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Article

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The Empirical Nexus between Data-Driven Decision-Making and Productivity: Evidence from Pakistan's Banking Sector

Raazia Gul^{1*}, Kelvin Leong², Ammara Mubashar³, Mamdouh Abdulaziz Saleh Al-Faryan⁴ and Anna Sung²

Abstract: The effective use of digital technologies to create business value has generated enormous data, and using data in decision-making is vital. Although there is growing empirical evidence in favour of a positive association between informed decision-making and firm performance in developed countries, there is little to no evidence of a large-scale study in an emerging economic context. Moreover, there has been scant empirical evidence on how DDDM affects productivity in the banking sector of developing countries. This study examined the impact of DDDM on the productivity of Pakistan's banking sector from 2016 to 2020 based on primary and secondary data collected from banks registered in Pakistan. The findings suggest that banks who adopt DDDM practices show a 4–7% increase in productivity depending on adjustment to change. We believe this study would shed light on the importance of DDDM in the banking sector of developing countries.

Subjects: Technology; Econometrics; Banking; Management of Technology; Information Technology

Keywords: Digitalization; Data-driven decision-making; Productivity; Banking

1. Introduction

Data-Driven Decision-Making (DDDM) refers to decision-making based on data instead of intuition or expertise (Brynjolfsson & McElharan, 2019; Davenport, 2013 &, 2014). The driving force behind the development of DDDM is the growing investment trend in IT and analytics. Worldwide IT spending in 2022 is about to exceed US\$4.4 trillion, which is a 4% increase over 2021 and future IT spending is expected to increase continuously (Stamford, 2022). Another report indicates that companies are increasing their revenue spending on digital technologies from 3.5% in 2020 to 4.7% in 2021 and estimated to be 5.8% in 2022 (Ulrich et al., 2022). In the Banking and securities sector, the IT budget even reached 10.14% of revenue (Kark et al., 2021). In terms of analytics, the big global data and business analytic market size in 2020 is US\$198.08 billion and is expected to reach more than triple in size (Allied Market Research, 2022).

The use of IT and analytics has increased significantly over the past decade (Corea, 2016; Persaud & Schillo, 2017), which encourages decision-makers to rely more on these analytics and related technologies rather than relying on their expertise and intuition while making decisions (Brynjolfsson & McElheran, 2016a; Erickson & Rothberg, 2018; Gandomi & Haider, 2015; Troisi et al., 2020). In brief, when companies adopt a data perspective to create value, they become more interested in “what do we know” instead of “what do we think” (Fredriksson, 2015; Hernandez et al., 2020; McAfee et al., 2012). They are no more going “with the gut” and understand that

digitalization-induced data provide an unprecedented opportunity to extract information for informed decision-making (Corea, 2016).

In the age of big data, the accessibility to data followed by insights derived from data for informed decision-making is changing the global business environment (Conejero et al., 2021; Gul & Ahsan, 2019). As a result, industries are reshaping their business models and practices with insights obtained from data to become more agile and responsive to the external and internal environments, thus creating competitive advantages for survival, growth and sustainability. With the help of data analytics, business managers can anticipate future trends, forecast risks and understand the dynamics of their business. To achieve these, data will need to be efficiently disseminated to managers in the decision-making process; otherwise, the resources input in working on data are wasted (Schrage, 2016).

This study was conducted with a specific focus on examining how DDDM impacts banks' productivity in Pakistan. In Pakistan, the financial sector predominantly comprises banks, holding the largest share of financial assets as a percentage of GDP. The banking sector's total asset size is approximately 44% of the national GDP (NFIS, 2019). Nevertheless, more than 50% of the population is deprived of formal financial services and only 16% were banked in 2015 (SBP, 2020).

The investment in data analytics by the banking sector has increased significantly over time due to its link to increased productivity (Gul et al., 2021; Gul & Ellahi, 2021; Mehmood et al., 2015; Ibrahim & Muhammad, 2013). While the dimension of a bank's digitalization includes online banking, digital channel and digital online intensity (Carbo-Valverde et al., 2020), this study digs deeper and explores the impact of DDDM. Many banks have started investing in data analytics (Gul et al., 2021), but how they use these analytics in decision-making is mainly unknown. Contrarily, FinTechs generally help their clients improve their business processes by leveraging technology to make data-driven decisions. For example, a local Fintech firm has been attempting to carve out a position in the agriculture sector by streamlining the entire value chain (SBP, n.d.).

This study makes various contributions to the literature. *First*, although there is growing empirical evidence in favour of a positive association between informed decision-making and firm performance in developed countries (Brynjolfsson & McElheran, 2019, 2016a; Chiheb et al., 2019; Davenport, 2014; Liberatore & Wagner, 2021; Troisi et al., 2020), there is little to no evidence of a large-scale study in an emerging economy context. *Second*, despite the growing fact that data-driven decision-making promises significant results for the financial sector (Lochy, 2019), there has been scant empirical evidence on how DDDM affects financial performance in this industry. *Third*, survey-based studies investigate relationships between dependent and independent variables based on data collected through a survey. However, our study connects the DDDM index developed through a questionnaire survey with the actual performance of banks over five years' period.

This paper is organized as follows: Section 2 reviews the relationship between decision-making and firm's performance. Section 3 explains the research methods of this study. The findings and analysis results are reported in section 4. Section 5 provides a discussion and conclusion of this paper.

2. Literature Review

This section aims to review how DDDM potentially affects the performance of banks and the rationale behind this. Building on this review, we developed the hypothesis of this study. Decision-making is the process of selecting the best alternative solution to a problem to achieve organizational goals (Hernandez et al., 2020). Further, decision-making is the most significant element of managerial function. The success of organizations depends on the richness of decision-making as it aids in gaining a competitive advantage.

Nowadays, data analytics can facilitate more powerful decision-making, such as automated decision-making using algorithms such as decision trees and neural networks, which is faster,

more efficient and potentially more accurate than ever (Li et al., 2020). Data-driven decisions based on algorithms extract valuable insights while minimizing risks (Grover et al., 2018). These algorithms help organizations make smarter and faster decisions in real-time (Manyika, 2011). Moreover, technology can also help reduce noise and errors in information (Bloom et al., 2012) and improve employee performance (Gul & Khan, 2019).

