternative Assumpt	
Education Intensive Industry Output Share	0.853	0.790	0.885	1.005
Non-Education-Intensive Industry Output Share	0.938	1.008	0.907	0.791
TFP Growth in Education Intensive Industries	0.37	0.25	0.43	0.52
Contribution of Education Intensive Industries	0.31	0.20	0.38	0.52
TFP Growth in Non-education Intensive Industries	0.14	0.11	0.11	0.29
Contribution of Non-education Intensive Industries	0.14	0.12	0.10	0.23
Other TFP Contribution	0.01	0.00	0.00	0.00
Capital Quality Growth	0.88	0.90	0.86	1.27
Implied Capital Deepening Contribution	0.88	0.73	0.78	1.18

Source: Authors' calculations. Capital share and reproducible capital stock shares are 1947-2015 averages, and output shares are averages for 2000-2015. Low growth projections use 1973-2015 average growth of capital quality and TFP growth. Base case projections use 1995-2015 averages and high growth projections use 1995-2007 averages. Output shares are defined as gross output over aggregate value added. Projections of hours and labour quality assume that employment-population ratios remain constant at 2017 levels and weekly hours worked remain constant at 2015 levels. Optimistic case assumes that the education intensive and non-education intensive industry output shares will change by the same amount it did between 1995 and 2015. Pessimistic case assumes that these shares will revert to the 1995 level.

Chart 11: Range of U.S. Potential Output Projections, 2017-2027



Source: Authors' Calculations

ital stock are set equal to the averages for the postwar period, 1947-2015. Next, we discuss the alternative assumptions that drive the differences between our three cases.

Chart 9 includes three alternative projections of total factor productivity growth for the period 2017-2027. For the Base Case we set future TFP growth rates for educationally intensive, and non-educationally intensive industries equal to growth rates for the period of Growth and Recession, 1995-2015. This includes the relative rapid TFP growth early in the period and slower TFP growth later in the sample, so that on average this yields the middle estimate of TFP growth over the projection period.

We set the share of educationally intensive and non-educationally intensive industries to the 2000-2015 share to reflect history. The Low Growth projection is based on total factor productivity growth rates for the period 1973-2015, which includes the Long Slump of 1973-1995, and we assume that the educationally and non-educationally intensive shares revert to the 1995 level. The High Growth projection incorporates high TFP growth during the period 1995-2007, which includes the Investment Boom and the Jobless Recovery of 2000-2007, but excludes the Great Recession. For the high growth case we assume that the economy will continue to shift toward more educationally intensive industries. In particular, we assume that over the next ten years, the output share of educationally intensive and non-educationally industries will change at the same rate as occurred during 1995-2015. Our assumptions on TFP growth reflect that the 1973-2015 period had the weakest TFP growth, followed by 1995-2015 and 1995-2007.

Chart 10 gives the growth rates of labour productivity and its components for the Base Case, Low Growth and High Growth projections; the components are labour quality, capital deepening and aggregate TFP. Chart 11 presents the projected growth rates of output as the sum of hours and labour productivity. We have now discussed all the ingredients for the projections except for the projections of hours and labour quality, described in the Base Case below.

#### **Base Case**

In our discussion of Chart 8 we noted that the employment-population ratios differ by gender, age, and education. They have slowly recovered towards the pre-recession peak in 2007 by the mid-2010s. Our projections of hours worked incorporate these differences for the two genders, seven age groups and six educational attainment groups. For each demographic category we assume that

the employment-population ratio remains equal to the ratio in 2017. We fix weekly hours for each gender-age-education group at the 2015 levels, the latest year of our labour data.

The educational intensity of workers had temporarily grown due to the higher unemployment of the lesseducated after 2000. A similar education index for the general population shows a steady fall in the growth rate after 2000 when the rapid rise in college enrollment decelerated. We examined the education attainment of the population for each gender-age cell in 2000, 2010 and 2015 using the Censuses and ASEC survey in comparison to the 1977-2000 history described in Jorgenson, Ho and Stiroh (2005). We see a rapid deceleration of improvement in educational attainment, especially for men, after 2000 compared to the prior period.

