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Stock Market Reactions to IT Endowment at the Onset of COVID-19

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Completed Research Paper

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Abstract

The COVID-19 crisis represented an unprecedented test to organizations with respect to its systemic severity and the unique policy response of governments around the world. Policies to curb the pandemic's spread resulted in severe cratering of demand and diverse supply disruptions to firms. Research demonstrates significant heterogeneity in the impacts of the pandemic and ensuing lockdowns on firm performance due to diverse firm characteristics. Our study advances this body of work by assessing the moderating impact of a firm's pre-existing Information Technology (IT) endowment on changes in market and operational performance caused by the pandemic. Impacts of specific classes of IT investments, analyses of the social media activity of the firm, and textual analyses of news articles pertaining to the firm provide insights into underlying mechanisms. More generally, our results provide insights into the resilience accorded by IT in the face of exogenous disasters.

Keywords: COVID-19, IT endowments, market response, abnormal returns, difference-in-differences.

Introduction

The COVID-19 crisis represented an unprecedented test to organizations (Reinhart 2020; Ding et al. 2021). A rich emergent body of research demonstrates significant heterogeneity in the impacts of the pandemic and ensuing lockdowns on firm performance. These studies implicate diverse firm characteristics such as environmental and social ratings (Albuquerque et al. 2020), access to liquidity (Acharya & Steffen 2020), high cash holdings (Ramelli & Wagner 2020), corporate governance and ownership structure (Ding et al. 2021) as well as occupational characteristics such as amenability to remote work, and human proximity (Dingel & Neiman 2020; and Rio-Chanona et al. 2020). Our study advances this body of work through an assessment of the moderating impact of a firm's pre-existing Information Technology (IT) endowment on changes in market and operational performance caused by the pandemic. Impacts of specific classes of IT investments, analyses of the social media activity of the firm, and textual analyses of news articles pertaining to the firm provide insights into underlying mechanisms. More generally, our results provide insights into the resilience accorded by IT in the face of exogenous disasters.

The COVID-19 pandemic and the associated lockdown provide the empirical context for our study. Four identifying assumptions in our empirical design allow for a causal interpretation of the impact of *IT Endowment* on market response. First, the pandemic and the subsequent lockdown were an unanticipated shock to stock markets. Second, this shock was uncorrelated with local economic conditions, firm economic activity, and underlying endowments. Third, firms had very limited ability to respond in a timely fashion to the unfolding crisis. Finally, it is unlikely that the economic outcomes we measure reflect the health effects of Covid-19 due to the low prevalence of cases at the time of the lockdown. For these reasons, we posit that stock market reactions during the COVID-19 crisis are a response to firms' preexisting conditions, including IT endowments, that impacted their resilience to endure the crisis.

We begin our analyses with an estimation of cross-sectional regressions of quarterly abnormal returns, return volatility, and operating performance of Fortune 500 firms during the first quarter of 2020. The cross-sectional regressions provide external validity by not being anchored to a specific shock date and allowing for comparisons of returns with operating performance that are only available on a quarterly basis. We complement these analyses with an estimation of difference-in-differences regressions of daily abnormal returns and daily return volatility again during the first quarter of 2020. We use both continuous treatments and binary treatments for IT endowments. Our empirical models include firm and day fixed effects to control for unobservable effects and cluster standard errors by firm and day. We also demonstrate the robustness of our results to alternate measures of key variables and industry heterogeneity. We use high-frequency data, specifically tweeting activity and textual analyses of news articles, to provide suggestive evidence of mechanisms underlying the observed economic resilience.

Our empirical analyses demonstrate broad and strong support for our theoretical proposition of increased market returns and operating performance of firms with high IT endowment. Specifically, we find that firms with high *IT Endowment* earn significantly greater daily abnormal returns during the post-Covid period while displaying lower volatility in returns. High *IT Endowment* firms earn an average abnormal daily return of 0.26% relative to other firms from February 24 to March 17, for a cumulative effect of 4.08%. We also find that firms with high *IT Endowment* experience a decrease in stock return volatility as compared to other firms. Consistent with greater market returns, firms with greater *IT Endowment* realized higher operating profit margins, higher asset turnover, and higher return on assets in the first quarter of 2020 relative to the last quarter of 2019 as compared to other firms. Specifically, one standard deviation increase in *IT Endowment* increased *Return on Assets* by 0.80 percentage points, *Operating Margin* by 2.14 percentage points, and *Asset Turnover* by 0.79 percentage points compared to the previous quarter.

Difference-in-differences estimations of daily abnormal returns for four categories of IT, wherein each category pertains to a specific common functionality, find that all categories contributed towards the observed market response during the onset of the pandemic. However, only *Value Chain Integration IT*, consisting of supplier and customer-focused IT that increases integration across the value chain, has significant but negative differences in returns when markets rebound. This decomposition of IT endowments indicates that while all IT endowments are considered important for enduring the crisis, value chain integration is detrimental to recovery as such endowments do not bestow any relative advantage.

Analysis of Twitter data immediately prior to and during the disaster shows that firms with high *IT Endowment* demonstrated greater tweet similarity with more positive sentiment, indicating greater business continuity during the pandemic. Qualitative and textual analysis of news articles uncovers four changes effected by firms with greater *IT Endowment*. First, the expansion or repurposing of capacity and resources, such as facilities, operating hours, and employees. Second, supply-side adjustments such as reconfiguration of supply chains and facilities. Third, new means to connect with customers, such as online pre-bookings and contactless customer service channels. Fourth, the realization of new work models and practices, such as working from home.

Our results have important implications for theory and practice. A rich body of research explores various drivers of reliance and ensuing performance heterogeneity during the severe COVID-19 pandemic and ensuing lockdowns. There is anecdotal evidence of how IT investments of firms helped provide important immunity and resilience to the pandemic, but this rests on a small number of unrepresentative firms. Using comprehensive data on IT investments and firm performance, our study provides systematic empirical evidence of the role of IT in managing business disruptions. In turn, we contribute to the growing literature on the role of IT in mitigating disasters and their variegated impact through resilience.

Related Literature and Theory

IT Endowment is a firm's stock of information and communication technologies — organizational resources that are vital to business activities. These include applications for collaboration within and across the organization, integration, and standardization of business processes, management and analysis of information, and other core IT applications. Prior research has documented that IT endowments and capabilities are fundamental to firm performance, value, and survival (Andrade-Rojas et al. 2021; Kathuria et al. 2018; Khuntia et al. 2021; Khuntia et al. 2019). The underlying mechanisms include increased productivity (Barua et al. 2004; Brynjolfsson and Hitt 2003; Tambe and Hitt 2012), improved product and process innovation (Andrade-Rojas et al. forthcoming; Kleis et al. 2012), and "informating" or providing information to the right organizational actor at the right time for rational decision-making (Benbasat and Nault 1990; Mendelson and Pillai 1999). However, these outcomes and mechanisms suggest the contribution of IT to firm value is primarily accrued during planned contexts. Yet, modern environments, characterized by several adverse events, both exogenous and endogenous, require firms to adapt and adjust to disruptions in their environment that represent discontinuous change. The business value of IT in these contexts remains under-investigated. This study addresses this gap in the literature by advancing the theoretical proposition that the pre-existing IT endowments of firms accorded them economic immunity during the onset of the COVID-19 pandemic, as reflected in stock market reactions.

