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Unveiling the Temporal Dynamics: The Impact of Knowledge Source Diversity, Breadth and Depth on Disruptive Innovation through Time-Series Analysis

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Abstract

Disruptive innovation plays a critical role in driving technological progress and reshaping industries by challenging established paradigms and fostering new opportunities for growth. While previous research has largely focused on the static relationship between knowledge characteristics and disruptive innovation, the temporal evolution of knowledge source diversity, breadth, and depth and their influence on disruptive innovation remain unclear. This study explores these dynamics by analysing multivariate time-series data from global patents spanning 1980 to 2010. The Autoregressive Distributed Lag (ARDL) model is employed to assess both the short-run and long-run effects of knowledge structures on disruptive innovation. The results reveal that, in the long run, knowledge source diversity positively influences disruptive innovation, whereas knowledge breadth has a negative effect, and knowledge depth shows no significant impact. In the short run, knowledge depth positively contributes to innovation, while knowledge source diversity exerts a negative effect, and knowledge breadth remains insignificant. These findings underscore the importance of aligning knowledge management strategies with temporal dynamics to foster sustained innovation.

Introduction

Disruptive innovation, which reshapes existing technological paradigms and drives progress in entirely new directions, has historically been a cornerstone of transformative development. However, recent studies reveal a worrying trend: the disruptive potential of innovations is steadily declining. Park et al. (2023) quantified this phenomenon using the CD index, a metric that captures the disruptiveness of patents and scientific publications by assessing their impact on subsequent citation patterns. Their findings highlighted a consistent decline in disruptiveness across technological fields, raising critical questions about the factors driving this shift. Despite growing attention to this phenomenon, it remains unclear whether and how different dimensions of knowledge influence this decline.

Existing studies have investigated various factors influencing innovation, including institutional frameworks such as intellectual property rights regime (Thakur-Wernzet al., 2022) and funding mechanisms (Irfan et al., 2022), technological ecosystems such as industry clusters (Kim et al., 2023) and R&D networks (Wen et al., 2021), and organizational characteristics such as team size (Wuchty et al., 2007), leadership styles (Alblooshi et al., 2021), and knowledge management practices (Darroch, 2005; Mardani et al., 2018). Among these factors, knowledge emerges as a cornerstone of the innovation process, enabling both exploration and exploitation, which form the basis for novel recombination and technical refinement (Grant, 1996). Evolutionary economics reinforces this perspective by emphasizing the cumulative nature of knowledge, where its recombination drives breakthroughs (Nelson, 1985). Despite these insights, most research adopts a static perspective, overlooking how the continuous evolution of knowledge influences disruptive innovation. Innovation is inherently dynamic, shaped by the transformation of knowledge and its interplay with external factors like technological advancements and market dynamics. As innovation systems mature, the complexity of integrating and applying knowledge evolves, potentially reshaping its impact on innovation outcomes. This highlights the need to examine how the dynamic restructuring of knowledge affects the trajectory of disruptive innovation.

Innovation does not occur in isolation; it is inherently shaped by the knowledge that drives it (Kaplan et al., 2015). From the perspective of the knowledge-based view, the evolution of disruptive innovation is fundamentally shaped by two critical dimensions of knowledge: *what knowledge is combined*, referring to Knowledge Source Diversity (KSD), and *how knowledge is applied*, referring to Knowledge Breadth (KB) and Depth (KD) (Grant, 1996). *what knowledge is combined* pertains to the sources of knowledge that contribute to an innovation, capturing the diversity of external knowledge inputs that provide the raw material for technological advancement. In contrast, *how knowledge is applied* focuses on the internal structuring and utilization of knowledge within the innovation process, reflecting the breadth and depth with which knowledge is synthesized and leveraged to achieve disruptive breakthroughs. Specifically, KSD refers to the variety of origins from which knowledge is drawn, including different technological domains, industries, and institutional sources. A high degree of KSD fosters novel recombination and cross-boundary integration, introducing fresh perspectives that challenge established paradigms (Rodriguez et al., 2017). However, the complexity of assimilating and coordinating diverse external knowledge inputs can impose integration challenges, potentially delaying the realization of innovation benefits. KB and KD, representing the *how* dimension, determine how acquired knowledge is internally structured and applied within an innovation. KB reflects the degree of interdisciplinarity within a single innovation effort. Greater KB facilitates the integration of diverse ideas, fostering interdisciplinary breakthroughs; however, it can also introduce internal coordination complexities that may hinder short-run efficiency. In contrast, KD signifies the extent of specialization within a particular domain, enabling focused technical advancements that build upon existing expertise. While deep specialization supports incremental innovation and enhances technical proficiency, it may limit adaptability and reduce the potential for radical disruption over time.

To better understand the dynamic relationship between disruptive innovation (DI) and the three critical dimensions of knowledge—source diversity, breadth, and depth—this study employs the Autoregressive Distributed Lag (ARDL) model (Pesaran, et al., 2001). In contrast to traditional static models, the ARDL approach enables the simultaneous estimation of short-run adjustments and long-run equilibrium relationships, providing deeper insights into the evolving impact of knowledge on DI. By distinguishing between short-run fluctuations and long-run trends, the ARDL model offers valuable insights into how DI responds to changes in knowledge dimensions over different time horizons. The short-run analysis reveals immediate responses to shifts in knowledge, while the long-run analysis captures persistent influences that shape innovation trajectories. This comprehensive approach contributes to a deeper understanding of how knowledge recombination and application influence DI.