As data analytics becomes more advanced, DDDM is becoming more promising for firms. DDDM is a process of collecting and analyzing data into meaningful findings and insights, then disseminating the findings and insights to concerned individuals that help managers improve firms' performance (Schelling & Rubenstein, 2021; Lohr, 2011; Marsh et al., 2006).

In brief, DDDM can help to convert data into valuable information and knowledge to be used in decision-making. Theories related to the value of information date back to the seminal work of Blackwell (1953). Adding to the uncertainties and imperfections of markets, Blackwell suggests that a decision-maker with more information (though imperfect) will make better decisions than those with poor information. If an individual's decision-making on resource allocation is based on limited knowledge, it may lead to the misallocation of resources and may result in reduced productivity (David et al., 2016; March, 1996). In contrast, technologies that ensure information collection and its dissemination to all concerned individuals will reduce production costs and enhance firms' productivity (Bloom et al., 2012; Brynjolfsson & McElheran, 2019). The decision-making will be valuable in most settings if the collection of data is economical, which is the case now due to increased digitalization (Lisowsky & Minnis, 2020), such as the application of cloud computing, advanced mobile connection technologies, new sensors and the integration of Internet of Things. Today, an abundance of data is freely available (Tambe, 2014), the tools and analytics are less expensive, more sophisticated and easier to deploy, which make the decision-making data-driven and more valuable (Ghasemaghaei et al., 2018; Lakkaraju et al., 2017; Pierce et al., 2015).

The empirical literature on the business value of DDDM is emerging but mainly focused on the US industries. Brynjolfsson et al. (2011) investigated the relationship between DDDM and financial performance of US firms. Their findings suggested an improvement of 5–6% in productivity through DDDM. Brynjolfsson and McElheran (2016a) find that DDDM practices have increased significantly in US organizations over time and performance gain was also due to huge investments in IT. This shows that data and analytics go side by side for DDDM practices to enhance firm performance (Anderson, 2015). Similarly, Liberatore et al. (2017) find that companies using DDDM practices are, on average, 5–6% more productive and profitable than their competitors. Acharya et al. (2018) suggest that data assists in knowledge co-creation, which leads to evidence-based decision-making and improved firm performance. Long (2018) also confirms that DDDM is highly correlated with major profitability ratios including return on investment, return on assets, market value and asset utilization. A recent study by Brynjolfsson and McElheran (2019) concludes that putting data into action and using it in decision-making improves production plants' productivity.

To sum up, it is suggested that DDDM has a positive impact on organizational performance. Since the literature on the nexus between DDDM and banks' performance is scarce, the current study investigates the impact of DDDM on the productivity of banking sector in Pakistan. Embedded on information theories and empirical evidence, the hypothesis below is derived to be tested in this study.

H1: DDDM has a significant positive impact on the productivity of banks in Pakistan.

In order to evaluate the hypothesis H1, we established a regression model for the purpose. The variables of the model were identified according to previous studies. For a more comprehensive

discussion, the construction of variables and the proposed model are explained in sections 3.2 and 3.4, respectively.

3. Materials and Methods

3.1. Data and Sources of Data

This study used both primary and secondary data, all data were collected from banks in Pakistan as both primary and secondary data were merged to perform an econometric analysis. There are 33 commercial and 11 microfinance banks registered with the State Bank of Pakistan (SBP). However, the study excluded foreign banks from the sample due to their small operation size in Pakistan. Additionally, we excluded four specialized banks from the sample due to the different nature of operations and target market. The final sample consists of 36 banks, representing 26 commercial and 10 microfinance banks operating in Pakistan. Secondary data was collected over 2016 to 2020 from online publicly available sources, including the State Bank of Pakistan and Banks' annual reports.

On the other hand, primary data was collected through a structured questionnaire survey administered to the chief information officer, data analyst, IT heads and senior bank managers from all banks in the sample. The questionnaires were sent to all banks in the sample and accessible online to respondents. The survey contains questions related to the use of IT in decision-making, IT usage by employees, adjustment to organizational change after IT adoption and DDDM. The primary data was collected in 2020 only and index, which was extended back to the previous 4 years i.e. 2016–2019, following Brynjolfsson and McElheran (2019, 2016). This makes DDDM a static variable, which is merged with secondary data to make econometric analysis for 5 years. The maximum time a static variable can be extended back is 5 years (Brynjolfsson & McElheran, 2019, p. 2016); therefore, our sample period is of 5 years.

3.2. Construction of Variables

Building on the data collected from the sources explained in the previous section, variables were constructed according to previous studies with corresponding literature as summarized in Table 1.

The variable $DDDM_{it}$ is an index constructed with reference to the work of Brynjolfsson and McElheran (2019). The index was calculated based on primary data collected from our survey. More specifically, the respondents were asked to choose a value on a 5-point Likert scale for five items. The responses to these five items were combined to develop an index through principal component analysis (PCA).

We also constructed one DDDM related instrumental variable, Adjustment Cost (AdjC). Adjustment Cost measures the cost of the change in the business environment due to the increased use of data. The AdjC composite index was constructed through six survey questions regarding the organizational factors, which facilitate or inhibit change. Other control variables that could affect the bank performance were also included in the analysis.

3.3. Research Methodology

Given our research involves DDDM and previous literature highlights that reverse causality and endogeneity lie between DDDM and firm performance (Brynjolfsson & McElheran, 2016a, 2019; Tambe & Hitt, 2011). Therefore, it is crucial to use an estimation technique that takes endogeneity and reverse causality into account, as otherwise the results would remain biased. We employed Instrumental Variable Two-Stage Least Squares (2SLS-IV) to obtain a consistent estimator of the coefficient of DDDM (Brynjolfsson & McElheran, 2019; Muller et al., 2018). We also employed Ordinary Least Squares (OLS) and Random Effect regression to ensure our findings are robust and provide increased room for policy relevance and consistency with recent studies (Adeabah & Andoh, 2020).

