Chapter 9
Technology and Employment: Empirical Evidences in Technology Product Exporting Asian Economies

Krishnendu Maji

9.1 Introduction

The technological progress over the last decade has undergone a very stiff positive transformation. This progress can be categorized into three different stages namely craftsmanship, mechanization and automation (Krishnan 2010). The craftsmanship represents a stage where workers or labor have full control over the entire production process. Although in the present-day scenario craftsmanship is not something which is sufficient enough for technological progress. End-to-end knowledge of the entire production process is not viable today due to the complex nature of the products. As a result, modern-day production process mostly governed by the second stage of technological progress, which is mechanization. Mechanization represents the stage of technological progress where the entire production process is subdivided into a finite number of parts. In this scenario, most workers are involved with a single part of the production. Therefore, this stage can be considered as a stage of specialization. Engineers as a class of labor evolved in this stage of specialization. After the stage of mechanization, as species, we are moving toward the stage of automation in our day-to-day life. The concept of automation is affecting production technology drastically. It has a very ambiguous effect on labor requirement in the production process. Whereas mechanization substitutes labors in the production process, automation replaces them by high-tech machinery. An increasing amount of investments in the field of robotics and artificial intelligence is making unskilled labor almost unemployable.

Therefore, automation in production technology triggers intense debate and headlines. Broadly speaking, there are two major views governing the debate about the employment effect of new technology. In one hand, as a director effect, labor-saving

K. Maji (✉)
Department of Economics, Goenka College of Commerce and Business Administration, 210, B.B. Ganguly Street, Kolkata 700012, India
e-mail: krish.eco@gmail.com

S. Sikdar et al. (eds.), *Role of IT- ITES in Economic Development of Asia*,
https://doi.org/10.1007/978-981-15-4206-0_9

innovations create technological unemployment as discussed above. On the other hand, as an indirect effect, technological progress contributes to the creation of new job opportunities by creating new products. Therefore, the net impact of technological progress on job creation is not unambiguous.

There is a number of ways by which innovation can increase employment opportunities. Firstly, under perfectly competitive market conditions, innovation improves the efficiency in the production process, which increases the demand for final goods and services. And as we all know the increase in demand always leads to an increase in employment opportunity. Even under imperfect competition, where the factor market is not perfectly competitive, innovation and automation may increase the level of employment. As we discussed above, new technology makes unskilled labor unemployable. Therefore, the introduction of new technology always leads to a certain degree of attrition, which eventually increases the profitability of firms. Firms eventually redistribute its profit among its skilled labor force, which eventually increases the demand for final goods and services due to higher consumption expenditures by the existing labor force, which indirectly improve the employment opportunities. Secondly, innovation always encourages the creation of new products and services which eventually increase employment. These new products sometimes create a new market which creates new employment opportunities.

As opposed to the scenarios discussed above, in a number of ways, innovation may cause unemployment. Firstly, and most importantly, innovations that create new products may replace or displays an existing mature product from the market (MP3 format replacing music CDs). Such a scenario may create permanent unemployment. Workers displaced due to replacement of the old product by modern products cannot find a demand for their skills. Those labors will drag into long-term unemployment or a sequence of short-term low-paying jobs with periods of unemployment in between. Secondly, technological progress, more specifically automation, substitutes humans by machines, which eventually reduce job opportunity.

As discussed above, economic theory does not have an unambiguous answer regarding the employment effect of innovation. Therefore, there is a need for empirical analyses that can address the issue of the employment impact of technological change. In manufacturing, employment level grew along with productivity for a century or more. But in this era of increasing automation in the industrial sector, it is necessary to reinvestigate the decade-old trend. This paper explores the possible job creation effect of innovation activity on a panel of twenty-two major technology product exporting Asian economies. The concerned study concentrates on a time horizon ranging between 1996 and 2015.

The remainder of the paper is organized as follows: Sect. 9.2 provides an overview of the previous empirical literature on the relationship between innovation and employment; Sect. 9.3 presents the dataset used for this analysis; Sects. 9.4 describes the empirical techniques used for this analysis and presents all the findings. Finally, we conclude in Sect. 9.5.