In order to validate our findings, this study analyses annual patent data from 1980 to 2010. Unit root tests, including the Augmented Dickey-Fuller and Phillips-Perron tests, are applied to ensure the stationarity of the variables. Given the mixed integration order commonly found in time-series data, the ARDL bounds test is applied to determine the presence of long-run relationships between DI and the knowledge examined in this study. The findings indicate that, over the long run, a higher diversity of knowledge sources enhances disruptive innovation, whereas broader knowledge integration has an adverse effect, and the influence of knowledge depth is not statistically significant. In the short run, increased knowledge depth plays a positive role in fostering disruptive innovation, while greater knowledge source diversity presents challenges, and knowledge breadth does not exhibit a noticeable impact.

Building on these findings, this study makes several contributions to the literature. First, they provide a deeper understanding of the mechanisms underlying the observed decline in disruptiveness, highlighting the lack of sufficient analysis on the temporal evolution of knowledge structures. Second, by employing the ARDL model, this study offers a methodological advancement that allows for the investigation of DI from a dynamic perspective, capturing both short-run adjustments and long-run equilibrium relationships. Third, the study provides actionable insights for policymakers and innovation managers by emphasizing the importance of balancing knowledge diversity, breadth, and depth across different time horizons to foster sustained disruptive innovation.

Related Work

The theory of disruptive innovation was first proposed by Christensen (1997), characterized by its non-linear technological trajectory. Unlike traditional mainstream technologies, disruptive innovation advances through differentiated strategies to achieve competitive advantage (Hang et al., 2015). Existing studies have defined the concept from various perspectives, including technological characteristics (Nagy et al., 2016; Reinhardt and Gurtner, 2015), innovation processes (Levina, 2017), and innovation impacts (Suseno, 2018). These studies have also explored disruptive innovation across multiple levels, including the individual (Osiyevskyy and Dewald, 2015), firm (Van Balen et al., 2019), industry (Chevalier-Roignant et al., 2019), and network/ecosystem levels (Ruan et al., 2014). Despite widespread attention from academia and practice, the core concept of disruptive innovation remains ambiguous and inconsistent, which limits the development of the theory. Specifically, the mechanisms of disruptive innovation in technological contexts and its relationship with knowledge structures require further exploration.

Knowledge structure, as a critical driver of innovation, is commonly described through two dimensions: knowledge breadth and depth. These dimensions constitute key elements of the knowledge base. Knowledge breadth refers to the extent to which a patent integrates knowledge from multiple fields, reflecting the degree to which diverse ideas are synthesized within the innovation itself. In contrast, knowledge depth represents specialized expertise within a specific field, emphasizing the sophistication of technological development (Zou et al., 2019). Existing research indicates that knowledge breadth facilitates innovation, particularly disruptive innovation, by enabling diverse combinations of technologies and cross-domain integration (Xu et al., 2015). However, excessive knowledge breadth may lead to resource dispersion and coordination complexities, thereby hindering innovation efficiency (Jin et al., 2015). In contrast, knowledge depth strengthens technological advantages in specific fields, supporting incremental innovation (Boh et al., 2014). Yet, over-reliance on knowledge depth may limit adaptability to emerging technologies, particularly in rapidly changing technological environments.

Knowledge source diversity introduces an external driving force for technological innovation. On one hand, diverse knowledge sources enrich opportunities for technological combinations and enhance innovation capacity. For instance, Dogru et al. (2019) highlighted that integrating knowledge from different sources significantly improves innovation performance, especially in resource-constrained contexts. Additionally, knowledge source diversity provides the necessary resilience and adaptability for disruptive innovation, enabling technical systems to address path dependency and uncertainties (Luo et al., 2024). On the other hand, excessive diversity in knowledge sources may increase coordination challenges and integration costs, thereby negatively impacting innovation efficiency. Hajialibeigi (2023) identified an inverted U-shaped relationship between knowledge source diversity and innovation performance, where moderate diversity optimizes resource utilization while excessive diversity exacerbates management complexity. Furthermore, the impact of knowledge source categories on technological innovation differs significantly. Abdul Basit and Medase (2019) demonstrated that public sector knowledge better promotes technological innovation in manufacturing, whereas private sector knowledge integration is more effective in service industries.

Data and Method

Data and variables

To investigate the short-run and long-run dynamics between disruptive innovation, knowledge source diversity, breadth and depth, this study utilizes patent data obtained from the PatentView database. This comprehensive database includes detailed information on patents from 1976 to 2024, encompassing inventor details, patent and application metadata, assignee and location information, as well as International Patent Classification (IPC) data.

The database further provides access to the full text of patents, which includes three key sections: abstract, claims, and description. The claims section outlines the scope of the legal protection granted to the patent, while the description section provides a detailed explanation of the invention or innovation’s technical characteristics. The abstract offers a summary of the content in both the claims and description sections.

To analyse the genuine technological attributes of patented inventions, this study exclusively relies on the description section.

Disruptive Innovation. Disruptive innovation is measured using the CD index, which was developed by Funk and Owen-Smith (2017) and later applied by Park et al. (2023). The CD index quantitatively captures whether a patent consolidates existing knowledge or disrupts the technological status quo. Consolidating patents build upon prior knowledge and reinforce established trajectories, whereas disruptive patents render earlier work obsolete and chart new technological directions. The CD index ranges from -1 to 1, where -1 indicates a highly consolidating innovation, and 1 signifies a highly disruptive innovation.

