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How Accurate Are Long-Run Employment Projections?

The occupational mix has been changing for decades. Planners and decision makers need to know how it will continue to change, and why.

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BY ENGHIN ATALAY

Projecting the future is immensely challenging. In October 1929, eight days before the stock market crash, economist Irving Fisher said that "stock prices have reached what looks like a permanently high plateau."[1] In a 2012 statement, Google cofounder Sergey Brin predicted that autonomous cars would be widely available within five years.[2] Closer to the focus of this article, although the U.S. Bureau of Labor Statistics' (BLS's) long-run projections of the labor market generally perform well, certain projections have not come to pass. In 2010, the BLS projected that the number of telemarketers would grow slightly, by 7 percent, over the next decade. Instead, the number of telemarketers has fallen by almost half.

None of us is Nostradamus. Yet, planners and decision-makers depend on projections of future conditions. Projections of financial market conditions and technology adoption shape individuals' and firms' investment decisions. BLS projections of future employment patterns guide career counseling for students, educational policy (for example, designing appropriate curricula), and state and local governments' planning for fiscal and regulatory policy.

In this article, I discuss long-run projections—looking 10 or more years ahead—of employment in different occupations.[3] I address three questions. First, why do some occupations tend to grow faster than others? Understanding the forces that have led workers to move out of certain occupations and into others will set the foundation for addressing our second question: How have economists, both those in governmental agencies and those in universities, developed projections for occupations' employment growth? And third, are their projections accurate, or is there room for improvement?

To preview the answers to these three questions: Computerization, globalization, and the declining importance of manufacturing are primary factors shaping the evolving occupational mix. Academic projections usually focus on individual factors, while the BLS approach is more comprehensive. Although BLS projections perform well, there may be room for improvement via incorporating certain projections from academic articles.

Why Some Occupations Grow Faster than Others

The share of workers in different occupations has changed dramatically in recent decades. Between 2000 and 2019 the share of production workers—including assemblers, machinists, and welders—within the workforce declined from 8.2 to 6.1 percent, a decrease of 25 percent (Figure 1).[4] The share of workers in office and administrative support occupations has also declined considerably. On the flip side, business and financial, computer and mathematical, and personal care and service occupations have all increased their share of the workforce by at least 25 percent since the turn of the century.

Economists have identified three phenomena that may account for these changes: computerization, offshoring, and the declining importance of manufacturing.

First, information technologies have proliferated in the American workplace. Since 1960 investment in information-processing equipment and software has increased nearly 25-fold, from $33 billion to $806 billion, in 2019 dollars (Figure 2).[5] These investments have reduced demand for worker-performed, "routine" tasks—such as conducting simple calculations, organizing records of office activities, and operating and monitoring production processes—that can now be performed automatically by computer-controlled systems.

Other, "nonroutine" tasks, such as providing companionship as part of convalescent care, meeting with customers or suppliers, and conducting original research, are difficult if not impossible to computerize. Human labor is increasingly in demand for these nonroutine tasks relative to routine tasks.

As a result of increasing computerization, employers' demand for workers in occupations rich in nonroutine tasks (such as the business and financial, computer, and personal care occupations mentioned above) is increasing relative to the demand for occupations rich in routine tasks (such as production and clerical occupations).

Second, facilitated by lower trade costs, easier communication between countries, and productivity gains abroad, trade between countries has grown considerably (Figure 3). For the U.S., the ratio of imports to GDP more than tripled between 1960 and 2019, increasing from 4 percent to 15 percent.[6] Over the same period, exports have also increased, though not as strongly, from 5 percent of GDP to 12 percent.[7]

Globalization has had two countervailing effects on the labor market. On the one hand, increased competition from more-recently industrializing countries like China, Mexico, and South Korea has reduced the share of U.S. workers in manufacturing,[8] lessening the demand for production workers. On the other hand, both trade policy and improvements in information technology have lowered the cost of transmitting services across national boundaries. Although certain services have moved offshore, the U.S. is a global leader in high-skill, high-technology service industries and so may gain from globalization. Globalization likely reduces the demand for certain types of workers—mainly those in manufacturing, like production occupation workers—but may increase the demand for workers in other occupations.

