

How Accurate Are Long-Run Employment Projections?ⁱ

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Opening Precis: Projections of economic activity are notoriously difficult to make yet critically important for policymaking. How reliable are projections of the future of the labor market?

Introduction

Projecting what is likely to come in the future is an immensely challenging endeavor. In October 1929, eight days before the 1929 stock market crash, economist Irving Fisher was quoted as saying that “stock prices have reached what looks like a permanently high plateau.”ⁱⁱ In a 2012 statement, Google co-founder Sergey Brin predicted that autonomous cars would be widely available within five years.ⁱⁱⁱ Closer to the focus of this article, while Bureau of Labor Statistics (BLS) 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 over the 2010s.

None of us are Nostradamus. Yet, projections of future conditions are critically important for planning and decision-making. 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 (designing appropriate curricula), and state and local governments’ planning for fiscal and regulatory policy.

This article discusses long-run projections – looking 10 or more years ahead – of employment in different occupations. In it, I address the following three questions: First, why is it that some occupations tend to grow faster than others? Understanding the forces which, in the past, have led workers to move out of certain occupations and into others will set the foundation for our second question: How have economists, both those in governmental agencies and those in universities, developed projections for occupations’ employment growth? Third, and, finally, how well do existing projections line up with the future? Are projections accurate, and is there room for improvement?

To preview the answers to these three questions: Computerization, globalization, and changes in consumption patterns are primary factors shaping the evolving occupational mix. Economists model the effect of these factors in developing their long-run projections. Academic projections have focused on individual factors, while the BLS has followed a more ground-up, comprehensive approach. And, finally, although BLS projections perform well, there may be room for improvement via incorporating certain projections from academic articles.

Why Do Some Occupations Grow Faster than Others?

Over long horizons, the share of workers in different occupations has changed dramatically. Between 2000 and 2019, the number of production workers – including assemblers, machinists, and welders – declined by more than 3 million, from 12.4 to 9.2 million.^{iv} The share of workers in construction and administrative support occupations have also declined considerably. On the flip side, business and financial occupations, computer occupations, and personal care occupations have each increased their share of the workforce by at least 40 percent since the turn of the century.

What accounts for changes like these? Economists have posited at least three distinct phenomena: computerization, offshoring, and changes in consumption patterns.

First, regarding computerization, the last six decades have seen the introduction and proliferation of information technologies in the American workplace. One piece of evidence for this spectacular growth, since 1960 investment in information processing equipment and software increased more than 25-fold, from \$31 billion to \$828 billion (stated in real terms, in 2019 dollars).^v These investments have largely led to a reduction in the demand for certain groups of worker-performed tasks, “routine” tasks, that can now be performed automatically by computer-controlled systems. These tasks include conducting simple calculations; organizing records of office activities; and operating and monitoring production processes. Other tasks, “non-routine” tasks, are more difficult, if not impossible, to computerize. Examples, here, include providing companionship as part of convalescent care, meeting with customers or suppliers, and conducting original research. Humans are increasingly in demand for these types of tasks. As a result of increasing computerization, employers’ demand for occupations rich in non-routine tasks (such as the business and financial occupations, computer occupations, and personal care occupations mentioned above) are 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 across countries, and productivity gains abroad, trade between countries has grown considerably. For the U.S., the ratio of imports to GDP has more than tripled between 1960 and 2019, increasing from 4 percent to 15 percent.^{vi} Over the same period, exports have also increased, though not as strongly, from 5 percent of GDP to 12 percent.^{vii} Globalization has had two countervailing effects on the labor market. On the one hand, the U.S. has a comparative disadvantage in many manufacturing industries: Increased competition from countries like China, Mexico, and South Korea has reduced the share of workers in manufacturing (Autor, Dorn, Hanson, 2016), reducing 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, in high-skill, high-technology service industries the U.S. is a global leader and so may gain from globalization. In sum, globalization likely reduces the demand for certain types of workers – mainly those in manufacturing, like production work – but may increase the demand for workers in other occupations.

A third factor contributing to changes in the share of workers across occupations: As countries develop, manufacturing comprises a shrinking share of the economy. This occurs for at least two reasons. First, richer households' consumption skews more heavily towards services and away from goods (Aguiar and Bils, 2015). So, as time passes and households on average become richer, the demand for manufactured products relative to services decreases. Second, productivity growth in the manufacturing sector has been faster than in the service sector. Because relatively fast productivity growth allows firms to produce more with less labor, this differential in productivity growth rates has led to a reduction in the demand for labor in manufacturing relative to services (Ngai and Pissarides, 2007).^{viii} Whatever the reason for the smaller relative size of manufacturing, since certain types of jobs (mainly production work) are concentrated in manufacturing, these trends also alter the occupational mix.