This study adopts the five-year post-publication window used by Park et al. (2023), referred to as CD_5, to evaluate the disruptive potential of patents. The starting year of analysis is 1980, aligns with Park et al.'s dataset to ensure consistency in the time window and methodology. The calculation of the CD index also follows the exact formula proposed by Park et al. (2023). Using this standardized approach ensures comparability with prior studies and allows for robust exploration of the relationships between disruptive innovation and knowledge dimensions, including breadth, depth, and source diversity.

Knowledge Source Diversity. The Knowledge Source Diversity (KSD) measures the extent to which a patent integrates knowledge from multiple technological categories, based on the NBER two-digit technology classification. The NBER classification system, developed by Hall et al. (2001), provides a standardized framework for categorizing patents into broad technological fields, facilitating cross-field comparisons, and enabling robust analyses of knowledge diversity. In this study, the classification of patents into NBER technology categories is obtained directly from the PatentView database, ensuring consistency and reliability in the analysis. To calculate KSD, the references cited by each patent are analysed to determine their distribution across NBER technology categories. The diversity of these references is quantified using an entropy-based approach, which accounts for both the number of categories referenced and the balance among them. Patents with higher KSD indicate a greater reliance on knowledge inputs from multiple distinct technological fields, reflecting their ability to integrate diverse sources of knowledge. This diversity is hypothesized to enhance the potential for creative recombination of ideas, which is often a critical driver of disruptive innovation.

Knowledge Breadth. The Knowledge breadth (KB) is defined as the extent to which a patent draws upon vocabulary from multiple technological fields. Following the methodology outlined in Bowen et al. (2023), this metric is constructed by first calculating the frequency of word usage across technological fields for each year. A word is tagged as *specialized* in a particular field if its usage in that field exceeds 150% of its usage in the second most prominent field during the same year. Words that do not meet this criterion are classified as *unspecialized* and excluded from further analysis. For each patent, the fraction of specialized words classified into each field is then calculated, with these fractions summing to one for every patent. Using this classification, technological breadth is defined as one minus the concentration of specialized words, thereby reflecting the diversity of fields from which a patent draws its vocabulary. Patents with high knowledge breadth integrate terminology from a wider range of fields, indicating a more diverse knowledge base:

Knowledge Depth. The Knowledge Depth (KD) measures the extent of focus within a single technological field, and is calculated based on the concentration of a patent's classification within a specific four-digit International Patent Classification (IPC4) code. The IPC4 system provides a highly granular framework for categorizing patents, often used as a proxy for defining technological fields. By examining the proportion of a patent's classifications that fall within its most dominant IPC4 category, knowledge depth captures the degree to which a patent concentrates on a single technological field. Patents with high knowledge depth often exhibit a deliberate emphasis on advancing a particular field, suggesting a refined specialization that may impact incremental innovations or significant technical improvements within that domain. By anchoring the measurement of depth in the IPC4 classification, the analysis ensures precision in capturing the technical focus of each patent. This reliance on established knowledge structures may enhance efficiency in knowledge utilization. All variables and their description are shown in Table 1.

Table 1. Variables description.

Variables	*Description*
CD	Measured using the CD index, developed by Funk and Owen-Smith (2017) and applied by Park et al. (2023). The index ranges from -1 (highly consolidating) to 1 (highly disruptive), with CD_5 calculated over a five-year post-publication window to evaluate a patent's influence on obsolescing or reinforcing prior knowledge.
Knowledge Source Diversity (KSD)	Reflects the variety of technological categories from which a patent integrates knowledge. Based on the NBER two-digit technology classification and calculated using entropy to measure the diversity of references cited by each patent across multiple fields.
Knowledge Breadth (KB)	Captures the diversity of technological fields from which a patent draws its vocabulary. Calculated as one minus the concentration of a patent's classification into six broad fields, reflecting the extent to which the patent spans multiple domains. Derived using field-specific data from the patent text and classification systems.
Knowledge Depth (KD)	Measures the extent of focus within a single technological field. Calculated based on the proportion of a patent's classifications concentrated within its most dominant IPC4 code, representing a refined specialization in a specific domain.

The rationale for employing distinct operational measures for KSD, KB, and KD is grounded in their theoretical separation, empirical complementarity, and granular alignment with the conceptual constructs. Although these dimensions are interrelated, they reflect fundamentally different structural layers of knowledge, which necessitates differentiated yet coherent measurement strategies. First, KSD captures the diversity of technological origins, for which the NBER 2-digit classification is particularly suited. Its coarse granularity reflects broader source fields (e.g., Chemicals, Electronics, Drugs), and has been widely used to proxy knowledge origin variety in macro-level innovation studies (Hall et al., 2001). NBER codes aggregate IPC-based patent classes according to economically meaningful technological sectors, thus aligning closely with the idea of where knowledge comes from. Second, KD is intended to reflect technological specialization, which demands greater classification precision. The IPC 4-digit level provides such fine-grained technical delineation, enabling us to observe how concentrated a patent's technical focus is. Compared with higher-level IPC or NBER codes, IPC4 provides domain stability and domain resolution, making it the most valid proxy for focused depth within a technological field. Third, KB concerns the semantic recombination and interdisciplinary expression of knowledge within the patent text. To this end, a vocabulary-based approach is employed, tracking the field-specific concentration of technical terms used in abstracts and claims. This textual metric captures horizontal conceptual integration at a finer level than taxonomic classifications, especially in domains where innovation involves hybrid or emergent concepts not yet classified in IPC/NBER systems. While the data sources and granularity differ across these three variables, they are intentionally selected to match the theoretical domain of each construct: broad origin domains (KSD), fine technical depth (KD), and semantic conceptual spread (KB). These differences do not imply inconsistency but rather reflect the layered nature of knowledge structures in innovation. We explicitly acknowledge that the classification schemes are non-nested and differ in dimensional logic. However, their temporal aggregation into annual panel data and their independent derivation from non-overlapping sources reduce concerns about collinearity or semantic redundancy. Moreover, our ARDL model framework allows for distinct lag structures, further reducing risks of artificial convergence.