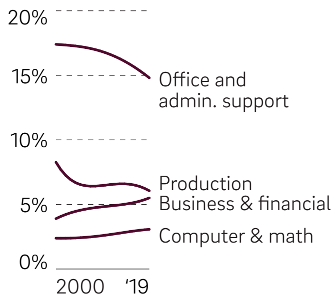
Third, as a country develops, its share of workers within the manufacturing sector declines. This occurs for two reasons. First, richer households consume more services—including education, restaurant services, and domestic services—in relation to goods. So, over time, as a country's households become richer, on average, the manufacturing sector's share of that country's economy shrinks.[9] In addition, productivity growth in the manufacturing sector has been faster than in the service sector. Because an increase in productivity enables firms to produce more with less labor, this differential in productivity growth rates has further reduced demand for labor in manufacturing relative to services.[10] Because certain types of jobs (mainly in production occupations) are concentrated in manufacturing, the decline of manufacturing relative to services also alters the occupational mix.

These three trends have transpired over the last several decades, are likely to persist for decades more, and underpin projections on the future of work.

FIGURE 1

Share of Employment Has Changed Dramatically

Employment by occupation category as share of total, 2000–2019



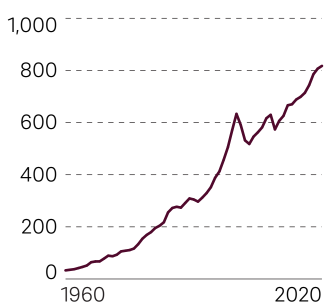
Source: U.S. Bureau of Labor Statistics; author's calculations.

Note: Data from 2019 are the most recently available.

FIGURE 2

Information Technology Proliferates

Investment in information processing equipment and software, billions of real 2019 U.S. dollars, 1960–2020

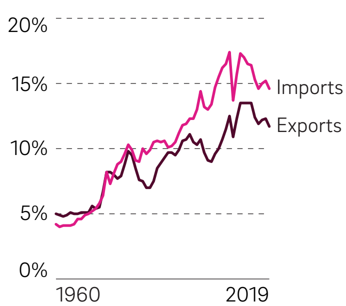


Source: FRED, Federal Reserve Bank of St. Louis.

FIGURE 3

U.S. Foreign Trade Has Grown Considerably

Exports and imports as percent of GDP, 1960–2019



Source: FRED, Federal Reserve Bank of St. Louis.

How Projections Are Made

Economists tend to take two complementary approaches for determining which occupations are likely to grow or shrink. Academic studies focus on individual explanations for occupations' differential growth rates, whereas the BLS occupational employment projections are comprehensive, encompassing multiple explanations for shifts in the relative size of occupations.

The BLS follows a multistep procedure to ensure that its employment projections are consistent with its other projections of economic activity. First, using its macroeconomic model, the BLS develops projections for three aggregate variables: population growth, GDP growth, and the aggregate labor force participation rate.[11] Then, the BLS projects future exports, imports, and consumers' final demand for each industry. To calculate future labor demand within each industry, the BLS combines its projections of the output that will be produced by each industry with estimates of how much labor is required to produce each unit of output. In the final step, the BLS uses its National Employment Matrix, which describes the share of each industry's workers who come from each occupation. This matrix gives, for example, the fraction of workers in the scheduled air transportation industry who are flight attendants (25.8 percent as of 2019); airline pilots, copilots, and flight engineers (16.1 percent); and reservation and transportation ticket agents (13.9 percent).[12] Knowing how much each industry's employment is likely to grow, and knowing each occupation's employment share within each industry, the BLS can thus compute the projected economy-wide size of each occupation.[13]

In contrast to the BLS projections, academic projections focus on individual sources of occupational change.