The Covid-19 pandemic is a useful context to empirically test our theory as it represents an unprecedented test of resilience with respect to its systemic severity (Ding et al. 2021; Reinhart 2020). Firms across diverse sectors were subjected to two simultaneous shocks during this event – a supply-side shock and a demand-side shock - as the event disrupted supply chains and affected consumer demand and behaviors across diverse sectors. Both these shocks are generally present, either in isolation or concurrently, during other adverse events. Further, the onset of the Covid-19 pandemic had a global scope. Hence, lessons from the COVID-19 pandemic are generalizable to other crises, and firms that demonstrate resilience during COVID-19 should be able to do so across other adverse events, irrespective of the type of shock and scope.

IT endowments enable adaptations to demand and supply disruptions from adverse events such as the COVID-19 pandemic. The literature identifies plausible adaptations that may underlie favorable market responses to pre-existing IT endowments. First, a firm's IT endowment enhances its ability to sense threats and opportunities in a timely and precise manner. Second, it facilitates digitized business processes, operations and work models that are malleable, flexible, and responsive to changing business needs due to process modularization and atomization (Khuntia et al. 2022; Sanchez and Mahoney 1996). Third, IT endowments enable firms to identify alternate sources of demand and supply during duress as they help firms sustain connectivity and collaboration with customers and suppliers (Konsynski 1993). Finally, a firm's IT endowment facilitates comprehensive and timely information sharing, which enhances visibility across the entire value chain (Brandon-Jones et al. 2014), ultimately promoting resilience (Christopher and Peck 2004). Hence, we hypothesize:

> **Hypothesis**: A firm's preexisting IT endowment is related to positive abnormal market returns during the onset of the COVID-19 pandemic.

Research Design

Data

Our sample, comprising Fortune 500 firms, is at the intersection of four archival data sources. First, we obtain data on *IT Endowment* of firms from the Harte Hanks Market Intelligence Computer Intelligence Technology database (hereafter *CI database*), which is populated through a survey of IT usage by nearly 17,000 sites across the U.S. These data have been widely used in prior research on the impacts of IT (Brynjolfsson and Hitt 2003; Dewan and Ren 2011; Forman 2005; Forman et al. 2005; Forman et al. 2008; Jia et al. 2020; Pincus et al. 2017; Tambe et al. 2012).

Second, we retrieve accounting data for these firms for the fourth quarter of 2019 and the first quarter of 2020 from the *Compustat* database to construct operating performance and control variables for our analyses. Third, we obtain data on daily stock returns from 2017 to 2020 from the *CRSP* database. Fourth, similar to prior studies in IS (e.g., Andrade-Rojas et al. 2021; Saldanha et al. 2020; Saldanha et al.

forthcoming), we collect news announcements pertaining to firms' responses to the Covid-19 pandemic during the first quarter of 2020 from *Factiva* database, which covers more than 30,000 news sources. Finally, to assess the business continuity in the customer-facing behavior of firms in our sample, we collect tweets from their official Twitter handles during the first quarter of 2020. Our final sample consists of 443 distinct firms.

We obtained the above data for the first quarter of 2020. During the onset of an adverse event, the effects of the demand or supply shocks are high, and firms can gain abnormal benefits from their *IT Endowment* as compared to their competition. In the long run, as the changes in the business environment caused by the adverse event become persistent, abnormal benefits may not persist as Bayesian updating, learning over time, or spillover effects take hold in competitors (Grenadier and Malenko 2010). For example, while a firm with a high IT endowment may rapidly repurpose operating facilities at the onset of the pandemic, as competing firms gain a better understanding of the shock, they may imitate the focal firm by undertaking similar operational expansions or repurposing. Thus, stock market reactions to pre-existing IT endowments will be salient during the onset of the COVID-19 pandemic.

Measures

IT Endowment

CI database provides information on the implementation of various information technologies at the firm level (1 if implemented at any of the sites of the firm, 0 otherwise). Consistent with prior research, the sum of all indicator variables provides an estimate of the *IT Endowment* of the firm (e.g., Jia et al. 2020; Pincus et al. 2017; Saldanha et al. 2022; Saldanha et al. 2020). We also formulate alternate weighted measurements of *IT Endowment* for use in robustness analysis. The sum of indicator variables across different application types provides measures of four different classes of IT endowments (Pincus et al. 2017). *Market Intelligence IT (MKIT)* comprises IT applications - business intelligence, data warehousing, and data storage digital technologies, that enable a firm to gather, store, and surface market insights. *Collaboration IT (CIT)* consists of information technologies for remote access, collaboration, document management, groupware, workflow, and email. *Enterprise Integration IT (EIIT)* contains enterprise resource planning, accounting, human resource management, asset management, and enterprise management technologies which increase the internal integration of the firm. Finally, *Value Chain Integration IT (VCIIT)* encompasses customer relationship management, supply chain management, and e-commerce technologies that bestow the functionality to increase integration across the value chain. These four categories are not exhaustive - other functionalities may be conferred by *IT Endowment*, and not all IT that constitute *IT Endowment* are part of a category.

IT endowment and its constituent categories are estimated at the end of 2018. Our choice of 2018 IT Endowment is motivated by the consideration that a one-year lag in the measurement accounts for information assimilation and processing by the market and technological adoption and assimilation by the firm. As is well established in prior literature, organizations require more than a year to assimilate new IT applications before they can bear their benefits. Also, IT Endowment data for 2018 was collected between early and mid-2019 and reflects firms' IT endowments at the end of 2018 — only 12 to 13 months before the pandemic was reported in the news. However, the IT Endowment data for 2019 was collected in early to mid-2020, which was after the pandemic had commenced and the period of our study. Since the pandemic was unforeseen in 2019, using 2018 data also ensures that the stock market reaction is to pre-pandemic IT endowments of the firm. This identification cannot be ensured if we use the IT Endowment data from 2019.

Market Response: Abnormal Stock Returns and Volatility

We use abnormal market returns during the COVID-19 event as dependent variables (Flammer 2015; Ramelli and Wagner 2020). *Quarterly Abnormal Return* of a stock is estimated as the difference between the logarithm of the stock's gross quarterly return and the logarithm of the market's expected gross quarterly return using the Fama French three-factor model. Similarly, *Daily Abnormal Return* of a stock is calculated as the difference between the daily logarithm return (i.e., the logarithm of gross return) of the stock and the daily logarithm expected return measured using the Fama French three-factor model. The betas are estimated using daily returns from 2017 and 2019 and the S&P 500 as the market index.

