Setting the beat of deals: acquisition and divestiture rhythms and their effect on innovation performance

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Abstract

Corporations in the high-technology industry are increasingly stimulated to enhance their innovation performance. Even though acquisitions and divestitures can be useful in realizing this objective, the ability to derive value from acquisitions and divestitures is challenging and complex. Drawing on organizational learning theory and the temporal perspective, the aim of this study is to investigate whether multi-business corporations can realize enhanced innovation performance by adopting specific acquisition and divestiture rhythms. This study argues that corporations can enhance their innovation performance by combining regular acquisition and divestiture rhythms with aspects of irregular rhythms – and thus adopting even-event paced rhythms. This study also argues that prior experience allows corporations to manage the negative aspects of irregular rhythms and leverage the positive aspects associated with regular rhythms. The findings indicate that an even-paced divestiture rhythm generally results in increased patent application quantity. This relationship is however contingent upon prior divestiture experience. Corporations possessing low amounts of divestiture experience apply for more patents when adopting an even-event paced divestiture rhythm, whereas experienced divestors can increase their subsequent patent application quantity by adopting an even-paced divestiture rhythm. For acquisition rhythms the findings indicate that its relation with the subsequent number of claims per patent is contingent upon prior acquisition experience. Experienced acquirors generally produce more claims per patent than less experienced acquirors regardless of the adopted rhythm. Furthermore, experienced acquirors adopting an even-paced acquisition rhythm generate more claims per patent, whereas less experienced acquirors produce more claims per patent by adopting an event-paced acquisition rhythm. These findings contribute to the literature on rhythms and the temporal perspective, organizational learning theory, acquisitions, divestitures, innovation, and prior experience.

Content

1. Introduction

Confronted by continuously changing environments and market dynamics, multi-business corporations are in constant need to restructure their business portfolios (Karim & Capron, 2016; D'Aveni et al., 2010). This is especially crucial for corporations operating within the high technology industry, because of its dynamic and rapidly changing context (D'Aveni et al., 2010). Additionally, innovating is critical within this industry, because it determines the ability of corporations to realize sustained competitive advantages (Cloodt et al., 2006; McCarthy & Aalbers, 2022). Acquisitions and divestitures are major options for corporations looking to both restructure their business portfolio and to stimulate innovation (Brauer, 2006; McCarthy & Aalbers, 2024).

A corporation's innovation performance is related to the knowledge it possesses, accesses, absorbs and integrates, which stimulates the adoption of an organizational learning perspective (Cohen & Levinthal, 1990; McCarthy & Aalbers, 2022). By applying acquisitions, corporations can access, absorb, and integrate novel knowledge (Schildt et al., 2005; Vermeulen & Barkema, 2001). However, given the limited ability of corporations to absorb, integrate and manage knowledge, divestitures can be utilized to create focus and reduce the scope (McCarthy & Aalbers, 2024). The combination of acquisitions and divestitures is therefore of importance for a portfolio perspective and for innovation.

Even though acquisitions and divestitures are essential to realize changes in a corporation's knowledge base, corporations are limited in their ability to learn from altering their knowledge base. The reason for this is because corporations have limited absorptive capacity and suffer from time compression diseconomies (Cohen & Levinthal, 1990; Dierickx & Cool, 1989). The former means the limited ability to access, absorb, and utilize novel knowledge (Cohen & Levinthal, 1990). The latter means being less efficient when trying to do more in a smaller time window (Dierickx & Cool, 1989). In order for corporations to deal with these learning limitations and to enhance innovation, introducing a temporal perspective is critical. Specifically, these aspects can be realized by applying a specific rhythm (Shi & Prescott, 2012). A rhythm indicates the variation in how often specific activities are conducted in a certain time window, which ranges from a regular rhythm (i.e., even-paced rhythm) to an irregular rhythm (i.e., event-paced rhythm). A combination of the two and what is found in between is referred to as an even-event paced rhythm (Shi & Prescott, 2012). Regular rhythms of acquisitions and divestitures generally allows corporations to minimize the negative constraints of time compression diseconomies, and therefore maximize organizational learning (Vermeulen & Barkema, 2002; Laamanen & Keil, 2008). An irregular rhythm of acquisitions and divestitures allows corporations to respond adequately to external demands (Shi & Prescott, 2012). By combining the two into an even-event paced rhythm, not only learning can be optimized, but this also allows corporations to respond adequately to the external environment (Shi & Prescott, 2012).

