EFFECTS OF TECHNOLOGY ON THE LABOR FORCE: FIRMS' ADOPTION OF PERSONAL COMPUTERS AND CHANGES IN THEIR WORKFORCE SIZE IN CENTRAL ASIA

A Thesis
submitted to the Faculty of the
Graduate School of Arts and Sciences
of Georgetown University
in partial fulfillment of the requirements for the
degree of
Master of Public Policy

By

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Washington, D.C.
April 9, 2019

EFFECTS OF TECHNOLOGY ON THE LABOR FORCE: FIRMS'ADOPTION OF PERSONAL COMPUTERS AND CHANGES IN THEIR WORKFORCE SIZE IN CENTRAL ASIA

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ABSTRACT

The effect of technological innovations on labor market outcomes has been widely studied. According to a recent World Bank report, 1.8 billion jobs in developing countries are at risk of being automated. However, little is known about how technological innovations will affect Central Asia. I hypothesize that, in Central Asian economies, a firm's level of computerization is negatively correlated with its workforce size. Given that a high proportion of Central Asian workers fill manual, low-skilled positions, a substantial number of these positions should, in theory, be susceptible to technology-induced labor substitution. To test my hypothesis, I use the World Bank's Business Environment and Enterprise Performance Survey (BEEPS) to assess the relationship between technological advancement, as measured by changes in a firm's personal computer (PC) adoption, and changes in its workforce size for the countries of Kazakhstan, Kyrgyzstan, Tajikistan, and Uzbekistan. My analysis finds no relationship between a firm's computer use and its workforce size. This finding withstands a battery of robustness checks. The World Bank asserts that the rapid growth and diffusion of digital technologies, along with the growing importance of the digital economy, necessitate a discussion among policymakers and policy researchers about the consequences of these new technologies. This paper contributes to a better understanding of the regional effect of technology on labor, which could help guide assessments of policy options in order to maximize the benefits, and minimize the adverse impacts, of new technologies.

Acknowledgements

I want to express my deepest gratitude to my advisor, Dr. Adam Thomas, for his valuable feedback and guidance, Dr. Jeffrey Mayer for his insightful stylistic recommendations, and Eric Gardner for his helpful advice with data.

I also want to offer special thanks to Dr. Andreas Kern, Dr. Harry Holzer, Dr. Robert Bednarzik, Dr. Shahid Yusuf, Molly Kinder, Sameer Khatiwada, and Ethan Pollack who shared their extensive knowledge and played a decisive role in narrowing down my research question.

I dedicate the research and writing of this thesis to my wife, family, and friends for their tremendous support and patience.

Many thanks,
Vadim Abanin

TABLE OF CONTENTS

Introduction 1

Background 3

Literature Review 7

Conceptual Framework 12

Data and Methods 15

Descriptive Statistics 18

Regression Results 21

Discussion 25

Conclusion 27

Appendix: Main Regression Results Disaggregated by Country 28

References 30

List Of Figures

Figure 1. 2016 Sector Composition in Central Asia,
Value Added as Percentage of GDP 5

Figure 2. Firm, Workforce, and Technology Factors Included in the Analysis 12

List Of Tables

Table 1. Variable Definitions 15

Table 2. Descriptive Statistics for Dependent,
Key Independent, and Control Variables 19

Table 3. The Means of Dependent, Key Independent,
and Control Variables Disaggregated by Country 20

Table 4. Main Regression Results: the Percent Change in Firms' PC Adoption
and Workforce Size in Central Asia 24

Table A-1. Main Regression Results Disaggregated by Country: the Percentage
Change in Firms' PC Adoption and Workforce Size 28

INTRODUCTION

According to a recent World Bank (WB) study, 1.8 billion jobs in developing countries are at risk of being automated (World Development Report, 2016). In the Central Asian countries of Kyrgyzstan, Tajikistan, and Uzbekistan, the estimated risk of job automation is 36 percent, 38 percent, and 34 percent, respectively, which is below the OECD average of 57 percent, but still quite high (World Development Report, 2016). In any given country, the level of technology diffusion is predictive of automation risks, and the lack of technology adoption in low-income countries indicates that it may take longer for automation to affect their labor markets.

In low-income countries, low wages and an abundance of manual labor make firms' investments in technology less cost-effective (World Development Report, 2019). In developed countries, studies of the risk of automation produce varying results, but all seem to conclude that the changing nature of work is apparent in the decline of routinized jobs requiring less advanced technical and cognitive skills (World Development Report, 2019). Therefore, it is important for policymakers in the developing world to study the extent to which existing technologies might affect their labor forces, both today and in the future.

In a process described by Joseph Schumpeter as "creative destruction," accelerated technological progress is likely to destroy jobs, but it is also likely to create new jobs that require new skills. These changes will have global effects, cutting across normal boundaries (low and high skilled workers, the young and old, advanced and less developed countries). While we can make predictions about the changes that might accompany new technologies, we cannot anticipate the degree and speed of the changes. The fact that jobs could be automated does not mean that they will. Economic and political factors could hinder automation. Moreover, it is important to consider particular countries' stages of development. In developing countries, about two-thirds of the labor force works in the informal sector, which is characterized by low productivity and limited access to technology (World Development Report, 2019).

Therefore, in Central Asia, the proliferation of technologies such as the Internet of Things (IoT), artificial intelligence (AI), and robotics have unclear implications for employment levels (Kelly et al., 2017). This paper uses small- and medium-sized enterprises (SMEs) data from the most recent (fifth) round of the European Bank for Reconstruction and Development's (EBRD) and World Bank's Business Environment and Enterprise Performance Survey (BEEPS) to assess the relationship between technological advancement, as measured by firms' personal computer (PC) adoption and changes in their workforce size in the Central Asian countries of Kyrgyzstan, Kazakhstan, Tajikistan, and Uzbekistan.[1]

[1] The World Bank's definition of the Central Asia region includes the countries of Kazakhstan, the Kyrgyz Republic, Tajikistan, Turkmenistan, and Uzbekistan. However, data on Turkmenistan are not available in the BEEPS survey. Therefore, my analysis omits Turkmenistan.

BACKGROUND

As the world becomes increasingly digital, connectivity becomes increasingly important for Central Asia's economic development (World Development Report, 2016). Landlocked and constrained by factors including corruption, low-skilled workforces, low productivity, and limited exports, the region's lack of connectivity hinders its economic growth (Asian Development Bank, 2018; OECD, 2018). Investment in, and adoption of, information and telecommunication technology (ICT) can help to increase the private sector's share of GDP, and to support the diversification of Central Asian economies (Pomfret, 2014).