9.2 Review of Literature

The interrelationship between innovation and employment is a classical debate. Academic research on this issue can be found as early as 1931 (Scheler 1931). As a result, it is quite clear that a large number of studies already have been conducted to test the interrelationship between innovation and employment. Therefore, a complex, multi-stage, and time-consuming process has to be followed to perform a systematic literature review on this area manually. In order to overcome this challenge, text mining techniques and tools are being used to facilitate systematic literature review activities (Feng et al. 2017). More than fifty studies have been analyzed (Abstract and Conclusion) to identify the pattern of result found and the possible explanations given for such results.

Primarily, a frequency-based study has been performed to identify the overall pattern in the literature substance. Not surprisingly, 'innovation' and 'labor' appeared to be the most frequently used words in the literature other than 'employment' and 'technology'. Words synonyms or antonyms to 'employment' (such as job, unemployment) appears among the most frequently used words. Among others, words such as 'manufacturing', 'firm', 'skill', 'wage', 'sector', 'growth', and 'industry' appear quite frequently. Words like 'robots' also have a rare appearance in the literature. Among the fifty studies used in this analysis, 32 share negative sentiment regarding the relationship between employment and technology. Negative words such as 'displaced', 'problems', 'decline', 'unskilled', 'destruction', 'limited', 'inequality', 'loss', and 'conflict' are being used in the literature quite extensively. Such use of words primarily reflects the negative side of innovation and technological progress, which is unemployment or layoff of unskilled workers. Among positive words 'innovation', 'skill', 'significant', 'advanced', 'important', 'benefits', 'complementary', 'variety', 'rapid' are found to be most frequent in the literature. These words explain how innovation and rapid technological progress can benefit economic growth and complement job creation.

The frequency-based analysis primarily can provide the broad domain of the literature. On the other hand, more sophisticated algorithms on text mining (such as hierarchical clustering and latent semantic analysis, etc.) need to be used in order to find out narrow more specific findings within the existing literature. Using hierarchical clustering technique (based on presence of positive and negative sentiments), it is possible to find out four major observations made in the literature, which represent 16, 10, 7, and 4 research publications or research activities, respectively, in the concerned area. The cluster that contains most number of research publications (see Encarnacion 1974; Pickett and Robson 1977; Henize 1981; Brooks 1983; Rumberger and Levin 1985; Blazejczak 1991; Zimmermann 1991; Alic 1997; Dunne et al. 1997; Hersh 1999; Fung 2006; Samaniego 2006; Malul 2009; Roessner 1985; Frey and Osborne 2017) primarily acknowledges needs for the introduction of new technologies and innovation in the production process for sustainability and efficiency. But, at the same time, these research works accept negative effect of technological progress on employment generation. Other major clusters in the literature (see Rothwell 1981;

Brouwer et al. 1993; Ducatel and Millard 1996; Van Reenen 1997; Klette and Førre 1998; Díaz et al. 2002; Piva and Vivarelli 2004; Bogliacino and Pianta 2010; Cirillo 2017; Roy et al. 2018) are quite optimistic about the job creation. According to this set of research works, labor-friendly innovation can potentially create jobs and increase the productivity of the labor force. The third cluster in the literature (see Paul and Siegel 2001; Kreickemeier 2009; Krishnan 2010; Howell 1985; Ernst 1986; McCurdy 1989; Lordan and Neumark 2017) is primarily talks about level of skill and employability under increasing automation in the production process. As expected, majority of studies in this set of research suggests that low-skilled workers become unemployable under increasing automation. On the other hand, technological progress potentially creates new job opportunities for high-skilled workers. Finally, the last major cluster in the literature (see Mortensen and Pissarides 1998; Gali 1999; Postel-Vinay 2002; Kemeny and Osman 2018) provided an ambiguous conclusion regarding the technology–employment association.