Table 1. Construction of Variables			
Variables	Notations	Definitions	References
Output	Y_{it}	Earning Assets (non-bank loans and investment in securities)	Koeter and Noth (2013); Martin-Oliver and Salas-Fumas (2008)
Data-driven Decision-making	$DDDM_{it}$	DDDM is a composite index derived from five items in the survey through PCA	Brynjolfsson and McElheran (2019)
Capital	K_{it}	Fixed Assets less depreciation	Octrina et al. (2019); Koeter and Noth (2013)
Employees	L_{it}	Number of full-time employees in banks	Brynjolfsson and McElheran (2019); Koeter and Noth (2013);
Information Technology expense	ITE_{it}	The log of the sum of IT expense under the administrative expenses.	Koeter and Noth (2013)
Type (Type)	X_{it}	Dummy variable, 1 for the commercial banks and “0” for microfinance banks	Gul and Ellahi (2021)
Listing (LIST)		Dummy variable, “1” for banks listed on Pakistan Stock exchange and “0” otherwise.	Gul and Ellahi (2021) Ehsan and Javid (2018)
Non-Performing Loans (NPL)		Non-performing loans taken as a ratio to total loans	Octrina et al. (2019)
Deposits to Assets Ratio		The sum of all types of deposits such as current deposits, savings deposits, and time deposits as a ratio to total assets	Coulibaly (2020); Onay and Ozsoz (2011)
Age (Age)	Instrument 1	Log of the age of a bank as a proxy for the size of banks	Ehsan and Javid (2018)
Adjustment Cost (AdjC)	Instrument 2	AdjC is a composite index derived from six items in the survey through PCA	Brynjolfsson et al. (2011)

The indices of DDDM and Adjustment Cost were constructed through PCA. PCA is a statistical approach for reducing the dimensionality of data without losing many variations (Jalil et al., 2010). PCA reduces the data size but grips the variation in data (Jalil et al., 2010), which is the most suitable way to build indices for DDDM and other control variables. The results of prerequisite tests including Bartlett test of sphericity and Kaiser–Meyer–Olkin Measure of Sampling Adequacy, prior to construction of indices, are provided below in Table 2.

Table 2. Diagnostic test for PCA		
	Bartlett test of sphericity	Kaiser-Meyer-Olkin
DDDM	Chi-square = 25.746 (0.004)	0.751
Adjustment Cost (AdjC)	Chi-square = 180.555 (0.000)	0.784

Note. Bartlett test of sphericity H0: variables are not intercorrelated. The p-values are in parentheses.

Table 3. Principal Component Analysis

	Eigenvalue (Component 1)	Variable (%age)
DDDM	1.822	0.7178
Adjustment Cost (AdjC)	2.984	0.7896

Since the values of Kaiser–Meyer–Olkin test for all variables are greater than 0.6 and items are intercorrelated (Kaiser & Rice, 1974), PCA can be used for these variables. The components with eigenvalue greater than 1 are kept for analysis purposes. The explained variance for component 1 of DDDM and related variables is presented below in Table 3.

3.4. Estimable Model

The following model was employed to identify the impact of DDDM on productivity of banks. The firm-level panel data was modelled from 2016 to 2020 using productive inputs and control variables. This gives us the following equation:

$$\log(Y_{it}) = \beta_0 + \beta_1 DDDM_{it} + \beta_2 \log(K_{it}) + \beta_3 \log(L_{it}) + \beta_4 \log(ITE_{it}) + \sum_{i=0}^t \beta_i X_{it} + U_{it} \quad (1)$$

For the equation, Y_{it} is the output of the extended Cobb–Douglas production function, measured as the log of the sum of the loans and investments. The output of the banking sector remains a debatable issue in the literature due to its different business structures. The differences in the approaches are based on the rationality and understanding of the role of banks and the resulting choice of inputs (Greenwood & Scharfstein, 2013). Pakistan’s banking sector works as an intermediary between borrowers and lenders; therefore, the intermediary approach has been used for this study. The intermediary method under the asset approach considers banks as the intermediary between borrowers and suppliers (Kovner et al., 2014); therefore, capital and labour are the main inputs other than investment in IT, whereas the sum of loans and investments are the output of banks (Koetter & Noth, 2013).

Data-Driven Decision-Making ($DDDM_{it}$) is an index whose value may vary from 0 to 1. Labor (K_{it}) is the fixed assets and L_{it} is the number of full-time employees. IT expense (ITE_{it}) is the information technology expense of a bank. Control Variable ($\sum \beta_i X_{it}$) includes deposits to asset ratio, non-performing loans to total loans, type dummy, and listing dummy. Error (U_{it}) is the white noise error term.

4. Result Analysis

4.1. Descriptive Statistics

The descriptive statistics for all primary and secondary variables are presented in Tables 4 and 5, respectively.

The value of Cronbach’s alpha of the primary variable of interest, i.e. DDDM and other control variables related to management practices, including adjustment cost captured on a 5-point Likert scale are presented in Table 4. The value of Cronbach’s alpha is 0.65 when DDDM is formed into a scale consistent with previous study (Brynjolfsson & McElheran, 2019). Adjustment costs are consistent when formed into a scale with Cronbach’s alpha values of 0.93.

There are 178 firm-level observations except for IT expense, which has 167 firm-level observations. The average bank size is large, with a mean value of the output of Rs.104 billion. Type and listing are dummy variables with a minimum value of 0 and a maximum of 1. The average non-performing loan ratio to total is less than one, which shows banks are productive in collecting their loans back.

4.2. Correlation Analysis

The pairwise Pearson correlation analysis is presented below in Table 6.