This research argues that corporations are expected to enhance their innovation performance by combining a regular acquisition (or divestiture) rhythm with periods of irregularity (i.e., an even-event rhythm). Additionally, prior experience is acknowledged as an important factor that influences the relationship between rhythms and innovation performance. It is expected that prior experience allows corporations to leverage the positive aspects of an even-paced rhythm and mitigate the negative aspects associated with an event-paced rhythm. To be more specific, prior experience increases a corporation's absorptive capacity, which can minimize the negative effect of time compression diseconomies associated with an event-paced rhythm (Laamanen & Keil, 2008). In addition, corporations adopting an even-paced rhythm can leverage the large amount of prior experience, because time compression diseconomies is not a constraining factor. Prior experience can therefore be optimally utilized and leveraged when adopting an even-paced rhythm (Vermeulen & Barkema, 2002).

1.1 Theoretical relevance

This study contributes to the relatively limited body of research conducted on the temporal perspective (Zhang et al., 2022; Blagoev et al., 2023). More specifically, this research adds to the limited literature on rhythms as part of the temporal perspective (Klarner & Raisch, 2013; Laamanen & Keil, 2008; Kim et al., 2021; Vermeulen & Barkema, 2002; Shi & Prescott, 2012; Zhang et al., 2022). Studies focussing on acquisition rhythms specifically are very limited (Laamanen & Keil, 2008; Shi & Prescott, 2012). Conversely, studies investigating business divestiture rhythms are absent. Kim et al. (2021) incorporated divestiture rhythms in their study, but this encompassed the divestment of technological resources and not business divestitures. Moreover, the studies that incorporated rhythms have mainly tested for a linear relationship, which stems from the binary view of rhythms being either regular or irregular (Vermeulen & Barkema, 2002; Laamanen & Keil, 2008; Kim et al., 2021; Klarner & Raisch, 2013). This research generates a deeper and more nuanced understanding by testing for a curvilinear relationship instead of a linear relationship (Haans et al., 2016; Shi & Prescott, 2012). Additionally, by adopting innovation performance measures, this research refrains from the typical idea of studying rhythms in relation to accounting or financial performance measures (Vermeulen & Barkema, 2002; Klarner & Raisch, 2013; Laamanen & Keil, 2008; Shi & Prescott, 2012). Furthermore, a temporal perspective is generally integrated implicitly in research on organizational learning (Berends & Antonacopoulou, 2014). By explicitly incorporating a temporal perspective and by using organizational learning theory to explain the relationships and outcomes, this research therefore enriches the literature on organizational learning theory and the temporal perspective. This research also adds to the literature on prior experience (Argote et al., 2021). Even though prior experience has been researched extensively, limited studies have applied experience to the temporal perspective. Additionally, only one study has integrated prior experience to explain how it affects the relationship between rhythms and performance (Laamanen & Keil, 2008).