In the process of economic development, countries go through multiple stages of structural transformation. At the initial stages of development, most economic activity and jobs are concentrated in agriculture, but as countries continue to develop, economic activity shifts to higher productivity manufacturing industries. Eventually, countries shift from manufacturing-based to service-based economies (Rodrik, 2016). For example, in 1820, the agricultural sector in the U.S. employed around 70 percent of the workforce; it now employs less than 2 percent (United Nations, 2017). Similarly, the share of agricultural employment in China went from roughly 80 percent in 1970 to about 28 percent in 2015 (United Nations, 2017). In the quest to catch up to developed countries, emerging economies often strive to leapfrog stages of development that seem obsolete. For example, instead of installing land lines, an emerging economy might choose to invest in cellular towers.

In the last few decades, advancements in digitalization and ICT have made service sector production and employment more appealing (United Nations, 2017). Nonetheless, a digital divide persists in Central Asia (World Development Report, 2016).[2] The region's firm-level absorption of new digital technologies is below the global average (Global Information Technology Report, 2016).[3] Furthermore, prices for Internet access and computer goods in Central Asia are higher than in OECD countries (International Telecommunication Union, 2017; World Development Report, 2016).

Economic growth in Central Asia has been driven primarily by exports of raw materials, labor, and remittances, which has rendered the region highly vulnerable to external economic shocks (OECD, 2018). Although the service sector dominates the labor force in Central Asia, agriculture still plays a vital role in the region's sector composition, as shown in Figure 1.

[2] For the purposes of this paper, the term "digital divide" refers to the imbalance in the availability and use of ICT between developed and developing countries. Other definitions of the digital divide focus on the imbalance in the availability and use of ICT between various socioeconomic groups within any given population (World Development Report, 2016).

[3] The World Economic Forum, in its Global Information Technology Report (2016), ranks countries according to its Networked Readiness Index, which includes 53 indicators to capture a broad spectrum of ICT characteristics, in 139 economies. The "firm-level technology absorption" metric corresponds to the question: "in your country, to what extent do businesses adopt new technology?" Answers are provided on a 1-to-7 Likert scale, where 1= "not at all" and 7 = "adopt extensively." The mean value globally is 4.7, while Kazakhstan ranks 90th with mean value of 4.4, Tajikistan ranks 116th with mean of 4.0, and Kyrgyz Republic ranks 118th with mean value of 3.9. Data on Uzbekistan are not available.

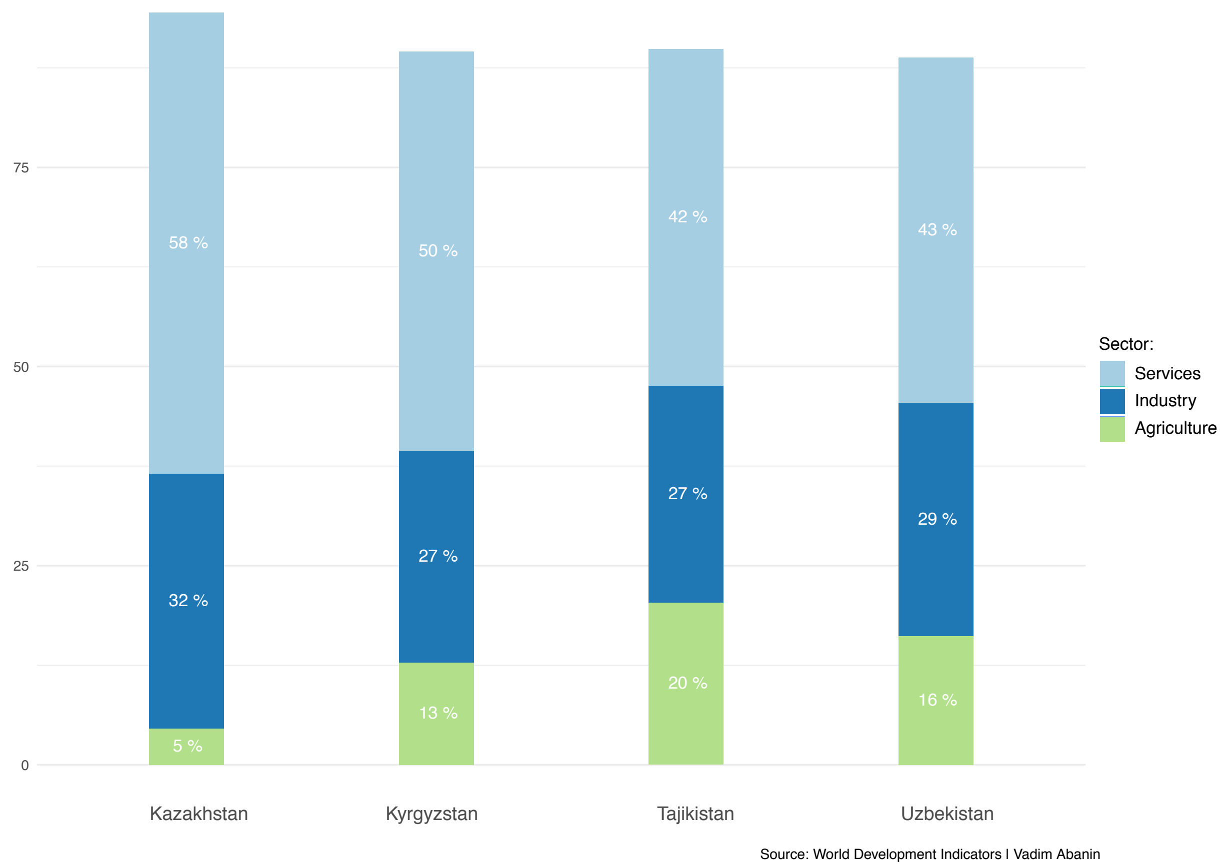

Figure 1. 2016 Sector Composition in Central Asia, Value Added as Percentage of GDP

The spread of digital technologies and the Internet across the world has produced tremendous social and economic benefits, primarily through reductions in the cost and increases in the access, sharing, and use of information (World Development Report, 2016). However, the digital divide between countries contributes to an underutilization of these technologies. The workforce in many developing countries lacks the skills to keep up with the latest technologies, which further limits the "digital dividends" that these countries are able to reap (World Development Report, 2016).[4] For example, the World Bank argues that the lack of computer skills is a barrier to employment in Tajikistan, Uzbekistan, and Kyrgyzstan (World Development

[4] The World Bank's 2016 report, Reaping Digital Dividends, broadly defines "digital dividends" as economic benefits derived from using digital technologies.

