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Abstract:

This dissertation discusses the role of intangible and technological investments in the dynamics of productivity growth, the valuation of firms, and the employment of human capital. The first essay describes the Productivity J-Curve. General purpose technologies (GPTs) such as AI enable and require significant complementary investments, including business process redesign, co-invention of new products and business models, and investments in human capital. These complementary investments are often intangible and poorly measured in the national accounts, even if they create valuable assets for the firm. We develop a model that shows how this leads to an underestimation of output and productivity in the early years of a new GPT, and how later, when the benefits of intangible investments are harvested, productivity will be overestimated. Our model generates a Productivity J-Curve that can explain the productivity slowdowns often accompanying the advent of GPTs, as well as the follow-on increase in productivity later. We use our model to assess how AIrelated intangible capital is currently affecting measured total factor productivity (TFP) and output. We also conduct a historical analysis of the roles of intangibles tied to R&D, software, and computer hardware, finding substantial and ongoing effects of software in particular and hardware to a lesser extent. The second essay investigates the role of engineering talent in predicting the market value of publicly traded firms, then looks in greater detail at AI Talent. Engineers, as implementers of technology, are highly complementary to the intangible knowledge assets that firms accumulate. This paper seeks to address whether technical talent is a source of rents for corporate employers, both in general and in the specific case of the surprising open-source launch of TensorFlow, a deep learning software package, by Google. First, I present a simple model of how employers can use job design as a tool to exercise monopsony power by partially allocating employee time to firm-specific tasks. Then, using over 180 million position records and over 52 million skill records from LinkedIn, I build a panel of firm-level investment in technological human capital (information technology, research, and engineering talent quantities) to measure the market value of technological talent. I find that on average, an additional engineer at a firm is correlated with approximately $855,000 more market value. Consistent with that finding, AI-intensive companies rapidly gained market value following the launch of TensorFlow. Using a difference-in-differences approach, I show that the launch of TensorFlow is associated with an approximate increase of 4-7% in firm market value for firms employing workers with AI skills compared to firms without AI talent exposure. The third essay is about which tasks done by workers in the U.S. economy are Suitable for Machine Learning (SML). Advances in machine learning (ML) are poised to transform numerous occupations and industries. This raises the question of which tasks will be most affected by ML. We present a model of labor demand in the presence of new technology and labor constraints following Autor, Levy, and Murnane (2003). We then apply the rubric evaluating task potential for ML in Brynjolfsson and Mitchell

(2017) and extended in Brynjolfsson, Mitchell, and Rock (2018) to build measures of “Suitability for Machine Learning” (SML) and apply it to 18,112 tasks in O*NET. We find that ML has the potential to affect many occupations in the economy, though few (if any) jobs can be completely automated by ML. We discuss the distribution of sensitivity to ML technologies across regions and industries, finding that the effects of ML will follow different patterns than earlier waves of automation. The fourth essay discusses shifts in the employment of routine labor. A large literature has documented occupational shifts in the US away from routine intensive tasks. Theories of skill-biased technological change differ in whether they predict changes in occupational mix within firms, or merely across different firms or industries. Using LinkedIn resume records, BLS OES data, and Compustat employee counts, we estimate occupational employment for publicly traded US firms from 2000 through 2016. We find that faster employment growth among firms that disproportionately employ non-routine workers is the most important cause of SBTC, followed by within firm occupational mix rebalancing. The entry of new firms also plays a role, although firm exit is slightly routine-worker biased. R&D leads firms to have a larger share of routine workers. These results are most consistent with a theory of routine task demand reduction caused by the diffusion of infra-marginally 3 implemented new technologies. We also introduce a new measure of business labor dynamism, capturing the frequency with which firms change their occupational mix. Consistent with trends in productivity and other measures of business and labor market dynamism, this measure has decreased steadily since 2000 4