When academic economists Blinder (2009) and Jentsen and Kletzer (2010) estimate individual occupations' risk of being offshored, their main input is the Occupational Information Network (O*NET) database. Developed by the U.S. Department of Labor (DOL), this database provides detailed information on each occupation's skill and knowledge requirements, main work activities, required tools and technologies, and other job characteristics. The DOL bases its measurements on extensive interviews with workers in each of more than 700 occupations. Both Blinder and Jentsen and Kletzer postulate that jobs that rely on face-to-face contact (for example, in child care) or where the work is done on site (for example, short-order cooking) are less likely to be offshored. (In addition, Jentsen and Kletzer's offshorability index is high for occupations with a high concentration of routine tasks and low for jobs that involve analyzing or processing information that is easily transmittable across space.) By applying these hypotheses and using different combinations of O*NET survey questions, Blinder and Jentsen and Kletzer each constructs an index of occupations' risk of being offshored. The two indices are not identical, but they strongly correlate with each another.

Another pair of academic economists, Frey and Osborne (2017), uses information from O*NET to assess the probability that jobs within each occupation will be lost due to automation within the next decade or two. (Although their paper was published in 2017, they made their main projections at the start of that decade.) As advised by machine learning experts, they began their procedure by hand-labeling 70 occupations as either automatable or not. Then they identified the characteristics of occupations at low risk of being lost to automation: They tend to require high levels of social perceptiveness, caring for others, originality, negotiation skills, and persuasion skills. Conversely, the occupations labeled as likely to be automated involve high levels of manual and finger dexterity.[14] Then, for each of the 702 occupations in their sample, Frey and Osborne used the occupation's measured social perceptiveness, originality, and so on to provide a summary measure of its risk of automation. They found that occupations in production, office and administrative support, and transportation and material moving are at high risk for automation, while education and healthcare occupations are among those at low risk of automation.

Before assessing the accuracy of different projections, it helps to examine whether they are correlated with one another. In other words, are the occupations that the BLS projects to shrink merely the ones that Frey and Osborne have identified as susceptible to automation, or that Blinder and Jentsen and Kletzer have identified as likely to be offshored? Table 1 presents the correlations[15] between the BLS 2010-2020 projections of employment growth, Frey and Osborne's measure of the probability of loss to automation, and the average of Blinder's and Jentsen and Kletzer's measures of offshoring.[16] In addition, I include in these correlations a measure of each occupation's routineness.[17] As this table makes clear, the BLS projections are correlated with each of the three occupational measures. Furthermore, Frey and Osborne's measure is highly correlated with each occupation's routine task intensity. Overall, the different measures—while applying different methods and emphasizing different factors contributing to changes in the occupational mix—yield similar but distinct projections of which occupations are likely to grow or shrink in the future.

TABLE 1

Correlations Among Projections

	Automation	Offshorability	Routineness	BLS Projection
Automation	1			
Offshorability	0.10	1		
Routineness	0.79	0.21	1	
BLS 2010–2020 Projection	−0.31	−0.30	−0.42	1

Sources: U.S. Bureau of Labor Statistics, Frey and Osborne (2017), Blinder (2009), Jentsen and Kletzer (2010), author's calculations.

The Accuracy of Employment Projections

To gauge the accuracy of the BLS projections (as of 2010), I compared them to the actual growth rates in the share of workers in each occupation (as a share of the overall workforce) between 2010 and 2019 (Figure 4, left panel). The BLS projections did a good job indicating which occupations were likely to grow or shrink over the following decade. They accurately predicted growth in many medical occupations (for example, occupational/physical therapy aides) and a decline in production-related occupations (for example, production workers in textile, apparel, and furnishings). But there are also some substantial misses. The BLS projections underpredicted the decline in statistical assistants and communications-equipment operators, and the growth of animal care and service providers and mathematical science workers. Overall, the BLS projections captured 25.6 percent—using an R^2 measure—of the variation in occupations' actual growth rates.[18,19] I also compared the BLS projections to actual growth rates for the 2000s (Figure 4, right panel). Here, BLS projections performed almost as well, capturing 16.3 percent of the variation in the employment growth rates in each occupation.