Report, 2016). At the same time, the growth in the Central Asian workforce is outpacing the growth of employment. Only 43 percent of Tajikistan's working-age population is employed (Kelly et al., 2017). Thus, the promotion of employment remains a high priority for Central Asian governments (ILO, 2019).

The World Bank report, "Promoting Economic Growth and Resilience in Europe and Central Asia", advises policymakers in European and Central Asian (ECA) countries to continue to promote regional connectivity, reduce barriers to entry in order to deepen economic integration, and concentrate on technology diffusion (Gould, 2018). The World Bank also asserts that the rapid growth and diffusion of digital technologies, along with the growing role of the digital economy, necessitate a discussion among policymakers and policy researchers about the consequences of these new technologies. The effect of these technologies on the future of work is not predetermined. Better regional understanding of the impact of technology on labor could help to guide assessments of policy options to maximize the benefits, and minimize the adverse impacts of, new technologies.

LITERATURE REVIEW

Job creation is important for economic growth and poverty reduction (Loayza et al., 2006; Melamed et al., 2011).[5] However, in developing countries, high concentrations of labor in agricultural, low-skilled, and low-productivity sectors create a greater risk related to automation (Schlogl & Sumner, 2018). In the last two centuries, humanity has witnessed the transformation of labor markets by rapid technological progress. Today, ICT is advancing at an ever-increasing rate, especially due to the expansion of computing and telecommunications networks such as fixed and mobile broadband (International Telecommunication Union, 2017). Because of the rapid emergence of such new technologies, the OECD has updated its definition of ICT bundles to include cloud and cognitive computing, among other technologies (Inaba & Squicciarini, 2017).[6]

The application, penetration, and use of ICT differs in advanced versus less advanced economies (Schlogl & Sumner, 2018). A substantial empirical literature exists on the relationship between technology and employment outcomes in developed countries (Acemoglu & Autor, 2010; Acemoglu & Restrepo, 2017; Autor et al., 2006; Autor et al., 1998; Bessen, 2016; Frey & Osborn, 2013). However, the literature on the same topic for developing countries is limited (Asian Development Bank, 2018; Kelly et al., 2017). One limiting factor for research in developing countries has been a lack of government oversight in the collection of the relevant

[5] Melamed et al. (2011) provide a literature review examining evidence of various sector employment impact on growth.

[6] In 2003, the OECD classified ICT technologies in the following bundles: (1) Telecommunications, (2) Consumer Electronics, (3) Computers, office machinery, and (4) Other ICT, which did not account for rapid development of new ICT technologies such as the Internet of Things (IoT), robotics, and artificial intelligence (AI). The more recent (2017) OECD classification of ICT technologies includes the following bundles: (1) High-speed networks, (2) Security, (3) Home-electronics networks, (4) High-speed computing, (5) Simulation, (6) Large-capacity and high-speed storage (i.e., the cloud), (7) Input-output, (8) Cognition and meaning understanding, (9) Human-interface evaluation, (10) Software, (11) Devices, and (12) Other.

data (UNESCO, 2010). Partly as a result, no empirical studies have examined the relationship between the diffusion of technology and labor force outcomes in Central Asia. This literature review begins with a discussion of studies that are closely related to my research question (although not my region) and then discusses the broader literature on technology and employment outcomes.

Studies of computer adoption and firm workforce size

Some scholars argue that computer technology is labor-enhancing, making workers more valuable because they are more productive, and thereby raises their wages via expanded demand for their labor (Alexopoulos & Cohen, 2016; Bessen, 2019; Graetz & Michaels, 2015; Gregory et al., 2016). Others argue that technology is labor-substituting – that tasks once performed by humans can now be performed by machines (Acemoglu & Restrepo, 2017; Brynjolfsson & McAfee, 2014; Ford, 2017; Frey & Osborn, 2013). A nuanced reading of this literature suggests that both views are true, but in different industries and occupations.

In developed economies, computerization has had many implications for SMEs. Im et al. (2013) canvas the research on IT and firm size in the U.S. and U.K., focusing specifically on whether large firms become smaller by using information technology (IT). The studies reviewed by these authors yield mixed results. Some suggest that IT adoption is associated with reductions in firm size (as measured by employment), while others suggest the opposite. The authors hypothesize that these differences in findings may be partially due to their different levels of analysis (e.g., establishment, firm, industry), the type of data analyzed (e.g., cross-sectional versus longitudinal), and the type of technology being studied (Im et al., 2013).

Brynjolfsson et. al.'s (1994) study was among the first to confirm empirically whether IT adoption, measured as the extent of IT investment in resources such as computers, led to smaller firm size. Their study used industry-level data on manufacturing and services businesses in the U.S. for the period 1976-1989 and found a negative association between IT use and firm size. Their study also found that this relationship was stronger in analyses that lagged their IT adoption measure by two or more years. The authors argued that the lag in the estimated effect of IT could have been the reason for the mixed results found in prior research on this topic. Bessen (2016) found that, at the industry level, a one percent increase in computer use was associated with a three percent annual job loss in the manufacturing sector and a one percent annual job gain in non-manufacturing sectors.

However, other studies have found either no evidence of a relationship or evidence of a positive relationship. Pantea and Biagi (2017) used firm-level EUROSTAT data and found no association between ICT use and labor substitution in three-year-lag models. In a more recent study on computer automation and employment in various types of jobs (i.e., jobs characterized by routine and non-routine tasks) in the U.S., Bessen (2019) found that a one percent increase in computer use was associated with a 1.7 percent increase in annual employment for these types of jobs. He also found that faster occupational growth, even for routine and mid-wage occupations, was followed by a rising wage gap within occupational categories.

