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The Impact of Crisis-Responsive Dynamic Capabilities on Firm Performance in the Post-COVID-19 Era: Evidence Across Technology Levels

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Abstract The COVID-19 pandemic heightened environmental uncertainty and challenged efficiency-oriented innovation strategies. This study examines how crisis-responsive dynamic capabilities affect firm performance in the post-COVID-19 era and whether these effects differ across technology levels. Using panel data on 174 firms from the Survey on Technology of Small and Medium Enterprises (2022– 2023), dynamic capabilities are measured by changes in R&D intensity and shifts in innovation types, while performance is captured by sales growth. The results show that dynamic capabilities do not uniformly improve short-term performance; changes in R&D intensity exhibit negative and nonlinear effects, reflecting adjustment costs and learning delays. Importantly, these effects vary by technology level, with pronounced nonlinear patterns observed among medium-high- and high-technology firms. The findings highlight the contingent and nonlinear nature of dynamic capabilities in the post-pandemic context.

Keywords COVID-19 pandemic, dynamic capabilities, innovation performance, technological level

I. Introduction

The COVID-19 pandemic fundamentally altered business environments, necessitating a structural transformation in firms' innovation activities. Prior to the pandemic, corporate innovation primarily focused on incremental innovation, efficiency-oriented R&D investment, and product and process innovation. In

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contrast, in the post-COVID era, firms' innovation activities have increasingly emphasized innovation capabilities, including speed, agility, and resilience. Firms have experienced fundamental changes in resource utilization patterns, encompassing not only the level of R&D investment but also shifts in the direction of R&D efforts, transitions across innovation types, and strengthened collaboration with external technologies and resources. Consequently, rapid adaptive capabilities-such as sensing rapid market changes, seizing emerging business opportunities, realigning strategic directions accordingly, and reconfiguring internal resources and organizational structures-along with organizational learning capabilities, have become central to firms' innovation activities. Thus, the importance of dynamic capabilities under conditions of high environmental uncertainty has been theoretically established by Teece (2007). From this perspective, the COVID-19 pandemic represents a prototypical case of an exogenous shock as conceptualized by Teece. The pandemic was characterized by sudden onset without prior warning, simultaneous and pervasive impacts across industries, a high degree of unpredictability that rendered prior experience insufficient, and a level of severity that posed existential threats to firm survival.

Small and medium-sized enterprises (SMEs), which were more vulnerable to external shocks, were especially compelled to develop survival strategies grounded in entrepreneurship and innovation in response to these challenges (Albaz et al., 2020; Gorzelany-Dziadkowiec, 2021). This shift underscores the growing importance of dynamic capabilities, as conceptualized by Teece et al, which refer to firms' bilities to sense and seize opportunities and to transform and reconfigure resources in response to rapidly changing environments, rather than relying on competitive strategies based on the absolute scale of resource endowments.

From this perspective, innovation research in the post-COVID era should reflect several key features. First, firms' nnovation logic needs to be reinterpreted beyond traditional technology- and efficiency-centered approaches toward a sustainable innovation perspective (Wang et al., 2022). UNIDO (2022) emphasizes that building resilient and sustainable supply chains requires a transition from "just-in-time" to "just-in-case" systems. This suggests that firms must reassess innovation strategies focused solely on new products and technologies and realign their business domains and innovation directions around sustainability and agility to better cope with external shocks and secure long-term viability. Second, while the pandemic caused short-term disruptions and delays in R&D activities, it functioned as an innovation catalyst in the long run by accelerating innovation processes and fostering transitions toward new organizational forms and managerial practices (Gorzelany-Dziadkowiec, 2021). Under conditions of extreme uncertainty, attention must be paid to how quickly firms experimented, learned, and reconfigured their organizations, particularly in terms of decision-making speed, R&D processes, and organizational structures. These changes empirically reaffirm a core proposition of dynamic capability theory: that sustained competitive advantage arises not from the possession of resources per se, but from firms' abilities to transform and reconfigure resources in response to environmental change. The pandemic thus serves as a large-scale social shock that highlights the practical relevance of dynamic capabilities.

Despite this growing recognition, existing studies exhibit several limitations. First, empirical evidence remains scarce regarding how dynamic capabilities influenced actual innovation outcomes, especially technological innovation performance, following the pandemic-induced external shock. While some studies have explored shifts in innovation research trends before and after COVID-19 through bibliometric analyses and literature reviews (Bachmann & Frutos-Bencze, 2022; Sharma et al., 2022; Wang et al., 2020), few have empirically examined the performance implications of dynamic capabilities. Moreover, much of the prior literature and policy reports focus on surface-level outcomes such as employment losses, revenue declines, or profitability deterioration, or provide fragmented accounts of response strategies. As a result, they fail to systematically examine how dynamic capabilities varied according to firms' ntrinsic characteristics, technology levels, and how such variation translated into performance outcomes.