We use the Fama and French three-factor model to estimate abnormal market returns. The model assumes:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it} \cdots (1)$$

where R_{it} is the return of stock i on day t, R_{ft} is the risk-free rate, R_{mt} is the market return on day t, HML_t is the difference between the returns on portfolios of high and low book-to-market stocks on day t, and α_i is the intercept of the relationship for stock i. β_i is the systematic risk (or beta) of stock i, which captures the sensitivity of stock i's return to the market return, while s_i and h_i capture the sensitivity of stock i's return to the respective event portfolios of the other two factors. ε_{it} is the error term and represents the portion of the return for stock i on day t that is unexplained by the three factors. We use ordinary least squares regression over a period of all trading days from 2017 to 2019 to estimate $\widehat{\alpha_i}$, $\widehat{\beta_i}$, $\widehat{s_i}$ and $\widehat{h_i}$.

The abnormal return for firm stock i on day t is the difference between the actual and the expected return for the stock, and is calculated as:

$$A_{it} = R_{it} - \left(\widehat{\alpha_i} + \widehat{\beta_i}\left\{R_{mt} - R_{ft}\right\} + \widehat{s_i} SMB_t + \widehat{h_i} HML_t\right) \cdots (2)$$

We then calculate the volatility of stock returns, both quarterly and daily. For quarterly volatility, *Total Quarterly Volatility* is measured as the standard deviation of daily raw log returns over the quarter, and *Idiosyncratic Volatility* is calculated as the standard deviation of Fama-French adjusted daily stock returns over the quarter. We estimate *Daily Price Range Volatility* in terms of the daily price range, that is, the highest traded price of the stock for the focal date less the lowest traded price of the stock for the focal date, scaled by the midpoint of the high and low daily prices of the stock for the focal date.

Operating Performance

We assess operating performance through seven variables that capture the quarterly change in operating performance of the firm over the previous quarter (from the fourth quarter of 2019 to the first quarter of 2020) as compared to its cohort of the same industry firms (Agarwal and Tiwana 2015). Hence, all variables are calculated as the variable value adjusted by the industry average in the previous quarter minus the variable value adjusted by the industry average in the focal quarter.

Quarterly Change in Return on Assets is measured as operating income before depreciation over book assets, multiplied by 100. *Quarterly Change in Operating Margin* is measured as operating income before depreciation over sales, multiplied by 100. *Quarterly Change in Asset Turnover* is sales over book assets multiplied by 100. *Quarterly Change in Inventory Turnover* is sales over average inventory. *Quarterly Change in Return on Equity* is net income over book equity multiplied by 100. *Quarterly Change in CapEx to Sales Ratio* is capital expenditure over sales, multiplied by 100. Finally, *Quarterly Change in Sales* is assessed as the logarithm of total sales.

Twitter Behavior

Social media-based communication of firms provides high-frequency and high-resolution data, widely accepted as a reliable method for nowcasting the status of business activities. Thus, we collect official tweets of firms in our sample during the first quarter of 2020. We use *Tweet Similarity*, which captures the similarity of firm-level tweets before and after the onset of the pandemic, as the dependent variable for this analysis.

Specifically, *Tweet Similarity* is estimated by calculating the distance between text corpora of the two sets of tweets for a given firm. First, all tweets by a given firm for a time period are cleaned, concatenated, and represented as a vector. This is realized by applying *TfidfVectorizer*, which quantifies the text in each time period based on term frequency by counting how often each word appears in a set of tweets.

Second, the frequency of all words in each text corpora is calculated while adjusting for over-weighing of common terms. For this purpose, we use the inverse document frequency, which gives higher weight to less common terms.

Finally, *Tweet Similarity* is derived by calculating the cosine of the angle between the text corpora vectors. We normalize the text corpora vectors by dividing each by its Euclidean norm, essentially scaling them to have a length of 1, thereby making the vectors comparable. The cosine similarity measure calculates the cosine of the angle between the vectors representing the tweet content, which provides a similarity score between 0 and 1. Thus, for a firm with similar tweet content before and after the onset of the pandemic, the *Tweet Similarity* value will be high (Hoberg and Phillips 2016; Tomar et al. 2020).

Controls

We include an extensive set of control variables in our regression specifications. *Tobin's Q* accounts for growth prospects and firm intangibles which may influence stock returns (Dyck et al. 2019; Ramelli and Wagner 2020). It is measured as the book value of assets minus the book value of equity plus the market value of equity, divided by the book value of assets. *Firm Size* may influence abnormal market returns and is measured as Total Sales – the natural log of sales plus one (Dyck et al. 2019; Kathuria et al. 2023). *Cash* holdings of a firm can affect its attractiveness to investors and are measured as cash holdings over book assets (Ramelli and Wagner 2020). *Leverage* accounts for the ability of the firm to raise funds and hence influences its stock price (Kathuria et al. 2023; Ramelli and Wagner 2020). It is calculated as the book value of debt over the book value of assets. Firms with high *Return on Equity* (ROE) are more attractive to investors and is measured as net income over book equity. We control for *Advertising Expenditures* scaled by the book value of assets as this reflects opportunities for future customer growth (Ramelli and Wagner 2020). We also control *Historical Volatility*, measured as the volatility of the daily logarithm return of the stock during 2019 (Ramelli and Wagner 2020). Finally, *Dividend* (Dividend per share over stock price, multiplied by 100) increases the attractiveness of a stock and is accounted for (Acharya and Steffen 2020).

All controls are measured in 2019 US dollars – a time period subsequent to the time period of the independent variable because their behavior and effect on the performance variable is different than the IT Endowment variable. We winsorize all accounting variables at the 1% level in each tail.

Methodology

Econometric Specifications

We employ two sets of regressions in our analysis. We initially show a correlation with cross-section regressions, and then in our main results, we utilize difference-in-differences models to causally infer the effect of IT Endowment on abnormal market returns during the Covid-19 pandemic (Bertrand et al. 2004). The cross-sectional regression of firms' market and operating performance on *IT Endowment* is as specified in equation (3):

$$Performance_i = \beta_0 + \beta_1 ITE_i + \beta_2 X_i + \beta_3 \varphi_i + \epsilon_i \tag{3}$$

Here, β_1 is the parameter of interest that captures the effect of *ITE* (*IT Endowment*) of firm *i* in 2018 on its performance during the first quarter of 2020. We assess the impact of *IT Endowment* on three performance outcomes: *Quarterly Abnormal Returns*, *Return Volatility* (including total and idiosyncratic volatility), and Operating Performance (including quarterly change in return on assets, operating profit margin, asset turnover, inventory turnover, capex to sales, and sales). X is an array of time-variant firm-level controls for firm *i* in 2019. φ accounts for industry fixed effects.