Broader studies of ICT and employment outcomes

The broader literature on this topic focuses primarily on the question of whether technology – and ICT in particular – complements non-routine tasks or substitutes for them (Acemoglu & Autor, 2010; Autor et al., 2003; Peng et al., 2018). Researchers tend to agree that increased use of ICT is associated with a decline in employment for less skilled workers and within manufacturing sectors (Bresnahan et al., 2002; Van Reenen & Chennels, 2002). In addition, digital capabilities, accessible via computers and the Internet, can further exacerbate employment problems for low-skilled workers (World Development Report, 2016). On the other hand, these technologies can complement the work of high-skilled employees and drive up demand for their labor (Autor et al., 2006). A study by Osborn and Frey (2013) on the susceptibility of jobs to computerization estimated that, given current levels of technology, about 47% of occupations in the U.S. could be automated.[7] Subsequently, a number of studies have examined the association between technology-led automation and jobs, primarily in high-income countries, but their findings vary substantially.[8]

Other significant contributions to this field of research have identified the phenomenon of job polarization (i.e., concentration of jobs at the low and high ends of the technology spectrum, and the hollowing out of middle-wage and middle-skilled workers) within technologically advanced countries (Autor et al., 2006; Autor et. al., 1998). For example, Michaels et al. (2010) found a strong correlation between ICT diffusion and job polarization in 11 OECD countries.[9] In contrast, in a study of 21 developing countries of Africa, Latin America and Asia, Maloney and Molina (2016) found no evidence of job polarization.[10]

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[7] The authors, with the assistance of machine learning experts, classified the risk of automation for detailed task descriptions of jobs within 70 occupations. An artificial intelligence (AI) algorithm was then trained on that dataset to identify and learn the patterns of about 20,000 automatable versus non-automatable task descriptions. These descriptions were adopted from O*Net data, a source of occupational information such as tasks, abilities, and work activities. The AI algorithm was then used to identify automatable versus non-automatable occupations (Frey & Osborn, 2018).
[8] See Schlogl and Sumner (2018) for a summary of the literature on automation and jobs.
[9] The 11 countries included in the study are Austria, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Spain, the UK and the USA. The authors limit their sample size to these core OECD countries in order to create a complete time series from 1980 to 2004.
[10] The 21 developing countries included in this study are Brazil, the Dominican Republic, Ecuador, El Salvador, Mexico, Nicaragua, Panama, and Peru for Latin America; India, Indonesia, Vietnam, and Fiji

The present study

The literature suggests that the digital divide between developed and developing countries is a salient concern for policymakers and an area ripe for future research. For example, Rodrik (2016) finds that rapid adoption of ICT within developing countries could lead to premature deindustrialization, with implications for employment and economic growth. This conclusion leads to the question of whether the dissemination of cutting-edge technologies in emerging economies will telescope or leap-frog conventional stages of development, or instead hinder economic and employment growth. Indeed, one might ask whether such technological diffusion is even feasible in the first place. According to this line of argument, emerging economies should replicate the traditional model of developed countries by transitioning from agriculture to manufacturing, and then to service-based economies, but only when economic growth through industrialization is completed.

More broadly, the literature on the effect of technology on employment outcomes in developed countries has arrived at different results for different industries and occupations. Additionally, most of this literature focuses on developed countries, or on developing countries in Africa and East Asia. There have been no attempts to study this relationship directly in Central Asia. Would more rapid introduction of ICT slow employment growth or lead to polarization of the labor market in Central Asia, or is the level of technological advancement there too low to produce these effects? To answer these questions, this paper studies the effects of ICT adoption (operationalized via a measure of the rate of PC adoption) on changes in firms' workforce sizes in four countries in Central Asia: Kazakhstan, Kyrgyzstan, Tajikistan, and Uzbekistan.

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for Asia; Arab Republic of Egypt, Morocco, and West Bank and Gaza for Middle East; Ghana, Liberia, Malawi, Mali, South Africa, and Zambia for Africa.

CONCEPTUAL FRAMEWORK

I hypothesize that, in the developing economies of Central Asia, a firm's level of computerization is negatively correlated with its workforce size. Given the high proportion of workers who fill manual, low-skilled positions in Central Asia, a substantial number of these positions should, in theory, be susceptible to technology-induced labor substitution. To study this relationship, I estimate a model similar to the one estimated by Brynjolfson et al. (1994) in their analysis of the relationship between computer use and firm size. The factors included in my regression are illustrated below in Figure 2.

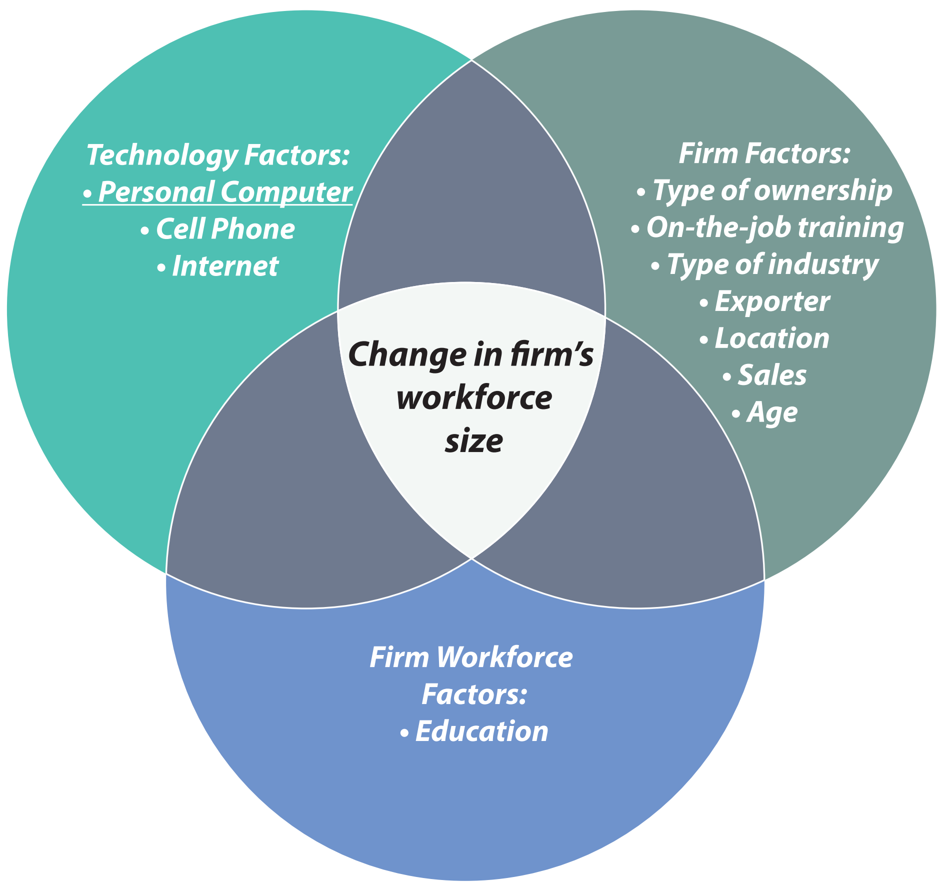

Figure 2. Firm, Workforce, and Technology Factors Included in the Analysis

The number of employees is a common measure of firm size in studies of the effects of PC adoption within firms (Brynjolfson et al., 1994; Im et al., 2013; Rosa & Hanoteau, 2012). Thus, I use this measure as my outcome.