Next, I assessed the accuracy of projections from academic studies. Occupations that Frey and Osborne have identified as susceptible to automation grew significantly more slowly than average between 2010 and 2019 (Figure 5, left panel). This one variable captured 18.5 percent of the variation in occupations' employment growth rates, smaller than the R^2 using BLS projections from the same period. The offshorability index captured only 6.5 percent of the variation in their 2010-2019 growth rates (Figure 5, right panel).

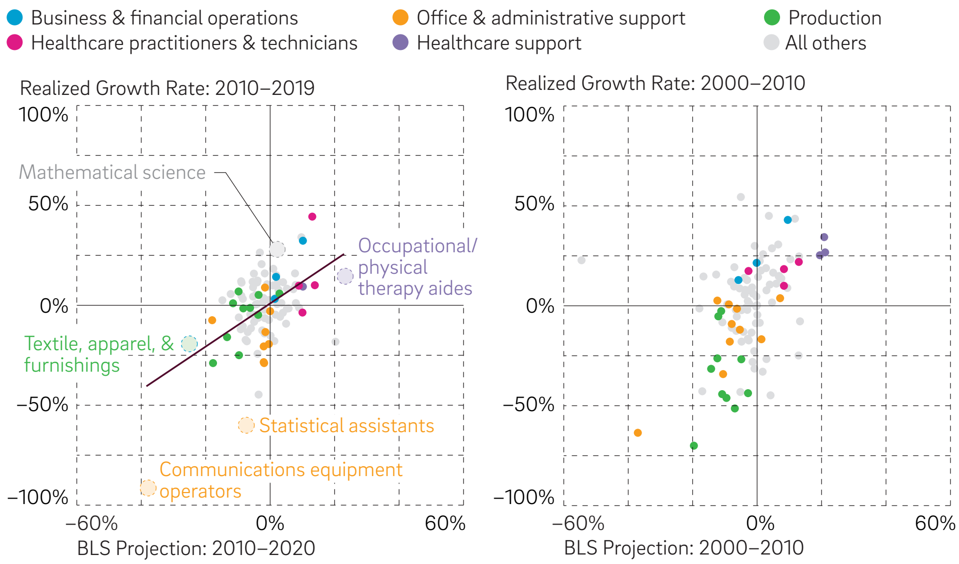
The BLS projections and the measures of occupations' susceptibility to automation both predict future employment growth rates, though neither is perfectly accurate. Can anything be gained by using information from both projections jointly?

To find out, I plotted the relationship between the probability of automation measure and the BLS-projected employment growth rates, along with the best fit regression line (Figure 6, left panel).[20]