From a program logic model perspective, the outcomes of targeted investments in R&D and technological innovation activities can be assessed through market-based performance indicators such as revenue growth and market share expansion. Among these, revenue growth has been widely employed as a representative proxy for capturing whether technological innovation has translated into commercial success (Artz et al., 2010; Cucculelli & Ermini, 2012; Demiral & Mazzucato, 2012).However, because the effects of technological innovation on firm performance may exhibit substantial time lags—extending up to 10–15 years in some cases—it is methodologically desirable to assess innovation outcomes across short-, medium-, and long-term horizons (Jordan, 2010). Given that only a limited period has elapsed since the conclusion of the COVID-19 pandemic, a rigorous examination of such long-term lagged effects remains beyond the scope of the present study and thus calls for more in-depth analysis in future research.

Second, reports by UNIDO (2022) and WIPO (2021) indicate substantial heterogeneity in post-pandemic recovery trajectories and structural transformation across industries. This can be attributed to fundamental differences in innovation and resource effectiveness across technology levels (Hirsch-Kreinsen, 2008), which in turn shaped firms' survival and recovery strategies after the shock. Although firms generally formulate strategies based on existing resources, responding to environmental change requires resource development, supplementation, and redeployment. Given that firms' responses to high-uncertainty shocks such as the pandemic differed by technology level, it is necessary to systematically investigate how dynamic capabilities operate through resource reallocation mechanisms across different technology regimes and how these mechanisms link to firm performance. Recent studies suggest that the effects of dynamic capabilities are contingent and nonlinear, depending on environmental dynamism (Schilke, 2014), intra-industry heterogeneity (Gelhard et al., 2016; Zott, 2003), and technological contexts (Mikalef et al., 2019). Piening and Salge (2015) further argue that average effects that ignore contextual contingencies are insufficient to explain the actual mechanisms of dynamic capabilities.

To address these research gaps, this study empirically examines the effects of crisis-responsive dynamic capabilities on firm performance in the post-pandemic period and investigates how these effects vary across technology levels. Firms are classified into High-, Medium-high-, and Medium-low-technology groups to capture technology-level heterogeneity in innovation outcomes.

This study adopts two core assumptions. First, the end of 2022 is defined as the transition point to the endemic phase; periods prior to this point are classified as the pandemic era, and subsequent periods as the post-COVID era. Second, because dynamic capabilities are embedded in firm-specific and difficult-to-imitate organizational processes, they face a measurement intractability dilemma, making it challenging to capture them directly using observable indicators (Barreto, 2010). In light of this limitation, the present study adopts R&D intensity as a proxy for dynamic capabilities, consistent with prior empirical research, while simultaneously incorporating organizational actions, strategic adjustments, and technological characteristics into the research model in order to more comprehensively capture how dynamic capabilities are manifested in practice.

Ⅱ. Theoretical Backgrounds

1. Dynamic Capability

Dynamic capabilities refer to a firm’s ability to sense opportunities and threats in rapidly changing business environments, seize these opportunities, and continuously transform and reconfigure organizational resources and capabilities to sustain competitive advantage (Teece, 2007). Unlike ordinary capabilities, which focus on the efficient utilization of existing resources, dynamic capabilities represent higher-order organizational abilities that enable firms to continually alter resource combinations in response to environmental change and proactively capture emerging technologies and new market opportunities. The theory of dynamic capabilities was systematized by Teece et al. (1997), who conceptualized it around three strategic dimensions: processes, positions, and paths. Subsequently, Teece (2007) advanced the framework by articulating the micro foundations of dynamic capabilities in terms of sensing, seizing, and transforming/reconfiguring, thereby rendering the concept more concrete and empirically tractable.

Teece et al. (1997) emphasized that dynamic capabilities are complex, non-imitable, and firm-specific in nature, deriving from idiosyncratic organizational characteristics. They argued that the value of dynamic capabilities is maximized in so-called high-velocity markets—external environments characterized by extreme uncertainty and turbulence—where such capabilities function as inherently creative and innovation-driven organizational mechanisms. From this perspective, dynamic capabilities are rooted in firms' unique historical paths and organizational processes, and it is precisely these idiosyncratic features that provide long-term competitive advantages that are difficult for competitors to imitate.