Table 4. Descriptive Statistics of Survey Items

	Range of scale	Mean	S.D.	Cronbach's Alpha
Measure 1: Data Driven Decision Making (DDDM)				0.6536
We rely on data for the creation of a new product or service	1-5	4.1388	0.6393	
We depend on data to support our decision making	1-5	3.9998	0.5855	
We have the data we need to make decisions	1-5	3.8888	0.7082	
Feedback based on data is integrated into existing system	1-5	3.9166	0.6491	
data is preferred over management's 'experience and intuition.	1-5	3.7777	0.7601	
Measure 2: Adjustment Cost (AdjC)				0.9363
Skill mix of existing staff	1-5	4.2501	0.8409	
Employment contracts	1-5	3.9166	0.9373	
Work Rules	1-5	4.2222	0.9594	
Organizational culture	1-5	4.3333	0.8618	
customer relationships	1-5	4.5001	0.7745	
senior management involvement	1-5	4.3055	0.9507	

Table 5. Descriptive Statistics of Production function variable

Variable	Obs	Mean	Std. Dev.	Min	Max
Log (Y)	178	8.019	0.967	4.841	9.413
Log(K)	178	6.500	0.841	3.869	7.878
Log(L)	178	3.463	0.509	1.973	4.324
Log(ITE)	167	5.034	0.915	2.496	7.357
TYPE	178	0.697	0.461	0.000	1.000
Listing	178	0.797	0.651	0.000	1.000
NPL ratio	178	0.478	0.301	0.157	0.710
Deposits ratio	178	0.078	0.071	0.123	0.442

All correlations significant at 5% are reported with a “*.” The correlation among explanatory variables is not high, reflecting no autocorrelation among independent variables. DDDM has a positive correlation with all the variables except the type of banks, which shows that DDDM is more practised in commercial banks than microfinance banks. The correlation between IT expense

Table 6. Correlation between DDDM and IT expense and employees

	Y	DDDM	K	L	ITE	TYPE	Listing	NPL	Deposits
Y	1.0000								
DDDM	0.2046*	1							
K	0.9459*	0.2520	1						
L	0.8980*	0.2557	0.9170	1					
ITE	0.7698*	0.1527	0.6164	0.5329	1				
TYPE	0.8027*	-0.0333	0.5031	0.5286	0.5820	1			
Listing	0.6311*	0.0589	0.6867	0.6224	0.5251	0.5086	1		
NPL	0.1630*	0.1087	0.1835	0.059*	0.0098	0.2715	0.1659	1	
Deposits	0.6049*	0.4511	0.6093	0.6105	0.4817	0.3750	0.3130	0.1664	1

*p< 0.05

and DDDM is only 0.15, which shows that as DDDM is a new practice, the diffusion rate of IT is still low.

4.3. Empirical Findings

4.3.1. Impact of DDDM on productivity

The main results regarding the impact of DDDM and other productivity inputs, including capital (K) and labour (L), on banks' output (Y) are presented in Table 7.

Since the Cobb-Douglas production function in equation 1 is log-transformed, the coefficient of inputs, including DDDM, can be expressed as the percent productivity change associated with an investment in DDDM (Muller et al., 2018). All results are from pooled OLS regressions with robust standard errors in parentheses to provide consistent estimates for the entire period, i.e. 2016–2020. Firm-specific control variables are included in all the models to avoid an alternative explanation of the estimated results.

A baseline estimate of the contribution of IT expense to productivity is reported in column 2. The DDDM measure is not included in this model to obtain productivity estimates of ITE and other input variables. The coefficient of ITE (log of IT expense) is 0.028, which is insignificant, whereas capital and labour have a significant and positive impact on banks' output. Column 3 includes the variable of interest, DDDM, to estimate the impact of DDDM on banks' output while controlling the impact of ITE. Data relating to DDDM practices were collected in 2020, and an index was developed through PCA based on five questions. However, for analysis purposes, the same index was extended to the prior period, i.e. 2016–2019. The coefficient estimate of DDDM on output is 0.0345, which is significant. The point estimate shows that the contribution to productivity due to DDDM is about 3.5%. The point estimate of ITE remains the same, which shows that banks, which use DDDM gain 3.5% higher productivity than their competitors and this result is significant regardless of the investment in IT.

Table 7. OLS Regressions of DDDM on Productivity Measures			
Column 1	Column 2	Column 3	Column 4
	2016-2020 (without DDDM)	2016-2020 (with DDDM)	2020 (with DDDM)
DDDM		0.0345* (0.0123)	0.0364* (0.0182)
Log (K)	0.307*** (0.074)	0.2928*** (0.0641)	0.4858** (0.1431)
Log (L)	0.866*** (0.081)	0.8766*** (0.0798)	0.7543*** (0.1946)
IT expense (ITE)	0.02847 0.0306	0.03056 0.03032	0.0873 (0.0887)
Type	0.788*** (0.052)	0.8225*** (0.0525)	0.7511*** (0.0989)
Listing	0.074* (0.040)	-0.0625 (0.0393)	-0.0567 (0.0809)
NPL	-0.172 (0.215)	-0.2286 (0.2121)	-0.3161 (0.3352)
Deposits	0.219** (0.101)	0.1461 (0.1030)	0.2529 (0.2395)
Observations	167	167	36

Note: Standard errors are in parentheses. *** p<0.001 ** p<0.05 * p<0.01

The column 4 “2020 (with DDDM)” shows the impact of DDDM on productivity for 2020 only because data for DDDM was collected in 2020 but extended for prior periods in the previous model. The coefficient estimate of DDDM remained the same when the estimation included the entire period, i.e. 2016–2020, which shows that the DDDM index is not affected by the time. The results are significant at 10% after controlling for IT use, suggesting that the variation in DDDM could explain the additional variation in output.

4.3.2. Sensitivity Analysis

A sensitivity analysis would be conducted to get more robust results to control for heterogeneity, endogeneity and DDDM extension to prior periods.

Extension of DDDM Index to prior years. The sample period is subdivided into smaller periods to ensure the robustness of the assumption that the DDDM index does not vary over the study time, i.e. 2016–2020, see, Table 8.

The productivity analysis is repeated for the entire panel (2016–2020) and two smaller periods of 2016–2017 and 2018–2019. It is found that despite dividing the sample into smaller periods, the results of column 3 (in 2020, when the survey was conducted) are almost the same as the whole sample period. The impact of DDDM on banks’ output is significant and causes the productivity to increase by 4.01% and 4.08% in two sub-samples, i.e. 2016–17 and 2018–19. Thus, results are not biased when the DDDM index is extended to prior years. The results of different sub-samples in three columns of Table 8 are almost identical with a slight variation in the coefficient. Nevertheless, the Chow test was employed to confirm that the coefficients of DDDM do not change between different periods.

Thus, our results are not biased when the DDDM panel is extended to the prior years (Brynjolfsson & McElheran, 2019).