Methodology and model specification

Econometric methods that investigate the temporal dynamics of innovation processes are essential for understanding how variables interact over time. These approaches enable the analysis of both short-run fluctuations and long-run equilibrium relationships, offering valuable insights into the mechanisms impacting disruptive innovation and its connections to knowledge dimensions such as source diversity, breadth and depth. Given the need to examine these dynamics comprehensively, this study adopts the Autoregressive Distributed Lag (ARDL) bounds testing model, introduced by Pesaran et al. (1999) and later developed further (Pesaran, et al., 2001), to explore the cointegration processes and temporal interactions among the variables. The ARDL approach not only estimates cointegration and long-run equilibrium relationships but also captures dynamic effects in both time horizons, offering a comprehensive framework for understanding temporal interactions.

The ARDL methodology is particularly advantageous for several reasons. First, it is highly flexible and can accommodate variables with mixed integration orders, whether I (0) or I (1). Second, the single-equation setup simplifies implementation and interpretation compared to traditional cointegration methods. Third, it allows for different lag lengths to be specified for different variables, enhancing the model's adaptability to the data. Fourth, the method is well-suited for small sample sizes, providing robust estimates of long-run relationships and parameters. Finally, the ARDL model effectively addresses potential issues of autocorrelation and endogeneity, ensuring unbiased and reliable results (Harris and Sollis, 2003; Jalil and Ma, 2008).

Given these strengths, the ARDL approach is employed in this study to examine the temporal dynamics between disruptive innovation and its key regressors, such as knowledge source diversity, breadth and depth. The method is applied to identify both the long-run equilibrium relationships and the short-run adjustments that occur in response to deviations from equilibrium. The subsequent steps for verifying these dynamics within the ARDL framework are outlined in the following sections.

Stationarity test. Stationarity is a critical consideration in time-series analysis, as it ensures the validity of econometric models and the reliability of their results. Time-series data have diverse applications across various fields, and identifying the appropriate trend structure of the data represents an essential econometric task (Mushtaq, 2011). To determine the stationarity of the variables, this study employs the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests. These tests are widely used to identify whether variables are stationary at their levels or become stationary after differencing. The results of these tests guide the appropriate application of the Autoregressive Distributed Lag (ARDL) approach, which is capable of handling variables integrated at different orders. Specifically, the ARDL model can accommodate variables that are stationary at level (I(0)), at first difference (I(1)), or a combination of the two, making it a robust method for analysing the cointegration and temporal dynamics among time-series variables.

Autoregressive Distributed Lag bounds test. The bounds testing procedure is utilized in this study to examine whether a single long-run relationship exists among the variables under investigation. The ARDL bounds test evaluates cointegration by testing the joint significance of the coefficients of the lagged levels of the variables in a single-equation model. The model for the bounds test is specified as follows:

$$\Delta CD_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta CD_{t-i} + \sum_{i=0}^{q} \gamma_i \Delta KB_{t-i} + \sum_{i=0}^{r} \delta_i \Delta KD_{t-i} + \sum_{i=0}^{s} \eta_i \Delta KSD_{t-i}$$
$$+\theta_1 CD_{t-1} + \theta_2 lnKB_{t-1} + \theta_3 lnKD_{t-1} + \theta_4 lnKSD_{t-1} + \epsilon_t$$

In this equation, Δ denotes the first-difference operator, CD_t is the disruptive innovation index, and KB_t, KD_t, and KSD_t represent knowledge breadth, depth, and source diversity, respectively. The optimal lag lengths (p, q, r, s) are determined using the Akaike Information Criterion (AIC), which minimizes information loss and ensures the model is parsimonious while retaining explanatory power. The coefficients θ_1, θ_2, θ_3, θ_4 capture the long-run equilibrium relationships, while the summations account for short-run dynamics. The term ϵ_t captures any variations unexplained by the model, ensuring the robustness of the estimation process.

To evaluate the existence of a cointegration relationship, the ARDL bounds test is applied. This test compares the calculated F-statistic to critical bounds for the null hypothesis (H_0), which assumes no cointegration among the variables, and the alternative hypothesis (H_1), which posits the presence of cointegration. A rejection of H_0 occurs when the F-statistic exceeds the upper critical bound, indicating a stable long-run relationship among the variables. Conversely, if the F-statistic falls below the lower bound, the null hypothesis cannot be rejected. When the F-statistic lies between the bounds, the result is inconclusive, requiring further investigation.

