Exploring the IT Productivity Paradox in Higher Education: The Influence of IT Funding on Institutional Productivity

Justin C. Ortagus, Dennis A. Kramer II & Mark R. Umbricht

To cite this article: Justin C. Ortagus, Dennis A. Kramer II & Mark R. Umbricht (2017): Exploring the IT Productivity Paradox in Higher Education: The Influence of IT Funding on Institutional Productivity, The Journal of Higher Education

To link to this article: http://dx.doi.org/10.1080/00221546.2017.1341756

Published online: 06 Jul 2017.
Exploring the IT Productivity Paradox in Higher Education: The Influence of IT Funding on Institutional Productivity

Justin C. Ortagus, Dennis A. Kramer, II, and Mark R. Umbricht

ABSTRACT
Information technology (IT) spending has increased in every sector of higher education during the past decade despite a lack of meaningful data pertaining to its impact on productivity. This study, which was guided by the production theory, used a unique data set and dynamic fixed-effects panel model to examine the relationship between IT funding and institutional productivity in the form of teaching, research, and service outputs. Findings revealed that investments in IT are positively related with teaching and service outputs for private and nondoctoral institutions, whereas investments in IT are positively associated with research outputs for public and doctoral institutions.

ARTICLE HISTORY
Received 18 January 2016
Accepted 22 May 2017

KEYWORDS
Dynamic fixed effects; information technology; IT funding; productivity; technology

Introduction
Within higher education, information technology (IT) refers to the provision of computer-based support and services for administrative functions, communication systems, infrastructure, research, and teaching and learning. The lure of new technologies has led to IT becoming an essential component of higher education operations, with institutional investments in IT increasing in every sector of higher education during the past decade (Lang, 2014). More specifically, IT spending increased from $765 per full-time student in 2002 (Hawkins, Rudy, & Madsen, 2003) to $925 per full-time student in 2013 (Lang, 2014). Although technological advances are typically adopted under the guise of improving productivity, colleges and universities continue to increase their investment in technology despite a lack of meaningful data pertaining to its impact on productivity (Archibald & Feldman, 2011; W. G. Bowen, 2013).

Archibald and Feldman (2011) showed that productivity measures for education services have actually declined since the 1980s. Although this and other claims of declining productivity in higher education may be overstated, technological progress has not improved productivity in higher education.
education in the same way advances in technology have improved the productivity of other sectors, such as manufacturing (W. G. Bowen, 2013). Many higher education institutions continue to employ duplicative processes in their daily operations, as different units within a college or university may be paying numerous people to do a very similar job (Coccia, 2009; Proenza & Church, 2011). As these organizational redundancies have been identified over the years, critics have called on colleges and universities to centralize their operations in areas that share basic functions, such as IT, finance, and human resources, to reduce costs (Proenza & Church, 2011).

From research to instruction, technological improvements have revolutionized the way colleges and universities operate, but little is known of the impact of these improvements. While IT has the potential to replace expensive labor and supplement cheaper labor (Archibald & Feldman, 2011; Cheslock, Ortagus, Umbricht, & Wymore, 2016), extant literature has yet to empirically examine the relationship between increases in IT funding and institutional productivity. To explore the relationship between investments in technology and the productivity of colleges and universities, this study will address the following research question: Does IT funding influence the productivity of colleges and universities?

**Literature review**

Researchers across disciplines rarely agree on the appropriate metric to use when assessing productivity. Consequently, management literature has revealed mixed results pertaining to the impact of technology spending on organizational productivity. Brynjolfsson (1993) conducted a review of empirical studies pertaining to the relationship between IT and productivity. Despite continued technological improvements over time, productivity—particularly in the service sector—did not appear to improve during the corresponding time periods. Given this disconnect between expectations and statistics, Brynjolfsson identified two shortcomings in research as potential explanations for the productivity paradox: mismeasurement of productivity and failure to account for lags due to learning and adjustment. Regarding the latter, Brynjolfsson, Malone, Gurbaxani, and Kambil (1994) found lags of 2 years before the strongest organizational impacts of IT were experienced.

**Improving quality**

Previous studies examining organizations within the corporate sector have offered conflicting findings related to the value of technology. Carr (2003) conducted an observational study and found that technology did not offer a strategic advantage for companies, but Collins (2001) utilized longitudinal
data to conclude that technology can be used to improve an organization’s performance relative to its market competitors. Fahy (2007) found that corporations were more likely to use technology to experience performance enhancement rather than increase their productivity or profitability. In addition, Oberlin (1996) suggested that technology may enhance the quality of operations, but it is not likely to reduce overall costs. Although technology-based operations may improve performance, they are not typically cheaper than the dated processes being replaced.

In higher education, IT has not appeared to increase administrative productivity in terms of efficiencies and cost savings (Archibald & Feldman, 2011; W. G. Bowen, 2013; Clotfelter, 1996; Hawkins & Oblinger, 2005; Martin, 2005), but increases in technology have been linked to corresponding increases in research productivity (Archibald & Feldman, 2011; Clotfelter, 1996; Mills, 2008) and learning productivity (Archibald & Feldman, 2011; Mills, 2008). According to Archibald and Feldman (2011), technology-induced changes throughout higher education are often implemented to enhance the quality, rather than the productivity, of a given product or service. Technological improvements in recent years have led to significant changes in the way higher education institutions conduct research, teach students, manage operations, and assess outcomes (Brint, 2002; Mills, 2008).