In the post-endemic period, firms have increasingly recognized the importance of strategic innovation activities to overcome the market disruptions and structural changes experienced during the pandemic and to secure new growth opportunities. Dynamic capabilities thus serve as a central theoretical foundation for explaining strategic innovation activities that enable firms to respond flexibly to environmental change. Specifically, dynamic capabilities constitute higher-order mechanisms through which firms modify existing ordinary capabilities or fundamentally transform and reconfigure their resource and capability portfolios in order to respond swiftly and effectively to external change (Teece, 2007; Zollo & Winter, 2002). Whereas ordinary capabilities are essential for sustaining competitive advantage through cost efficiency and operational stability under stable conditions, dynamic capabilities represent a necessary condition for firms to survive and redefine their growth trajectories in the face of technological change, regulatory shifts, and abrupt exogenous shocks such as pandemics.

The resource-based view (RBV) and dynamic capabilities are complementary perspectives. From an RBV standpoint, Grant (1991) argues that strategy formation should begin with the question of what a firm possesses, emphasizing that strategy is not about searching for opportunities per se but about determining what the firm can do well based on its resources and capabilities. Building on this logic, dynamic capabilities extend the resource-based approach by focusing on how firms adapt and renew their resource bases over time.

Specifically, firms first assess their internal resource structures rather than external industry conditions, identify how combinations of resources give rise to capabilities, and evaluate whether these resources and capabilities can generate competitive advantage. Firms then select strategies that best leverage existing resources while addressing resource gaps required for strategy execution through replenishing, augmenting, or upgrading their resource bases. While static resources provide the foundation for competitive advantage, dynamic resources enable firms to create new opportunities over time. In this sense, dynamic capabilities function as mechanisms through which firms go beyond maintaining existing resources to create new resource configurations and capabilities, thereby constructing firm-specific resource structures that are difficult for competitors to imitate in changing market and technological environments.

Teece et al. (1997) argue that dynamic capabilities constitute a source of sustained competitive advantage precisely because they are embedded in firm-specific and difficult-to-imitate organizational processes. However, this very embeddedness creates a measurement paradox: the characteristics that render dynamic capabilities strategically valuable simultaneously make them empirically elusive and difficult to operationalize through observable indicators. Owing to this limitation, prior studies have recognized the use of proxy variables that represent the development and manifestation of dynamic capabilities as a practically and theoretically valid alternative to direct measurement (Ambrosini & Bowman, 2009; Helfat, 1997; Zahra et al., 2006).

As Ambrosini and Bowman (2009) note, R&D expenditure should be understood not as dynamic capabilities per se, but rather as an input into the development of dynamic capabilities, and even identical levels of R&D investment may yield heterogeneous outcomes depending on the availability of complementary assets, organizational context, and path dependence. Nevertheless, R&D investment carries important theoretical significance in that it enables firms to move beyond the incremental improvement of existing products or processes (exploitation) and engage in the exploration of new technological domains. In rapidly changing environments, R&D investment thus serves as a critical foundation for sensing capability, allowing firms to identify emerging technological and market opportunities.

Moreover, accumulated R&D experience enhances firms' problem-solving capabilities and technological expertise within specific domains, thereby facilitating the rapid commercialization of identified opportunities and linking R&D activities to seizing capability. Beyond its immediate technological outputs, the R&D process itself involves the internalization of learning routines through repeated experimentation and feedback (Zollo & Winter, 2002). Through sustained engagement in research and development, firms gradually develop organizational routines related to knowledge integration, project management, and cross-functional collaboration, which ultimately form the foundation of reconfiguring capability, enabling the reallocation and transformation of existing resources and capabilities.

2. Dynamic Capabilities across Technology Levels

Dynamic capabilities differ fundamentally in their structure and modes of enactment according to firms' technology levels. High-technology firms require a high degree of flexibility and adaptability to respond to rapid technological change, and such capabilities enable the swift identification of new business opportunities, the expansion of technological categories, and the integration of diverse solutions in highly volatile markets. Lee (2024) provides empirical evidence from small and medium-sized manufacturing firms, showing that the effects of dynamic capabilities on exploratory and innovative activities are especially pronounced in high-technology groups, with R&D activities and the utilization of external knowledge networks playing a critical role in enhancing innovation performance. Similarly, Hwang and Lee (2016) demonstrate that, in technology-convergent firms, dynamic capabilities exert a substantial influence on technological innovation performance through convergence capability as a mediating mechanism.

In contrast, in low-technology industries, dynamic capabilities are relatively less oriented toward R&D investment and the creation of new technologies and are instead more closely associated with incremental innovation driven by improvements in production processes, cost reduction, quality management, and routine managerial and improvement activities. Protogerou et al. (2014) argue that low-technology firms adapt to changes in the external environment not through exploratory dynamic capabilities, but through the accumulation of practical capabilities based on learning-by-doing and learning-by-using, as well as continuous process improvement. Consistent with Krishnaswamy et al. (2015), SME growth is not driven by technological intensity per se, but by firms' abilities to adapt, upgrade, and reconfigure existing technological capabilities along their specific development paths.