Cross-sectional regressions are limited in their ability to provide clean causal estimates as the quarter incorporates both the effect of the crisis as well as the fiscal response to the crisis. However, the advantage of such a regression specification is that since it is not associated with a specific shock date, it provides external validity. The cross-sectional regressions also allow for the examination of the consistency between the market returns and operating performance regressions, for which we have quarterly data.

We complement our cross-sectional regressions with our main analysis that uses a difference-in-differences regression to better causally infer the effect of *IT Endowment* on market response during the Covid-19 pandemic (Bertrand et al. 2004). Our focus in the difference-in-differences regression is stock market performance that we estimate using the following specification:

$$Abnormal\ Returns_{it} = \beta_0 + \beta_1 (ITE_i \times Post\_Covid_t) + \beta_2 (ITE_i \times Post\_Fiscal_t) + \beta_3 \nu_i + \beta_4 \tau_t + \epsilon_{it} \tag{4}$$

We use this specification to study two dependent variables, *Daily Abnormal Returns* and *Daily Return Volatility*, for firm *i* on day *t* during the first quarter of 2020. Hence, subscripts *i* and *t* index firm and time, respectively. *ITE* is the treatment intensity (Danaher et al. 2020) and equals the count/intensity of total *IT*

Endowment of firms. In subsequent robustness analysis, we replace *ITE* with an indicator variable *High_ITE* that takes the value of one for firm *i* if its pertinent measure of *IT Endowment* is in the top quartile of the sample in 2018, and zero otherwise. *Post_Covid* is an indicator variable that is set equal to one from February 24 to March 31, 2020, and zero before this period. *Post_Fiscal* is an indicator variable equal to one from March 18 to March 31, 2020, and zero otherwise. Controlling for the second event enables us to achieve a cleaner identification of the effect of the COVID-19 pandemic. We include firm fixed effects ν_i and day fixed effects τ_t to control for unobservable factors. Standard errors are clustered by firm and day. We subsequently demonstrate the robustness of our results to alternate measures of IT Endowment, industry heterogeneity, and decomposed functional categories of IT Endowment.

The first date used to identify the COVID-19 shock in our difference-in-differences regressions is February 24, 2020. This was the first trading day after the first lockdown was announced in Europe and has been identified as the start of the "fever" period in the pandemic (Ramelli and Wagner 2020). Stock markets witnessed a strong decline after this date. Markets continued to decline intensely despite the release of a fiscal relief package on March 6. On March 11, 2020, the United States announced a travel ban and declared the COVID-19 pandemic a national emergency on March 13, 2020. The Dow Jones Industrial Index witnessed three of its fifteen worst trading days ever between March 9 and March 16, 2020.

On March 18, 2020, a much larger second Coronavirus Emergency Aid Package was signed into law, and the Federal Reserve commenced purchases in short-term credit markets. These interventions resulted in stock markets rebounding. March 18, 2020, therefore signifies the day when the U.S. fiscal and monetary policy response to the pandemic led to a stock market recovery. We use this date to isolate the effect of the U.S. fiscal and monetary response on abnormal market returns.

These two dates present a narrow window within the first quarter of 2020 to test the causal link between *IT Endowment* and *market response*. Therefore, in Equation (4), β_1 captures the causal impact of *IT Endowment* on abnormal stock returns during the crisis while β_2 reflects the additional impact of the endowment during the second time window that is expected to be muted by the government's fiscal response.

Overall, our research design uses the Covid-induced stock market crash to detect how IT endowment affords differential impacts on changes in market response and operational performance caused by adverse events. Our examination of the effect of ex ante *IT Endowment* on market and operating performance during the crisis has two critical characteristics. First, we measure firms' *IT Endowment* with a lag of more than a year – a time when the pandemic was unforeseen. Second, the adverse event of the Covid-19 crisis itself occurred within a narrow window of time – a period so short that firms had little time to respond. Consequently, the stock market reaction and subsequent abnormal returns and operating performance of a firm can be attributed to pre-pandemic endowment of information technologies.

Main Analysis

Cross-Sectional Analysis of Market Response and Operating Performance

Table 1 presents results of cross-sectional analysis. We assess the market response through results presented in columns 1 and 2, where *Quarterly Abnormal Return* is the dependent variable. The effect of *IT Endowment* ($p < 0.01$) is positive and significant in both specifications. The magnitude of the coefficient estimate suggests that one standard deviation increase in *IT Endowment* is associated with a higher quarterly stock return of 4.27% (beta coefficient x standard deviation = 0.147 x 29.030) on average. This stock return comprises market response both to the Covid-19 pandemic as well as to the fiscal response. Commensurate with prior research, firms with larger size, greater cash, lower leverage, lower advertising expenses, and lower dividends perform better (Albuquerque et al. 2020; Albuquerque et al. 2019; Ramelli and Wagner 2020).

To complement the analysis of stock returns, we examine the impact of *IT Endowment* on the volatility of the stock returns by repeating the cross-sectional regressions for *Total Volatility* and *Idiosyncratic Volatility*. *Total Volatility* is measured as the standard deviation of daily raw log returns over the quarter and *Idiosyncratic Volatility* is calculated as the standard deviation of adjusted daily stock returns over the quarter. The results for *Total Volatility* are presented in columns 3 and 4, and for *Idiosyncratic Volatility* are presented in columns 5 and 6 of Table 1. In both regression specifications, we find that firms with high *IT Endowment* have consistently decreased stock return volatility as compared to other firms (p< 0.01).

We focus on stock market performance as an indicator of resilience to the Covid-19 pandemic because capital markets are efficient and stock returns are forward-looking and incorporate information quickly. Accounting metrics of performance are slower at incorporating information, especially given that the effects from the pandemic continue to unfold. However, an analysis of metrics of operating performance can provide validity to our overall thesis and supporting results. Hence, we conduct an *ex post* examination of the effect of *IT Endowment* on operating performance metrics as firms respond to the Covid-19 pandemic.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
VARIABLES	**Cumulative Abnormal Returns**		**Total Volatility**		**Idiosyncratic Volatility**	
IT_Endowment	0.169***	0.147***	-0.192***	-0.126***	-0.227***	-0.139***
	(0.295)	(0.277)	(0.023)	(0.018)	(0.023)	(0.017)
Observations	456	453	456	453	456	453
R-squared	0.029	0.141	0.037	0.367	0.052	0.448
Industry Fixed Effects	No	Yes	No	Yes	No	Yes
F	11.61	4.633	13.99	11.30	19.90	15.40

Notes: (1) This table reports the results of cross-sectional regressions of the first quarter of 2020 abnormal returns, total volatility, and idiosyncratic volatility on firms' total IT Endowment under several specifications: without firm controls and industry fixed effects (Columns 1, 3 and 5), and with firm controls and industry fixed effects (Columns 2, 4 and 6). (2) Controls included are Tobin's Q, Size, Cash, Leverage, ROE, Advertising, Historical Volatility, and Dividend. (3) Dependent and control variables are winsorized at the 1% level in each tail. (4) There are differences in observations across the different columns because values for one or more of the control variables are not available for the missing firms. (5) Coefficients are standardized, and the regression constant is omitted for brevity. (6) The numbers in parentheses are heteroscedasticity robust standard errors. (7) *p < .1; **p < .05; ***p < .01.