IT has helped to remove many of the geographic barriers previously inherent in higher education, as many working or place-bound postsecondary students are now able to register for classes, pay student fees, meet with an advisor, or attend orientation from a distance. IT can also be used to support teaching practices with instructional technologies and advance knowledge through research. However, the fixed (or upfront) costs associated with the equipment, training, and personnel required to implement IT and its capital infrastructure are substantial and seldom understood (Finkelstein & Scholz, 2000).

**IT productivity paradox**

You can see the computer age everywhere but in the productivity statistics. (Robert Solow [1987], economist and Nobel laureate, Massachusetts Institute of Technology)

The IT productivity paradox has been described as the tendency for computerization to fail to improve standards of productivity. Jones, Heaton, Rudin, and Schneider (2012) explained the IT productivity paradox by suggesting that “important dimensions of service output such as accessibility and convenience—factors that are greatly improved by IT—are difficult to quantify and are rarely captured by productivity metrics” (p. 2243). Although Jones et al. studied the IT productivity paradox in relation to the health industry,
many of their core arguments connect to the use of IT in higher education, such as the tendency of online instruction to simply mimic the face-to-face learning experience by videotaping lectures instead of transforming the teaching process (W. G. Bowen, 2013).

IT costs are expected to continue to rise in future years (Camp & DeBlois, 2007), but evidence of corresponding gains in productivity are lacking in the literature. Technological improvements within the higher education sector have not appeared to affect administrative productivity, enhance efficiencies, or generate cost savings (Archibald & Feldman, 2011; W. G. Bowen, 2013; Clotfelter, 1996; Martin, 2005; Mills, 2008). Although Martin (2005) characterized higher education as inefficient in its employment of IT personnel, Clotfelter (1996) suggested that the failure of computers and other technological innovations to bring reductions in staffing in higher education did not necessarily mean future reductions in personnel could not eventually occur in later years.

**Instructional technologies**

Instructional technologies have the potential to increase flexibility and improve access for working or place-bound postsecondary students (Christensen & Eyring, 2011; Jefferson, 2006). Massy and Zemsky (1995) outlined the potential of instructional technologies to increase economies of scale such that more students can be taught by fewer faculty. The authors stated that increases in technology typically increase costs, but nonprofit higher education must find a way to scale instructional technologies and thereby improve the productivity of faculty to curb labor costs, decrease or maintain tuition, and compete with for-profit institutions. The University of Illinois (1999) reported that increasing the scalability of online courses would result in diminished quality of learning despite considerable investments of time and resources. The researchers claimed that high fixed costs associated with the implementation of instructional technologies would not be recouped. However, Lack (2013) found that empirical studies of the quality of online courses have been largely inconclusive. Sullivan, Mackie, Massy, and Sinha (2012) cautioned against simplified measures of productivity as “quality should always be a core part of productivity conversations, even when it cannot be captured in the metrics” (W. G. Bowen, 2013, p. 6).

Navarro (2000) found that technological problems are frequent for faculty engaging with instructional technologies, which may require increases in the number of personnel needed to manage technical support. Navarro examined faculty survey data and determined that fixed costs associated with developing online courses were considerably higher, variable costs of offering the developed online course were surprisingly higher, and the marginal cost associated with the demand on faculty time to educate each student in an
online setting was much lower when compared with face-to-face offerings. Due to the total costs associated with online course development, maintenance, complications, infrastructure, and technical support, costs of instructional technologies and online courses would not appear to be less than the costs associated with face-to-face delivery.\(^3\)

**The impact of technological improvements**

Archibald and Feldman (2011) argued “that the primary impact of technological progress in higher education has been to change what we do and how we do it rather than to lower the cost of the existing ‘output’ or the current way of doing things” (p. 67). Unlike organizations in many other sectors, colleges and universities do not necessarily adopt new technologies to lower production costs or produce the same output with less input. Although new technologies are typically implemented with the intent of reducing costs, higher education continues to experience rising costs alongside its technological improvements.

Technology-induced changes may not necessarily cut costs, but researchers have argued that colleges and universities cannot afford to not adopt new techniques associated with technological improvements (Archibald & Feldman, 2011; Bement, 2007). Higher education institutions face a unique obligation to implement technological advances to develop new or improved teaching methods and content delivery to advance knowledge and meet the demand for lifelong learning (Duderstadt, Atkins, & Douglas, 2002). Similar pressures are associated with the advancement of knowledge through scholarship (Geiger, 2004) and improvements in access for underrepresented student populations (Rhoades, 2001). Many of the studies outlined previously have provided anecdotal or observational findings without empirically examining the influence of investments in technology on the productivity of colleges and universities, which may help to explain the contrasting claims offered throughout extant scholarship.

**Conceptual framework**

This study was guided by concepts from the production theory,\(^4\) which describes the relationship between outputs, such as degrees awarded, and a combination of inputs, such as capital and labor (Hopkins, 1990; Hopkins & Massy, 1981; Johnes, 1996). Previous researchers have argued that attempts to identify a single overall measure of educational output are unrealistic; however, one can use multiple measures that are sufficiently broad to capture the key outcomes associated with the provision of higher education (Hopkins, 1990). For colleges and universities, output measures drawn from production theory should relate to the three primary missions of higher
education: the transmission of knowledge (instruction), the creation of
knowledge (research), and public service (Hopkins, 1990; Hopkins &
Massy, 1981). Several additional researchers have categorized the primary
outputs of colleges and universities as output from teaching activity, output
from research activity, and output from service to the public good
(Hendrickson, Lane, Harris, & Dorman, 2013; Johnes, 1996).