Firms operating in medium-technology industries exhibit a hybrid configuration in which characteristics of high- and low-technology sectors coexist. Accordingly, dynamic capabilities in this group tend to display a complementary and integrative nature, combining elements of exploration and exploitation.

III. Research Method

1. Hypothesis and Research Model

According to dynamic capability theory, firms generate innovation performance by sensing opportunities and threats in rapidly changing environments, seizing these opportunities, and transforming and reconfiguring their resources and capabilities (Teece, 2007). In highly uncertain contexts such as the post-pandemic period, these capabilities are expected to play an even more critical role in enhancing firms' technological innovation performance.

Dynamic capabilities are inherently abstract and difficult to observe directly, which poses fundamental limitations on their direct empirical measurement. Accordingly, rather than attempting to measure dynamic capabilities per se, this study follows prior research by employing proxy variables that indirectly capture the processes through which dynamic capabilities are built and the outcomes through which they are manifested (Ambrosini & Bowman, 2009; Helfat, 1997; Zahra et al., 2006). Although such proxies do not fully represent dynamic capabilities themselves, they are theoretically justified insofar as they reflect firms' strategic intention and effort to develop capabilities in response to environmental change, as well as the observable footprints of enactment that emerge when those intentions are translated into organizational action (Eisenhardt & Martin, 2000). Following the classification proposed by Ambrosini and Bowman (2009), this study combines input-based measures and activity-based measures to more comprehensively capture the multidimensional nature of dynamic capabilities. Specifically, the former is operationalized as changes in R&D intensity, while the latter is measured by shifts in firms' concentrated investment across innovation types during crisis conditions.

First, from the perspective of absorptive capacity theory (Cohen & Levinthal, 1990), R&D investment constitutes a foundational organizational capability for sensing external technological developments and seizing new knowledge by integrating it into the firm. Importantly, this study focuses not on the absolute level of R&D investment but on the rate of change in R&D intensity. This approach is grounded in Teece et al.'s (1997) definition of dynamic capabilities as the firm's ability to change its resource base. In this view, static investment levels are less informative than the firm's ability to dynamically adjust investment patterns in response to environmental turbulence, which more directly reflects a "capability to change capabilities."

Empirical studies examining the relationship between R&D investment and innovation performance have reported mixed findings. While some studies document a positive relationship (Hall, 1993; Artz et al., 2010), others find no significant effects (Del Monte & Papagni, 2003) or identify non-linear, inverted U-shaped relationships (Yeh et al., 2010; Falk, 2012). Such inconsistencies may stem from differences in environmental stability, nonlinear investment effects, and the unique conditions associated with crisis contexts. Against this backdrop, the present study focuses on the COVID-19 pandemic as a major exogenous shock and examines how firms adjusted their R&D investments under such conditions. We argue that firms that effectively sensed the crisis and increased R&D investment were better positioned to seize emerging technological opportunities and proactively respond to market restructuring, thereby enhancing innovation performance.

In addition, shifts in concentrated investment across innovation types can be interpreted as concrete manifestations of the asset orchestration and resource reconfiguration capabilities emphasized by Teece (2007). Such shifts represent not merely quantitative reallocations of resources but strategically consequential decisions that redefine the firm's core capability trajectory (Benner & Tushman, 2003). Because they require altering accumulated technological paths and organizational routines, these transitions entail path-switching costs and initial learning burdens in new innovation domains, which may temporarily depress performance. Nevertheless, under conditions of rapid environmental change, changing innovation focus may constitute a strategic response aimed at rapidly building capabilities that better align with transformed market demand and technological paradigms. Accordingly, this study posits that firms that switch innovation types in response to crisis conditions are likely to achieve superior technological innovation performance in the medium to long term, as improved environment–strategy fit offsets short-term adjustment costs.

H1. Dynamic capabilities have a positive effect on firm innovation performance (financial performance)

Prior research suggests that the manifestation and effectiveness of dynamic capabilities are contingent upon firms' technology levels. From the perspective of absorptive capacity theory, the extent to which firms can recognize, assimilate, and exploit new knowledge depends on the accumulation of prior related knowledge (Cohen & Levinthal, 1990). As a result, firms operating at different technological levels are likely to differ in their ability to activate and benefit from dynamic capabilities.