The three trends highlighted above have transpired over the last several decades, are likely to persist for decades more, and underpin projections on the future of work. I turn to these projections in the following section.

How Are Projections Made?

In determining which occupations are likely to grow or shrink in the future, economists have taken two complementary tracks. Academic studies focus on individual explanations for occupations' differential growth rates, while the BLS occupational employment projections are developed to be comprehensive, encompassing multiple potential sources of shifts in the occupations' relative sizes.

The BLS employment projections are developed following a multi-step procedure, designed to be consistent with the agency's other projections of economic activity. First, the BLS, using its macroeconomic model, develops projections for aggregate variables: population growth, GDP growth, and the aggregate labor force participation rate.^{ix} Second, reflecting the trends discussed in the previous section, the BLS projects future exports, imports, and consumers' final demand for each industry. Projections of the output that will be produced by each industry, in combination with estimates of how much labor is required to produce each unit of output, yields projections of future labor demand in each industry. A third component of this procedure is the National Employment Matrix, also produced by the

BLS, which describes the share of each industry's workers who come from each occupation. This matrix gives, for example, the number of workers in the scheduled air transportation industry who are flight attendants (114 thousand as of 2018), pilots (73 thousand), or reservation ticket agents (67 thousand).^x Knowing how much each industry's employment is likely to grow in the future, and how many workers of each occupation will work in each industry, the BLS can thus compute the projected size of each occupation.^{xi}

In contrast to the BLS, academic projections focus on individual sources of occupational change. First, Blinder (2009) and Jentsen and Kletzer (2010) estimate individual occupations' risk of being offshored. A main input into their projections is the Occupational Information Network (O*NET) database. Developed by the Department of Labor, this database provides detailed information on occupations' skill and knowledge requirements, main work activities, required tools and technologies, and other job characteristics. These measurements are based off of extensive interviews with workers in each of 700+ occupations. Both Blinder (2009) and Jentsen and Kletzer (2010) postulate that jobs that rely on face-to-face contact (e.g., child care workers) or where the work is done on site (e.g., short order cooks) 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.) Applying these hypotheses, using different combinations of O*NET survey questions, Blinder and Jentsen and Kletzer each constructs an index of occupations' risk of being offshored. While differences exist, the two indices are strongly correlated with one another.

Second, in order to assess the probability that jobs within each occupation will be lost due to automation within the next decade or two, Frey and Osborne (2017) also use information from O*NET. (While this paper was published in 2017, the main projections were made at the start of the decade.) Their procedure begins, with the advice of machine learning experts, in hand-labeling 70 occupations as either being automatable or not. Then, for these 70 occupations, the authors identify the characteristics of occupations which have 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 dexterity and finger dexterity.^{xii} For the remaining 632 occupations in their sample, Frey and Osborne use the occupations' measured social perceptiveness, originality, etc... to estimate the probability that it would have been labeled as having a high-risk of automation. Occupations at high risk of automation include production

workers, office and administrative support, and transportation and material moving, while education and healthcare occupations are among those at low risk of automation.

Before assessing how accurate different projections are, it will be helpful to examine whether they are correlated with one another: In other words, are the occupations that the BLS projects to shrink merely the ones which Frey and Osborne have identified as susceptible to automation, or Blinder, Jentsen, and Kletzer have identified as likely to be offshored? Table 1 presents the correlations between BLS 2010-2020 projections of employment growth, Frey and Osborne's measure of probability of loss to automation, and the average of Blinder's and Jentsen and Kletzer's measures of offshoring.^{xiii} In addition, I include in these correlations a measure of occupations' routineness, due to Acemoglu and Autor (2011).^{xiv} As this table makes clear, BLS' projections are correlated with each of the three occupational measures. Furthermore, Frey and Osborne (2017) measure is highly negatively correlated with occupations' routine task intensity. Yet a lot of independent variation exists across different measures.

How Accurate Are Employment Projections?