Once a long-run relationship is confirmed through the ARDL bounds testing approach, the model is re-specified into an Error Correction Model (ECM) to estimate both short-run dynamics and the speed of adjustment back to the long-run equilibrium. The ECM effectively integrates short-run fluctuations and long-run relationships within a single framework, ensuring the model captures both immediate and equilibrium effects of the independent variables on disruptive innovation. The ECM for this study is specified as follows:

$$\Delta CD_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta CD_{t-i} + \sum_{i=0}^{q} \gamma_i \Delta KB_{t-i} + \sum_{i=0}^{r} \delta_i \Delta KD_{t-i} + \sum_{i=0}^{s} \eta_i \Delta KSD_{t-i} + \tau ECT_{t-1} + \epsilon_t$$

The ECM framework is particularly valuable because it allows the separation of short-run dynamics from long-run equilibrium behaviour while maintaining a consistent representation of the temporal relationships among variables. The short-run effects are captured by the coefficients of the lagged differences, which provide insights into the immediate impacts of changes in knowledge dimensions on disruptive innovation. Meanwhile, the Error Correction Term (ECT) integrates the short-run adjustments with the long-run relationship, ensuring that deviations from equilibrium are systematically corrected over time.

By applying the ECM within the ARDL framework, this study is able to investigate not only how knowledge breadth, depth, and source diversity influence disruptive innovation in the long run, but also how these variables interact dynamically in the short run. This dual focus provides a comprehensive understanding of the temporal mechanisms impacting innovation processes.

Stability test. Ensuring the stability of regression models is critical when working with autoregressive structures, as stability confirms the robustness of estimated coefficients over time. In this study, the CUSUM of squares approach, as proposed by Brown et al. (1975), is employed to evaluate the dynamic stability of the model. The CUSUM of squares test provides a graphical representation of stability, where the plotted test statistic is compared against a confidence interval. If the test statistic remains within the confidence bounds, the model is considered stable, indicating no significant changes in the regression coefficients over time. Conversely, if the statistic crosses the bounds, it suggests potential instability, requiring further investigation.

Empirical findings

This study employs multivariate time-series data from 1980 to 2010, with annual observations to mitigate the influence of seasonal variations. The annual data are derived by calculating patent-level indicators for each year and then averaging these values at the yearly level, ensuring a consistent representation of trends over time. The analysis focuses on identifying the relationships between disruptive innovation and various knowledge dimensions over time.

Summary statistics

The descriptive statistics for the key study variables is provided in Table 2, including disruptive innovation (CD), knowledge breadth (lnKB), knowledge depth (lnKD), and knowledge source diversity (lnKSD). The mean value of CD is 0.127, with a standard deviation of 0.098, indicating moderate variation in disruptive innovation across the sample period. The minimum and maximum values of CD range from 0.030 to 0.388, reflecting substantial differences in the disruptiveness of innovations over time. Knowledge breadth (lnKB) exhibits a mean value of 0.364 with relatively low variability (S.D. = 0.023), suggesting a consistent level of knowledge integration across patents. Knowledge depth (lnKD) has a slightly higher mean of 0.528 and also demonstrates low variability (S.D. = 0.017), highlighting the stable specialization within individual technological fields. In contrast, knowledge source diversity (lnKSD) shows the highest mean of 0.684 with minimal variation (S.D. = 0.003), indicating that patents consistently rely on a diverse set of external knowledge sources.

Table 2. Summary statistics of study variables.

Variables	*Mean*	*S.D.*	*Min*	*Max*
CD	0.127	0.098	0.030	0.388
lnKB	0.364	0.023	0.313	0.397
lnKD	0.528	0.017	0.488	0.561
lnKSD	0.684	0.003	0.677	0.687

Together, these descriptive statistics and time trends highlight the dynamic relationships between disruptive innovation and the key knowledge dimensions, providing a foundation for exploring their short-run and long-run interactions in subsequent analyses.

Stationarity test

In this study, stationarity of the variables was tested using both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, with the results summarized in Table 3. The stationarity test results reveal that, except for the variable CD, all variables become stationary after applying the first difference. Specifically, the results indicate that at the level, none of the variables, except for CD, exhibit stationarity. However, after taking the first difference, all variables—namely the logarithms of knowledge breadth (lnKB), knowledge depth (lnKD), and knowledge source diversity (lnKSD)—become stationary. The variable CD, on the other hand, is stationary at the level, confirming that it does not require differencing. This mixed order of integration among the variables suggests that an Autoregressive Distributed Lag (ARDL) bound approach is appropriate for modeling the relationship between the variables, as it can accommodate variables with different integration orders (i.e., I (0) and I (1)).

Table 3. Stationarity test statistics.

Variables	*ADF Test*		*PP Test*		*Stationary Remark*
	Level	*First difference*	*Level*	*First difference*	
CD	-4.873*** (0.000)	-	-3.870*** (0.013)	-	I (0)
lnKB	-0.191 (0.992)	-5.894*** (0.000)	-0.196 (0.992)	-5.872*** (0.000)	I (1)
lnKD	-2.676 (0.246)	-4.637*** (0.001)	-2.722 (0.227)	-4.574*** (0.001)	I (1)
lnKSD	-1.596 (0.794)	-7.120*** (0.000)	-1.325 (0.882)	-7.105 (0.000)	I (1)

Note: An intercept term and a trend term have been included in all unit-root tests. Significance levels are denoted as 1%, 5%, and 10% with ***, **, and * respectively.

ARDL bounds test

To determine the optimal lag length for the model, the Akaike Information Criterion (AIC) was utilized. Based on this criterion, the chosen model is ARDL (1, 0, 2, 2). This means that the optimum lag lengths for the variables CD, lnKB, lnKD, and lnKSD are p=1, q=0, r=2 and s=2, respectively. The results of the ARDL bounds test are presented in Table 4, which includes the F-statistics values for testing the presence of a long-run relationship between the variables.

Table 4. ARDL bounds test (F-statistic).