1.2 Practical relevance

Given the dynamic and rapidly changing nature of the business environment, especially in the high-tech context, it is crucial for corporations to continuously change, reconfigure, and alter their knowledge-bases (D'Aveni et al., 2010; Brauer, 2006; Karim & Capron, 2016). This is additionally critical, because it allows corporations to innovate, which is crucial for sustained competitive advantage (Cloodt et al., 2006; Lee & Roh, 2020). Acquisitions and divestitures are main ways for corporations to alter the knowledge base and to innovate (Vermeulen & Barkema, 2001; Brauer, 2006; McCarthy & Aalbers, 2024). In general, divestitures are linked to enhanced innovation performance, whereas most acquisitions fail to do so (McCarthy & Aalbers, 2024). Corporations would benefit from leveraging the generally positive aspects associated with divestitures and managing the possible negative outcomes associated with acquisitions. Enhancing the ability to learn from acquisitions and divestitures is essential to maximize subsequent innovation outcomes. Explained by limited absorptive capacity and time compression diseconomies, corporations are limited in their learning capabilities (Cohen & Levinthal, 1990; Dierickx & Cool, 1989). To facilitate optimal learning conditions and to enhance innovation performance, corporations can benefit from adopting specific rhythms (Zhang et al., 2022). The findings of this research therefore allows corporations to apply the rhythm most suitable for optimal innovation performance. By doing so, corporations can aim to outperform competition and to remain competitive in the long-term. Furthermore, the insights on how prior experience impacts the relationship between acquisition and divestiture rhythms and innovation performance will allow corporations to make more informed decisions.

1.3 Research objective

The objective of this research is to examine how acquisition and divestiture rhythms affect the innovation performance of corporations. More specifically, the objective of this research is to investigate whether even-event paced acquisition and divestiture rhythms result in increased patent applications and average number of claims per patent, compared to even-paced and event-paced rhythms. This research is therefore looking to answer the following research question:

1. Do corporations in the high-tech industry experience increased innovation performance by adopting an even-event paced rhythm of acquisitions and an even-event paced rhythm of divestitures compared to the even-paced and event-paced rhythms?

In addition, this research aims to understand what the role of experience is on the relationship between rhythms and innovation performance. The literature combining experience and rhythms is very limited. In their research, Laamanen & Keil (2008) found that experience contributes to absorptive capacity, which aids corporations in dealing with the negative effects of an event-paced rhythm. The research by Vermeulen & Barkema (2002) stated that an even-paced rhythm enhances a corporation's ability to extract insights from prior experiences. However, the exact relation between prior experience and rhythms is inconclusive and further research is warranted. Taken together, this research is therefore looking to answer two additional questions:

2. How does prior acquisition experience impact the relationship between acquisition rhythm and innovation performance?
3. How does prior divestiture experience impact the relationship between divestiture rhythm and innovation performance?

The following conceptual model is depicted to visualise the main concepts in this research:

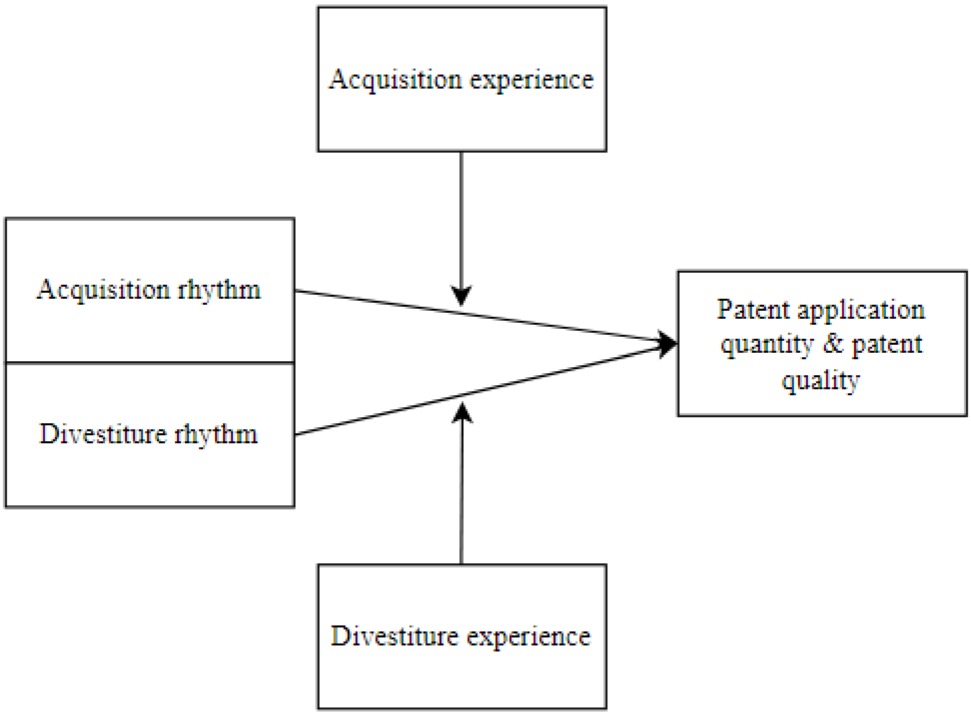

Figure 1: Conceptual model

1.4 Research outline

This research is structured as follows: it starts with outlining the main concepts in the theoretical framework, which serves as the foundation of this research. Methodology is the following section, where the research design and proposed data analysis techniques are described. After this, the results of the analyses are presented. Followed by this is a discussion of these findings, the subsequent theoretical contributions and managerial implications. Next are the limitations and further recommendations. The final section is the conclusion in which the research questions are answered.

2. Theoretical framework

An organizational learning theory perspective will be applied to investigate how acquisition and divestiture rhythms affect corporations' innovation performance and how prior experience impacts this relationship.

2.1 Organizational learning theory

Organizational learning theory is a widely adopted and researched topic (Argote et al., 2021). Organizational learning concerns how new knowledge is generated, absorbed, retained, and transferred within the boundaries of the corporation. This is then translated to other aspects within the corporation, such as its behaviour (e.g. strategies, procedures) and its outcomes (Argote & Miron-Spektor, 2011). Corporations search for new knowledge in order to stimulate innovation and to realise a sustained competitive advantage (McCarthy & Aalbers, 2022; Liao et al., 2008). When searching for new knowledge, corporations can either develop this internally or search for this externally, such as by conducting acquisitions.

Even though organizational learning leads to new knowledge that can be beneficial for corporations, certain factors can limit and negatively affect learning. Specifically, organizational learning is constrained by a corporation's limited absorptive capacity and time compression diseconomies (Cohen & Levinthal, 1990; Dierickx & Cool, 1989). Absorptive capacity refers to the degree to which corporations are able to absorb and exploit new knowledge (Cohen & Levinthal, 1990; Levitt & March, 1988). Corporations with high absorptive capacity are more effective in integrating novel knowledge, which means they can generally learn more effectively (Argote et al., 2021). The other organizational learning constraint is time compression diseconomies. This entails that corporations' efficiency in absorbing and exploiting knowledge is negatively impacted when being exposed to a high degree of knowledge in a small time window (Dierickx & Cool, 1989). Considering the limited absorptive capacity and time compression diseconomies, it is essential for corporations to manage their knowledge intake in order to optimize organizational learning. Regarding time compression diseconomies, this would mean not doing too much in too little time (Dierickx & Cool, 1989). Additionally, in order for corporations to not to exhaust their absorptive capacity, knowledge intake might need to be limited and match the degree of absorptive capacity (Cohen & Levinthal, 1990).

Conversely, corporations should not limit their exposure to new knowledge too much, because corporations need new knowledge to realise specific outcomes, such as innovation (McCarthy & Aalbers, 2022). By limiting the knowledge intake corporations might experience reductions in their absorptive capacity and this can also result in corporations becoming rigidly locked into their routines, strategies, and other processes (Cohen & Levinthal, 1990). This is referred to as inertia and limits the learning potential of corporations (Liao et al., 2008). It is proposed that one way to address the challenges of limited absorptive capacity and time compression diseconomies, the concepts of rhythms and prior experience can be adopted (Vermeulen & Barkema, 2002; Zhang et al., 2022; Shi & Prescott, 2012; Kim et al., 2021; Laamanen & Keil, 2008).