In this section, I evaluate the projections due to the BLS, those that emphasize job loss due to automation, and those that emphasize job loss due to offshoring. To begin, consider the left panel of Figure 1. Here, on the horizontal axis, I plot BLS projections (as of 2010) of the growth rate in the share of workers in each occupation, looking over the subsequent decade. The vertical axis presents occupations' actual growth rates (in the share of the overall workforce) between 2010 and 2019. The BLS projections mostly perform well in indicating which occupations are likely to grow and shrink over the following decade: They accurately predict growth in many medical occupations (e.g., occupational/physical therapy aides) and decline in production-related occupations (e.g., production workers in textile, apparel, and furnishings). There are some substantial misses as well: The BLS projections under-predict 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 capture 25.6 percent — using an R^2 measure — of the variation in occupations' growth rates.^{xv} The right panel displays a similar comparison for the 2000s. Here, BLS projections perform almost as well, capturing 16.3 percent of the variation in predicting the growth rate in the share of workers in each occupation.

Figure 2 assesses the accuracy of projections from academic studies. In the left panel, I present the projections based on occupations' risk of automation. Occupations which Frey and Osborne have identified as being susceptible to automation grew significantly slower than average between 2010 and 2019. This one variable captures 18.5 percent of the variation in occupations' employment growth rates,

smaller than the R^2 using BLS projections from the same period. The right panel of Figure 2 presents the relationship between occupations' offshorability and realized growth rates. Here, the offshorability index captures only 6.5 percent of the variation in their 2010-2019 growth rates.

Summarizing Figures 1 and 2, both the BLS projections and measures of occupations' susceptibility to automation predict future employment growth rates, though neither set of measures is perfectly accurate. Can anything be gained by using information from both projections jointly?

The two panels of Figure 3 address this question. In the left panel, I plot the relationship between the index of automatability versus the BLS-projected employment growth rates, along with the best fit regression line. The differences between the BLS-projected employment growth rates and the regression line ("the residuals") represent variation that is unexplained by the automatability index. In the right panel, I use the residuals that were constructed in the left panel to measure the explanatory power of the Frey automatability index that comes *on top* of the BLS projections. In the vertical axis in this figure, I plot the residuals from the right panel of Figure 1: this is the component of realized employment growth rates that the BLS projections couldn't predict. The strength of the relationship depicted in this panel captures the extent to which the automatability measure provides extra explanatory power (on top of 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.

What Does the Future Hold?

In this section, I briefly consider how the occupational mix might change over the next decade. Table 2 presents the occupations that the BLS has projected to grow or shrink most quickly between 2018 — the year with the most recent projections — and 2028. (In this table, we focus only on the occupations comprising at least 0.1 percent of total employment as of 2018.) The BLS projects that the decline of production and office clerical occupations will continue into the 2020s. As a share of the workforce, assemblers and fabricators; textile, apparel, and furnishings workers; secretaries and administrative assistants; office and administrative support; and other production occupations will each shrink by at least 10 percent, while other personal care and service occupations and other healthcare-support occupations will each grow by 10 percent. (See the penultimate column of Table 2.)

In the final column of this table, I incorporate information from Frey and Osborne's probability of automation measure, which I have documented in the previous section to be a useful measure in constructing projections of employment growth. Overall, incorporating information from the Frey and

Osborne measure modestly alters projections of employment growth to 2028. According to both BLS projections and projections which blend in information from Frey and Osborne's measure, office clerical and production occupations are likely to shrink, while health and service-related occupations are likely to grow. One notable exception, since Frey and Osborne (2017) assess Food and Beverage occupations as likely to be lost to automation, projections including their measure indicate that these occupations are not likely to grow over the next decade (contrary to what the BLS project.)

Caveats abound! As noted in the introduction, projections of the future are inherently difficult. Moreover, the projections that form the basis for Table 2 were formulated before the COVID-19 pandemic. Undoubtedly, 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

This article discusses projections on the future of work. Work changes over time for a number of reasons, including improvements in technology, increasing globalization, and shifting consumption patterns. 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.