F-statistic		*Null hypothesis: no levels of relationship*		
	Value	*Significance level*	*I (0)*	*I (1)*
Value of F-statistic	31.232	10.0%	2.72	3.77
K	3	5.0%	3.23	4.35
Critical Value Bounds	0.1-0.01	2.5%	3.69	4.89
		1.0%	4.29	5.61

Since the F-statistic value exceeds the critical values for both I (0) and I (1), this provides strong evidence of a long-run relationship among the variables. The results suggest that the knowledge dimensions (KB, KD, KSD) are jointly influencing disruptive innovation in the long-run, while the variables move together toward an equilibrium over time.

ARDL adjustment estimation, long-run and short-run relationships

The ARDL adjustment estimates is reported in Table 5, indicating how the variables align with the long-run equilibrium following deviations. The coefficient of CD L1 is −0.135, which is negative and statistically significant at the 1% level. This value reflects the proportion of the adjustment toward long-run equilibrium in response to deviations. Specifically, approximately 13.5% of the disequilibrium is corrected within one year, indicating that the variables are gradually realigned with their long-run equilibrium. The statistically significant negative coefficient also suggests a stable long-run relationship, with adjustments occurring systematically over time.

Table 5. ARDL adjustment estimates.

D.CD	*Coef.*	*Std.error*	*T*	*P >|t|*	*[95% Conf. Interval]*	
CD. L1.	-0.135***	0.023	-5.98	0.00	-0.181	-0.088

Note: Significance levels are denoted as 1%, 5%, and 10% with ***, **, and * respectively.

The long-run estimates obtained from the ARDL model is presented in Table 6, illustrating the sustained relationships between disruptive innovation and the knowledge dimensions: breadth, depth, and source diversity. The coefficient of knowledge breadth (lnKB) is negative and statistically significant at the 1% level. This indicates that in the long run, an increase in knowledge breadth is associated with a reduction in disruptive innovation. This may reflect the trade-off between generalization and specialization, where increased knowledge breadth could dilute the focus needed for achieving disruptive breakthroughs. The coefficient of knowledge depth (lnKD) is negative but not statistically significant. This result implies that knowledge depth does not show a strong long-run influence on disruptive innovation during the study period. This finding may suggest that depth alone is insufficient to drive innovation without the complementary effects of breadth or diversity. The coefficient of knowledge source diversity (lnKSD) is positive and statistically significant at the 1% level. This indicates a strong positive long-run relationship between knowledge source diversity and disruptive innovation. The result suggests that integrating diverse sources of knowledge significantly enhances the potential for disruptive breakthroughs, potentially due to the cross-pollination of ideas from different fields or disciplines.

Table 6. ARDL long-run estimates.

Variables	*Coef.*	*Std.error*	*T*	*P* >|*t*|	*[95% Conf. Interval]*	
lnKB	-1.276***	0.396	-3.23	0.004	-2.101	-0.451
lnKD	-0.558	0.988	-0.57	0.578	-2.619	1.503
lnKSD	18.942***	4.209	4.50	0.000	10.161	27.722

Note: Significance levels are denoted as 1%, 5%, and 10% with ***, **, and * respectively.

Table 7 reports the short-run estimates from the ARDL model, capturing the immediate effects of knowledge dimensions on disruptive innovation. The results indicate that the variable knowledge breadth (lnKB) does not return significant short-run coefficients, suggesting that it may not play a measurable role in influencing disruptive innovation within the short-run time horizon. This lack of significant results could be attributed to the inherently gradual nature of the effects of knowledge breadth, which may require longer periods to manifest its impact on innovation outcomes. For knowledge depth (lnKD), the results reveal a positive and statistically significant short-run relationship with disruptive innovation. At lag order 0, the coefficient is 0.270, significant at the 1% level, indicating that an immediate increase in knowledge depth is associated with a rise in disruptive innovation. This positive relationship persists at lag order 1, with a smaller coefficient of 0.185, which is significant at the 10% level. These findings suggest that while knowledge depth contributes positively to disruptive innovation in the short run, the magnitude of its impact diminishes slightly over time. In contrast, knowledge source diversity (lnKSD) shows a consistently negative and statistically significant short-run relationship with disruptive innovation. At lag order 0, the coefficient is -4.829, significant at the 1% level, indicating that an increase in knowledge source diversity imposes short-run challenges on innovation processes. This negative impact persists at lag order 1, with a coefficient of -4.953, also significant at the 1% level. The consistent short-run negative effects of knowledge diversity suggest that the integration of diverse knowledge sources may introduce complexities and inefficiencies that hinder immediate innovation outcomes, despite its positive influence in the long run. The overall model demonstrates a strong fit, as reflected by the R-squared value of 0.936, which indicates that 93.6% of the variation in disruptive innovation can be explained by the short-run dynamics of the model.

Table 7. ARDL short-run estimates.

Variables	*Coefficient*	*Estimates*
Lag order	0	1
ΔlnKB	-	-
ΔlnKD	0.270*** (0.011)	0.185* (0.092)
ΔlnKSD	-4.829*** (0.001)	-4.953*** (0.000)
R^2	0.936	

Note: Short-run estimators for first lagged have been depicted by Δ. Significance levels are denoted as 1%, 5%, and 10% with ***, **, and * respectively.

Stability test findings

The cumulative sum of squares (CUSUM square) plot is illustrated in Figure 1, which is used to assess the stability of the regression coefficients in the specified model. The test was conducted with a 5% significance level, and the shaded area represents the confidence interval under the null hypothesis of stability. The red plot line indicates the recursive cumulative sum of squares. The stability of the model is determined by examining whether the red plot line remains within the shaded confidence bands throughout the observation period. As shown in Figure 1, the cumulative sum of squares stays entirely within the 95% confidence interval. This confirms that there is no significant deviation from stability over the study period. At the 5% significance level, the results provide evidence of the stability of the regression coefficients. The findings indicate that the model is robust and the relationships among the variables remain consistent over time.