Endogeneity. Our findings suggest that DDDM causes productivity to enhance, the results may be considered biased due to endogeneity and reverse causality issues for two reasons. *First*, the high performing banks may have slack resources, which enable them to invest in DDDM and other innovative activities. *Second*, there might be some omitted variable bias, such as management practices. Therefore, the current study also employs IV 2SLS estimation to test for the endogeneity of DDDM in determining banks’ productivity. To address these problems, DDDM will be treated as endogenous (Brynjolfsson & McElheran, 2019, p. 2016). Since IV regression requires at least one instrumental variable that is related to the endogenous variable (i.e. DDDM) but not related to the dependent variable (i.e. banks’ performance), the instruments for DDDM include the age of banks and adjustment cost for the change in banks (Brynjolfsson & McElheran, 2019). The adjustment cost for the change in banks is solely related to DDDM and is uncorrelated to banks’ performance; the instrument is valid and passed the weak instrument test with Cragg-Donald Wald F-statistic of 19.208 (p-value = 0.000).

Following Brynjolfsson et al. (2011), we use firm age as an additional instrument as we expect that it will help explain cross-sectional variations in DDD. However, previous work indicates that firm age is linked with organization experience and inertia. Against this backdrop, younger firms are more likely able to adopt new technology, practices and innovations such as DDD, thus leading to a negative or very low correlation between DDD and firm age (which is observed in our data; the correlation between DDDM and age is only 0.17). To reduce the possibility that our instrument would be invalidated by a correlation between DDDM-driven productivity and firm age, we include controls for DDDM (adjustment cost to change if DDDM is adopted) when this instrument is used. We further assume that if banks’ productivity is linked with its age due to the learning by doing, any bias arising from using banks’ age as instrument likely reduce our observed effect of DDDM, making the results more conservative.

Table 8. Panel Regression analysis when the sample period was divided into two periods

Column 1	Column 2	Column 3	Column 4
DV = Log(output)	2016-2020	2016-2017	2018-2019
DDDM	0.0391* (0.0241)	0.0401* (0.0269)	0.0408** (0.0287)
Log (K)	0.3116*** (0.0765)	0.2188* (0.0545)	0.4714*** (0.0936)
Log (L)	0.8460*** (0.0955)	0.8958*** (0.1103)	0.7884*** (0.1203)
ITE	0.0162 (0.0242)	0.0355 (0.0575)	0.0026 (0.0495)
Type	0.7683*** (0.0826)	0.8947*** (0.0974)	0.8473*** (0.1170)
Listing	-0.0834 (0.0734)	0.01484 (0.0922)	0.0474 (0.0974)
NPL	-0.2751** (0.1813)	-0.5102 (0.2007)	-0.3220 (0.2799)
Deposits	0.1348 (0.1064)	-0.1219 (0.1844)	-0.2110 (0.1748)
Observations	167	72	72
R-squared	0.3501	0.406	0.3545

Note: Standard errors are in parentheses. *** p<0.001 ** p<0.05 * p<0.01

Two models were run: OLS and IV2SLS, and the results are presented in Table 9.

The coefficient of DDDM is 0.041 which is significant at 10% under the OLS method. IV 2SLS regression is also estimated, and the results are reported in column 3. The coefficient of DDDM increases to 0.0701 and significant at 1%. The size of the coefficients of DDDM is larger under IV 2SLS than that of OLS, consistent with previous studies that show that 2SLS estimates can give higher coefficients as IV 2SLS is estimating the local average treatment effect. We are instrumenting for DDDM and measuring the productivity estimates to DDDM. OLS, on the other hand, estimates the average treatment effect over the entire population (Card, 2001). So our instruments, age and adjustment cost, shift the behaviour of a subgroup of banks for whom the returns to DDDM is higher than the average. We have already tested for the weak instruments and know that our instruments are not weak. Thus, IV estimates are larger than OLS estimates because of heterogeneity in the population under study.

Finally, the Sargan test was conducted to test for over-identification as with one endogenous variable, two instruments (age of firm and adjustment cost) were used. The Sargan tests the null hypothesis of over-identification, which was rejected at 0.12. It shows that the estimates of the impact of DDDM on productivity are unaffected by the choice of instruments and that the model is free from omitted variable bias and endogeneity. The coefficients of employees, fixed assets and IT expense are same under both models. The impact of non-performing loans and listing on productivity is significant and negative, consistent with previous studies (Ehsan & Javid, 2018; Gul et al., 2021). Increase in NPL causes the productivity to fall, whereas the increase in deposits reduces banks' productivity. These findings are in line with the literature as banks with higher NPL cannot perform better due to the non-payment by creditors (Octrina & Setiawati, 2019).

Overall, it is suggested that banks, which adopt DDDM gain 4–7% approximately higher productivity than the competitors who do not invest in DDDM practices. The results are consistent with previous studies (e.g., Brynjolfsson & McElheran, 2019). However, the coefficient of DDDM under the 2SLS/IV model in column 3 is 0.0701, which is relatively high compared to previous models. It shows that banks that are old and spend more on adjustment costs are performing well with

Table 9. IV-Regressions of DDDM on Productivity Measures

DV = Log(output)	OLS (2016-2020)	2SLS/IV (2016-2020)
DDDM	0.0410*** (0.0123)	0.0701*** (0.0330)
Log (K)	0.2928*** (0.0641)	0.2138*** (0.0759)
Log (L)	0.8766*** (0.0798)	0.9375*** (0.0917)
ITE	0.0318 (0.0340)	0.0341 (0.0420)
Type	0.8225*** (0.0525)	0.9137*** (0.0638)
List	-0.0626 (0.0393)	-0.0303 (0.0436)
NPL	-0.2284 (0.2121)	-0.4119* (0.2319)
Deposits	0.1462* (0.1030)	0.0609* (0.1271)
Observations	167	167
Adj. R-squared	0.6485	0.6369
OverID test (Sargan Test) Chi-sq (p-value)		2.33 (0.124)
Under identification Chi-sq (P-value)		27.85 (0.000)
Weak instrument: Cragg-Donald Wald F statistic		19.208 (0.0000)
Endogeneity Chi-sq (P-value)		8.989 (0.0023)

Notes: Sargan Test- Ho: over identifying restrictions are valid. The weak instrument hypothesis is rejected for all specifications. Endogeneity of IV- H0: instruments are endogenous. The given values are test statistics and standard errors are in parenthesis.