FIGURE 4

BLS Accurately Predicted Changes in Many Occupations

BLS projections and realized growth rates, 2000–2010 and 2010–2019



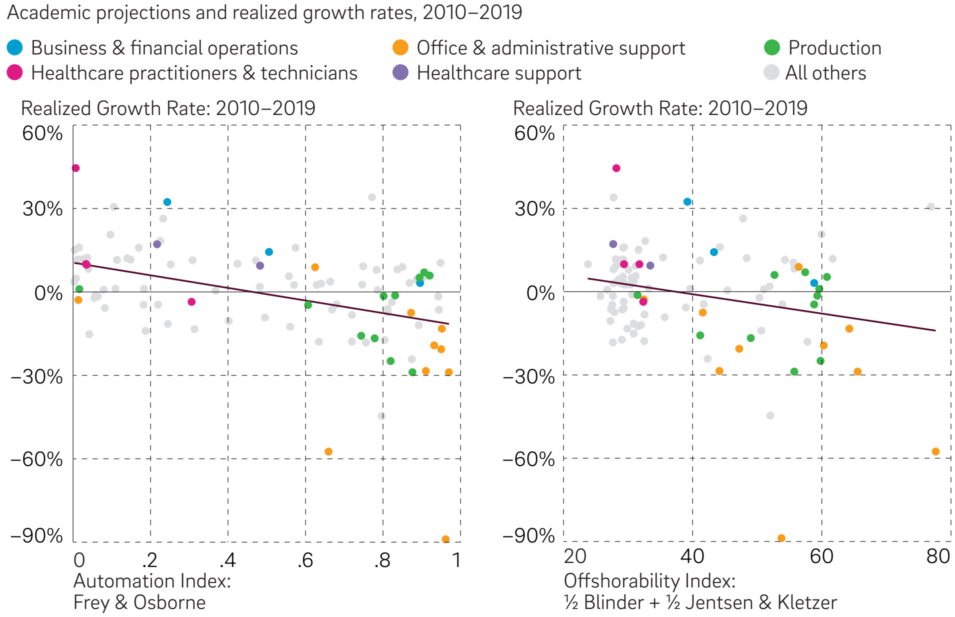
Source: U.S. Bureau of Labor Statistics; author's calculations.

Note: Each panel presents BLS projections of the succeeding decade's growth rate for each occupation (measured as a share of the workforce) on the horizontal axis, and the realized growth rate on the vertical axis. The left panel applies the realized growth rate to 2019, as this is the most recent year for which we have data available.

FIGURE 5

Academic Projections Predict Some Occupational Change

Academic projections and realized growth rates, 2010–2019



Source: Author's calculations based on Frey and Osborne (2017), Blinder (2009), and Jentsen and Kletzer (2010); U.S. Bureau of Labor Statistics.

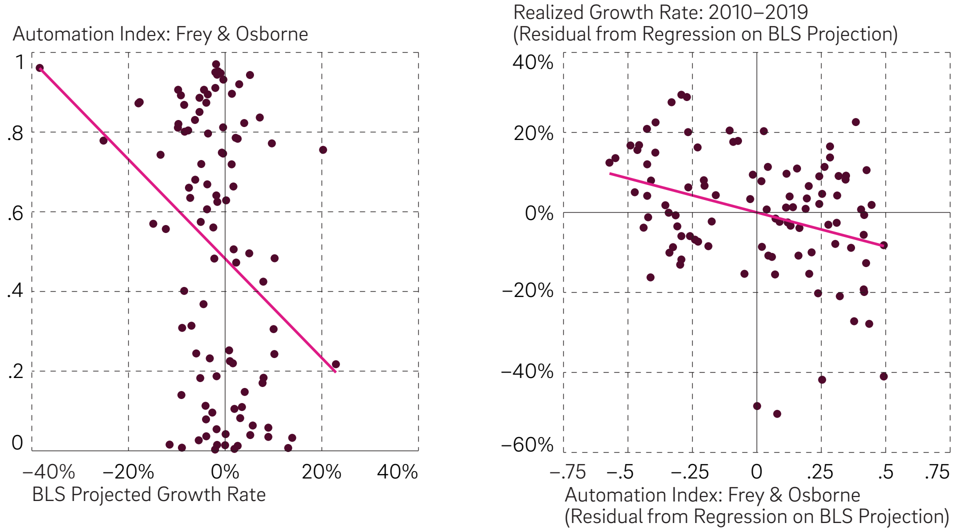
Note: Each panel presents projections of the succeeding decade's growth rate for each occupation (measured as a share of the workforce) on the horizontal axis, and the realized growth rate on the vertical axis. Both panels apply the realized growth rate to 2019, as this is the most recent year for which we have data available. The left panel applies the Frey and Osborne probability of automation measure; the right panel blends offshorability measures from Blinder and Jentsen and Kletzer.