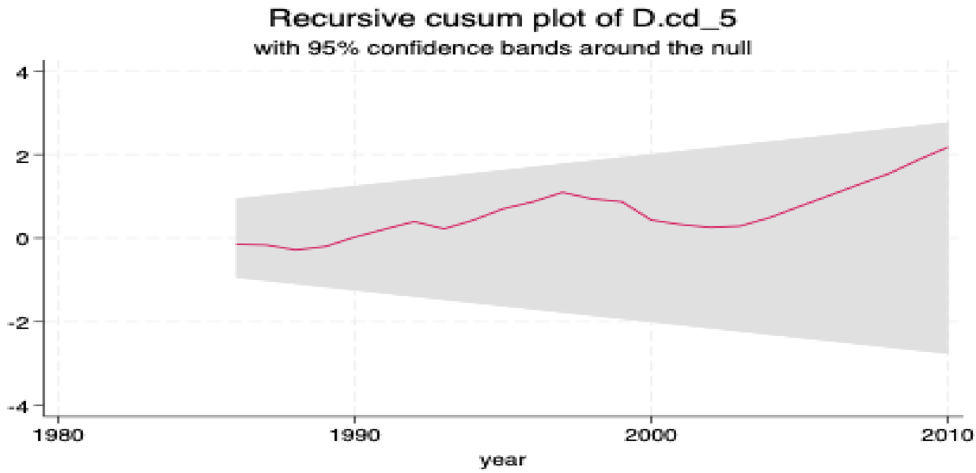

Figure 1. CUSUM Squares Plot with a 5 % level of significance.

Discussion

The findings of *what knowledge is combined* (knowledge source diversity) and *how knowledge is applied* (knowledge breadth and depth) reveal dynamic and time-dependent patterns in their effects on innovation. Knowledge source diversity, representing the richness of external inputs, negatively impacts innovation in the short run, reflecting integration challenges, yet demonstrates significant positive effects in the long run, highlighting its transformative potential. In contrast, knowledge breadth and depth, which capture the internal application of knowledge, present opposite dynamics: breadth remains insignificant in the short term but negatively influences innovation over time, while depth fosters short-run advancements but loses its significance in the long run. These seemingly paradoxical results raise important questions about the temporal trade-offs and interactions between external diversity and internal application, providing the foundation for a deeper analysis of the mechanisms underlying these patterns.

Table 8. Long-run and short-run effects of different variables.

Dependent Variable: CD	*Long-run estimate*	*Short-run estimate*
lnKB	Significant negative	-
lnKD	-	Significant positive
lnKSD	Significant positive	Significant negative

Focused paths or fragmented horizons: the temporal trade-offs of leveraging knowledge

The contrasting short- and long-run effects of knowledge breadth and depth reveal the dynamic complexities of how knowledge is leveraged in impacting innovation. In the short run, knowledge depth emerges as a significant positive factor, underscoring the power of specialization to provide focused pathways for immediate technical advancements. By concentrating resources within specific fields, depth enables the swift resolution of technical challenges and accelerates innovation within well-defined domains. However, over time, this very focus can lead to diminishing returns, as excessive specialization restricts adaptability and reduces opportunities for cross-domain exploration, ultimately limiting its long-run influence on innovation.

Conversely, knowledge breadth shows no significant impact in the short run, suggesting that the integration of diverse knowledge inputs often requires time to coordinate. Yet, in the long run, breadth exhibits a negative effect, pointing to the potential pitfalls of excessive diversification. While broader knowledge integration holds promise for fostering interdisciplinary breakthroughs, it also increases the complexity of coordination and the risk of resource fragmentation. Over time, these challenges may outweigh the benefits, resulting in innovations that are incremental rather than disruptive. This temporal trade-off highlights the critical balance required between specialization and diversification to optimize innovation outcomes over different time horizons.

A double-edged sword: the temporal dynamics of knowledge source diversity

The dual impacts of knowledge source diversity (KSD) on innovation over the short and long run highlight its role as both a catalyst and a challenge. In the short term, KSD exhibits a significant negative effect, suggesting that the inherent complexity of integrating diverse external knowledge sources can temporarily hinder innovation. This may arise from the increased coordination costs, alignment challenges, and the need for firms or inventors to navigate conflicting perspectives and methodologies. Such complexities often delay the realization of tangible innovation benefits, creating a temporal "integration burden" that suppresses short-run performance.

In contrast, the long-run positive impact of KSD underscores its transformative potential once integration barriers are overcome. Diverse knowledge sources enrich the innovation process by introducing novel ideas, fostering cross-boundary synergies, and enabling adaptability to changing technological and market landscapes. Over time, these benefits accumulate, impacting breakthroughs that are less likely to emerge from homogenous or narrowly focused knowledge pools. This positive effect reflects the delayed yet powerful rewards of leveraging external diversity, as innovation systems adapt to complexity and transform it into a source of competitive advantage.

The contrasting short- and long-run effects of KSD illustrate the importance of temporal dynamics in understanding the innovation process. While diversity can impose short-run costs, its long-run benefits reveal the necessity of investing in mechanisms that facilitate the effective integration and utilization of heterogeneous knowledge sources. This *double-edged sword* demands strategic foresight to balance the immediate challenges with the long-run opportunities it affords.