9.3 Data, Variables, and Exploratory Analysis

The study examines a panel of twenty-two major technology products exporting Asian economies with data from the Web site of World Development Indicators (Source: (a) World Bank national accounts data, (b) International Labour Organization, ILOSTAT database, and (c) United Nations, Comtrade database through the WITS platform) for the period 1996–2015. Restriction to only twenty-two countries in the continent is due to constraints in data availability. Finally, the chosen time horizon (1996–2015) primarily determined by the availability of data. At the same time, Asian developing economics has shown rapid technological progress within the given time horizon. The variables used for this analysis include (a) real GDP, (b) employment-to-population ratio in percentage form for 15+ age group (Rate of Employment), and (c) high-technology exports, respectively.

The study used high-technology exports to real GDP ratio as an indicator of technical progress of an economy. Acceleration in this ratio is going to be considered as an improvement in the competitive power of technology products produced in a particular country, which most of the time can be concluded as improvement in the technological level in the production process. Finally, median of first difference of log of real GDP has been used for the computation of average acceleration of economic activity in a particular economy within given time horizon (1996–2015).

In order to explore the data, the correlation coefficient between high-technology exports to real GDP ratio and employment-to-population ratio being plotted against the average acceleration of economic activity within 1996–2015.

As the diagram suggests, there is a negative relation between the two variables. The diagram also suggests that countries having a high degree of economic acceleration encountered a trade-off between technological progress and employment generation. On the other hand, countries with low levels of economic acceleration found to have a positive association between the two. More interestingly, the upper segment of the diagram suggests a small acceleration in economic activity potentially can worsen technology–employment complementarily drastically in countries with a low level of economic acceleration. But, in order to neutralize the degree of trade-off between technology and employment, countries having a high level of economic acceleration must sacrifice a large chunk of economic growth.

In Fig. 9.1, out of 22 major technology products exporting Asian economies, 21 have been used for analysis. Japan remains excluded from the above diagram because the study considered it as an outlier (having a very low degree of association between technology and employment along with very low level of economic acceleration). Six more countries remain outside of further empirical investigation (Kyrgyzstan, Republic of Korea, Thailand, Jordan, Singapore, and Georgia). All these six countries have very weak association between technology and rate of employment (±0.15). The study concentrates only on a set of Asian countries having a strong association between high-technology exports to real GDP ratio and employment-to-population ratio (either positive or negative).

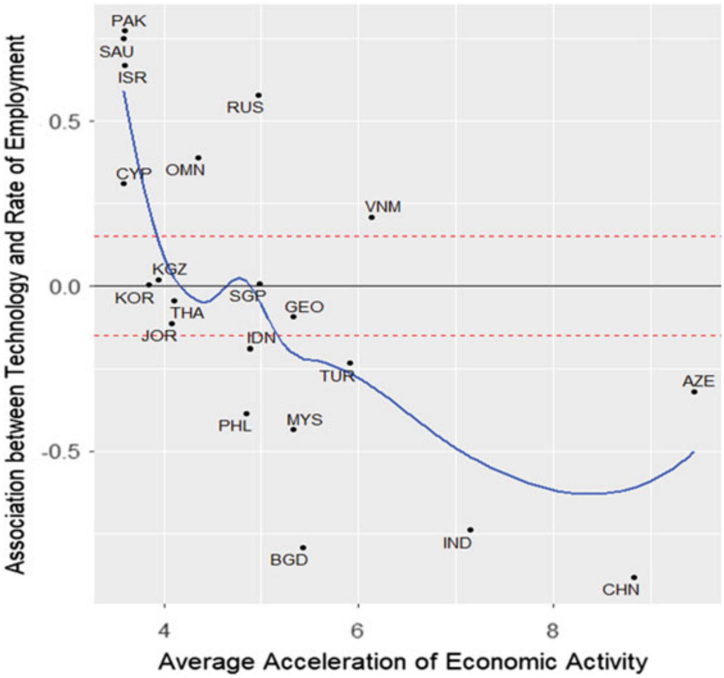

Fig. 9.1 Dependence of ITES-Employment relationship on economic acceleration. *Source* World Bank national accounts data, International Labour Organization, ILOSTAT database, United Nations, Comtrade database through the WITS platform

9.4 Methodology and Results

As explained earlier, primary objective of the study is to analyze the association between employment and technological progress (i.e., responsiveness of employment with respect to change in technology). In this context, two sets of countries are being analyzed separately: Set I: countries having positive correlation between technology and the rate of employment (Pakistan, Israel, Saudi Arabia, Russia Federation, Oman, Cyprus, and Vietnam) and Set II: countries having negative correlation between technology and the rate of employment (Indonesia, Philippines, Turkey, Malaysia, Bangladesh, India, China, and Azerbaijan).