The controls in my regressions include a measure of educational attainment. The levels of education can be used as a proxy for the ability to reskill or for skill levels more generally. Many studies find evidence of higher levels of automation among firms with unskilled workers (Autor et al., 2006; Bresnahan et al., 2002; Reshef, 2013; Van Reenen & Chennels, 2002). As a result, I control for educational attainment.

Other studies similar to mine control for firm characteristics including industry type, sales, firm age, type of ownership, exporter status, on-the-job training, and location, which I also include as controls in my regressions (Bessen, 2016; Bessen 2019; Im et al., 2013).[11] Some industries might be affected more substantially than others by the adoption of new technologies. For example, Gaggl and Wright (2017) find that ICT leads to increased employment in non-repetitive sectors such as the wholesale, retail, and finance industries. However, the authors find no statistically significant effect in the manufacturing sector.[12]

The literature is undecided about how to measure ICT use. This is likely attributable in part to the fact that many different information technologies are used to achieve many different workforce purposes. As a result, some authors advocate for the use of an index capturing the use

[11] Gorodnichenko and Schnitzer (2013) control for skills, firm age, and location in their study of the determinants of firms' access to finance. Although this outcome is different from mine, it is also possible that these factors are related to the change in firms' workforce size, especially given that access to financial resources could allow a firm to expand its workforce.

[12] The authors, in their analysis of the effect of expanded ICT use on firms' employment levels for employees performing different tasks, instrument for expanded ICT use with a measure reflecting exogenous variation in ICT investments generated by a temporary tax incentive in the U.K. The different jobs and the tasks performed for those jobs were classified using Acemoglu and Autor's (2010) classification of routine, non-routine, cognitive, and manual occupations.

of many different forms of IT (Sharafat & Lehr, 2017). For purposes of simplicity, I focus in particular on PC use, while controlling for two other key aspects of technology: the use of cell phones and access to the Internet. These three technological factors have all been found to be associated with faster economic growth in developing countries (Stanley et al., 2018).

DATA AND METHODS

I estimate a multivariate regression to study the relationship between change in computer use among a firm's employees and change in the size of its workforce, while controlling for other possible explanatory variables. A firm's employment and its employees' PC use are measured as percent changes over a two-year period: i.e., in the last fiscal year (2011) versus three fiscal years ago (2009). I estimate this regression using cross-sectional, firm-level data from the latest (fifth) round of the Business Environment and Enterprise Performance Survey (BEEPS), which was conducted in 2013 as a joint initiative of the European Bank for Reconstruction and Development (EBRD) and the World Bank Group. In total, the BEEPS data cover 16,566 enterprises in 32 countries in Eastern Europe and Central Asia. To conduct my analysis, I extract a sub-sample containing data on firms from the Central Asian countries of Kazakhstan, the Kyrgyz Republic, Tajikistan, and Uzbekistan.[13] Consequently, my sub-sample contains 490 firms. Table 1 provides definitions for all variables included in my model.

Table 1. Variable Definitions

Dependent Variable	Definition
Employment Change	A continuous variable indicating the percentage change in the firm's number of permanent employees between 2009 (three years before the administration of the survey) and 2011 (one year before the administration of the survey).
Key Independent Variable	
Personal Computer Use Change	A continuous variable indicating the percentage change in the number of employees who regularly used PCs in their jobs between 2009 (three years before the administration of the survey) and 2011 (one year before the administration of the survey).
Firm Factors	

[13] As discussed in a previous footnote, data on Turkmenistan are not provided in the survey.

Table 1. (Cont'd.)

Firm Factors	Definition
Sales Change	A continuous variable indicating the percentage change in firm's sales between 2009 (three years before the administration of the survey) and 2011 (one year before the administration of the survey).
Firm Age	A continuous variable indicating the difference between the survey year and the year that the firm began operations.
Exports	A continuous variable indicating the share of total sales accounted for by direct exports.
On the Job Training	A dichotomous variable indicating whether or not the firm has formal training programs in place for permanent workers.
Ownership Type	
Private Domestic Ownership	A continuous variable indicating in percentage terms how much of a firm is owned by private domestic individuals.
Government Ownership	A continuous variable indicating in percentage terms how much of a firm is owned by the central or state government.
Private Foreign Ownership	A continuous variable indicating in percentage terms how much of a firm is owned by private foreign individuals.
Other Ownership	A continuous variable indicating in percentage terms how much of a firm is owned by any other entity aside from the government, private domestic or foreign individuals.
Location	
Capital	A dichotomous variable indicating whether a firm is located in the capital city.
Other; 250,000 - over 1 million	A dichotomous variable indicating whether a firm is located in a locality with a population of 250,000 or more.
Other; 50,000 - 250,000	A dichotomous variable indicating whether a firm is located in a locality with a population of 50,000 to 250,000.
Under 50,000	A dichotomous variable indicating whether a firm is located in a locality with a population of 50,000 or less.
Firm Workforce Factors	
Skilled Workers (%)	A continuous variable indicating the percentage of full time employees who completed a university degree.
Technology Factors	
Cell Phone Use	A dichotomous variable indicating whether a firm uses cell phones in its operations.
Internet Use	A dichotomous variable indicating whether a firm has a high-speed Internet connection on its premises.