Internal Breadth vs. External Diversity: divergent long-run paths to innovation

The contrasting long-run effects of knowledge breadth (KB) and knowledge source diversity (KSD) underscore their fundamentally different mechanisms in shaping innovation outcomes. While both dimensions represent forms of diversity, their influence diverges due to the distinct ways they interact with innovation systems over time.

Knowledge breadth, rooted in the internal integration of diverse knowledge fields within a patent, exerts a negative long-run impact on innovation. This outcome suggests that an overly broad internal knowledge base can lead to resource dispersion and coordination challenges that dilute focus. As the complexity of managing disparate knowledge fields grows, the innovation process may become fragmented, resulting in incremental improvements rather than disruptive breakthroughs. The negative effect of KB highlights the inherent difficulty of maintaining coherence and depth when attempting to integrate too many diverse internal elements over extended periods.

In contrast, knowledge source diversity, which reflects the richness of external inputs, exhibits a significant positive impact in the long run. This result points to the cumulative advantages of drawing from diverse external knowledge sources, which enrich the innovation process by introducing novel perspectives and fostering cross-boundary synergies. Unlike internal breadth, external diversity benefits from the broader ecosystem's adaptability and collaborative potential. Over time, organizations and inventors are better able to overcome the initial challenges of integrating diverse sources, transforming external complexity into a platform for sustained innovation and adaptability to emerging trends.

The divergent long-run effects of KB and KSD highlight the critical distinction between internal and external diversity. While internal breadth often struggles with the constraints of resource allocation and focus, external diversity thrives on the dynamism of collaborative ecosystems and the ability to recombine knowledge from varied origins. Understanding these differences underscores the importance of aligning knowledge strategies with the unique demands of long-run innovation, leveraging external diversity to complement and counterbalance the limitations of internal breadth.

Conclusion

In recent decades, the innovation landscape has undergone profound changes driven by increasingly complex knowledge structures. This study contributes to a more dynamic understanding of how knowledge source diversity (KSD), breadth (KB), and depth (KD) influence disruptive innovation over time. By applying an Autoregressive Distributed Lag (ARDL) model to global patent data from 1980 to 2010, we reveal that the innovation impact of different knowledge structures varies significantly across temporal dimensions. Specifically, KSD exerts a positive influence on disruptive innovation in the long run, affirming its role in enabling cross-boundary novelty and technological recombination. However, its short-run effect is negative, reflecting the coordination burdens and integration frictions associated with heterogeneous knowledge inputs. KB shows a significant long-run negative effect, suggesting that excessive internal diversification may dilute technological coherence and hinder breakthrough potential. In contrast, KD contributes positively in the short run, but its long-run influence is not significant, highlighting the temporal limits of domain-specific specialization.

These findings offer practical insights into how innovation systems can reconcile the temporal trade-offs inherent in leveraging diverse knowledge structures. In particular, the short-term coordination burden and long-term disruptive potential of KSD underscore the need for governance structures that are explicitly designed to absorb temporal friction. Rather than merely increasing collaboration, innovation infrastructures must function as temporal bridges—buffering early-stage integration inefficiencies while preserving long-term recombinability. To achieve this, governments and funding agencies should support modular and phase-based knowledge integration mechanisms, such as two-stage public-private R&D consortia that separate exploratory knowledge matching from solution development phases. Additionally, platform-based digital infrastructure (e.g., centralized research asset registries, structured metadata repositories) can be developed to reduce search and alignment costs among disparate actors during early-stage collaboration. Regarding the long-run negative effects of KB, the results suggest that while internal interdisciplinarity holds conceptual appeal, it may introduce latent coordination complexity over time. Therefore, knowledge integration within single organizations should be governed through strategic modularization. Funding programs and institutional evaluations should move away from undirected interdisciplinarity and instead encourage bounded integration, such as matrix organizational structures that allow domain-specific subunits to recombine outputs selectively, avoiding wholesale internal diffusion. Furthermore, mid-term evaluation checkpoints can help prevent project over-extension by identifying when internal breadth begins to hinder coherence. Finally, the short-run positive but long-run insignificant role of KD highlights that short-term technical expertise alone is insufficient to sustain breakthrough trajectories. Policy frameworks should therefore incentivize depth-to-diversity transitions over time. For example, project funding could adopt tapered incentive schemes, in which early-stage funding rewards technical depth, while renewal or scaling-up depends on demonstrable cross-domain expansion. Additionally, career development tracks in public R&D institutions can be designed to encourage temporal diversification—starting from vertical expertise and gradually incorporating horizontal collaborations, ensuring that individual-level knowledge accumulation aligns with systemic innovation needs.

This study also has several limitations that warrant further investigation. First, our analysis adopts the CD index as the sole measure of disruptive innovation. While this indicator has been validated in recent large-scale studies, alternative metrics such as novelty scores, radicalness indicators, or paradigm-shift detection frameworks may capture different facets of disruption. Future research could explore the robustness of our results by substituting or triangulating CD with these alternative outcome measures. Second, although this study treats KB and KSD as independent dimensions, we acknowledge that their relationship may be more complex. In particular, conceptual breadth may partially arise from exposure to diverse knowledge sources, suggesting potential endogeneity or interaction effects. Our current model specification does not explicitly test for such interdependencies. Future work could address this by introducing interaction terms, structural equation model, or dynamic panel techniques to capture potential co-evolution or causal links between KB and KSD over time.

Acknowledgments

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