2.2 Acquisitions & divestitures

Corporations in the high-tech industry can not only rely on their internal knowledge (McCarthy & Aalbers, 2022). A common way to acquire knowledge, facilitate learning and stimulate innovation is through acquisitions (Schildt et al., 2005). Even though accessing novel knowledge can be beneficial, corporations are limited in the amount of knowledge that can be absorbed and exploited. Absorbing too much knowledge (i.e., performing too many acquisitions) relative to the absorptive capacity or in a narrow time window can have adverse effects (Cohen & Levinthal, 1990; Dierickx & Cool, 1989). These aspects can pressure a corporation's absorptive capacity and can result in corporations going beyond the limits of their absorptive capacity (McCarthy & Aalbers, 2024). In addition, new knowledge can result in corporations becoming overdiversified and too complex to manage (McCarthy & Aalbers, 2024). It can also result in corporations drifting away from their core businesses and knowledge base (Qi Dong et al., 2017). Taken together, these aspects can negatively impact innovation. Moreover, McCarthy & Aalbers (2024) state that 21% of the innovation-based acquisitions are successful. Given this low success-rate, the amount of acquisitions conducted, and the importance of innovation, further research to discover its intricacies is therefore warranted.

Divestitures can be utilized as a means to address the issues associated with an increasing knowledge base (McCarthy & Aalbers, 2024). Divestitures can be defined as adjustments of ownership and the business portfolio by disposing of certain assets (Brauer, 2006). Previous literature has mostly focussed on divestitures as being reactions to specific situations of distress, such as underperforming businesses or low liquidity (Brauer et al., 2017; Lee & Roh, 2020). Contrastingly, divestitures can also be utilized as a proactive strategy focussed on the realization of future positive outcomes (Lee & Roh, 2020). Multi-business corporations can employ divestitures to reduce its scope, streamline its operations, increase focus, exploit opportunities and grow its core business(es) (Brauer, 2006; Feldman & McGrath, 2016; Lee & Roh, 2020). Additionally, by divesting businesses, corporations can free up managerial and financial flexibility to leverage future acquisitions (McCarthy & Aalbers, 2024).

2.3 Temporal perspective

Temporality is an underlying concept of organizational learning, because organizational learning occurs over time and is not a single event (Argote & Miron-Spektor, 2011). A temporal perspective can therefore be integrated to capture a more complete understanding of organizational learning. Additionally, it can result in an increased understanding of acquisitions and divestitures, because these happen over time (Brauer, 2006). Time addresses another influential dimension that shapes and is shaped by corporations and their decisions. By applying a temporal perspective to the context of acquisitions and divestitures, additional insights can be therefore be gained.

In a recent systematic review by Blagoev et al. (2023), it was stated that time can be regarded as a strategic asset or resource that can be used instrumentally by corporations to realise certain outcomes. The specific moments at which and how corporations acts is therefore of importance. More concrete and specific for this research, an essential topic of investigation related to timing are rhythms.

2.4 Rhythms

As the external environment is changing rapidly, corporations might find it difficult to respond to and match these changes. Corporations have limited absorptive capacity and can suffer from time compression diseconomies when changing too much in a small time window (Zhang et al., 2022; Vermeulen & Barkema, 2002; Shi & Prescott, 2012). These factors limit organizational learning and corporations would benefit from adopting and managing specific rhythms to optimize learning conditions (Shi & Prescott, 2012).

According to literature, the negative aspect of time compression diseconomies can be managed by adopting a regular rhythm (Kim et al., 2021; Vermeulen & Barkema, 2002). Without the sudden concentrated peaks of activities, regular rhythms generally result in more optimal learning conditions than irregular rhythms (Laamanen & Keil, 2008; Shi & Prescott, 2012). Regular rhythms allows corporations to change according to its internal capabilities and aids corporations in efficiently and effectively absorbing novel knowledge (Shi & Prescott, 2012). This results in generally more optimal learning conditions. Moreover, by acting irregularly, there is no clear plan on what the required actions are going to be and the responsibilities that need to be assigned (Laamanen & Keil, 2008). The predictability of a regular rhythm can therefore be beneficial.