DDDM practices. The magnitude of the increase in productivity due to DDDM investment is promising for the banking industry. Thus, hypothesis 1 is entirely accepted and concludes that DDDM significantly and positively impacts banks' productivity in Pakistan.

5. Discussion of Results

The present study quantifies the impact of DDDM on the productivity of the banking sector in Pakistan. The secondary data collected through multiple sources and primary data collected through the survey were merged to perform an econometric analysis. Multiple estimation techniques were used to obtain robust, consistent and unbiased results. First, Ordinary Least Square was employed because the data of the DDDM index were available for 2020 only. The same data for the DDDM index was extended to the prior period, i.e. 2016–2020 and OLS regression was employed for an entire period and 2020. The DDDM coefficient estimates under both models remained at 3.5% approximately. The DDDM index was cross-sectional, so the sample was subdivided into different periods. Random effect panel estimation was employed and the results remained consistent over different sample periods. Next, to address the endogeneity and potential reverse causality 2SLS-IV regression model was also employed with instruments (adjustment cost and age of the banks). Based on all the robustness tests, the DDDM estimates on productivity are significant, robust and consistent. The change in estimation methods, control variable and time do not affect the results, though slight variation in the point estimate of DDDM is observed. The findings suggest that, on average, the banking sector's productivity is enhanced by 4–7% if DDDM practices are adopted in Pakistan.

The current study suggests that banks should ensure the availability of better quality and audited data and disseminate it to the right people at the right time (Lisowsky & Minnis, 2020). The use and

availability of data for decision-making with the capability of adjustment to change would encourage banks to make decisions in real-time and remain productive. Thus, the investment in analytics, adoption of DDDM practices and learning of new skills would increase banks' productivity.

6. Conclusion

The current study was conducted using an IV 2SLS, which entails enhanced productivity due to DDDM adoption rather than a reverse casualty. With digital transformation and advancement in technology, business models are disruptively changing and becoming more data-driven. Traditional decision-making based on the expertise and intuition of senior management is being replaced with data-driven decision-making. The current study attempted to identify the impact of DDDM on banks' productivity in Pakistan. The findings in this study suggest a 4–7% increase in banks' output if banks adopt DDDM practices. Given increased investment in IT and analytics by the financial sector of Pakistan, it is foreseeable that the adoption of DDDM will increase as well as banks' productivity.

Troisi et al. (2020) find that data-driven orientation to big data leads to improved co-innovation, smart supply chain management, enhanced relationships with customers and better engineering infrastructure of sample firms in Italy. Various other studies have confirmed that DDDM leads to enhanced productivity and firm performance in the US (Brynjolfsson & McElheran, 2019, p. 2016a, Brynjolfsson et al., 2011). Ashaari et al. (2021) find that DDDM strengthen the positive relationship between big data and firm performance of higher educational institutes in Malaysia. Another study by Rejikumar et al. (2018) indicates that new technology and the use of reliable data for decision-making is well sought-out and favoured by managers in Indian industries.

6.1. Theoretical Contributions

This study contributes to the emerging knowledge base related to DDDM practices and gives an estimate of productivity increment, which is valuable for cost–benefit analysis. Most of the current literature on investment in IT and digitalization are not focused on how technology is used in decision-making, although it plays a crucial role on the performance of banks. The current study offers an insight into the actual outcome of the investment in DDDM practices in an emerging economy, Pakistan. This study will help incumbents to recognize the benefits of investing in DDDM.

6.2. Managerial Implications and policy Relevance

The results of this study provide various implications for shareholders, investors, bank managers, policymakers, and regulators. In recent years, digital transformation becomes the trend in the business world, in particular the Covid-19 pandemic has sped up such transformations. Many firms make significant investments in IT in order to transform their business for survival and competitive advantages. However, firms only have limited capital and resources, but demand in implementing new technologies could be unlimited. Therefore, careful selection on what to invest in IT within budget should be made. In this study, we concluded that DDDM positively contributes to the productivity of banks in Pakistan. This finding is important in different aspects.

Firstly, as mentioned before, firms have limited resources for investment, our finding provides an evidence-based reference showing that DDDM can improve the productivity of banks in the context of Pakistan. Therefore, spending on DDDM implementation and in relevant areas is important for improving the productivity of banks in Pakistan. This study informs banks that in budgetary preparation on IT spending, DDDM-related spending should not be overlooked.

Secondly, the adoption of DDDM has hardly ever been explored in developing countries like Pakistan. Studies on banks in developing countries are very limited. This study provides evidence to inform policymakers and related industrial leaders to encourage related DDDM development, adoption and training to support banks and the banking system to be more efficient and effective, and thus more productive and sustainable.

Thirdly, the banking system plays a crucial role in economic development. It is already known that the failure of a bank may have spillover effects (Ehsan & Javid, 2018), and the riskiness of one bank can be seen as a threat to the stability of the whole banking sector. In developing countries, their banking system and economy are considered more fragile as they are more prone to be exposed to more risk factors (Malpass, 2022) when compared to the banking system in developed countries. Given this study showed that DDDM has a positive impact on banks' productivity, it can serve as a support to encourage banks to adopt and improve DDDM implementation strategy. As a collective result, stability of the banking system and overall economy could be improved in particular among the developing countries.

Hopefully, this study is a small step to encourage further studies in related area in DDDM adoption and ultimately, helping more banks and firms in developing countries to be able to response to fast-changing environment to achieve sustainable growth and improve the quality of living among people in these countries.

6.3. Limitations of Study and Future Work

Using DDDM extensively can give banks a significant competitive advantage and the performance gains are pretty promising. Since this study focused on the financial sector only, other sectors such as health care, telecommunication, and other service sectors could also be explored in the future. Also, what are the difficulties in adopting DDDM and what needs to be done to overcome such difficulties should be explored. In the future, the impact of DDDM on other performance measures such as risk management and credit management could also be explored. This study is limited to the banking sector of an emerging economics context of Pakistan; therefore, the findings of this study should be generalised with caution.