We therefore project a modest further improvement in educational attainment over the next ten years, as discussed in greater detail in Jorgenson, Ho, and Samuels (2019, eqn. 1A6, 1A7). The projection of the population by gender and age taken from the Census Bureau, combined with our projection of educational attainment and assumed EP ratios, gives

the implied projection of labour quality. Our projections of the growth rates of labour quality for 2017-2027 are considerably below the averages for the period 1990-2015, due to declines in the rates of growth of average educational attainment and the entry of young workers who are the echo of the Baby Boomers.

In the Base Case we assume that the growth rates of capital quality and total factor productivity growth for the next ten years will equal average growth rates for the period of Growth and Recession, 1995-2015.<sup>12</sup> To recall, the Investment Boom of 1995-2000 combined rapid accumulation of IT capital and robust productivity growth. The Jobless Recovery of 2000-2007 had strong productivity growth but slower growth of IT capital. The Recession and Recovery of 2007-2015 had weak productivity growth and much slower accumulation of IT capital.

It should be noted that the growth rate of capital quality during the period 1995-2015 used in the projection is below the growth rate for the period that included five earlier years, 1990-2015, perhaps unintuitively, given the recession of 1991. In the projection period 2017-2027, capital deep-

<sup>12</sup> We computed capital quality using our estimates of capital stocks and flows covering the 1947-2012 period in Jorgenson, Ho and Samuels (2016). In the extension to 2015 we use the capital flows estimated in the BEA-BLS integrated Industry accounts which, unfortunately, does not include stock estimates. For the projections we assume that the rate of capital quality growth during 1995-2015 is equal to the rate for 1995-2012 estimated using the data in Jorgenson, Ho, and Samuels (2016).

ening makes the largest contribution to labour productivity growth (0.86 points out of 1.38) while the growth of TFP in the education intensive sector makes the second largest contribution (0.38 points). We project that total factor productivity growth in the non-education intensive sector will be smaller than its contribution during 1990-2015, reflecting the observed deceleration.

Our Base Case projection of labour productivity growth over the period 2017-2027 is lower than growth during the period 1990-2015, 1.38 per cent per year versus 1.59 per cent. Our projection of labour quality growth in the Base Case is half that in 1990-2015. Total hours worked are projected to grow at 0.47 per cent per year, compared to 0.77 per cent during 1990-2015, reflecting the future changes in the age-structure and the assumption of fixed annual hours at 2015 levels for each demographic group.

Combining our projected growth rates in hours worked and average labour productivity, we project the GDP growth rate at 1.86 per cent per year over the period 2017-2027. This is a substantial decline from the growth rate of 2.37 per cent per year during the period 1990-2015. The slower growth in hours worked is reinforced by the slower growth of average labour productivity. We conclude

by emphasizing that we do not model the determinants of employment, but rely on extrapolations of trends from the historical data.

#### Low Growth Case

Our first alternative assumption to the Base Case is that capital quality and total factor productivity growth over the period 2017-2027 will equal the averages over 1973-2015, a period that includes the Long Slump and the Recession and Recovery. By including the Long Slump we dampen the growth rates compared to the Base Case. This Low Case takes averages over 1973-2015, and for capital quality growth this yields a rate that is very close to the growth rate for the period 1990-2015.

Our procedure gives a TFP growth in the education intensive sector that is below the rate for 1990-2015 (0.25 per cent versus 0.37 per cent per year). Using the 2000-2015 average share of that sector in output, we obtain a substantial contribution of TFP growth from the education intensive sector to growth of aggregate labour productivity. We project that the growth of total factor productivity in the non-education intensive sector will be slightly below that for the period 1990-2015 (0.11 per cent versus 0.14 per cent).