Even though literature supports the benefits associated with regular rhythms, research also acknowledges that regular rhythms have negative aspects (Vermeulen & Barkema, 2002; Laamanen & Keil, 2008). Shi & Prescott (2012) state that regular rhythms can result in not being responsive to external demands. In other words, focussing too much on internal aspects and capabilities can result in blind spots with regards to the external environment. To provide an example, by not deviating from a regular rhythm, the need for a specific acquisition might be ignored. This is especially problematic if the environment is dynamic and external demands change rapidly, such as in the high-tech context (Shi & Prescott, 2012). Additionally, regular rhythms can result in inertia (Shi & Prescott, 2012; Klarner & Raisch, 2013). Corporations might establish routines by repeatedly conducting the same amount of activities in specific time periods, which in its turn can inhibit learning (Liao et al., 2008). Moreover, given the dynamic context of the high-tech industry, the frequent changes in this environment might render previously established best practices derived from routines as outdated or ineffective (Shi & Prescott, 2012).

This raises the question what rhythm corporations should adopt. The limited previous research on rhythms has generally considered a binary view of rhythms either being regular (i.e., even rhythm) or irregular (i.e., event rhythm) (Vermeulen & Barkema, 2002; Kim et al., 2021; Klarner & Raisch, 2013; Laamanen & Keil, 2008). However, Shi & Prescott (2012) argued that both an even-paced and an event-paced rhythm are suboptimal.

2.4.1 Acquisition rhythms & innovation performance

Based on the previously discussed literature, it is expected that even-event paced rhythms allow corporations to minimize the negative aspects of both event-paced and even-paced rhythms, whilst also providing the ability to reap the benefits associated with both. To elaborate, event-paced rhythms negatively affect organizational learning explained by the concepts of limited absorptive capacity and time compression diseconomies (Cohen & Levinthal, 1990; Dierickx & Cool, 1989). This limited ability to extract knowledge from acquisitions is expected to negatively affect the amount of subsequent patent applications and the average number of claims per patent. An even-paced acquisition rhythm provide corporations with an increased ability to extract knowledge from acquisitions. However, even-paced rhythms can also result in routines and inertia, which limits organizational learning and the subsequent ability to increase the number of patent applications and claims (Shi & Prescott, 2012). In addition, an even-paced acquisition rhythm does not provide corporations with the flexibility and responsiveness needed to acquire novel and disruptive innovations or businesses (Shi & Prescott, 2012).

It is therefore expected that an even-event paced acquisition rhythm is ideal for innovation performance. This rhythm balances the benefits of the generally optimal learning conditions from the even-paced rhythm, with the flexibility and responsiveness of the event-paced rhythm, whilst also mitigating their shortcomings. It is expected to result in increased patent application quantity and patent quality. Based on this, the following hypotheses are formulated:

Hypothesis 1a: An even-event paced acquisition rhythm results in higher patent application quantity than both the even-paced and event-paced rhythm, such that the relationship follows an inverted U-shaped pattern.

Hypothesis 1b: An even-event paced acquisition rhythm results in higher patent quality than both the even-paced and event-paced rhythm, such that the relationship follows an inverted U-shaped pattern.

2.4.2 Divestiture rhythms & innovation performance

Following similar reasoning, it is expected that an even-event paced divestiture rhythm results in increased patent application quantity and quality. An even-event paced divestiture rhythm allows corporations to leverage the benefits associated with the even-paced and event-paced rhythms, whilst also minimizing the negative aspects associated with both. In line with the acquisition rhythm hypotheses, this is expected to result in increased patent application quantity and patent quality. The following hypotheses are therefore formulated:

Hypothesis 2a: An even-event paced divestiture rhythm results in higher patent application quantity than both the even-paced and event-paced rhythm, such that the relationship follows an inverted U-shaped pattern.