In order to evaluate the relationship between PC adoption and employment change, I estimate the following model:

$$Employment\_Change_{ijk} = \beta_0 + \beta_1 PC\_change_{ijk} + \beta_2 sales\_change_{ijk} + \beta_3 firm\_age_{ijk} + \beta_4 exporter_{ijk} + \beta_5 job\_training_{ijk} + \beta_6 private\_domestic\_owned_{ijk} + \beta_7 government\_owned_{ijk} + \beta_8 private\_foreign\_owned_{ijk} + \beta_9 other\_owned_{ijk} + \beta_{10} location\_capital_{ijk} + \beta_{11} location\_250K\_ormore_{ijk} + \beta_{12} location\_50K\_to250K_{ijk} + \beta_{13} location\_50K\_orlessl_{ijk} + \beta_{14} education_{ijk} + \beta_{15} cell\_phone_{ijk} + \beta_{16} internet_{ijk} + \gamma_j + \propto_k + e$$

where γ_j denotes a vector of industry dummies, and $\propto_k$ a vector of country dummies. I am mainly interested in β_1, the relationship between the rate of PC adoption and the change in a firm's workforce size, controlling for the other variables incorporated in the model. The inclusion of industry fixed effects, γ_j, allows me to control for all industry-level characteristics that are common to all firms in a given industry. The inclusion of country fixed effects, $\propto_k$, allows me to control for all country-level characteristics that are common to all the firms in a given country. The inclusion of these fixed effects terms in my analysis reduces the extent of omitted variable bias in my estimates.

DESCRIPTIVE STATISTICS

Descriptive statistics for my dependent, key independent, and control variables are presented in Table 2 below.[14] All estimates are weighted using weights provided by the survey's administrators.[15] On average, firms' workforce sizes increased by about 7 percent over the period captured by my analysis. There is substantial variation in this variable, which ranges from a reduction of 87 percent to a more-than-100-fold increase in firm size. The average change in firms' PC use is 17 percent, with a range for this variable from a reduction of approximately 80 percent to a 34-fold increase in PC use. In terms of sales change, the firms had seen a tremendous growth. Less than half of the workforce in my sample (approximately 43 percent) obtained a university degree. On average, firms are 70 percent owned by private domestic individuals. The use of cell phones is slightly more prevalent in the region than access to the Internet.

[14] Out of 1619 observations, the following variables had missing data (the number of observations with missing data is denoted in parentheses): employment change (239), PC change (1,094), sales change (180), exports (1), on the job training (6), and education (15). For continuous control variables (sales change, exports, on the job training, and education), I performed single imputation. I did not perform imputations for my dependent and key independent variables. A series of t-tests suggest that there was no notable difference in cell phone use, Internet use, type of ownership, firm age, and location characteristics between observations for whom sales change, exports, on the job training, and education data were imputed and observations for whom these data were not imputed. I did not find statistically significant difference between my key independent variable in regression results when I exclude imputed data from my analysis. In total, among observations with valid values for the dependent and key independent variables, 39 percent had missing values for controls. After performing imputations, I am left with 490 observations with non-missing values for all of the variables included in the regression. The remaining observations in the dataset are excluded from my analysis.

[15] In this survey, there are three different weights available for use. Here, I rely on the weighting scheme recommended by the survey's administrators. My results are not substantially different when I use the other sets of weights available in the survey.

Table 2. Descriptive Statistics for Dependent, Key Independent, and Control Variables

Dependent Variable	Mean	SD	Min	Max
Employment Change (%)	7.03	107.51	-87	119
Key Independent Variable				
Personal Computer Use Change (%)	17.12	66.91	-80	34
Firm Factors				
Sales Change (%)	152.60	2049.80	-1887	174913
Firm Age (Years)	9.39	5.67	1	86
Exports (%)	4.82	10.19	0	100
On the Job Training (%)	36.44	48.11	0	100
Ownership Type				
Private Domestic Ownership (%)	70.79	43.97	0	100
Government Ownership (%)	0.10	2.32	0	97
Private Foreign Ownership (%)	28.94	43.89	0	100
Other Ownership (%)	0.17	4.06	0	100
Location of Firms				
Capital City (%)	55.05	49.80	0	100
Other; 250,000 - over 1 million (%)	39.79	49.00	0	100
Other; 50,000 - 250,000 (%)	3.61	18.67	0	100
Under 50,000 (%)	1.55	12.38	0	100
Firm Workforce Factors				
Workers w/ University Degree (%)	42.94	29.83	0	100
Technology Factors				
Cell Phone Use (%)	98.94	10.26	0	100
Internet Use (%)	97.67	15.10	0	100
N=490				

Table 3 reports mean values for my dependent, key independent, and control variables disaggregated by country. Tajik firms have the greatest average employment change at approximately 85 percent and also experienced the largest growth in computer use, at around 50 percent. Among the remaining three subsamples, firms in Kazakhstan and Kyrgyzstan experienced lower relative employment and PC use growth, than did Uzbekistan. Firms are youngest in Kyrgyzstan, at an average of 8.6 years, whereas Tajikistan firms are the oldest, at an average of 14 years.[16] Private domestic ownership is lowest (47 percent) in Kyrgyzstan. However, Kyrgyz firms have the highest share of skilled (university-educated) workers at 62 percent. Tajik firms are more likely to offer on-the-job training (73 percent).

Table 3. The Means of Dependent, Key Independent, and Control Variables Disaggregated by Country

Dependent Variable	Kazakhstan	Kyrgyzstan	Tajikistan	Uzbekistan
Employment Change (%)	3.56	5.2	85.08	49.09
Key Independent Variable				
Personal Computer Use Change (%)	15.32	17.05	50.43	23.81
Firm Factors				
Sales Change (%)	13.43	207.1	1590.03	199.83
Firm Age (Years)	10.06	8.63	14.30	10.89
Exports (%)	0.02	8.09	4.15	9.40
On the Job Training (%)	0.41	55.24	72.92	39.00
Ownership Type				
Private Domestic Ownership (%)	98.71	47.62	95.28	81.10
Government Ownership (%)	0.01	0.01	1.22	3.04
Private Foreign Ownership (%)	0.89	52.37	3.13	15.87
Other Ownership (%)	0.39	0.00	0.36	0.00
Location of Firms				
Capital City (%)	0.62	99.23	19.69	48.21
Other; 250,000 - over 1 million (%)	94.16	0.00	0.00	6.74
Other; 50,000 - 250,000 (%)	3.36	0.25	72.58	29.53
Under 50,000 (%)	1.87	0.52	7.73	15.53
Firm Workforce Factors				
Workers w/ University Degree (%)	19.58	62.01	35.50	30.40
Technology Factors				
Cell Phone Use (%)	98.09	99.86	93.18	97.76
Internet Use (%)	97.87	99.45	86.23	59.83
Observations	**192**	**159**	**92**	**47**

[16] International Labour Organization's World Employment and Social Outlook 2017 report canvased multiple studies to define firms' age as young (0-5 years), mature (6–10 years), or old (11+ years).