As a result, this analysis specified the following output variables to exam-
ine the production of instruction, research, and service at colleges and
universities: bachelor’s degrees awarded per full-time-equivalent (FTE) stu-
dent, total research funds per FTE student, and the proportion of minority
students enrolled at the institution. Previous research has examined bache-
lor’s degrees awarded (Titus, 2009) and research output (Johnes, 1996)
through the lens of production theory, but measures of service to the public
good have been largely missing in empirical work studying the productivity
of colleges and universities. In a review of the literature pertaining to
productivity in higher education, Rhoades (2001) argued that higher learning
is the catalyst for achieving upward mobility and social justice, suggesting
that “higher education should focus on the public interest, as defined in part
by increasing access” (p. 629). We specified the proportion of underrepre-
sented minority students at a college or university to measure, at least in part,
its service to the public good.

The specification of the combined inputs is also critical to any application
of the production theory. To measure whether institutions are using IT to
enhance productivity, we specified the capital-to-labor ratio as the primary
input, as represented by the ratio of IT costs to total labor costs. By increas-
ing its capital-to-labor ratio, a college or university would effectively be
increasing its commitment to technology and shifting resources away from
the handicraft mode of operations (Massy & Zemsky, 1995). This study used
concepts from the production theory to examine whether the productivity of
colleges and universities is influenced by this shift in resources toward
technology.

Massy and Zemsky (1995) outlined two major ways in which IT can
improve labor productivity in higher education: (a) IT allows institutions
to achieve economies of scale such that high fixed costs can be recouped
through decreases in variable costs per student. (b) IT, particularly central IT,
offers the potential for mass customization, which suggests that IT can
provide flexibility for its consumers and low per-student costs due largely
to mass transmission and production of information. This study aimed to
examine the relationship between IT and productivity in higher education,
but such an analysis brings considerable challenges.

W. G. Bowen (2013) and other researchers have noted that measuring
productivity in higher education is extremely challenging for numerous
reasons, including the joint production of outputs (Cheslock et al., 2016;
National Research Council, 2012; Paulsen & Toutkoushian, 2006) and the difficulty associated with measuring hidden productivity growth in the form of qualitative or intangible improvements (Archibald & Feldman, 2011; Cheslock et al., 2016; Hopkins & Massy, 1981). Johnes (1996) also described similar challenges associated with the practical application of the production theory to the higher education sector. Despite these complexities, the production theory provides a useful framework within which to identify the relationship between IT and productivity in higher education.

Data and methods

Sample

In this study, we constructed a panel data set drawing data from the Integrated Postsecondary Education Data System (IPEDS), the National Science Foundation (NSF) WebCASPAR database, and the EDUCAUSE Core Data Service (CDS) Survey. IPEDS is a National Center for Education Statistics (NCES) survey that collects data from all institutions that offer federal financial aid on numerous topics, such as enrollments, finances, and human resource data. The NSF WebCASPAR database provides information on science and engineering resources, such as degree production and research funding, at academic institutions throughout the United States. Data are collected through six surveys sponsored by NSF and four additional surveys sponsored by the NCES. Finally, the EDUCAUSE CDS Survey is a benchmarking resource that provides comparative data to inform IT strategic planning and management for participating higher education institutions. The annual survey collects IT staffing, financial, and service data at participating colleges and universities during the previous year. Higher education institutions that completed the EDUCAUSE CDS Survey from 2005 through 2013 were included in this study. Data retrieved from IPEDS and WebCASPAR covered 2004 through 2011. These years were selected because they correspond with the 2005 through 2013 EDUCAUSE CDS Surveys. EDUCAUSE CDS Surveys from 2005 to 2009 used data from the previous fiscal year, meaning the 2005 EDUCAUSE CDS Survey included data from the 2004 to 2005 fiscal year. To ensure we covered an equivalent time frame, we merged 2004 IPEDS and WebCASPAR data, which also covered the 2004 to 2005 fiscal year. After 2010, EDUCAUSE changed its naming scheme such that the 2011 EDUCAUSE CDS Survey reported data from Fiscal Year 2009 to 2010, which corresponds with 2009 IPEDS and WebCASPAR data. After accounting for all the previously mentioned changes, 8 years of EDUCAUSE CDS, IPEDS, and WebCASPAR data were used for this study.
There were 6,436 observations covering the 8 years of EDUCAUSE CDS Surveys across 1,519 institutions. Institutions that were classified as international or as missing key data related to IT or human resource variables were removed from the sample. Four additional institutions were removed from our sample because they were reported as part of a system, rather than an individual institution. We ran additional specifications modeling lags of 1 year and 2 years to account for the possibility of delayed effects, so higher education institutions with fewer than 4 consecutive years of EDUCAUSE CDS Survey data were removed to ensure a consistent sample of institutions. After the identified changes were made, a total of 587 colleges and universities were included in the analysis.

To show how EDUCAUSE-participating institutions within our sample compare with 4-year colleges and universities throughout the U.S. population, we merged IPEDS data with the corresponding EDUCAUSE CDS Surveys. Table 1 provides characteristics of the student composition, financial indicators, and staffing composition of institutions within the sample and population for comparative purposes. EDUCAUSE-participating institutions within the sample, on average, have more FTE students, a lower proportion of students receiving federal Pell Grants, higher tuition and fees, and more staff members. All other characteristics, such as the proportion of minority students and total expenditures per FTE student, were relatively similar for colleges and universities within the sample and overall population.