The differences between the Frey and Osborne measure and the regression line ("the residuals") represent variation within the Frey and Osborne measure left unexplained by the BLS projections. I used these residuals to measure the explanatory power of the Frey and Osborne measure on top of the BLS projections (Figure 6, right panel). That is, I compared the Frey and Osborne measure with the component of realized employment growth rates that the BLS projections couldn't predict. The strength of the relationship captures the extent to which the measure of the probability of automation provides extra explanatory power (on top of the BLS projection) in employment growth rates. The main result of this exercise is that, starting with information from the BLS projections, an extra 8.3 percent of the variation in occupations' growth rates can be explained using the Frey and Osborne measure. This means that the BLS and academic measures, together, combined account for more than a third of the variation in occupations' growth rates.

FIGURE 6

An Extra 8.3 Percent of the Variation in Occupations' Growth Rates Can Be Explained Using the Frey and Osborne Measure

Frey and Osborne automation index, BLS projected growth rate, realized growth rate, 2010–2019



Source: U.S. Bureau of Labor Statistics; author's calculations based on Frey and Osborne (2017).

Note: The left panel presents the relationship between BLS projections of 2010–2020 occupations' growth rates and the Frey and Osborne probability of automation measure. For the right panel, the vertical axis presents the residual of the realized growth rate (taking the difference between circles and the best-fit line from the left panel of Figure 4); the horizontal axis presents the residual from the left panel of this figure. The relationship between the two residuals thus gives the extra variation in the realized growth rate explained by the Frey and Osborne automation index.

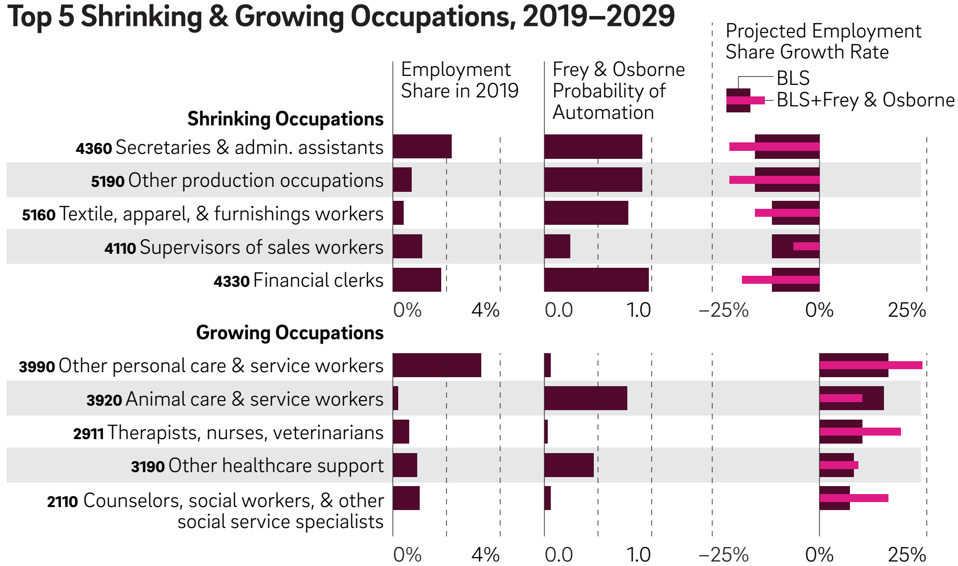
What the Future Holds

Figure 7 lists the occupations that the BLS has projected to grow or shrink most quickly between 2019—the year with the most recent projections—and 2029. (I exclude every occupation that comprises less than 0.2 percent of total employment as of 2019.) The BLS projects that the decline of production and office clerical occupations will continue in the 2020s. As a share of the workforce, secretaries and administrative assistants; other production occupations; textile, apparel, and furnishings workers; supervisors of sales workers; and financial clerks are each projected to shrink by at least 10 percent, while other personal care and service occupations; animal care and service workers; and therapists, nurses, and veterinarians will each grow by 10 percent.