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References

Acharya, A., Singh, S., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision-making in fashion industry. *International Journal Of Information*

- Management*, 42, 90–101. <https://doi.org/10.1016/j.ijinfomgt.2018.06.008>
- Adeabah, D., & Andoh, C. (2020). Market power, efficiency and welfare performance of banks: Evidence from the Ghanaian banking industry. *EconStor Preprints* 192967, ZBW - Leibniz Information Centre for Economics.
- Allied Market Research. (2022). *Big Data and Business Analytics Market Statistics – 2030*. Available from: <https://www.alliedmarketresearch.com/big-data-and-business-analytics-market>
- Anderson, C. (2015). Creating a data-driven organization: Practical advice from the trenches. *Data-Driven Healthcare*, 55–65. <https://doi.org/10.1002/9781119205012.ch5>
- Ashaari, M. A., Singh, K. S. D., Abbasi, G. A., Amran, A., & Liebana-Cabanillas, F. J. (2021). Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: A multi-analytical SEM & ANN perspective. *Technological Forecasting and Social Change*, 173, 121119. <https://doi.org/10.1016/j.techfore.2021.121119>
- Blackwell, D. (1953). Equivalent comparisons of experiments. *Annals of Mathematical Statistics*, 24(2), 265–272. <https://doi.org/10.1214/aoms/1177729032galbr>
- Bloom, N., Sadun, R., & Van Reenen, J. (2012). Americans do IT better: US multinationals and the productivity miracle. *American Economic Review*, 102(1), 167–201. <https://doi.org/10.1257/aer.102.1.167>
- Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in numbers: How does data-driven decisionmaking affect firm performance? Available at SSRN 1819486.
- Brynjolfsson, E., & McElheran, K. (2016a). The rapid adoption of data-driven decision-making. *American Economic Review*, 106(5), 133–139. <https://doi.org/10.1257/aer.p20161016>
- Brynjolfsson, E., & McElheran, K. (2019). Data in action: Data-driven decision-making and predictive analytics in US manufacturing. *Rotman School of Management*

- Working Paper, (3422397). <https://doi.org/10.2139/ssrn.3422397>
- Card, D. (2001). Estimating the Return to Schooling. *Econometrica*, 1127-1152. <https://doi.org/10.1111/1468-0262.00237>
- Chiheb, F., Boumahdi, F., & Bouarfa, H. (2019). A New Model for Integrating Big Data into Phases of Decision-Making Process. *Procedia Computer Science*, 151, 636-642. <https://doi.org/10.1016/j.procs.2019.04.085>
- Conejero, J. M., Preciado, J. C., Prieto, A. E., Bas, M. C., & Bolós, V. J. (2021). Applying data-driven decision-making to rank vocational and educational training programs with TOPSIS. *Decision Support Systems*, 142, 113470. <https://doi.org/10.1016/j.dss.2020.113470>
- Corea, F. (2016). *Big data analytics: A management perspective* (Vol. 21). Springer.
- Coulibaly, M. (2020). Effects of Information and Communication Technologies on the Banking Inclusion of Populations in the West African Economic and Monetary Union. *International Journal of Finance and Banking Research*, 6(4), 74. <https://doi.org/10.11648/j.jfbr.20200604.13>
- Curley, M., & Salmelin, B. (2017). *Open innovation 2.0: The new mode of digital innovation for prosperity and sustainability*. Springer. <https://doi.org/10.1007/978-3-319-62878-3>
- Davenport, T. H. (2013). Big data and the role of intuition. *Harvard Business Review*, 12(24), 2-3. <https://hbr.org/2013/12/big-data-and-the-role-of-intuition>
- Davenport, T. H. (2014). How strategists use "big data" to support internal business decisions, discovery and production. *Strategy and Leadership*, 42(4), 45-50. <https://doi.org/10.1108/SL-05-2014-0034>
- David, J. M., Hopenhayn, H. A., & Venkateswaran, V. (2016). Information, Misallocation, and Aggregate Productivity. *The Quarterly Journal of Economics*, 131(2), 943-1005. <https://doi.org/10.1093/qje/qjw006>
- Ehsan, S., & Javid, A. Y. (2018). Bank ownership structure, regulations and risk-taking: Evidence from commercial banks in Pakistan. *Portuguese Economic Journal*, 17(3), 185-209. <https://doi.org/10.1007/s10258-018-0147-3>
- Erickson, G. S., & Rothberg, H. N. (2018). Intangible Dynamics: Knowledge Assets in the Context of Big Data and Business Intelligence. *Analytics and Knowledge Management*, 325-354. <https://doi.org/10.1201/9781315209555-11>
- Fredriksson, C. (2015). *Knowledge management with big data creating new possibilities for organizations*. The XXIVth Nordic Local Government Research Conference (NORKOM). <https://www.semanticscholar.org/paper/KNOWLEDGE-MANAGEMENT-WITH-BIG-DATA-CREATING-NEW-FOR-Fredriksson/42a0f1e7b358b71a9636cc9cf353ffdb94c8b8a2>
- Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35(2), 137-144. <https://doi.org/10.1016/j.ijinfomgt.2014.10.007>
- Greenwood, R., & Scharfstein, D. (2013). The Growth of Finance. *Journal of Economic Perspectives*, 27(2), 3-28. <https://doi.org/10.1257/jep.27.2.3>
- Grover, V., Chiang, R. H., Liang, T. P., & Zhang, D. (2018). Creating strategic business value from BDA: A research framework. *Journal of Management Information Systems*, 35(2), 388-423. <https://doi.org/10.1080/07421222.2018.1451951>
- Gul, R., & Ahsan, A. (2019, January). Big data and analytics: Case study of good governance and government power. In *European Conference on Intangibles and Intellectual Capital* (pp. 128-XI). Academic Conferences International Limited.
- Gul, R., & Ellahi, N. (2021). The nexus between data analytics and firm performance. *Cogent Business & Management*, 8(1), 1923360. <https://doi.org/10.1080/23311975.2021.1923360>
- Gul, R., Ellahi, N., Leong, K., & Malik, Q. A. (2021). The complementarities of digitalisation and productivity: Redefining boundaries for financial sector. *Technology Analysis & Strategic Management*, 2, 1-13.B. <https://doi.org/10.1080/09537325.2021.2013463>
- Gul, R., & Khan, K. (2019). Measuring Employee Retention and Organizational Development through Competency Development. *KASBIT Business Journal*, 15(3): 88-100.
- Hernandez, L. C., Dantas, P. P., & Cavalcante, C. A. (2020). Using multi-criteria decision-making for selecting picking strategies. *Operational Research*, 4, 1-26.
- Jalil, A., Feridun, M., & Ma, Y. (2010). Finance-growth nexus in China revisited: New evidence from principal components and ARDL bounds tests. *International Review of Economics & Finance*, 19(2), 189-195. <https://doi.org/10.1016/j.iref.2009.10.005>
- Kark, K., Gill, J., & Smith, T. (2021). Maximizing the impact of technology investments in the new normal. *Deloitte Insights*, 3, 1.
- Koetter, M., & Noth, F. (2013). IT use, productivity, and market power in banking. *Journal of Financial Stability*, 9(4), 695-704. <https://doi.org/10.1016/j.jfs.2012.06.001>
- Kovner, A., Vickery, J., & Zhou, L. (2014, December). Do big banks have lower operating costs? FRBNY Economic.
- Lakkaraju, K. J., Leskovec, H., Ludwig, J., & Mullainathan, S. (2017). Human decisions and machine predictions. *Quarterly Journal of Economics*, 133(1), 237-293. <https://doi.org/10.3386/w23180>
- Liberatore, M. J., Pollack-Johnson, B., & Clain, S. H. (2017). Analytics capabilities and the decision to invest in analytics. *Journal of Computer Information Systems*, 57(4), 364-373. <https://doi.org/10.1080/08874417.2016.1232995>
- Liberatore, M. J., & Wagner, W. P. (2021). Simon's Decision Phases and User Performance: An Experimental Study. *Journal of Computer Information Systems*, 62(4), 667-679. <https://doi.org/10.1080/08874417.2021.1878476>
- Li, T., Ma, L., Liu, Z., & Liang, K. (2020). Economic Granularity Interval in Decision Tree Algorithm Standardization from an Open Innovation Perspective: Towards a Platform for Sustainable Matching. *Journal of Open Innovation: Technology, Market, and Complexity*, 6(4), 149. <https://doi.org/10.3390/joitmc6040149>
- Lisowsky, P., & Minnis, M. (2020). The Silent Majority: Private U.S. Firms and Financial Reporting Choices. *Journal of Accounting Research*, 58(3), 547-588. <https://doi.org/10.1111/1475-679x.12306>
- Lochy, J. (2019). *Big data in the financial services industry - from data to insights*, Finextra. <https://www.finextra.com/blogposting/17847/big-data-in-the-financial-services-industry—from-data-to-insights>
- Lohr, S. (2011). *When there's no such thing as too much information*. The New York Times. http://www.nytimes.com/2011/04/24/business/24unboxed.html?_r=1
- Malpass, D. (2022). Opening Remarks by World Bank Group David Malpass at the Launch of the 2022 World Development Report (WDR): Finance for an Equitable Recovery. World Bank.
- Manyika, J. (2011). *Big data: The next frontier for innovation, competition, and productivity*. Big data. <http://>