Moreover, the development and deployment of capabilities are inherently path dependent, as they are shaped by firms' historical technological trajectories and accumulated learning processes (Teece et al., 1997; Helfat, 1997). This implies that the effectiveness of dynamic capabilities cannot be assumed to be uniform across firms, but instead varies with the technological context in which firms are embedded. Firms at higher technology levels typically face richer learning opportunities, greater knowledge recombination potential, and more flexibility in reconfiguring existing capabilities (Levinthal & March, 1993; Zahra & George, 2002). In contrast, firms operating at lower technology levels may encounter more constrained learning environments and a narrower scope for capability transformation.

Accordingly, the relationship between dynamic capabilities and innovation performance is expected to be heterogeneous across technology groups, with stronger and more pronounced effects among firms with higher technological capabilities.

H2. The effect of dynamic capabilities on innovation performance (financial performance) differs according to firms' technology levels.

More specifically, the following sub-hypotheses are proposed:

H2a. The effect of dynamic capabilities on innovation performance is strongest in high-technology firms.

H2b. In medium-technology firms, the effect of dynamic capabilities on innovation performance is weaker than in high-technology firms but stronger than in low-technology firms.

H2c. In low-technology firms, dynamic capabilities have a significant effect on innovation performance, but the magnitude of the effect is relatively limited.

Based on these hypotheses, the research model specifies dynamic capabilities as the independent variable and firm innovation performance as the dependent variable, while incorporating technology level (high, medium-high, and medium-low technology) as a grouping variable. This model enables an examination of the effect of dynamic capabilities on innovation performance in the post-pandemic environment and an analysis of how this effect varies across technology levels.

The research model was estimated using regression analysis in Stata 17.0.

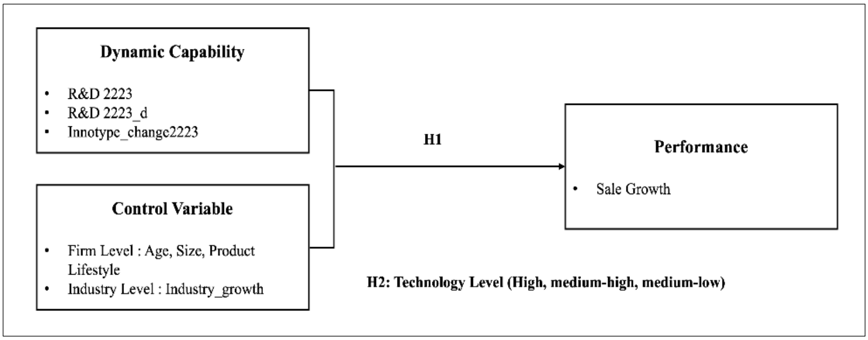

Figure 1. Research Model

2. Data and Variable

This study utilizes data from the Survey on Technology of Small and Medium Enterprises. The analysis is based on survey waves conducted in 2023 and 2024, which capture firms' activities and performance for the years 2022 and 2023, respectively. To examine changes between 2022 and 2023, firm-level data were matched across the two years using business registration numbers, and only firms surveyed in both years were retained. Technology level and industry-specific characteristics were classified according to the major industry trend indicators provided by the Korea Institute for Industrial Economics and Trade (KIET). As a result, a balanced panel dataset comprising 174 firms was constructed.

The key variables included in the analytical model are operationalized as follows, based on the underlying theoretical framework. The independent variable, dynamic capabilities, is conceptualized as a firm's ability to reconfigure innovative resources and adjust strategic orientation in response to environmental change. Accordingly, dynamic capabilities are measured by the rate of change in R&D intensity between 2022 and 2023(R&D2223) and by whether the firm shifted its primary innovation type during the same period (Innotype_ change2223). This operationalization is intended to capture the processual nature of dynamic capabilities—namely, resource reallocation and strategic reorientation—rather than a static level of resource endowment.

In addition, recognizing that the performance implications of R&D investment adjustments may not be linear, the squared term of R&D intensity (R&D2223_d) is incorporated into the model to examine potential nonlinear effects over time. A considerable stream of prior research has documented a positive association between R&D expenditure and firm performance (Branch, 1974; Tassey, 1983; Morbey & Reithner, 1990; Hall, 1993). Nevertheless, subsequent empirical studies have produced inconclusive and sometimes contradictory evidence, indicating that R&D investment does not invariably translate into superior performance outcomes (Del Monte & Papagni, 2003). Such inconsistencies in the literature imply that the relationship between R&D investment and firm performance is unlikely to be adequately captured by a simple linear specification. Rather, scholars have increasingly emphasized the presence of nonlinear dynamics, including diminishing returns to R&D investment—whereby the marginal productivity of R&D declines beyond a certain level—as well as threshold effects, under which the performance implications of R&D vary across different investment regimes. In response to these theoretical considerations, a growing body of empirical research has explicitly modeled nonlinearity by incorporating the squared term of R&D investment into regression frameworks (Falk, 2012; Wang, 2011; Yeh et al., 2010). When statistically significant, this specification allows researchers to identify an optimal level of R&D investment and to more rigorously assess the performance risks associated with both underinvestment and overinvestment in innovative activities.