Other than technological progress, economic growth also can affect the employment level. In most macroeconomic models, economic growth and growth in employment level are considered to be synonyms. But such a scenario is possible only if there is perfect competition in all the markets (both, product as well as factor markets), which is not true in reality. Most often, employment growth lags behind the growth of GDP—the scenario best described as 'jobless growth'.

The model used in this study to assess the relationship between level of employment and technological growth is a first-order auto-regressive model described below:

$$\mathrm{EMP}_{it} = \alpha_{it} + \beta_{it}^{1}\mathrm{TECH} + \beta_{it}^{2}\mathrm{GDP}_{it}^{g} + \rho_{it}\mathrm{EMP}_{it-1} + \delta_i t + u_{it}$$

where $i = 1, 2 \ldots, N$ is the country index, $t = 1, 2, \ldots, T$ is the time index and u_{it} a random disturbance term of mean 0. EMP stands for rate of employment, TECH stands for high-technology exports to real GDP ratio (an indicator of level of technology), t stands for individual trend, and GDP^{g} stands for growth rate of GDP represented by the following formula:

$$\mathrm{GDP}_{it}^{g} = \log\left(\frac{\mathrm{GDP}_{it}}{\mathrm{GDP}_{it-1}}\right)$$

where GDP_{it} represents level of real GDP at period t for ith country.

Therefore, the model specification is a dynamic one as it incorporates the lag values of the dependent variable as an explanatory variable.

A number of assumptions can be made regarding the parameters, errors, and the exogeneity of the regressors of this model. The most common one is parameter homogeneity (or pooled linear regression), which means that $\alpha_{it} = \alpha \forall i \,\&\, t$, $\beta_{it}^{k} = \beta^{k} \forall i \,\&\, t$, $\delta_i = \delta$ and $\rho_{it} = \rho \forall i \,\&\, t$.

The error term has two separate components under the assumption of individual heterogeneity: (a) the individual-specific component (μ_i) that does not change over time and (unobserved effects model) (b) the idiosyncratic error or innovation (ϵ_{it}): well-behaved (generally, normally distributed, mutually uncorrelated, and stationary) and independent from both the regressors and the individual error component. That is, $u_{it} = \mu_i + \epsilon_{it}$. Now, under a fixed effect model, this individual component is correlated to regressors, and therefore, $\alpha_{it} = \alpha_i \forall t$. On the other hand, in the random effect model, individual-specific component is uncorrelated with the regressors.

The present study utilizes a dynamic mean group estimation technique as prescribed by Pesaran and Smith (1995). Pooling, aggregating, averaging group estimates, and cross-section regression are the most widely used estimation techniques for paned data. All the four procedures provide unbiased estimates of coefficient means in the static scenario if the coefficients vary randomly. On the other hand, as shown by Pesaran and Smith (1995), in the dynamic case, when the coefficients differ across groups, pooling and aggregating can give inconsistent and potentially highly misleading estimates of the coefficients. They consider the mean group (MG) estimator in dynamic models. A simple MG method uses less restrictive parametric assumptions relative to other estimation techniques. More importantly, unlike aggregated or pooled regressions, it provides consistent estimates of both coefficients and standard errors. As in the original paper, this study also includes individual trends in the model specification. The estimated regression results corresponding to two sets of countries are given in Table 9.1.