REGRESSION RESULTS

The results of my regressions are summarized in Table 4. Column 1 reports results for a bivariate regression. Column 2 is a multivariate regression, where I control for a variety of characteristics, including ownership type, location, workforce, and technology factors. Column 3 adds country fixed effects, which control for unobserved country-level characteristics that are common to all the firms in a given country. Column 4 is fully specified, adding industry fixed effects. Industry fixed effects allow me to control for unobserved industry-level characteristics that are common to all firms in a given industry. In columns 5 and 6, I report results for models that include interactions between change in the employees' PC use and firm age and location in a country's capital city.

The results shown in Table 4 reject my hypothesis that a firm's employment levels are likely to decline with PC use by its employees. The results show no statistically significant relationship between changes in employment and changes in PC use. Moreover, the magnitudes of the estimated coefficients are extremely small.[17]

In column 5, I use an interaction term to test whether the relationship between the percent change in the number of workers who use PCs and employment change is different for firms located a capital city. The magnitude of this relationship for firms in a capital city (-0.016 + 0.103= 0.09) is comparatively large and positive, However, as can be seen from the F-test result at the bottom of Table 3, it is not statistically significant at conventional levels. For firms that are not located in a capital city, the relationship is negative, much smaller (-0.02), and not statistically significant at conventional levels.

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[17] Appendix 1 provides full-model regression results disaggregated by country, where only in Kazakhstan is the coefficient on the change in PC use positive and statistically significant at the 10 percent level.

In column 6, I use another interaction term to test for whether or not the relationship of interest is different for firms with workers that have a university degree. As can be seen from the F-test result at the bottom of Table 4, model 6, the magnitude of this relationship for employees at firms whose workforces are above the median in university degree attainment (-0.026+0.046 = 0.02) is positive, but extremely small, and not statistically significant at conventional levels.

The only variable in my regressions that has a statistically significant relationship with employment change across all models is exports. The sign and magnitude of this variable also remain stable across all models. In the full model (column 4), the coefficient on exports implies that a one percentage point increase in the share of a firm's output that is exported is associated with a 1.4 percentage point reduction in the change in employment over time. In other words, as Central Asian firms increase exports, they are more likely to reduce their employment levels. This finding suggests opportunities for additional research.

The R-squared for all six of my regressions is quite low. Clearly, these regressions fail to capture the key determinants of employment change in the Central Asian countries that I examine. Overall, my results suggest that there is no meaningful relationship between the change in PC use and the change in employment among firms in Central Asia. This is true for my sample overall and when I disaggregate my analysis to explore variation in the relationship according to whether firms are located inside or outside the capital city and the level of education of their workers.

Table 4. Main Regression Results: the Percentage Change in Firms' PC Adoption and Workforce Size in Central Asia

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
Employment Change (%)	Bivariate OLS	Multivariate OLS	Country Fixed Effects	Country & Industry Fixed Effects	County & Industry Fixed Effects w/ Interaction	County & Industry Fixed Effects w/ Interaction
PC Use Change (%)	0.051	0.017	0.010	-0.000	-0.016	-0.026
	(0.032)	(0.029)	(0.034)	(0.042)	(0.035)	(0.058)
Firm Factors						
Sales Change (%)		-0.001	-0.001	-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Age (Years)		0.968	0.896	1.047	1.068	1.304
		(1.415)	(1.295)	(1.469)	(1.458)	(1.470)
Exports (%)		-1.370**	-1.469**	-1.431**	-1.405**	-1.476***
		(0.625)	(0.649)	(0.636)	(0.644)	(0.568)
On the Job Training (%)		0.035	0.032	0.021	0.0167	0.101
		(0.122)	(0.124)	(0.119)	(0.116)	(0.106)
Ownership Type						
Private Domestic Ownership (%)		0.110	-0.016	-0.502	-0.502	-0.538
		(0.199)	(0.278)	(0.406)	(0.404)	(0.422)
Government Ownership (%)		-0.671	-1.312	-1.860	-1.860	-2.004*
		(0.797)	(0.941)	(1.211)	(1.208)	(1.215)
Private Foreign Ownership (%)		0.260	0.157	-0.367	-0.332	-0.339
		(0.221)	(0.267)	(0.330)	(0.340)	(0.369)
Location of Firms						
Capital City (%)		-0.027	-0.066	-0.035		-0.092
		(0.140)	(0.258)	(0.276)		(0.285)
Capital City (Dummy)					-2.836	
					(27.550)	
Other; 50,000 to 250,000 (%)		0.181	-0.229	-0.231	-0.199	-0.298
		(0.184)	(0.344)	(0.341)	(0.283)	(0.355)
Other; 50,000 or less (%)		0.857	0.711	0.739	0.762	0.693
		(0.580)	(0.630)	(0.659)	(0.588)	(0.647)
Firm Workforce Factors						
Workers w/ University degree (%)		0.112	0.143	0.203	0.257	
		(0.283)	(0.269)	(0.288)	(0.305)	
Workers w/ University Degree (Dummy)						-10.632
						(11.670)

Table 4. (Cont'd.)

Technology Factors	(1)	(2)	(3)	(4)	(5)	(6)
Cell Phone Use (%)		-0.571	-0.572	-0.799	-0.775	-0.851
		(0.813)	(0.779)	(0.907)	(0.920)	(0.906)
Internet Use (%)		-0.239	-0.082	-0.067	-0.067	-0.044
		(0.218)	(0.306)	(0.296)	(0.294)	(0.298)
Interactions						
PC Use Change*Capital City					0.103	
					(0.110)	
PC Use Change*Workers w/ University Degree						0.046
						(0.054)
F-statistics and p-values for joint hypothesis tests						
H_0: *Personal Computer Use Change + Interaction = 0*					0.500	0.260
					(0.480)	(0.610)
Constant	6.157	61.910	63.130	128.300	121.600	141.700
	(6.688)	(99.030)	(89.510)	(125.600)	(129.500)	(127.700)
Country fixed effects	No	No	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	Yes	Yes	Yes
Observations	490	490	490	490	490	490
R-squared	0.001	0.032	0.042	0.045	0.046	0.045

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

DISCUSSION

My analysis tested the relationship between changes in PC use among Central Asian SMEs and changes in these firms' employment. I expected to find a negative relationship. However, there seems to be no relationship. Although the sign on my key coefficient was as expected, its magnitude was extremely small and not statistically significant at conventional levels.