References

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Tables and Figures

	Automation	Offshorability	Routineness	BLS Projection
Automation	1			
Offshorability	0.10	1		
Routineness	0.74	0.34	1	
BLS 2010-20 Projection	-0.31	-0.30	-0.45	1

Table 1—Correlations Among Projections

			Projected Employment Share Growth Rate	
	Employment Share in 2018	Frey & Osborne Automation	BLS	BLS + Frey & Osborne
Panel A: Shrinking Occupations				
5120: Assemblers and Fabricators	0.8%	0.61	-0.16	-0.17
5160: Textile, Apparel, and Furnishings Workers	0.2%	0.78	-0.13	-0.17
4360: Secretaries and Admin. Assistants	1.1%	0.91	-0.13	-0.19
4390: Other Office and Admin. Support	1.2%	0.95	-0.10	-0.17
5190: Other Production Occupations	0.6%	0.91	-0.10	-0.16
Panel B: Growing Occupations				
3990: Other Personal Care and Service Workers	1.4%	0.06	0.14	0.22
3190: Other Healthcare Support Occupations	0.7%	0.48	0.10	0.11
2911: Therapists, Nurses, Veterinarians	0.7%	0.03	0.09	0.18
3530: Food and Beverage Serving Workers	2.8%	0.91	0.07	0.00
2110:Counselors, Social Workers, and Other Social Service Specialists	1.0%	0.06	0.07	0.15

Table 2—Top 5 Shrinking and Growing Occupations, 2018-2028

Notes: Occupations are sorted according to their BLS projected growth rates. The first column gives each occupation's employment share, according to the Bureau of Labor Statistics. The second column presents the Frey and Osborne (2017) probability of automation. The third column presents the BLS projected growth rate, to 2028. The final column presents projected growth rates, now blending in information from the Frey and Osborne (2017) probability of automation measure. Specifically, the value given in this column equals $10/9 \cdot (0.087 + 0.880 \cdot \text{BLS Projection} - 0.160 \cdot \text{Automation Probability})$. 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 (2017) automation probability. The 10/9 scaling factor is necessary, as the regression coefficients were generated from a regression of 9 years of employment growth, while we are projecting 10 years of employment growth from 2018 to 2028.

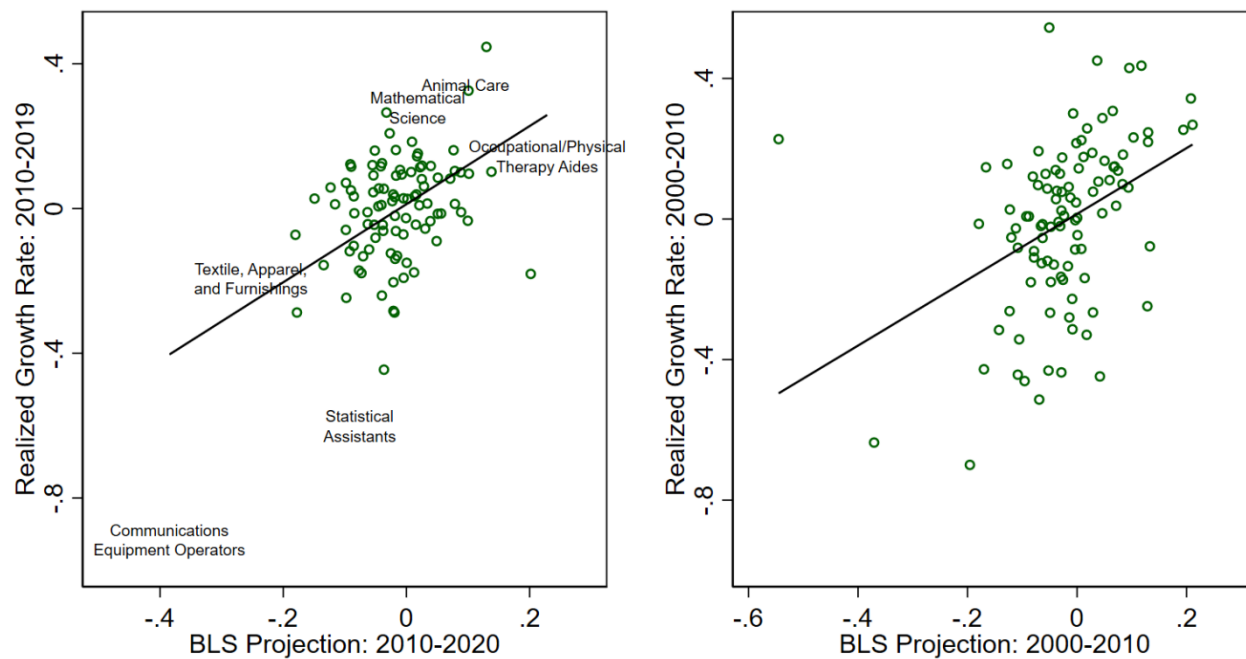


Figure 1—BLS Projections and Realized Growth Rates

Notes: 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.