Also I incorporate information from Frey and Osborne's measure of the probability of automation, which I have shown in the previous section to be useful in constructing projections of employment growth. (I assume that the relationships—among realized occupational growth, BLS projections, and the Frey and Osborne measure—that I had estimated using

FIGURE 7

Top 5 Shrinking & Growing Occupations, 2019–2029



Sources: U.S. Bureau of Labor Statistics, Frey and Osborne (2017), author's calculations.

Notes: Occupations are sorted according to their BLS projected growth rates. The bold numbers before each occupation title refer to SOC occupation codes. The first column gives each occupation's employment share, according to the BLS. The second column presents the Frey and Osborne probability of automation. The third column compares the BLS projected growth rate to 2029 with information from the Frey and Osborne probability of automation measure—specifically, the value equals 10/9 × (0.087 + 0.880 × BLS Projection − 0.160 × Automation Probability). The values 0.087, 0.880, and −0.160 come from a regression of actual 2010–2019 occupation growth rates on the 2010–2020 BLS projection and the Frey and Osborne automation probability. The 10/9 scaling factor is necessary, as the regression coefficients were generated from a regression of nine years of employment growth, while I am projecting 10 years of employment growth, from 2019 to 2029.

data from the 2010s will apply as well over the next 10 years.) Incorporating information from the Frey and Osborne measure modestly alters projections of employment growth to 2029. According to BLS projections and projections that incorporate Frey and Osborne's measure, office clerical and production occupations are likely to shrink, while health and service-related occupations are likely to grow. However, there are interesting differences: The BLS projects financial clerks and supervisors of sales operations to shrink at a similar rate, while Frey and Osborne conclude that the former occupation is substantially more likely to be lost to automation. Projections incorporating Frey and Osborne's measure suggest that financial clerks will shrink 12 percent faster than supervisors of sales operations.

Caveats abound. Even under normal circumstances, projections of the future are inherently difficult: Each of the trends highlighted in this paper—computerization, globalization, and the shift toward services—could accelerate or decelerate in the coming decades, and each trend may shape labor demand in the future somewhat differently than in the past. Moreover, the projections that form the basis for Figure 7 preceded the COVID-19 pandemic. The pandemic and its aftermath will shape the labor market profoundly in some predictable ways—in the future, more people may be working from home, and fewer people may be working in occupations that involve high levels of human-to-human physical contact—and in some ways that are currently beyond our collective imagination.

Conclusion

Work changes over time for many reasons, including improvements in technology, increasing globalization, and the declining importance of manufacturing relative to services. Existing projections focus on different combinations of these reasons. Projections by the BLS perform well in predicting the shares of workers in each occupation a decade into the future. However, information from academic articles could improve the accuracy of these projections.

Notes

1 See New York Times (1929).

2 See Tam (2012).

3 I thank Roc Armenter, Mike Dotsey, Makoto Nakajima, and Dave Terkanian for helpful comments during the early stages of this project, and Ryan Kobler for excellent research assistance. The replication materials for this note can be found at https://enghinatalay.github.io.

4 These figures come from the BLS Occupational Employment Statistics program; see https://www.bls.gov/oes/tables.htm. Data from 2019 are the most recently available.

5 See FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/A679RC1Q027SBEA and https://fred.stlouisfed.org/series/DPCERD3Q086SBEA, accessed September 1, 2020).

6 See FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/B021RE1A156NBEA, accessed September 1, 2020).

7 See FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/B020RE1A156NBEA, accessed September 1, 2020).

8 See Autor, Dorn, and Hanson (2013).

9 See Aguiar and Bils (2015).

10 Whether employment grows more quickly in industries with relatively fast or relatively slow productivity growth depends on the substitutability between different industries' products. The empirically relevant case is one in which manufactured products and services complement each other. In this case, industries with faster productivity growth employ a decreasing share of the labor force. See Ngai and Pissarides (2007).