Firm-level control variables include firm age, firm size, and product life cycle. Industry-level control variables are measured using industry-specific growth rates in 2023. The dependent variable is firm sales growth, measured as the rate of change in sales revenue between 2022 and 2023.

Table 1. Cross-tabulation (Dynamic Capability-Technology Level)

Technology Level	Dynamic Capability		Total
	Yes	No	
High	19	21	38
Medium-high	32	54	86
Medium-low	24	26	50
Total	77	97	174

IV. Result

1. Variable Characteristics

Table 2 reports the descriptive statistics of the continuous variables, excluding nominal variables.

Table 2. Descriptive statistics of variables

Variable	Mean	SE
Dependent Variable		
Sale_growth2223 : Log of sales growth (2022–2023)	8.73	35.27
Independent Variable		
R&D 2223: Log of R&D intensity growth	-0.48	4.64
Age	25.04	10.69
Size : Log of employees size	3.15	1.46
Industry_growth : Industry sales growth rate	1.80	14.51

The results of the correlation analysis are presented in the table.

Table 3. correlation analysis

		1	2	3	4	5	6	7
1	Sale_growth2223	1.000						
2	R&D 2223	-0.13*	1.000					
3	Innotype_change	-0.11	0.00	1.000				
4	Age	-0.04	0.23**	0.06	1.000			
5	Size	0.059	0.49***	0.02	0.19**	1.000		
6	Product Lifecycle	-0.16**	0.16**	0.00	0.29***	0.18	1.000	
7	Industry_growth	0.18**	-0.06	-0.06	-0.04	-0.08	-0.09	1.000

2. Results of Hypothesis Testing

Hypothesis 1 (H1) proposed that dynamic capabilities would have a positive effect on firm innovation performance. The empirical results, however, indicate that the rate of change in R&D intensity (R&D_2223) has a statistically significant negative effect on sales growth ($\beta = -7.67$, $t = -6.80$, $p < 0.001$). In addition, the squared term of the change in R&D intensity (R&D_2223_d) also exhibits a significant negative coefficient ($\beta = -0.14$, $t = -5.41$, $p < 0.001$). These findings suggest that changes in R&D intensity exert a nonlinear effect on firm performance and that, in the short run, excessive adjustments in R&D intensity may adversely affect sales performance. In contrast, changes in firms' primary innovation type (Innotype_change2223) do not show a statistically significant effect.

In the highly uncertain post-pandemic environment, the performance implications of dynamic capabilities appear to operate through mechanisms such as short-term adjustment costs, time-lag effects, or over-adjustment. Accordingly, H1 is only partially supported.

Table 4. Result of H1

Dependent Variable : Sale_growth2223	Model 1 (total)	
	Coef	**t**
Dynamic Capability		
R&D 2223	-7.67	-6.8***
R&D 2223_d	-0.14	-5.41***
Innotype_change2223	-5.93	-1.27
Control variable_firm level		
Age	-0.04	-0.16

Size	2.58	1.59
Product Lifecycle	-2.96	-2.52**
Control variable_Industry level		
Industry_growth	0.25	1.56
Cons	14.39	1.86*
Number of obs	174	
R-squared	0.286	
Adj R-squared	0.256	

*p<.1, **p<.05, ***p<.01

Hypothesis 2 (H2) proposed that the effect of dynamic capabilities on innovation performance would differ across firms' technology levels. To test this hypothesis, the sample was divided by technology level and separate regression analyses were conducted. Model 2 presents the results for High technology firms, Model 3 for Medium-high technology firms, and Model 4 for Medium-low technology firms.

First, for High technology firms (Model 2), the most pronounced differentiated effects are observed. In this group, the rate of change in R&D intensity exhibits a strong negative effect on sales growth ($\beta = -16.84$, $p < 0.001$), while the squared term of R&D intensity change displays a significant positive coefficient ($\beta = 1.95$, $p < 0.001$). This pattern suggests a clear nonlinear relationship between dynamic capabilities and performance in high-technology firms, whereby initial adjustments are associated with performance declines, followed by performance improvements beyond a certain threshold. Moreover, changes in firms' primary innovation type have a significant negative effect ($\beta = -9.55$, $p < 0.05$), indicating that innovation strategy shifts in high-technology firms entail substantial short-term adjustment costs. The explanatory power of the model for high-technology firms ($R^2 = 0.714$) is substantially higher than that of the other technology groups, underscoring the central role of dynamic capabilities in explaining performance outcomes in this context.