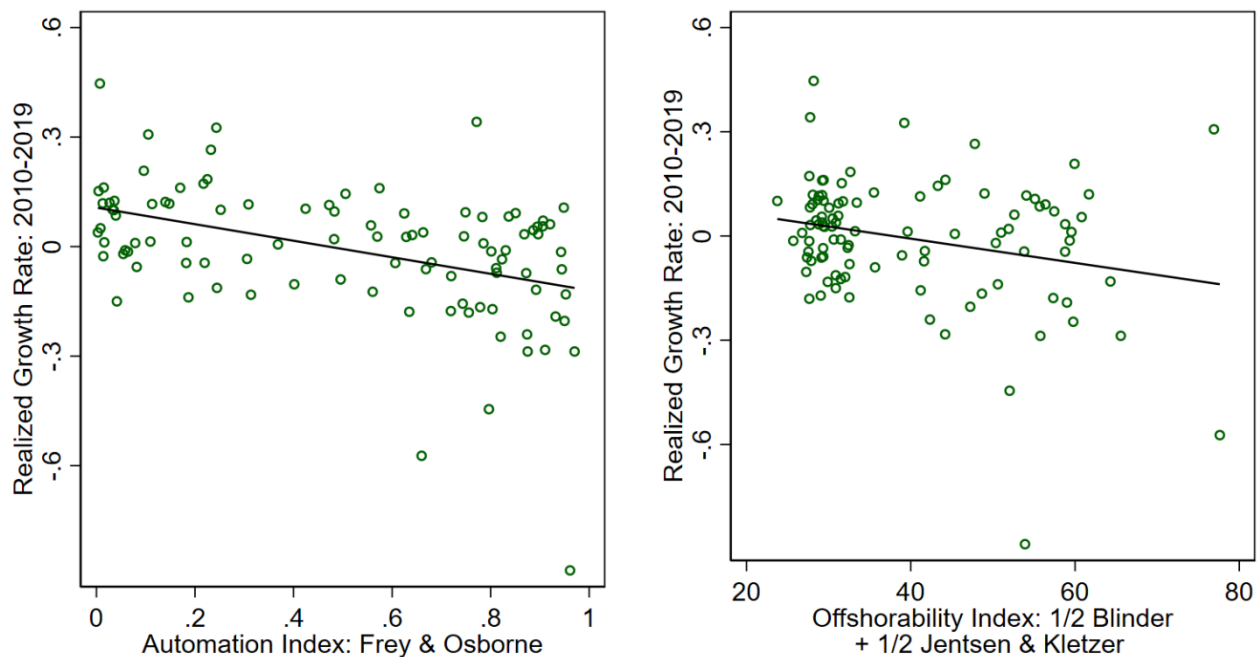


Figure 2—Academic Projections and Realized Growth Rates

Notes: 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 (2017) probability of automation measure; the right panel blends offshorability measures from Blinder (2009) and Jentsen and Kletzer (2010).