- www.mckinsey.com/Insights/MGI/Research/Technology_and_Innovation/Big_data_The_next_frontier_for_innovation
- March, J. G. (1996). Understanding how decisions happen in organizations. *Organizational Decision-making*, 10, 9–32.
- Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006). *Making sense of data-driven decision-making in education: Evidence from Recent RAND Research*, Santa Monica, CA: RAND Corporation, 2006. https://www.rand.org/pubs/occasional_papers/OP170.html
- McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data: The management revolution. *Harvard Business Review*, 90(10), 60–68. <https://hbr.org/2012/10/big-data-the-management-revolution>
- Muller, O., Fay, M., & Vom Brocke, J. (2018). The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics. *Journal of Management Information Systems*, 35(2), 488–509. <https://doi.org/10.1080/07421222.2018.1451955>
- Octrina, F., & Setiawati, R. (2019). Competitiveness of Indonesian banking industry based on commercial bank business group: Panzar Rosse Model. *Jurnal Perspektif Pembiayaan Dan Pembangunan Daerah*, 7 (1), 37–48. <https://doi.org/10.22437/ppd.v7i1.7475>
- Persaud, A., & Schillo, S. (2017). *Big Data Analytics: Accelerating Innovation and Value Creation*. University of Ottawa.
- Pierce, L., Snow, D. C., & McAfee, A. (2015). Cleaning house: The impact of information technology monitoring on employee theft and productivity. *Management Science*, 61(10), 2299–2319. <https://doi.org/10.1287/mnsc.2014.2103>
- SBP. (n.d.). *Digitalization of services in Pakistan*. State Bank of Pakistan. Available from: <https://www.sbp.org.pk/reports/annual/arFY18/Chapter-07.pdf>
- Schelling, N., & Rubenstein, L. D. (2021). Elementary teachers' perceptions of data-driven decision-making. *Educational Assessment, Evaluation and Accountability*, 33, 317–344.
- Stamford, C. (2022). Gartner Forecasts Worldwide IT Spending to Reach \$4.4 Trillion in 2022. In *Gartner*. <https://www.gartner.com/en/newsroom/press-releases/2022-06-14-gartner-forecasts-worldwide-it-spending-to-grow-3-percent-in-2022#:~:text=Worldwide%20IT%20spending%20is%20projected,latest%20forecast%20by%20Gartner%2C%20Inc>
- Tambe, P. (2014). Big data investment, skills, and firm value. *Management Science*, 60(6), 1452–1469. <https://doi.org/10.1287/mnsc.2014.1899>
- Tambe, P., & Hitt, L. M. (2011). Now IT's Personal: Offshoring and the Shifting Skill Composition of the US Information Technology Workforce. *Management Science*, 58(4), 678–695. <https://doi.org/10.1287/mnsc.1110.1445>
- Troisi, O., Maione, G., Grimaldi, M., & Loia, F. (2020). Growth hacking: Insights on data-driven decision-making from three firms. *Industrial Marketing Management*, 90, 538–557. <https://doi.org/10.1016/j.indmarman.2019.08.005>
- Ulrich, P., Prabhakaran, S., & McGarrity, L. (2022). Digital Investment Report: How can your digital investment strategy reach higher returns. *EY Parthenon*. https://www.ey.com/en_gl/strategy/digital-investment-report



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