In the Low Growth Case our projected labour productivity growth for



the period 2017-2027 is 1.18 per cent per year, compared to 1.38 per cent in the Base Case and 1.59 per cent observed for 1990-2015. The growth of hours worked is assumed to be the same in both scenarios. Summing the growth rates in hours worked and labour productivity, the Low Growth Case projects output growth at 1.65 per cent for the period 2017-2027 compared to 1.86 per cent in the Base Case.

#### **High Growth Case**

For the High Growth Case we assume the same growth of hours and labour quality as the Base Case. We assume that growth rates of capital quality and total factor productivity for the period 2017-2027 will equal their averages over the period 1995-2007. This includes the Investment Boom and the Jobless Growth periods but excludes the Long Slump and the Great Recession as temporary slowdowns in economic growth. Taking averages over 1995-2007 yields a capital quality growth rate significantly higher than the growth rate over the period 1990-2015, 1.27 per cent versus 0.88 per cent.

In the High Growth Case TFP growth in the education intensive sector is more rapid than in the Base Case (0.52 per cent versus 0.43 per cent). This translates into a relatively high contribution of growth in total

factor productivity to growth in average labour productivity. The growth of TFP in the NEI sector is also projected at a higher rate than in the Base Case (0.29 per cent versus 0.11 per cent). Adding over the capital quality, labour quality and TFP components, the growth rate of labour productivity is 2.00 per cent per year compared to 1.38 per cent in the Base Case.

Combining projections of growth in labour productivity and hours worked, the High Growth projection of GDP growth is 2.47 per cent per year, only slightly above the growth rate of 2.37 per cent during the period 1990-2015. Higher growth of total factor productivity and capital quality are offset by lower growth of labour quality and hours. Only if there is a recovery of participation rates to the 2000 peak during the Investment Boom will hours growth be much higher.

### Discussion and Comparison to Other Projections

Fernald, Hall, Stock and Watson (2017) attribute the slow recovery since 2009 to the slow growth of TFP and decline in labour force participation (adjusted for demographic changes), arguing that the capital shortfall was due to the fall in trend output. Our growth accounts are consistent with those observations and

our projections reflect the slow growth of TFP and the slow growth of hours. Fernald (2016) presents a number of alternative projections of U.S. GDP growth and chooses a modal forecast of 1.6 per cent per year as the most likely outcome.

The Congressional Budget Office (2018, Table 1-2) presents potential GDP projections for 10 years. For the 2018-2028 horizon they project aggregate labour productivity at 1.4 per cent per year (1.8 per cent for nonfarm business) and hours worked at 0.4 per cent, very close to our Base Case values. Their projection of TFP is 1.1 per cent per year; however, their definition of TFP would include our measures of TFP (0.54), labour quality (0.21\*labour share) and capital quality (0.86\*capital share).

The BLS (Lacey et al. 2017) projects the labour force to grow at 0.6 per cent over the 2016-2026 period. This combines the Census Bureau population projections with their participation rate projections. They also make macro projections using a model from Macroeconomic Advisers, and project GDP to grow at 2.0 per cent. These numbers are slightly higher that our base case hours growth of 0.5 per cent and GDP growth of 1.9 per cent.

#### Conclusion

We have determined that it is important to account for industry educational intensity in analyzing both the sources of, and prospects for, U.S. economic growth. This conclusion is based on a new industry classification that we have implemented in this article to divide industries into those that are intensive in educated workers and those that are not. Based on this classification, we have found that since 1995, the contribution of education intensive industries to aggregate value added growth exceeds that of non-education intensive industries. This difference was driven by larger contributions of capital, labour, and TFP growth in educationally intensive industries.

The larger contribution of labour was driven entirely by the contribution of workers with a college degree or above. Because the economy is shifting toward educationally intensive industries, it is important to take this into account when constructing medium term projections of labour productivity and GDP growth. This shift enters our projection via relatively faster growth in the TFP of education intensive industries and an ongoing shift in the share of economic output originating in these industries. Even so, we conclude that in the medium term, both labour productivity and aggregate value added growth will be below the historical 1995-2015 average, unless our most optimistic scenario comes to fruition. This is driven by our projections of slower labour and capital quality growth for the next ten years.

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