**Variables**

**Dependent variables**
In line with our conceptual framework, the dependent variables measured outputs related to the three core areas of institutional productivity in higher

<table>
<thead>
<tr>
<th>Table 1. Representativeness of sample.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Student Composition</strong></td>
</tr>
<tr>
<td>Total Student FTE</td>
</tr>
<tr>
<td>Percent of Students White</td>
</tr>
<tr>
<td>Percent of Students Receiving Pell</td>
</tr>
<tr>
<td><strong>Financial Indicators</strong></td>
</tr>
<tr>
<td>Total Core Expenditures Per FTE</td>
</tr>
<tr>
<td>Instructional Expenditures Per FTE</td>
</tr>
<tr>
<td>Published In-State Tuition &amp; Fees</td>
</tr>
<tr>
<td><strong>Staffing Indicators</strong></td>
</tr>
<tr>
<td>Total Staff FTE</td>
</tr>
<tr>
<td>Instruction/Research and Public Service FTE</td>
</tr>
<tr>
<td>Executive/Administrative and Managerial FTE</td>
</tr>
</tbody>
</table>

*Note.* FTE = full-time-equivalent. Sample characteristics based on 2011 data, which is the final year of our analytical sample.
education: (a) instruction, (b) research, and (c) service. The number of bachelor’s degrees produced per 100 FTE students represented the outputs for instructional productivity. Because we chose to examine bachelor’s degrees and research funding for this study, the final sample only included 4-year colleges and universities. Research output was measured by changes in total research funding based on data retrieved from the NSF WebCASPAR database. This variable included sponsored research funding from federal and nonfederal agencies, research funds received as part of a subcontract, research training grants intended to fund organized research, and a few others. To account for variations in institutional size, the research output variable was also adjusted per FTE student. As described earlier, outputs measuring service to the public good were complicated to measure, but this study followed Rhoades’s (2001) conceptualization that the public interest is served by increasing access to higher education. As a result, we measured service output by examining changes in the proportion of underrepresented minorities at a given college or university.

**Independent variables**

To examine whether colleges and universities invest in IT to improve productivity, we measured the IT capital-to-labor ratio, as represented by the ratio of IT costs to total labor costs on salaries and benefits. According to Massy and Zemsky (1995), the use of IT to improve productivity will increase the ratio of IT costs to total labor costs. Due to changes made to the EDUCAUSE CDS Survey after 2009, this study could only measure central IT funding as opposed to total IT funding. In higher education, a central IT unit is distinct from decentralized units in that a central IT unit typically streamlines its efforts and reports to a single administrator, whereas decentralized IT units operate independently within individual departments or local units throughout the institution. Previous research has shown that senior leaders who increase or decrease technology spending typically focus specifically on central IT support and services (Voloudakis, 2010).

We also included numerous control variables to account for confounding factors in these analyses. Because the IT capital-to-labor ratio only captures central IT funding, as opposed to total IT funding, we controlled for the proportion of decentralized IT staff. Although EDUCAUSE CDS Surveys do not capture decentralized IT funding, we were able to approximate the level of centralization of IT at the institution through the inclusion of the percentage of decentralized IT staff. We also accounted for differences by institution types by controlling for urbanicity, Carnegie classification, sector, and the historically Black college and university status of the institution. In addition, we controlled for institution size and scope by including the number of FTE undergraduate and graduate students, instructional spending per FTE student, and the total institutional budget at the college or university.
To examine the influence of changes in personnel, we controlled for FTE counts of the following categories of higher education employees: central IT professionals, tenured or tenure-track faculty, fixed-term faculty, clerical staff, executive/administration personnel, and other professionals. The category of central IT professionals included the total number of FTE central IT staff according to the corresponding EDUCAUSE CDS Survey. The remaining variables represented the higher education employee category as indicated by the primary function or occupational activity referenced in the IPEDS Human Resources Surveys.

Analytic strategy

In this study, we used a dynamic fixed-effects (DFE) panel model combined with a system of equations (generalized method of moments [GMM]) to analyze our data (Blundell, Bond, & Windmeijer, 2000; Bond, 2002; Hansen, 1982; Roodman, 2006). For researchers seeking to assess outcomes using panel data, difficulties arise after discovering that previous outcomes are correlated with current outcomes. In this study, we anticipated that previous levels of productivity output would be relevant predictors of future productivity output values. Although one could attempt to resolve the problem by introducing a lagged version of the dependent variable to the righthand side of the regression equation, both standard ordinary least squares (OLS) and fixed-effects regression models would produce biased estimates (Kiviet, 1995; Nickell, 1981). Consequently, numerous researchers have turned to dynamic models, such as DFE via GMM, to allow a lagged dependent variable as a regressor (Arellano & Bond, 1991; Blundell & Bond, 1998).

Within higher education literature, this analytic strategy has been used to examine the influence of state higher education finance on the production of bachelor’s degrees (Titus, 2009), how changes in student loan interest rates affect student loan volume (Austin, 2010), and whether the provision of financial aid yields financial benefits to public colleges and universities (Hillman, 2012). Hillman (2012) suggested that DFE models are preferable to two-stage least square methods because these models produce a larger number of instruments from within the existing data set and minimize the problem of weak or invalid instruments (Bond, 2002; Wooldridge, 2002). Estimates produced by DFE models are thereby considered consistent, efficient, and robust to endogeneity. The DFE model also accounts for unobserved variables that have an effect within and across institutions while allowing for the inclusion of time-invariant variables, such as institutional characteristics, which cannot be modeled using fixed-effects models.