11 BLS employment projections assume "full employment"—in other words, that the 10-year-ahead unemployment rate will be at the rate consistent with nonaccelerating inflation. See Dubina (2017).

12 See https://data.bls.gov/projections/nationalMatrix?queryParams=481100&ioType=i . Accessed September 1, 2020.

13 To see how the National Employment Matrix and projections of industries' labor demand interact, consider a hypothetical economy with two occupations ("production" and "nonproduction") and two industries ("manufacturing" and "services"). Suppose that, initially, manufacturing and services each employs half of the workers in the economy, and that our hypothetical National Employment Matrix indicates that manufacturing employs production and nonproduction workers in equal share, while services employs only nonproduction workers. If we project that manufacturing will shrink from 50 percent to 20 percent of labor demand over the next decade, and that the mix of workers within each sector will remain constant, then we would project that the share of workers in production occupations will shrink from 25 percent (0.5 × 0.5) to 10 percent (0.5 × 0.2). Within this example, each occupation's employment share within each industry is assumed to be fixed. In practice, the BLS allows for the importance of different occupations within each industry to change over time.

14 "Finger dexterity" and "manual dexterity" may—in certain circumstances—protect workers from automation. In Table 1 of their paper, Frey and Osborne refer to these skills as "automation bottlenecks." However, among all 702 occupations in their analysis, these two skills are positively correlated with their automation index.

15 The (Pearson) correlation coefficient summarizes the strength of the linear relationship between any two variables, and can take any value between –1 and 1. With a value of 1 (or –1) a scatterplot between the two variables would take the form of a positively (or negatively) sloped line. Values strictly between 0 and 1, as in most of Table 1, indicate that the measures are positively related with one another, but that the relationship is far from perfect.

16 Although the different projections are constructed for each individual 6-digit Standard Occupational Classification (SOC), I aggregate to the 4-digit level. Under the finer 6-digit level of aggregation, the correlations across different occupational measures are weaker. So, too, is the ability of any occupation measure to predict future employment growth.

17 See page 1163 of Acemoglu and Autor (2011) for the O*NET elements that correspond to nonroutine analytic, nonroutine cognitive, nonroutine manual, routine cognitive, and routine manual tasks. For each occupation, the Acemoglu and Autor routineness index subtracts the sum of the three nonroutine task measures from the sum of the two routine task measures.

18 R^2 measures the fraction of the variability in a variable—in this case, realized growth rates in occupations' employment shares—that is predictable using information from another variable or set of variables—in this case, projections of employment growth rates.

19 For each of the regressions discussed in this section, I present the coefficient estimates in the appendix to this article.

20 This line represents what the data plot would look like if the measure of the probability of automation and the BLS-projected employment growth rates were perfectly identical. The more dispersed the data points are around this line, the less the two measures agree as to what will happen in the future.

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Appendix: Regression Results

In this short appendix, I present the results of the regressions underlying the discussion in the section titled "The Accuracy of Employment Projections."

	(1)	(2)	(3)	(4)	(5)
BLS 2010–2020 Projection	1.079 (0.186)				0.880 (0.185)
BLS 2000–2010 Projection		0.937 (0.216)			
Frey and Osborne Prob. of Automation			−0.227 (0.048)		−0.160 (0.046)
Offshorability Index				−0.003 (0.001)	
Constant	0.009 (0.016)	0.014 (0.023)	0.105 (0.029)	0.130 (0.056)	0.087 (0.027)
R^2	**0.256**	**0.163**	**0.185**	**0.065**	**0.339**
Number of Occupations	100	99	100	100	100
Period	2010–2019	2000–2010	2010–2019	2010–2019	2010–2019

Notes: Each observation corresponds to a 4-digit SOC code occupation. Except for column (2), the dependent variable is the occupation's growth—as a share of the workforce—between 2010 and 2019. In column (2), the dependent variable is the occupation's growth between 2000 and 2010. Standard errors are in parentheses.