Table 1: Cross Sectional Quarterly Abnormal Returns Analysis

For this purpose, we investigate seven different metrics. *Quarterly Change in Return on Assets* indicates if firms are able to maintain efficiency of operations during the pandemic as compared to industry peers. *Quarterly Change in Operating Margin* is an indicator of firm's ability to maintain costs and prices as compared to industry peers. *Quarterly Change in Asset Turnover* indicates how efficient a firm is at generating revenues from its assets as compared to industry peers. *Quarterly Change in Inventory Turnover* indicates the number of times a firm sells and replaces inventory during a quarter as compared to industry peers. *Quarterly Change in Return on Equity* indicates a firm's ability to generate profits from stakeholder's equity during the pandemic as compared to industry peers. *Quarterly Change in Capex to Sales Ratio* is an indicator of a firm's current financial well-being and investment into future opportunities during the pandemic as compared to industry peers. To demonstrate validity, we also assess *Quarterly Change in Sales*. We use the change in these metrics from the fourth quarter of 2019 to the first quarter of 2020 as the dependent variables in our specifications. All measures are industry-adjusted by subtracting the median value of the firm's *Fama-French* industry (Hartzmark and Sussman 2019).

The results are presented in Table 2. Several insights emerge from these analyses. First, we find that firms with high *IT Endowment* have consistently higher operating performance as captured by four different measures, thereby confirming our expectation that IT endowments provided immunity to the pandemic. One standard deviation increase in *IT Endowment* increases the *Return on Assets* by 0.80 percentage points, the *Operating Profit Margin* by 2.14 percentage points, and *Asset Turnover* by 0.79 percentage points. Finally, a one standard deviation increase in *IT Endowment* increases the *Capex to Sales Ratio* by 17.12 percentage points. Note that we use one standard deviation increase (and not one unit increase) in *IT Endowment* to interpret the results because we report standardized regression coefficients as these provide comparability, interpretability, and variable scaling across the models.

Second, we find evidence of inconsistent returns across three other accounting-based measures, thereby validating our assertion that at the onset of the pandemic, market-based measures are quicker to distill and incorporate multiple facets of information. *IT Endowment* has a marginal impact at the 10% level on the change in *Sales* but no impact on the change in *Inventory Turnover* and *Return on Equity* witnessed by firms between the last quarter of 2019 and the first quarter of 2020.

These results imply that despite the economic duress and decreasing sales during the first quarter of 2020, which encompasses the Covid-19 pandemic, firms with high *IT Endowment* witnessed greater operating performance reflected in their margins and their ability to sweat their capital assets and inventories. Thus, *IT Endowment* enabled firms to maintain their margins by holding operating costs low and avoiding disruptions in the production cycle through increases in capacity utilization and alternate sourcing. Furthermore, firms with high *IT Endowment* also made higher investments in capital assets, which constitute resources that can service increases in demand and exploit future business opportunities. These results validate our choice of market-based measures of abnormal returns as a credible indicator and further affirm support for our main prediction that firms with greater *IT Endowment* observed better market response indicating greater economic resilience.

Dependent Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	Quarterly Change in						
	Return on Assets	**Operating Margin**	**Asset Turnover**	**Inventory Turnover**	**Return on Equity**	**Log Sales**	**Capex to Sales Ratio**
IT_Endowment	0.104**	0.098**	0.085**	-0.031	0.048	0.065*	0.250***
	(0.021)	(0.132)	(0.053)	(0.015)	(0.333)	(0.002)	(0.283)
Observations	389	389	407	335	389	404	407
R-squared	0.099	0.086	0.083	0.162	0.035	0.140	0.189
F	6.335	4.051	4.003	6.977	1.178	7.279	6.908

Notes: (1) This table reports the results of cross-sectional regressions of change in operating performance measures between the fourth quarter of 2019 and the first quarter of 2020 on firms' IT Endowment. (2) Dependent and control variables are winsorized at the 1% level in each tail. (3) Quarter fixed effects, industry fixed effects, Change in Industry Growth rate, Change in GDP Growth rate, and firm controls (Tobin's Q, Cash, and Leverage) included in all models. (4) There are differences in observations across the different columns because values for one or more of the control variables are not available for the missing firms. (5) Coefficients are standardized, and regression constant and controls are omitted for brevity. (6) The numbers in parentheses are heteroscedasticity robust standard errors. (7) *p < .1; **p < .05; ***p < .01.

Table 2: Cross Sectional Quarterly Operating Performance Analysis

Difference-in-Differences Analysis of Market Response

The results of a difference-in-differences estimation can facilitate causal inference between high *IT Endowment* of firms and market response during the onset of the COVID-19 pandemic reflected by daily abnormal stock market returns. By regressing *Daily Abnormal Returns* on *IT Endowment* and dummy variables for the two events that occurred during the COVID-19 pandemic, we can capture a tighter link between the variables of interest. *Post_Covid* and *Post_Fiscal* capture the two events of the COVID-19 pandemic and the fiscal response. Table 3 reports results using a continuous measure of *IT_Endowment*, which reflects *IT Endowment Intensity* and captures the entire ambit of business-critical information technologies implemented in a firm. The difference-in-differences specification satisfies the parallel trends assumption (Bertrand et al. 2004).

Overall, the results in Column 1 and Column 2 show that the coefficient of the interaction between *Post_Covid* and *IT_Endowment* is significant and positive at the 1% level. Firms with high *IT Endowment* earned an average abnormal daily return of 0.255% relative to other firms from February 24, 2020 to March 17, 2020, resulting in a cumulative abnormal of 4.08% over the 16-day period between *Post_Covid* and *Post_Fiscal* and 6.89% over the 27 trading days from *Post_Covid* till the end of the quarter. In sum, investors paid more for firms with high *IT Endowment* as the market collapsed due to the Covid-19 pandemic. The fiscal response dummy, *Post_Fiscal*, interacted with *IT_Endowment* is negative and significant at the 5% level, implying that firms with high *IT Endowment* witnessed lower stock returns once the market began to rise. This is ostensibly because these stocks witnessed a lower fall during the market meltdown. Since we are able to identify the response of stock returns to the pandemic with daily data, we can concretely identify these economically significant results. These results corroborate the results of the cross-sectional regression specifications. Note that we also estimated a two-way fixed effects model with the treatment dummy. The results, omitted for brevity, were similar and stronger in magnitude.