For this study, the reduced form of the structural model was estimated by:

\[ y_{i,t} = \alpha y_{i,t-1} + \gamma W_{i,t} + \gamma_2 X_{i,t} + \eta + \lambda_t + \varepsilon_{i,t} \]  

(1)
where $y_{i,t}$ is the dependent variable (number of bachelor’s degrees awarded, underrepresented minority percentage, and total research funding), $\gamma$ is the coefficient, $W$ is a vector of endogenous variables, $X_{it}$ is a vector of endogenous variables, $\eta_i$ is the institution-specific effect, $\lambda_t$ is the year-specific effect, and $\epsilon_{i,t}$ is an error term. Institution-specific factors that are not accounted for in the vector of exogenous variables $X_{it}$ are present in this equation. These time-invariant, institution-specific effects were accounted for by taking the first difference of Equation 1, which can be written as:

$$y_{i,t} - y_{i,t-1} = \alpha(y_{i,t-1} - y_{i,t-2}) + \gamma_1(W_{i,t} - W_{i,t-1}) + \gamma_2(X_{i,t} - X_{i,t-1}) + \lambda_t + \epsilon_{i,t} - \epsilon_{i,t-1}$$  

(2)

The lagged dependent variable in Equation 2 ($y_{i,t} - y_{i,t-1}$) and the variables in vector $W$ are endogenous. As a result, OLS or fixed-effects regression analyses would have led to biased estimates (Kiviet, 1995; Nickell, 1981). Given these dynamics, previous researchers have recommended the use of system GMM estimation (Arellano & Bover, 1995; Blundell & Bond, 1998), which addresses the issue of reverse causality through its inclusion of lagged dependent variables on the right side of the equation. The GMM estimation also uses an instrument matrix including previous levels and differences of both lagged dependent and independent variables as instruments. Using a system GMM estimation, the previous equation can be rewritten in the following way:

$$y_{i,t} = \alpha + \beta y_{i,t-1} + \gamma_1(W_{i,t} - W_{i,t-1}) + \gamma_2(X_{i,t} - X_{i,t-1}) + \lambda_t + \epsilon_{i,t} - \epsilon_{i,t-1}$$  

(3)

Equation 3 represents our DFE model, where $\beta$ represents the coefficient of the lagged dependent variable. Combining Equations 1 and 3, a system of equations can be estimated here with the following equation:

$$y_i = W_i\delta + i_i\eta_i + v_i$$  

(4)

where $\delta$ represents the coefficients and $\lambda$ from Equation 3, while $W_i$ is a matrix that includes the lagged dependent and lagged differences of the endogenous variables. The $\eta_i$ term is the institution effect and $v_i$ represents the error term. By using a GMM estimator, institution-specific effects are unlikely to be correlated with the instruments (Arellano & Bover, 1995; Blundell & Bond, 1998).

The inclusion of too many instruments can complicate this type of model and lead to an inflation of the consistency of parameter estimates (Roodman, 2009). To avoid this complication, the general rule is to ensure the number of instruments does not exceed the number of groups in the model, leading to biased estimates and overspecification of the model (Hillman, 2012).
study used a total of 415 instruments and 485 groups. Finally, system GMM was used with a finite sample correction procedure to produce robust standard errors and avoid the production of standard errors with a downward bias (Windmeijer, 2004).

**Limitations**

This study had numerous limitations. First, EDUCAUSE CDS Surveys only measure funding, as opposed to expenditures, of central IT units. This study operated under the assumption that central IT units will spend most, if not all, of the money they receive. Drawing from Bowen’s revenue theory of cost (H. R. Bowen, 1980), we were confident that central IT units typically spend the vast majority, if not all, of their available funding. Second, EDUCAUSE CDS Survey data only have measures for central IT funding and not total IT funding. Although senior leaders who increase or decrease technology spending typically focus on central IT services (Voloudakis, 2010), we chose to be cautious and generated a control variable for each model that accounted for the degree to which IT staff and services are centralized (or decentralized) at each institution.

Third, we were unable to include the EDUCAUSE CDS Survey from 2014 because it based its responses on IPEDS Human Resources Survey data from 2012. Unfortunately, IPEDS changed its classifications of employee types in 2012, which caused FTE counts to change drastically and would have produced unreliable estimates for the purposes of this study. Fourth, outsourcing is a noteworthy limitation of this study given that colleges and universities may make a substantial investment in IT before merely outsourcing the management of the technology to a third-party company. Such an arrangement would not show up in IPEDS data. We sought to create a variable to represent outsourcing and address this potential issue, but changes across the EDUCAUSE CDS Surveys led to unstable estimates that could not be included in the models. Finally, extant literature pertaining to IT and productivity in higher education is fairly limited. IT in higher education is an understudied topic area, and many of the empirical studies related to IT or productivity are older and from other sectors. Given that technology is constantly changing, limitations associated with the available literature should be noted.