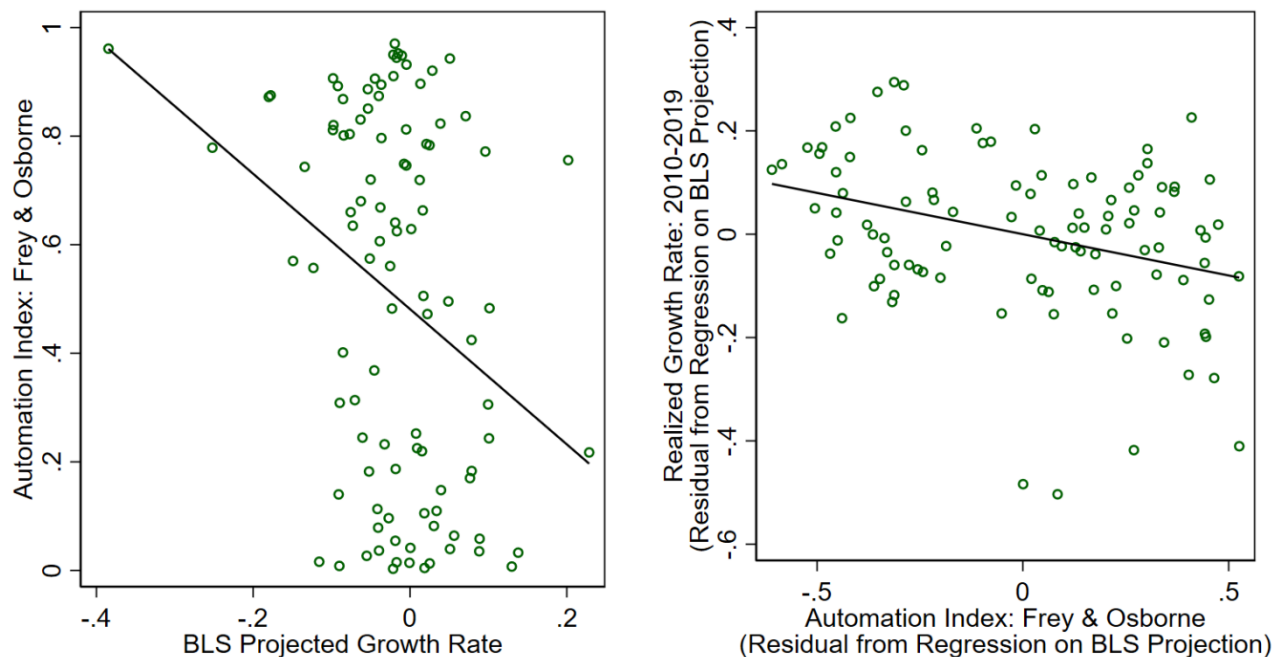


Figure 3—Blending BLS and Frey and Osborne (2017) Projections

Notes: The left panel presents the relationship between BLS projections of 2010-2020 occupations' growth rates and the Frey and Osborne (2017) 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 1); 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.

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ⁱⁱ "Fisher Sees Stocks Permanently High," *New York Times*, October 16, 1929, Page 8.

ⁱⁱⁱ See <https://www.cnet.com/news/googles-sergey-brin-youll-ride-in-robot-cars-within-5-years/>.

^{iv} These figures come from the BLS Occupational Employment Statistics program. Data from 2019 are the most recently available.

^v See <https://fred.stlouisfed.org/series/A679RC1Q027SBEA> and <https://fred.stlouisfed.org/series/DPCERD3Q086SBEA>.

^{vi} See <https://fred.stlouisfed.org/series/B021RE1A156NBEA>.

^{vii} See <https://fred.stlouisfed.org/series/A019RE1Q156NBEA>.

^{viii} Whether employment grows more quickly in industries with relatively fast or relatively slow productivity growth industries depends on the substitutability between different industries' products. The empirically relevant case is one in which manufactured products and services are complements with one another. In this case, industries with faster productivity growth employ a decreasing share of the labor force.

^{ix} BLS employment projections assume “full employment,” in other words that the 10-year ahead unemployment rate will be at the rate consistent with non-accelerating inflation. See:

^x See <https://data.bls.gov/projections/nationalMatrix?queryParams=481100&ioType=i>.

^{xi} To see how the National Employment Matrix and projections of industries’ labor demand interact, consider, as an example, a hypothetical economy with two occupations (call them “production” and “nonproduction”) and two industries (“manufacturing” and “services”). Suppose that, initially, manufacturing and services each employ 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 only employs nonproduction workers. If one were to project that manufacturing will shrink to from 50 percent to 20 percent of labor demand over the next decade, and that the mix of workers within each sector will remain unchanged over that time period, then we would project that the share of workers in production occupations will shrink from 25 percent ($0.5 \cdot 0.5$) to 10 percent ($0.5 \cdot 0.2$).

^{xii} Judging from Table 1 of Frey and Osborne (2017), it seems as if “finger dexterity” and “manual dexterity” may – in certain circumstances – be skills which protect workers from automation. In that table, Frey and Osborne refer to these skills as “automation bottlenecks”. It turns out, however, that among all 702 occupations these two skills are positively correlated with the Frey and Osborne (2017) automation index.

^{xiii} While the different projections are constructed for each individual 6-digit Standard Occupation Classification (SOC) occupation, I aggregate to the 4-digit level. Under the finer 6-digit level of aggregation, the correlation across different occupational measures are weaker. So, too, is the ability of any occupation measure to predict future employment growth.

^{xiv} See page 1163 of Acemoglu and Autor (2011) for the O*NET elements that correspond to non-routine analytic, non-routine cognitive, non-routine manual, routine cognitive, and routine manual tasks. For each occupation, the routineness measure takes subtracts the sum of the three non-routine task measures from the sum of the two routine task measures.

^{xv} R^2 measures the fraction of the variability in a given variable – for us, realized growth rates in occupations’ employment shares – that is predictable using information from another variable or set of variables – for us, projections of employment growth rates.