To complement the main analysis of abnormal stock market returns, we examine the impact of *IT Endowment* on the volatility of these returns during the Covid-19 pandemic. We also estimate a difference-in-differences specification to strongly associate the variation in volatility of abnormal stock returns during the Covid-19 pandemic to *IT Endowment*. In this specification, our dependent variable is *Daily Return Volatility*, which is measured as the daily high price minus the daily low price divided by the average price of the stock during the day.

The results in Column 4 demonstrate that the decrease in range-based volatility of stock returns in the post-Covid period can be attributed to *IT Endowment*. The coefficient of the interaction between *Post_Covid* and *IT_Endowment* is significant and negative at the 1% level. Firms with high *IT Endowment* experienced an average daily decrease in price-range volatility of 0.46% (0.093 x 4.931) relative to other firms. The coefficient between *Post_Fiscal* and *IT_Endowment* is also negative and statistically significant at the 5% level, implying that firms with greater IT endowments witnessed lesser daily volatility of stock returns during both the market meltdown and recovery. Overall, the effects of *IT Endowment* on stock returns volatility complement our main results and imply that a positive market response is reflected in both mean abnormal returns and in the volatility of the abnormal returns. Thus, we find support for our hypothesis that *IT Endowment* influences a positive market response during adverse events, such as COVID-19.

	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	**Daily Abnormal Returns**		**Daily Return Volatility**	
Post_Covid x IT_Endowment	0.095***	0.095***	-0.093***	-0.093***
	(0.011)	(0.011)	(0.012)	(0.008)
Post_Fiscal x IT_Endowment	-0.059**	-0.059**	-0.050**	-0.050***
	(0.022)	(0.021)	(0.022)	(0.015)
IT_Endowment	-0.001	0.052	-0.024***	-0.298***
	(0.003)	(0.085)	(0.003)	(0.054)
Post_Covid	-0.179***	-0.324***	0.592***	1.198***
	(0.148)	(0.406)	(0.160)	(0.255)
Post_Fiscal	0.112***	0.247***	0.311***	-0.484***
	(0.279)	(0.486)	(0.289)	(0.302)
Observations	27,466	27,466	27,466	27,466
R-squared	0.008	0.050	0.474	0.760
Firm and Day FE	No	Yes	No	Yes
F	34.99	1.767	3603	106.4

Notes: (1) This table reports the results of a difference-in-differences estimation of daily abnormal returns and daily return volatility during the first quarter of 2020. (2) IT_Endowment equals the count/intensity of IT Endowment of firms and is specified as the treatment intensity (Danaher et al. 2020). (3) Post_COVID equals one from February 24 to March 31, 2020, and zero before this period. (4) Post_Fiscal equals one from March 18 to March 31, 2020, and zero before this period. (5) Firm and day fixed effects are (not) included in specifications 2 and 4 (1 and 3). (6) Dependent variables are winsorized at the 1% level in each tail. (7) Coefficients are standardized, and the regression constant is omitted for brevity. (8) The numbers in parentheses are standard errors clustered by firm and day. (9) *p < .1; **p < .05; ***p < .01.

Table 3: Difference-in-Differences Daily Abnormal Returns Analysis

Matched Sample Analysis

We reiterate that the premise of our identification strategy is that the pandemic and the subsequent lockdown was an unanticipated shock to stock markets to which firms had very limited ability and time to respond. We utilize this market crash as an exogenous shock. In this context, firms with higher levels of pre-COVID *IT Endowment*, which is the treatment in our study, accrued more positive market response relative to other firms. Despite our strong identification strategy and elaborate robustness tests, there is still a remote possibility that abnormal market returns accrued during the onset of the Covid-19 pandemic are confounded by other, unobserved, pre-Covid firm-level characteristics and thus are not the result of the treatment effect. To address this prospect, in the absence of a pure control group, we use a matched sample approach to construct samples that consist of similar firms (using pre-Covid firm characteristics) with high and low *IT Endowment*. To reduce industry heterogeneity bias, we split the *IT Endowment* into high and low using the median within a one-digit SIC classification, as well as a Fama-French 12-level industry classification. We divide the trading days of the first quarter of 2020 into two periods – pre-Covid (January 1 to February 23) and post-Covid (February 24 to March 31).

We implement two matching methods – coarsened exact matching (CEM) and propensity score matching (PSM). In both the methods, matching is based on the book-to-market ratio (i.e., equity capitalization divided by the book value of equity in the years 2018 and 2019), size (i.e., equity capitalization in years 2018 and 2019), Tobin's Q (in quarter 4 of 2019) and cash holdings (in quarter 4 of 2019). We perform CEM within each Fama-French 5-level industry classification to obtain a group of matched firms. Thereafter, we perform a one-to-one nearest-neighbor matching with replacement and common support in the matched sample obtained previously. Nearest-neighbor matching estimators impute the missing potential outcome for each firm by using an average of the outcomes of similar firms that receive the treatment (high *IT Endowment* in our case). We restrict the number of matches to one per treated firm.

To ensure that the results are not sensitive to our choice of matching estimator, we also provide evidence from PSM. To implement PSM, we use the nearest-neighbor matching procedure with replacement (Abadie and Imbens 2002) to identify matched firms that are nearest to our sample firm based on propensity scores. We restrict the number of matches to two per treated firm. We obtain consistent and robust results that are similar to our main findings for both matches. The treatment effect on the treated group is insignificant and close to zero in the pre-Covid period, while it is positive and significant in the post-Covid period. This reaffirms our finding that firms with high *IT Endowment* witnessed superior market response (higher abnormal returns and lower volatility) only during the post-Covid and not during the pre-Covid period.

Investigating Alternate Explanations

Alternate Measures of IT Endowment

We assess the sensitivity of our results to alternate measures of *IT Endowment*. First, we estimate the difference-in-differences specifications with a binary treatment for IT endowments. Here, the treatment group of firms is represented by an indicator variable *High_IT_Endowment* that takes the value of one for firms in the top quartile for the *IT Endowment* measure (this identification strategy is consistently used in prior research (Lins et al. 2017)). Consistent with our main results, the coefficient of the interaction between *Post_Covid* and *High_ IT_Endowment* is positive for the *Daily Abnormal Returns* columns, negative for the *Daily Return Volatility* columns, and significant at the 1% level across all models. However, the coefficient of the interaction between *Post_Fiscal* and *High_ IT_Endowment* is significant (and negative) only for *Daily Return Volatility*.