**Results**

Table 2 provides descriptive statistics for the output variables for instruction, research, and service. Descriptives for the variables included in the IT capital-to-labor ratio and each higher education employee type can also be found in Table 2. Figures 1 through 3 provide visual depictions of how each of these
variables have changed over time. Most notably, all types of higher education employees have grown over time except clerical workers, who have been

### Table 2. Descriptive statistics.

<table>
<thead>
<tr>
<th></th>
<th>Total Sample</th>
<th>2004</th>
<th>2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>IT Funding (per FTE)</td>
<td>1,429.14</td>
<td>1,256.81</td>
<td>1,629.23</td>
</tr>
<tr>
<td></td>
<td>(1,290.82)</td>
<td>(1,300.42)</td>
<td>(1,396.67)</td>
</tr>
<tr>
<td>Total Labor Expenditures (per FTE)</td>
<td>18,896.00</td>
<td>16,636.80</td>
<td>20,678.46</td>
</tr>
<tr>
<td></td>
<td>(14,519.68)</td>
<td>(12,680.69)</td>
<td>(16,313.58)</td>
</tr>
<tr>
<td>Bachelor’s Degrees (per FTE)</td>
<td>0.21</td>
<td>0.20</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.047)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Undergraduate Minority Percentage</td>
<td>28.43</td>
<td>27.12</td>
<td>26.07</td>
</tr>
<tr>
<td></td>
<td>(18.39)</td>
<td>(18.84)</td>
<td>(15.36)</td>
</tr>
<tr>
<td>Total Research Funding (Per FTE)</td>
<td>2,728.69</td>
<td>2,231.38</td>
<td>3,301.81</td>
</tr>
<tr>
<td></td>
<td>(7,217.0)</td>
<td>(5,933.74)</td>
<td>(7,905.14)</td>
</tr>
<tr>
<td>IT Employees (FTE)</td>
<td>90.73</td>
<td>86.54</td>
<td>90.18</td>
</tr>
<tr>
<td></td>
<td>(105.88)</td>
<td>(101.05)</td>
<td>(98.09)</td>
</tr>
<tr>
<td>Executive/Admin. Employees (FTE)</td>
<td>119.05</td>
<td>110.28</td>
<td>126.11</td>
</tr>
<tr>
<td></td>
<td>(204.24)</td>
<td>(187.95)</td>
<td>(224.61)</td>
</tr>
<tr>
<td>Other Professional (FTE)</td>
<td>592.93</td>
<td>544.13</td>
<td>647.40</td>
</tr>
<tr>
<td></td>
<td>(1,108.18)</td>
<td>(1,036.01)</td>
<td>(1,273.95)</td>
</tr>
<tr>
<td>Clerical (FTE)</td>
<td>269.87</td>
<td>275.98</td>
<td>253.26</td>
</tr>
<tr>
<td></td>
<td>(389.91)</td>
<td>(406.02)</td>
<td>(378.83)</td>
</tr>
<tr>
<td>Tenured/Tenure-Track Faculty (FTE)</td>
<td>402.57</td>
<td>389.10</td>
<td>406.29</td>
</tr>
<tr>
<td></td>
<td>(461.83)</td>
<td>(450.45)</td>
<td>(460.03)</td>
</tr>
<tr>
<td>Contingent/Nontenured Eligible Faculty (FTE)</td>
<td>158.88</td>
<td>149.88</td>
<td>174.46</td>
</tr>
<tr>
<td></td>
<td>(263.68)</td>
<td>(303.66)</td>
<td>(288.62)</td>
</tr>
</tbody>
</table>

**Note.** IT = information technology; FTE = full-time-equivalent. Standard deviations in parentheses.

**Figure 1.** Percentage change in outputs and information technology (IT) funding per full-time-equivalent (FTE) student.
labeled previously as those who are most susceptible to being replaced by technology (Archibald & Feldman, 2011). Consistent with previous claims of the shrinking proportion of tenure-track and tenured faculty (Kezar & Maxey, 2015; Schuster & Finkelstein, 2006), Figure 3 shows a greater
magnitude in the growth of fixed-term faculty relative to tenure-track and tenured faculty.

Table 3 provides the results from the DFE panel model showing the influence of the IT capital-to-labor ratio on productivity for all 4-year institutions. In line with previous research suggesting that the strongest organizational impacts of IT were experienced after lags of 2 years (Brynjolfsson et al., 1994), the IT capital-to-labor ratio was lagged 2 years. The number of bachelor’s degrees produced was positively related to increases in the IT capital-to-labor ratio (β = 0.316, p < .001). Table 3 also shows a positive relationship between the percentage of underrepresented minority students and the IT capital-to-labor ratio (β = 0.169, p < .01), which suggests that a 10% increase in the IT capital-to-labor ratio is associated with a 1.69% increase in the proportion of underrepresented minority students. Table 4 displays the timing effect of the influence of the IT capital-to-labor ratio on various institutional productivity outputs.
Table 4. Timing effect of IT capital-to-labor ratio on productivity—all 4-year institutions.

<table>
<thead>
<tr>
<th>All 4-Year Institutions</th>
<th>No Lag</th>
<th>1-Year Lag</th>
<th>2-Year Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bachelor's Degrees per 100 FTE</td>
<td>0.005</td>
<td>0.151**</td>
<td>0.338***</td>
</tr>
<tr>
<td>(0.031)</td>
<td>(0.046)</td>
<td>(0.057)</td>
<td></td>
</tr>
<tr>
<td>Percent Undergraduate Minority</td>
<td>−0.041</td>
<td>0.058</td>
<td>0.169**</td>
</tr>
<tr>
<td>(0.041)</td>
<td>(0.063)</td>
<td>(0.063)</td>
<td></td>
</tr>
<tr>
<td>Total Research Funds per FTE</td>
<td>6.654</td>
<td>1.698</td>
<td>11.819</td>
</tr>
<tr>
<td>(8.287)</td>
<td>(6.001)</td>
<td>(12.874)</td>
<td></td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>2,077</td>
<td>2,077</td>
<td>2,077</td>
</tr>
<tr>
<td>Number of Groups</td>
<td>485</td>
<td>485</td>
<td>485</td>
</tr>
</tbody>
</table>

Note. IT = information technology; FTE = full-time-equivalent. Small sample standard errors (Windmeijer, 2004) presented in parentheses. * p < .05. ** p < .01. *** p < .001.