As Table 9.1 suggests the intercept and lagged dependent variable turns out to be significant in both the regression equations, along with that, the sigh and the magnitude of both the estimated coefficients found to be almost identical for both set of countries. Both the regression equations fit the data very strongly. Other than these similarities, estimated results in two regression equations differ in certain aspect. Firstly, coefficient corresponding to acceleration of economic activity (i.e., growth rate of GDP) found to be significant and positive only for those countries that have positive correlation between technological growth and the rate of employment. For the other set of countries (having negative correlation between technological growth and the rate of employment), the acceleration of economic activity has no significant

Table 9.1 Regression result (dynamic mean groups)

	Set I: Countries having positive correlation	Set II: Countries having negative correlation
Intercept	20.85 (<0.1)	19.89 (<0.01)
Technology	0.13 (>0.1)	−0.77 (<0.05)
Growth rate of GDP	0.11 (<0.05)	0.02 (>0.1)
Lag of rate of employment	0.66 (<0.01)	0.67 (<0.01)
Trend	0.1 (<0.1)	0.02 (>0.1)
Goodness of fit (R^2)	0.997	0.997

Note: *P*-values corresponding to coefficients are in the parentheses impact on employment generation. Secondly, the coefficient corresponding to indicator of technological progress found to be significant and negative corresponding to countries having negative correlation between technological growth and the rate of employment. For the other sets of countries, the coefficient remains insignificant.

Therefore, the above results suggest that Asian countries which show relatively high degree of economic acceleration in the given time horizon adapt production technologies which are primarily labor displacing, and economic acceleration does not contribute to creation of jobs. In contrast to that, economic acceleration in Asian countries which shows relatively low degree of economic acceleration in the same time horizon contributes significantly to creation of employment opportunities. Finally, micro-level country-specific estimates of parameters are given Table 9.2.

As shown in Table 9.2, firstly, for most countries (Set I and Set II taken together), coefficient corresponding to the acceleration of economic activity found to be positive (Except: Oman, Vietnam, Indonesia and Philippines). Secondly, major chunk of countries belonging to Set II has negative coefficient corresponding to indicator of technological progress (Except: Malaysia and Indonesia). Finally, most countries belonging to Set I have positive coefficient corresponding to indicator of technological progress (Except: Israel, Russia Federation, and Saudi Arabia). Although too much conclusion should not be made out of Table 9.1, statistical significance of country-specific estimated parameters is not available from the estimation technique.

The entire study primarily is limited by the availability of data (especially the time dimension). On the other hand, criticism regarding the regression equation may come

Table 9.2 Country-specific estimated parameters

Set	Country	Intercept	Technology	Growth rate of GDP	Lag of rate of employment	Trend
Set I	Israel	11.82	**−0.23**	0.22	0.76	0.17
	Oman	4.47	0.40	**−0.005**	0.89	0.24
	Pakistan	−0.14	4.15	0.16	0.99	−0.04
	Russia Federation	36.66	**−0.25**	0.16	0.29	0.35
	Saudi Arabia	1.03	**−4.40**	0.05	0.96	0.08
	Vietnam	83.39	0.13	**−0.08**	−0.10	−0.07
	Cyprus	8.68	1.14	0.27	0.84	−0.02
Set II	Azerbaijan	24.72	−0.94	0.02	0.55	0.20
	Bangladesh	37.86	−2.44	0.17	0.31	−0.07
	China	34.44	−0.20	0.02	0.54	−0.15
	Indonesia	17.92	**0.03**	**−0.02**	0.71	0.01
	India	11.85	−2.49	0.01	0.80	0.004
	Malaysia	−1.23	**0.002**	0.007	1.01	0.05
	Philippines	32.76	−0.04	**−0.05**	0.47	0.002
	Turkey	0.83	−0.10	0.03	0.95	0.10

from the incorporation of the lag of the dependent variable as the explanatory variable (Reed and Zhu 2017). Reed and Zhu (2017) have shown the hazards associated with this practice. Finally, the study should be extended to countries belonging to other continents to get a more general understanding regarding the relationship between technological progress and job creation.

9.5 Conclusions

Primarily, the exploratory analysis in the study suggests that countries having a high degree of economic acceleration encountered a trade-off between technological progress and employment generation. On the other hand, countries with low levels of economic acceleration found to have a positive association between the two.

Finally, empirical model used in the study suggests following findings:

(a) Acceleration of economic activity significantly and positively affects employment generation for those countries that have positive correlation between technological progress and the rate of employment (also having relatively low degree of economic acceleration in 1996–2015).
(b) Asian countries which show relatively high degree of economic acceleration in the given time horizon adapt production technologies which are primarily labor displacing, and economic acceleration does not contribute to creation of jobs.