I attempt to control for as many firm characteristics as possible, and for industry and country fixed effects. However, there are factors that I could not control for and whose omission may exert omitted variable bias in my estimates. For example, gender or, more specifically, the ratio of female to male full-time permanent workers might upwardly bias my coefficient of interest. I hypothesize that female participation may be negatively related to changes in PC use because women in developing countries have tended to be comparatively late adopters of technology (Doss & Morris, 2000; Mishra et al., 2015). I also hypothesize that female participation may be negatively related to changes in employment because women are a more vulnerable population than men in Central Asia (Strokova et al., 2017). If these hypotheses are correct, then the omission of a gender variable would upwardly bias my estimate of the relationship between the changes in PC use and firm size. Another variable that I could not control for is Internet speed, which plausibly is positively related to both PC use and employment. The omission of this variable may also exert an upward bias on my estimates. It is, therefore, possible that even the small magnitudes reflected in my estimates actually overstate the effect of PC adoption on workforce size and that the relationship might in fact be shown to be positive if I were to control for these variables.

Another constraint in my analysis is the limited variation in the change in PC use within my sample. The degree of saturation (i.e., the proportion of the firm's total full-time permanent workforce who use PCs) changes very little over the two-year timeframe of my study. Thus, there is limited opportunity to estimate a relationship between this change and my dependent variable. Data that provide more variation in PC use would be useful. A panel dataset covering multiple years could provide such variation and, more importantly, allow me to reduce omitted variable bias by estimating a fixed effects model.

In addition, I do not disaggregate my estimates according to worker tasks. Peng et al. (2018), among other scholars, found that the effect of ICT depends on the type of tasks performed (i.e., routine or non-routine) (Acemoglu & Autor, 2010; Autor et al., 2003). Workers performing non-routine, cognitive tasks are less likely to be susceptible to technology-driven substitution. However, my data did not allow me to disaggregate my findings for workers performing routine versus non-routine tasks. A final limitation is that I am only focusing on computers, while there are many other types of IT. Perhaps the adoption of IT more generally has a different effect than the adoption of PCs in particular.

I did find evidence of a relationship (at the 5 percent confidence level) between direct exports as a percent of total sales and changes in employment, which might be an avenue for future research.

CONCLUSION

Disruptive technology is increasingly being adopted in Central Asia. However, at least in regard to PC use and employment, my analysis indicates no meaningful relationship between the two. Policymakers can bear this in mind when they are deciding whether to enable SMEs to improve their access to technologies that increase their productivity and competitiveness.

Ultimately, if technology-driven unemployment in Central Asia is not a threat, policymakers should focus on mechanisms for maximizing the positive impact of technology adoption on economic growth. Most importantly, policymakers should focus on ensuring that workers have the skills needed to unleash the full potential of technology adoption. Investments in technology alone cannot yield meaningful productivity gains without complementary digital skills and policy reforms. In order to complement new technologies, educational programs should ensure that the labor supply in Central Asian countries matches the changing skills demands of firms in these countries' labor markets.

APPENDIX. MAIN REGRESSION RESULTS DISAGGREGATED BY COUNTRY: THE PERCENTAGE CHANGE IN FIRMS' PC ADOPTION AND WORKFORCE SIZE

Table A-1. Main Regression Results Disaggregated by Country: the Percentage Change in Firms' PC Adoption and Workforce Size

Dependent Variable:				
Employment Change (%)	Multivariate OLS w/ Country & Industry Fixed Effects			
	Kazakhstan	Kyrgyzstan	Tajikistan	Uzbekistan
PC Use Change (%)	0.0209*	0.107	-0.047	-1.315
	(-0.012)	(-0.068)	(-0.166)	(-1.878)
Firm Factors				
Sales Change (%)	0.003	-0.0460***	0.000	0.106
	(-0.005)	(-0.015)	(-0.001)	(-0.125)
Firm Age (Years)	-0.18	-2.054	26.49***	-5.803
	(-0.138)	(-2.024)	(-7.923)	(-6.197)
Exports (%)	-0.318	-0.441	-5.987	-0.850
	(-0.229)	(-0.509)	(-3.867)	(-1.586)
On the Job Training (%)	0.0758*	-0.129	0.116	-2.247
	(-0.0416)	(-0.203)	(-1.076)	(-2.165)
Ownership Type				
Private Domestic Ownership (%)	-0.199	0.354**	-1.853	-3.008
	(-0.192)	(-0.150)	(-2.201)	(-3.074)
Government Ownership (%)	8.298***	-0.567**	-11.6	-1.956
	(-1.737)	(-0.283)	(-7.819)	(-3.032)
Private Foreign Ownership (%)	-0.073		-4.317	
	(-0.231)		(-4.735)	
Location of Firms				
Capital City (%)	0.050			-0.214
	(-0.086)			(-1.354)
Other; 50,000 to 250,000 (%)	0.106	-0.084	-0.244	1.449
	(-0.103)	(-0.201)	(-1.262)	(-1.010)
Other; 50,000 or less (%)	0.193*	0.183	5.734***	0.257
	(-0.107)	(-0.158)	(-1.991)	(-0.794)
Firm Workforce Factors				
Workers w/ University Degree (%)	0.154**	1.390**	2.329	-1.943
	(-0.069)	(-0.632)	(-2.280)	(-4.557)
Technology Factors				
Cell Phone Use (%)	0.020	0.311	-5.852**	0.106
	(-0.114)	(-0.270)	(-2.651)	(-0.781)

Table A-1. (Cont'd.)

Technology Factors	Kazakhstan	Kyrgyzstan	Tajikistan	Uzbekistan
Internet Use (%)	0.035	-0.242	-2.229*	2.102
	(-0.075)	(-0.187)	(-1.217)	(-2.643)
Constant	9.919	-38.950	608.80	333.7
	(-30.89)	(-29.49)	(-489.6)	(-373.4)
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	192	159	92	47
R-squared	0.414	0.720	0.183	0.239

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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