In contrast, the effects of dynamic capabilities are more pronounced among medium-high technology firms (Model 3). The rate of change in R&D intensity has a significant negative effect on sales growth ($\beta = -6.97$, $p < 0.001$), and its squared term also shows a significant negative coefficient ($\beta = -0.12$, $p < 0.01$). These results indicate that, in medium-high-technology firms, adjustments in R&D structure exert a nonlinear influence on performance, with short-term adjustment costs and uncertainty potentially constraining sales growth. In addition, the product life cycle variable has a significant negative effect, reflecting structural constraints faced by firms operating in transitional industrial and technological environments.

For Medium-low technology firms (Model 4), the key variables capturing dynamic capabilities do not exhibit statistically significant effects. This suggests that, in medium-low-technology industries, short-term adjustments in R&D structure or changes in innovation type are less likely to translate directly into performance outcomes, and that incremental process improvements and operationally oriented capabilities may play a more important role.

Overall, the results demonstrate that the effects of dynamic capabilities on innovation performance differ markedly across technology levels, with the magnitude and structural characteristics of these effects being most pronounced in high-technology firms. These findings support Hypothesis 2 (H2) and provide empirical evidence that the performance implications of dynamic capabilities are strongly contingent on firms' technology levels.

Table 5. Result of H2

	Model 2 (High)		Model 3 (Medium-high)		Model 4 (Medium-low)	
	Coef	t	Coef	t	Coef	t
Dynamic Capability						
R&D 2223	-16.84	-7.09***	-6.97	-4.04***	-8.15	-1.21
R&D 2223_d	1.95	4.04***	-0.12	-3.28**	0.06	0.1
Innotype_change2223	-9.55	-1.73**	-5.17	-0.66	-8.50	-0.86
Control variable_firm level						
Age	-0.31	-0.99	0.27	0.82	-0.04	-0.79
Size	1.54	0.74	2.41	0.91	2.79	0.81
Product Lifecycle	-2.49	-1.92*	-4.49	-2.6**	-0.59	-0.23
Control variable_Industry level						
Industry_growth	-0.33	-0.81	0.15	0.41	0.43	1.52
Cons	18.50	1.66	10.27	0.82	18.33	1.16
Number of obs	38		86		50	
R-squared	0.714		0.273		0.326	
Adj R-squared	0.685		0.208		0.214	
F-statistic	18.56***		8.96***		7.35***	

*p<.1, **p<.05, ***p<.01

3. Technology-level Heterogeneity Analysis

To examine technology-level heterogeneity, we conducted split-sample regression analyses across three technology-level subgroups. Table 6 presents the results along with formal statistical tests of coefficient differences for the key dynamic capability variables. Using the Chow test, we assessed whether the overall regression structure varies by technology level. The null hypothesis of parameter stability across all groups was strongly rejected ($F = 12.47$, $p<0.001$), providing clear evidence of significant structural heterogeneity. These findings suggest that the relationship between dynamic capabilities and innovation performance varies fundamentally depending on the technology-level context, lending strong support to our theoretical justification for conducting split-sample analyses.

Table 6.Heterogeneity Analysis

	Model 5 (High)	Model 6 (Medium-high)	Model 7 (Medium-low)
	Coef (SE)	**Coef(SE)**	**Coef(SE)**
Dynamic Capability			
R&D 2223	-15.75*** (2.09)	-6.58** (1.75)	-10.76 (7.57)
Pairwise Comparisons:			
High vs. Medium-high	8.72 (0.003)***		
High vs. Medium-low	0.89 (0.345)		
Medium-high vs. Medium-low	1.34(0.247)		
Joint Test (All Equal)	10.45 (0.005)***		
R&D 2223_d	1.784*** (0.40)	-0.12** (0.03)	-0.04 (0.70)
Pairwise Comparisons:			
High vs. Medium-high	19.47 (0.000)***		
High vs. Medium-low	6.89 (0.009) ***		
Medium-high vs. Medium-low	0.11(0.740)		
Joint Test (All Equal)	22.38 (0.000)***		
Innotype_change2223	14.14*** (5.29)	-4.88 (7.59)	-7.46 (10.52)
Pairwise Comparisons:			
High vs. Medium-high	1.98 (0.159)		
High vs. Medium-low	0.32 (0.571)		
Medium-high vs. Medium-low	0.04(0.841)		
Joint Test (All Equal)	2.84(0.242)		
Number of obs	38	86	50
R-squared	0.799	0.32	0.34
Chow Test (F)	12.47***		
Overall Equality (F)	15.67***		