References

Alic, J. A. (1997). Technological change, employment, and sustainability. *Technological Forecasting and Social Change, 55,* 1–13.

Antonucci, T., & Pianta, M. (2002). Employment effects of product and process innovation in Europe. *International Review of Applied Economics, 16,* 295–307.

Bauer, T. K., & Bender, S. (2004). Technological change, organizational change, and job turnover. *Labour Economics, 11,* 265–291.

Blazejczak, J. (1991). Evaluation of the long-term effects of technological trends on the structure of employment. *Futures, 23,* 594–604.

Bogliacino, F., & Pianta, M. (2010). Innovation and employment: A reinvestigation using revised Pavitt classes. *Research Policy, 39,* 799–809.

Brooks, H. (1983). Technology, competition, and employment. *The Annals of the American Academy of Political and Social Science, 470,* 115–122.

Brouwer, E., Kleinknecht, A., & Reijnen, J. O. (1993). Employment growth and innovation at the firm level. *Journal of Evolutionary Economics, 3,* 153–159.

Button, K., Lall, S., Stough, R., & Trice, M. (1999). High-technology employment and hub airports. *Journal of Air Transport Management, 5,* 53–59.

Cirillo, V. (2017). Technology, employment and skills†. *Economics of Innovation and New Technology, 26,* 734–754.

Crespi, G., & Tacsir, E. (2011). Effects of innovation on employment in Latin America. In *2011 Atlanta Conference on Science and Innovation Policy* (pp. 1–11).

Croissant, Y., & Millo, G. (2008). Panel data econometrics in R: The plm package. *Journal of Statistical Software, 27,* 1–43.

Croissant, Y., & Millo, G. (2018). *Panel data econometrics with R.*

Denise, M. L. (1962). Automation and unemployment: A management viewpoint. *The Annals of the American Academy of Political and Social Science, 340,* 90–99.

Díaz, M. S., & Tomás, F. J. (2002). Technological innovation and employment: Data from a decade in Spain. *International Journal of Production Economics, 75*, 245–256.

Ducatel, K., & Millard, J. (1996). Employment and innovation in advanced communication technologies: Strategies for growth and the growth of employment. *Futures, 28,* 121–138.

Dunne, T., Haltiwanger, J., & Troske, K. R. (1997). Technology and jobs: Secular changes and cyclical dynamics. *Carnegie-Rochester Conference Series on Public Policy, 46,* 107–178.

Encarnacion, J. (1974). On appropriate technology, saving and employment. *Journal of Development Economics, 1,* 71–79.

Ernst, D. (1986). Automation, employment and third world: Case of electronics industry. *Economic and Political Weekly*, 1213–1223.

Evangelista, R., & Savona, M. (2002). The impact of innovation on employment in services: Evidence from Italy. *International Review of Applied Economics, 16,* 309–318.

Feng, L., Chiam, Y. K., & Lo, S. K. (2017). Text-mining techniques and tools for systematic literature reviews: A systematic literature review. In *2017 24th Asia-Pacific Software Engineering Conference (APSEC)* (pp. 41–50).

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114,* 254–280.

Fung, M. K. (2006). Are labor-saving technologies lowering employment in the banking industry? *Journal of Banking and Finance, 30,* 179–198.

Gali, J. (1999). Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review, 89,* 249–271.

Goldberg, K., Highfill, J., & McAsey, M. (1998). Technology choice: The output and employment tradeoff. *American Journal of Economics and Sociology, 57,* 27–46.

Henize, J. (1981). Evaluating the employment impact of information technology. *Technological Forecasting and Social Change, 20,* 41–61.

Hersh, M. (1999). Technology, gender and employment in the 'developing' countries. *IFAC Proceedings Volumes, 32,* 6597–6602.

Howell, D. R. (1985). The future employment impacts of industrial robots: An input-output approach. *Technological Forecasting and Social Change, 28,* 297–310.

Kemeny, T., & Osman, T. (2018). The wider impacts of high-technology employment: Evidence from U.S. cities. *Research Policy, 47*, 1729–1740.