Second, we construct alternate measures of *IT Endowment* through the weighted average method used in prior literature (Dewan and Ren 2011). We compute these two alternate measures with revenue per organizational site and number of employees per organizational site as weights. While the coefficient of the interaction between *Post_Covid* and *IT_Endowment* is significant and positive for both alternate measures, we find stronger effects with higher significance for the revenue weighted alternate measure, demonstrating strong validation for our main results. The interaction of *IT_Endowment* with *Post_Fiscal* is not significant for both measures. We repeat all subsequent analyses using these weighted average formulations of all the *IT Endowment* variables and broadly find stronger or similar estimates for all specifications. Together, these imply that our main analysis has conservative estimates.

Industry-level Heterogeneity

While the inclusion of industry fixed effects in the difference-in-differences specifications do not adversely affect our results, we conduct a series of further analyses to rule out industry heterogeneity and demonstrate within-industry effects of *IT Endowment* on abnormal returns. We investigate three alternative explanations for our findings by estimating the difference-in-differences specifications after excluding firms in industries (per the *Fama-French* industry classification) that witnessed increased economic activity.

First, quarter one of 2020 witnessed a collapse in oil prices. Thus, we estimate our main analysis for *Daily Abnormal Returns* after excluding firms in the energy sector from our sample and find similar results Second, essential industries were allowed to continue operations without disruption during lockdowns (Papanikolaou and Schmidt 2021). Accordingly, we estimate the difference-in-differences specification after excluding these industries and find consistent results. Third, firms in high-tech industries experienced higher demand; thus, we estimate the regression specification after excluding firms from the high-tech industry from our sample (Decker et al. 2017). The results remain similar.

We also repeat our analysis after excluding the remaining industries from the sample one at a time, with consistent results. We attempt to assess within-industry effects by repeating the difference-in-differences analysis for each industry sub-sample in isolation. Though the results are marginally significant in most cases, the small size of the industry sub-samples precludes us from drawing reliable conclusions from this exercise. Instead, we repeat the difference-in-differences regression with triple interactions between *Post_Covid*, *IT_Endowment*, and indicator variables which take the value 1 if the firm is present in a specific industry as per the *Fama-French* industry classification. The difference-in-differences regressions also include triple interactions with *Post_Fiscal*. All triple interaction terms with *Post_Covid* are significant, suggesting that our findings are not associated with any industry. Finally, to further support that our results are not an artifact of sample composition or the heterogeneous effect of *IT Endowment* across industries, we compute the binary treatment variable *High_IT_Endowment* at the industry level. Specifically, instead of *High_IT_Endowment* indicating that the firm's IT endowment is in the top quartile of the sample (thus pooled across industries), *High_IT_Endowment* indicates if the firm has IT endowment in the top quartile within its industry. We continue to find consistent results.

Firm-level Heterogeneity

We assess the sensitivity of our results of the difference-in-differences specification to two sources of firm-level heterogeneity — firm size and slack, by expanding the specification to triple interaction specifications. We find that the triple interaction of *Firm_Size* is not significant, while the triple interaction of *Slack* is significant at the 1% level.

Alternate Event Windows and Time Period

We perturbate the event windows in the difference-in-differences specification and find qualitatively similar, though weaker results. Specifically, we change the indicator variable *Post_Covid* to equal one from January 30, 2020 onwards as the World Health Organization declared the outbreak a public health emergency on this day. We also reran the analysis after changing the start of the *Post_Covid* to different dates between January 30, 2020 and February 24, 2020. Finally, we also redid the analysis with *Post_Covid* set to one only between the dates of February 24, 2020 and March 18, 2020 while excluding the *Post_Fiscal* indicator. As an additional robustness test, we assess the long term market response to *IT Endowment*, as reflected by daily abnormal stock market returns, by estimating the difference-in-differences specification with data for the entire year of 2020. Overall, primary results are *persistent* in the long run, with coefficients of interactions between the fiscal response dummy *Post_Fiscal* and *IT_Endowment* increasing in magnitude. This reflects both the presence of confounding events, as well as Bayesian updating or learning over time of competitors about the environment (Grenadier and Malenko 2010).

Unobserved Sources of Endogeneity

Though our difference-in-differences specification and the battery of robustness tests allow us to rule out several sources of endogeneity that may bias our results, there may still exist some unobservable factors that affect both IT endowment and daily abnormal returns. To correct for such omitted variable bias, we estimate our main difference-in-differences specification as a 2 stage least squares (2SLS) specification. For this purpose, we use the *Industry-Mean IT Endowment* as an instrument for a firm's *IT Endowment*, which is a well-established approach in the literature. While it is plausible that unobserved firm specific variables, such as the CEO's skills and capability, may simultaneously influence the firm's IT endowment and market response, it is unlikely that such variables (or the CEO in this example) would be able to influence the IT endowment of all the firms in the industry. We estimate the 2SLS specification with both the continuous and binary treatments for IT endowments. The results are qualitatively similar, albeit marginally weaker, to our main results, thereby enabling us to rule out any remaining endogeneity concerns.

Mechanisms

As demonstrated in our primary difference-in-differences analysis, the presence of *IT Endowment* has a causal relationship with market response and operating performance during the onset of the COVID-19 pandemic. We now provide suggestive evidence of mechanisms underlying the observed resilience.

Analysis of IT Endowment Decomposition

To isolate the mechanisms that underlie the observed effect of *IT Endowment* on market response, we repeat our difference-in-differences estimation, regressing *Daily Abnormal Returns* on four categories of *IT Endowment — Market Intelligence IT (MKIT)*, *Collaboration IT (CIT)*, *Enterprise Integration IT (EIIT)*, and *Value Chain Integration IT (VCIIT)*. Each category pertains to a specific common functionality bestowed by the constituent information technologies. We conduct this analysis using continuous treatments for the IT endowments.

Scrutinizing the coefficients of the functional categories of *IT Endowment* reveals that in isolation, all four categories of IT endowment accrued positive abnormal returns as the market declined during the onset of the Covid-19 pandemic. However, only *Value Chain Integration IT* had significant negative differences in returns when the market rebounded. This endowment enabled firms to earn a high average abnormal daily return of 0.318% (0.092 x 3.452) relative to other firms during the post-Covid period but earned 0.245% (0.071 x 3.452) less than other firms in the post-fiscal period.

Analysis of Twitter Behavior

Social media-based behavior of firms provides high-frequency and high-resolution data, which is widely accepted as a reliable method for nowcasting the status of business activities of firms (Lee et al. 2013; Tomar et al. 2020). Thus, we analyze Twitter data immediately prior to and during the onset of the COVID-19 pandemic to conduct validation analysis that provides suggestive evidence of business continuity during the pandemic.