Table 5. Timing effects of IT capital-to-labor ratio on productivity—public and private 4-year institutions.

<table>
<thead>
<tr>
<th>Public 4-Year Institutions</th>
<th>Private 4-Year Institutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Lag</td>
<td>1-Year Lag</td>
</tr>
<tr>
<td>Bachelor's Degrees per 100 FTE</td>
<td>0.080**</td>
</tr>
<tr>
<td>(0.027)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Compared with Public 4-Year:</td>
<td>p &lt; .05</td>
</tr>
<tr>
<td>Percent Undergraduate Minority</td>
<td>−0.018</td>
</tr>
<tr>
<td>(0.037)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Compared with Public 4-Year:</td>
<td>p &lt; .05</td>
</tr>
<tr>
<td>Total Research Funds per FTE</td>
<td>34.586***</td>
</tr>
<tr>
<td>Compared with Public 4-Year:</td>
<td>p &lt; .05</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>227</td>
</tr>
<tr>
<td>Number of Groups</td>
<td>1,174</td>
</tr>
</tbody>
</table>

Note. IT = information technology; FTE = full-time-equivalent. Small sample standard errors (Windmeijer, 2004) presented in parentheses. * p < .05. ** p < .01. *** p < .001.

Table 5 shows the timing effect of the influence of the IT capital-to-labor ratio on productivity when comparing public and private 4-year institutions. In general, public and private institutions appeared to respond differently to increases in the IT capital-to-labor ratio. For public colleges and universities, the specification modeling the preferred 2-year lag revealed that total research funding is positively related to the IT capital-to-labor ratio ($\beta = 70.431$, $p < .001$). For private institutions, the preferred 2-year lag showed that bachelor’s degree production ($\beta = 0.320$, $p < .001$) and the percentage of underrepresented minority students ($\beta = 0.162$, $p < .001$) are positively related to the IT capital-to-labor ratio.

Table 6 provides the timing effect of the impact of the IT capital-to-labor ratio on productivity outputs for doctoral and nondoctoral 4-year
institutions.Doctoralandnondothoral4-yearinstitutionsrespondedsimilarlytopublicandprivateinstitutionsfollowingincreasesintheITcapital-to-laborratio.Fordoctoralinstitutions,thespecificationmodelingthepreferreddoctoral2-yearlagshowedthattotalresearchfundingwaspositivelyrelatedtotheITcapital-to-laborratio ($\beta = 70.101$, $p < .001$).ThisfindingsuggeststhatdoctoralinstitutionsincreaseresearchfundingperFTEstudentby$701.01$innresponseato10%increaseintheITcapital-to-laborratio.Fornondothoralcollegesanduniversities,thepreferrednondoctoral2-yearlagrevealedadivergenteffect,asthenumberofbachelor’sdegreespere100FTEstudents($\beta = 0.306$, $p < .001$)andthepercentageofunderrepresentedminoritystudents($\beta = 0.257$, $p < .001$)werenpositivelyrelatedtotheITcapital-to-laborratio.

### Discussion and conclusions

In response to previous calls for empirical studies on how technological change alters the production of educational outputs (W. G. Bowen, 2013; Schapiro, 1993), this study examined the influence of investments in IT on the productivity of colleges and universities. Despite continual increases in technology funding in higher education (Lang, 2014), technology-induced changes have not been found to improve productivity (Clotfelter, 1996; Martin, 2005). Colleges and universities typically invest in technology to enhance their productivity, but previous researchers have suggested that technological progress in higher education typically fails to achieve that aim (Archibald & Feldman, 2011).
In line with our conceptual framework, we examined productivity outputs related to the three primary missions of higher education—teaching, research, and service (Hopkins, 1990; Hopkins & Massy, 1981). Previous studies have examined bachelor’s degree production (Titus, 2009) and research output (Johnes, 1996) through the lens of production theory, but measures of service to the public good have been scant in empirical research associated with the productivity of colleges and universities. Borrowing from Rhoades’s (2001) argument that higher education is the catalyst for the achievement of upward mobility and social justice, this study extended previous work by specifying the percentage of underrepresented minority students as a proxy for an institution’s service to the public good. To measure whether institutions are using IT to enhance productivity, we specified the IT capital-to-labor ratio by the ratio of IT costs to total labor costs. By increasing its IT capital-to-labor ratio, a college or university would appear to increase its commitment to technology rather than the traditional mode of higher education operations (Massy & Zemsky, 1995).

This study revealed a positive relationship between investments in IT and institutional productivity in the form of bachelor’s degree production and the proportion of underrepresented minority students. However, these findings vary according to institution type given that public institutions respond differently to increases in technology funding when compared with private colleges and universities. While public institutions increase their research productivity, private institutions increase their productivity outputs related to teaching and service. This same general pattern holds when comparing responses by doctoral institutions (research productivity growth) relative to nondoctoral institutions (teaching and service productivity growth). In general, investments in IT capital at the relative expense of investments in labor appear to positively influence productivity gains associated with a college or university’s primary mission. Even though public institutions do not improve productivity outputs intended to serve the public good (by increasing access), previous research has contended that public universities often undertake entrepreneurial behavior in pursuit of research revenues rather than serve the public good (Slaughter & Rhoades, 2004).