*p<.1, **p<.05, ***p<.01

V. Conclusion

This study empirically examines the impact of dynamic capabilities on innovation performance in the post–COVID-19 period under the unprecedented uncertainty triggered by the pandemic, and analyzes whether these effects are structurally heterogeneous across technology-level contexts. Recognizing that dynamic capabilities are embedded in firm-specific organizational processes that are difficult to observe directly, this study adopts changes in R&D intensity and innovation-type transitions—widely used in prior empirical research—as core proxy variables. By integrating these proxies with organizational actions, strategic adjustments, and technological characteristics, the study seeks to more comprehensively capture how dynamic capabilities are manifested in practice.

The results indicate that adjustments in R&D intensity are associated with a statistically significant decline in sales growth, accompanied by a significant negative nonlinear effect captured by the squared term. By contrast, innovation-type change does not exert a statistically significant effect. These patterns imply that dynamic capability–related strategic adjustments involve short-term costs and learning frictions, with performance consequences that evolve nonlinearly over time, especially under the heightened uncertainty of the post-pandemic context. In addition, the results indicate that the performance effects of dynamic capabilities differ markedly across technology levels. The findings reveal that the performance effects of dynamic capabilities do not follow a uniform average pattern but instead unfold in heterogeneous and nonlinear ways depending on the technology-level context. These results further substantiate the theoretical and empirical validity of employing split-sample analyses and nonlinear modeling approaches in this study.

This study contributes to the dynamic capabilities literature in three important ways. First, it provides empirical evidence on the relationship between dynamic capabilities and firm performance in the post-pandemic context. Second, by introducing technology level as a conditioning factor, it demonstrates that the effects of dynamic capabilities vary depending on the technological regime in which firms operate. Third, by identifying nonlinear effects, the study shows that dynamic capabilities function as path-dependent and cost-intensive adjustment mechanisms.

The empirical findings of this study provide technology level differentiated practical implications in the context of post-pandemic recovery and preparedness for future crises. The COVID-19 pandemic generated multilayered shocks, including global supply chain disruptions, abrupt shifts in consumption patterns, and the accelerated transition to non-face-to-face operations, compelling many firms to suspend existing R&D projects or redirect them toward new strategic orientations. However, the analytical results of this study reveal that maintaining or expanding R&D budgets during crises is not always an optimal response. Rapid R&D reconfiguration can entail substantially higher switching costs than anticipated, and these costs vary across technology levels. For high-technology firms, a clear nonlinear pattern emerges: performance declines during the initial stages of R&D reconfiguration, followed by recovery and improvement once a certain inflection point is surpassed. This finding indicates that dynamic capabilities in high-technology environments function not as short-term performance enhancement mechanisms but as medium- to long-term strategic investments. Accordingly, managers should approach R&D reconfiguration not as a short-term, performance-driven response strategy, but rather as a medium- to long-term strategic commitment predicated on sufficient financial and organizational slack to absorb initial performance declines. To this end, securing adequate cash reserves or diversifying revenue streams to mitigate risk constitutes a critical strategic imperative. For medium-high-technology firms, the negative effects observed in both the linear and squared terms of R&D adjustment suggest that a gradual and incremental approach may be more effective than radical R&D reconfiguration. These firms need to pursue a balance between short-term performance and long-term growth through hybrid innovation portfolios, or to leverage collaborative R&D projects with universities, public research institutes, and large firms in order to reduce internal investment burdens while maintaining access to advanced technologies. By contrast, for medium-low-technology firms, the performance effects of dynamic capabilities are not statistically significant, suggesting that strengthening operational capabilities, process improvement, and cost efficiency may constitute more urgent strategic priorities than R&D reconfiguration in the short term. These firms need to make strategic choices toward stabilizing existing operations and enhancing execution capabilities, rather than committing scarce resources to aggressive innovation investments. Second, although firms that shifted their innovation type—from product innovation to process innovation, or vice versa—in the post-pandemic period were expected to exhibit greater flexibility and adaptability, this study finds that changes in innovation type do not yield statistically significant performance effects ($p > 0.10$). Notably, among high-technology firms, such changes are even associated with negative performance outcomes. These findings suggest that, under crisis conditions, hastily altering innovation strategies in response to pressure to "do something" may be less effective than deepening existing capabilities. Moreover, redirecting innovation efforts without clear market validation may exacerbate organizational disruption rather than enhance performance.

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