We conduct multiple regression specifications that use *Tweet Similarity* and *Tweet Sentiment* to assess the twitter-based behavior of firms *during* the pandemic. First, we gauge the effect of *IT Endowment* on business continuity during the COVID-19 pandemic by regressing *Tweet Similarity* on *Total Digital Endowment*. We conduct this cross-sectional regression analysis for two comparative time periods. We assess the results of comparing tweet corpora for the entire first quarter of 2020, divided into pre-Covid and post-Covid periods (1 January to 23 February compared with 24 February to 31 March). We also assess the results wherein the post-Covid period is curtailed by the fiscal event (1 January to 23 February compared with 24 February to 17 March). The analyses show that firms with higher *IT Endowment* demonstrated higher *Tweet Similarity*, indicating business-as-usual market practices.

Second, we estimate a difference-in-differences regression specification with *Tweet Sentiment* as the variable of interest. Here we assess the results of the estimation conducted on a per-tweet basis, as well as the results of a per-day estimation specification. Both analyses indicate that tweets of firms with higher *IT Endowment* have more positive sentiments. Finally, we expand the difference-in-differences specification of the primary analysis to include a three-way interaction term with *High_Sentiment* (an indicator variable for the top quartile of firms by *Tweet Sentiment*). Results indicate that firms with high *IT Endowment* received greater abnormal returns when indulging in positive social media-based communication.

Overall, these analyses corroborate the notion that during the adverse event of the COVID-19 induced market meltdown, firms with high *IT Endowment* exhibited business-as-usual market practices as their Twitter behavior was similar both prior to and during the event and thus exhibited business continuity and resilience in practice *during* the crisis.

Textual Analysis of News Announcements

To elaborate upon our empirical findings, we collected additional fine-grained data on the actual mechanisms utilized by firms in adapting to disruptions during the onset of the COVID-19 pandemic (Pratt 2009). For this purpose, we extracted media articles and news announcements from the *Factiva* database related to the COVID-19 pandemic during quarter 1 of 2020 for all firms with *IT Endowment* in the top quartile. We found more than 200 unique articles that described actions taken by firms as they coped with and responded creatively to the adverse event. We analyzed the text both computationally as well as manually.

In the computational process, after pre-processing the data using stemming techniques, we employed a latent Dirichlet allocation (LDA) model (Blei et al. 2003). LDA is a probabilistic generative model for natural language processing that extracts topics (which are vectors of statistically related words) from a corpus. We then studied the term distribution to assign a label to the topic. We then compared and contrasted the actions taken by firms across these labels (Pratt 2008). As we performed this analysis, several key themes offered mechanisms to explain the observed market response and operating performance benefits accrued to firms with high IT endowments (Pratt 2009).

First, firms with high IT endowment made several changes related to raising, conserving, or repurposing capacity and resources. For example, when faced with decreasing sales, some organizations reduced operating hours of stores or factories, whereas others, when faced with increasing sales, increased operating hours, added shifts, and hired additional employees. Some organizations repurposed existing facilities to produce products and services that witnessed a spike in demand. Given the urgency and scale of adaptations necessary to respond to the rapidly unfolding events, firms undertook these adjustments both in isolation as well as in partnership with other organizations and external stakeholders All these adjustments required expansion or repurposing of capacity and resources, informed and facilitated by IT endowments.

Second, IT endowed firms undertook supply-side adjustments such as increasing supply by paying advances, resolving bottlenecks, locating and activating alternate sources of supply, and identifying substitute raw materials. Firms also reconfigured their supply chains and associated logistics and storage facilities in response to localized disruptions and changes in their operating arrangements.

Third, firms with high *IT Endowment* adopted new or alternate means to connect with their customers. For example, some firms adapted to spikes in demand for essential commodities by limiting purchases through online pre-bookings. Others introduced online pre-bookings to avoid congestion at their retail locations. Many organizations introduced new contactless customer service channels and online services to deliver existing offerings. These customer-facing adjustments leveraged prevailing IT endowments.

Fourth, firms realized remote business practices and new work models that directly built upon their IT endowments. For instance, many organizations in our sample offered new ways to work, including work-from-home options to their employees. Others leveraged IT endowments to remotely engage with their ecosystem partners for innovation-related activities. Some firms adjusted to the vagaries of the pandemic by making their existing offerings and solutions available to consumers digitally. Additionally, organizations repurposed their existing capabilities into virtual offerings to meet new and pressing requirements.

Discussion and Conclusion

Our research makes two significant contributions to the literature. First, we contribute to the emergent, growing literature on the role of IT in mitigating the variegated impact of the Covid-19 pandemic. Recent research has uncovered a growing list of factors that are contributing to our growth and recovery in the face of the COVID-19 crisis (Acharya and Steffen 2020; Albuquerque et al. 2020; Ramelli and Wagner 2020). Information systems scholars have also explored the varied benefits of IT in this context. Our rigorous analysis of comprehensive data on IT investments and firm performance provides early systematic empirical evidence of the role of IT in managing business disruptions arising at the onset of the pandemic. The demonstration of market response and operating performance outcomes of ex-ante *IT Endowment*, along with plausible mechanisms to explain these effects, adds to this growing discourse.

Second, our compelling empirical evidence offers a distinct contribution by way of a nuance to our collective understanding of how value from IT is derived over time. Though IT endowments may be planned for the benefit of business-as-usual activities, the unplanned effects that realize preparedness for unforeseen events point towards the notion of a "planning for the unplanned" value of IT and enable us to join the emerging conversation on an adaptive capability-based temporal understanding of IT value (Agarwal and Tiwana 2015; Tiwana 2015).

The findings of our research must be considered while accounting for its limitations. Due to our difference-in-differences empirical design which controls for time-invariant effects, it is unlikely that our results are an artifact of systematic unobservable differences between firms with high and low *IT Endowment* (Angrist and Pischke 2008; Barua and Mani 2018; Bertrand et al. 2004). However, this specification cannot fully control for time-varying factors that may affect the market performance of firms. Future research can attempt to identify such alternate theoretical mechanisms that may enable firms with high *IT Endowment* to exhibit immunity to adverse events.

Furthermore, our empirical analysis does not capture the lasting effects of the firm's recovery after COVID-19. The focus of our current work is to showcase how IT Endowments function as a harbinger or early indicator of a firm's resilience to adverse events. Accordingly, we conduct a limited long-term analysis of firm recoveries for one year beyond the COVID event that we capture in our primary analysis. Nonetheless, we acknowledge this as a limitation of our research.

Finally, our study examines a particular type of adverse event within a specific market. While the theoretical foundations of our work espouse the generalizability of our findings, future research can attempt to replicate and improve upon these for different adverse events (e.g., Hendricks et al. 2020; Jacobs and Singhal 2017) across different contexts, such as GREAT (Karhade and Kathuria 2020) economies (e.g., Kathuria et al. 2020).

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