Klette, J., & Førre, S. E. (1998). Innovation and job creation in a small open economy-evidence from Norwegian manufacturing plants 1982–92. *Economics of Innovation and New Technology, 5,* 247–272.

Kreickemeier, U. (2009). Trade, technology, and unemployment: The role of endogenous skill formation. *Canadian Journal of Economics, 42,* 639–664.

Krishnan, T. N. (2010). Technological change & employment relations in India. *Indian Journal of Industrial Relations: Economics & Social Dev, 45,* 367–380.

Kwartler, T. (2017). *Text mining in practice with R.*

Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization, 29,* 210–220.

Lordan, G., & Neumark, D. (2017). People versus machines: The impact of minimum wages on automatable jobs. *Labour Economics, 52,* 40–53.

Malul, M. (2009). Older workers' employment in dynamic technology changes. *Journal of Socio-Economics, 38,* 809–813.

McCurdy, T. H. (1989). Some potential job displacements associated with computer-based automation in Canada. *Technological Forecasting and Social Change, 35,* 299–317.

Morrison Paul, C. J., & Siegel, D. S. (2001). The impacts of technology, trade and outsourcing on employment and labor composition. *The Scandinavian Journal of Economics, 103,* 241–264.
Mortensen, D. T., & Pissarides, C. A. (1998). Technological progress, job creation, and job destruction. *Review of Economic dynamics, 1,* 733–753.
Oakey, R. P. (1983). New technology, government policy and regional manufacturing employment. *Area*, 61–65.
Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels☆. *Journal of Econometrics, 68,* 79–113.
Pickett, J., & Robson, R. (1977). Technology and employment in the production of cotton cloth. *World Development, 5,* 203–215.
Piva, M., & Vivarelli, M. (2004). Technological change and employment: Some micro evidence from Italy. *Applied Economics Letters, 11,* 373–376.
Postel-Vinay, F. (2002). The dynamics of technological unemployment. *International Economic Review, 43,* 737–760.
Qureshi, M. O., & Syed, R. S. (2014). The impact of robotics on employment and motivation of employees in the service sector, with special reference to health care. *Safety and Health at Work, 5,* 198–202.
Reed, W. R., & Zhu, M. (2017). On estimating long-run effects in models with lagged dependent variables. *Economic Modelling, 64,* 302–311.
Roessner, J. D. (1985). Forecasting the impact of office automation on clerical employment, 1985–2000. *Technological Forecasting and Social Change, 28,* 203–216.
Rothwell, R. (1981). Technology, structural change and manufacturing employment. *Omega, 9,* 229–245.
Roy, V. V., Vértesy, D., & Vivarelli, M. (2018). Technology and employment: Mass unemployment or job creation? Empirical evidence from European patenting firms. *Research Policy, 47,* 1762–1776.
Rumberger, R. W. (1984). High technology and job loss. *Technology in Society, 6,* 263–284.
Rumberger, R. W., & Levin, H. M. (1985). Forecasting the impact of new technologies on the future job market. *Technological Forecasting and Social Change, 27,* 399–417.
Samaniego, R. M. (2006). Employment protection and high-tech aversion. *Review of Economic Dynamics, 9,* 224–241.
Scheler, M. B. (1931). Technological unemployment. *The Annals of the American Academy of Political and Social Science, 154,* 17–27. https://doi.org/10.1177/000271623115400105
Silva, H. C., & Lima, F. (2017). Technology, employment and skills: A look into job duration. *Research Policy, 46,* 1519–1530.
Stewart, F. (1974). Technology and employment in LDCs. *World Development, 2,* 17–46.
Van Reenen, J. (1997). Employment and technological innovation: Evidence from UK manufacturing firms. *Journal of Labor Economics, 15,* 255–284.
Vivarelli, M. (1995). *The economics of technology and employment*.
Vivarelli, M., Evangelista, R., & Pianta, M. (1996). Innovation and employment in Italian manufacturing industry. *Research Policy, 7,* 1013–1026.
Zimmermann, K. F. (1991). The employment consequences of technological advance, demand and labor costs in 16 German industries. *Empirical Economics, 16,* 253–266.