These specifications modeling the preferred 2-year lag suggest that the public discourse pertaining to the detrimental impact of investments in technology may be exaggerated, as each institution type included in this study experienced some form of productivity growth. As mentioned earlier, previous researchers examining the benefit of technology typically failed to account for potential time lags due to learning and adjustment (Brynjolfsson, 1993). Brynjolfsson et al. (1994) later identified lags of 2 years before the strongest organizational impacts of IT were experienced. If lags between cost and benefit exist, short-term results may appear to be poor, but the benefit of investments in technology may be significantly larger after allowing for time...
to learn or adjust to the new technology. These timing dynamics could help explain previous claims suggesting that new technologies do not typically improve productivity (Archibald & Feldman, 2011; Fahy, 2007; Massy, 2002; Massy & Zemsky, 1995).

Descriptive findings also revealed some interesting trends, as all categories of higher education employees, except clerical workers, increased over time. The decline in clerical workers and increase in the proportion of IT personnel may give credence to previous claims that technology has allowed colleges and universities to replace relatively low-skilled workers, such as typists or clerical staff, with technology and fewer highly skilled workers charged with administering the networks and offering support for the software. These types of decisions would only make financial sense if colleges and universities are able to leverage technology to achieve economies of scale, as a back-of-the-envelope estimate demonstrates that replacing the median salary of a clerical worker ($46,673) with the median salary of an IT professional ($73,163) would generate a net loss of $26,490 (The College and University Professional Association for Human Resources, 2016).

**Implications for policy and research**

This study makes important contributions to higher education policy and scholarship in several ways. IT has revolutionized the production of higher education, but the suggestion that technological enhancements do not improve institutional productivity—commonly known as the IT productivity paradox—has caused some policymakers and scholars to question the merit of investments in IT. Previous researchers have suggested that notions of the IT productivity paradox are likely due to the difficulty of capturing and quantifying the ways IT improves higher education operations (Cheslock et al., 2016; Jones et al., 2012). For example, Archibald and Feldman (2011) noted that technology has improved the convenience and quality of student services, but those improvements were not reflected by traditional measures of productivity.

Colleges and universities often attempt to measure productivity by examining the number of enrolled students, the number of degrees conferred, or the number of credit hours awarded, yet these productivity metrics only measure the teaching component of the institutional mission and fail to consider research and service outputs alongside the teaching mission (Archibald & Feldman, 2011). We accounted for the multifaceted nature of educational productivity across institution types to show that investments in IT are associated with productivity gains in (a) research for public and doctoral institutions and (b) teaching and service for private and nondoctoral institutions. These findings have direct implications for policymakers and researchers seeking greater nuance in discussions of the influence of
technology on educational productivity, as productivity gains appear to be tied closely to a college or university’s primary mission. In addition, we showed a time lag of 2 years before investments in technology were positively associated with educational productivity, which suggests that practitioners, policymakers, and researchers must allow for time to learn or adjust to new technologies before productivity gains can be realized.

As technology continues to grow in prominence throughout higher education, additional research is needed to offer empirical evidence of the effects of institutional investments in these new technologies. First, further research should explore whether productivity gains associated with previous investments in technology extend beyond 2 years. Second, this study provided descriptive information regarding how the makeup of higher education personnel has changed over time, but additional studies could examine the extent to which labor composition is influenced by investments in technology. In other words, is technology being used to replace or reduce the usefulness of certain types of labor within the higher education workforce? Finally, the financial benefit of instructional technologies is typically associated with economies of scale, which suggests that the financial advantage of instructional technologies is present at larger enrollment levels (Cheslock et al., 2016). Future research should explore whether the financial advantages related to instructional technologies can be experienced without unduly harming the quality of instruction and student learning.

**Acknowledgments**

The authors would like to thank EDUCAUSE for providing data. Additional thanks to Joshua Wymore, John Cheslock, and two anonymous reviewers for their helpful feedback at various stages of the development of this manuscript.

**Notes**

1. These increases in investment only account for central IT spending per full-time-equivalent student and do not include decentralized IT expenditures. In general, central IT units typically streamline their efforts and report to a single administrator within the institution, whereas decentralized IT units operate independently within individual departments or local units of the institution.

2. The measure fails to account for hidden productivity growth, such as improvements in the quality of services.

3. Navarro’s (2000) work provides a first step toward answering the cost question related to instructional technologies and online course delivery, but his research focused on a small sample of respondents from one institution and consequently lacks generalizability across higher education institutions.

4. Previous studies have used variations of this term, such as the “higher education production function,” but we will continue to use “production theory” hereafter.
5. We did not include EDUCAUSE CDS Survey data from 2014 because the survey based its responses on institutional data from the 2012 fiscal year. In 2012, the IPEDS Human Resources Survey changed its classifications of employee types, which would have resulted in unstable estimates for the purposes of this study.

6. These institutions were identified using the parent–child reporting flag in the IPEDS Human Resources Survey.

7. To test the potential for weak instruments, we followed the recommendation of Kapetanios and Marcellino (2010) and reestimated our models with factor-derived instruments. This approach reduced the number of instruments in our GMM specification but did not significantly alter the directionality, statistical significance, or magnitude of our initial results.

References