Hypothesis 2b: An even-event paced divestiture rhythm results in higher patent quality than both the even-paced and event-paced rhythm, such that the relationship follows an inverted U-shaped pattern.

2.5 Acquisition & divestiture experience

Experience forms the foundation for organizational learning (Argote et al., 2021; Bergh & Lim, 2008). Organizational learning can be understood as the act of transferring insights from previous experience into knowledge and best practices that can be used for current and future activities (Barkema & Schijven, 2008). In other words, corporations interpret the experiences they have gathered, derive knowledge and best practices from this, which is then applied to the current context (Argote et al., 2021). From an organizational learning theory perspective, experience shapes and contributes to the absorptive capacity of corporations (Argote et al., 2021). Argote et al. (2021) state that experience provides corporations with the ability to learn from their failures and successes. It can also improve decision-making and problem-solving capabilities. In addition, experiences can enhance the absorptive capacity of corporations, which results in corporations being more effective in utilizing and leveraging novel knowledge. Even though experience can result in learning opportunities and increased performance, the findings of experience on firm performance are complex and even contradictory (Argote et al., 2021; Barkema & Schijven, 2008).

For acquisitions, the relationship between performance and prior experience is especially complex. Barkema & Schijven (2008) describe that no acquisition is the same. This heterogeneity makes it difficult to translate insights from one acquisition to another, which means that corporations experience difficulty in learning from previous acquisitions. Another major challenge is that the relationship between actions taken during previous acquisitions and their subsequent outcomes can be ambiguous (Barkema & Schijven, 2008). In other words, difficulties can arise when deriving causal inferences from previous acquisitions and their consequences. Additionally, even if corporations manage to learn and derive best practices from previous acquisitions, it is possible that these best practices are applied to subsequent acquisitions in settings where these best practices are not relevant and could even be detrimental (Haleblian & Finkelstein, 1999; Barkema & Schijven, 2008). One more aspect contributing to the complexity of experience is that learning is not realised or triggered simply by experience itself

(Bingham et al., 2015; Barkema & Schijven, 2008). The extent that corporations learn from previous experience depends on their different mechanisms in place, such as the codification of experience. These aspects highlight the complexity of prior experience.

Prior divestiture experience has also been researched (Bergh & Lim, 2008; Lee & Roh, 2020). Humphery-Jenner et al. (2019) found that prior divestiture experience results in future divestitures being more strategically sound and in increased post-divestiture performance. Having undertaken prior divestitures results in the creation of institutional memory, increased absorptive capacity and best practices that a corporation can utilize – to increase innovation performance (Humphery-Jenner et al., 2019; Lee & Roh, 2020; Bergh & Lim, 2008).

Very limited research has applied prior experience to the concept of rhythms. Laamanen & Keil (2008) moderate for experience and find that it can aid corporations in reducing the negative aspects of an irregular acquisition rhythm. In their study it is argued that experience can increase the absorptive capacity, which in its turn allows corporations to deal with time compression diseconomies resulting from an irregular rhythm. In other words, it is expected that when prior experience increases, corporations are better equipped to deal with the negative effects of irregularity. In addition, a regular rhythm allows corporations to have an increased ability to connect prior experience with current experience (Vermeulen & Barkema, 2002). Without the sudden peaks in activity, corporations can maximally utilize and leverage their prior experience.

2.5.1 Acquisition experience

From an organizational learning perspective, it is argued that prior acquisition experience increases the absorptive capacity. This allows corporations that adopt an event-paced rhythm to minimize its major negative aspect: time compression diseconomies. Organizational learning conditions are more optimal when this constraint is minimized. This is expected to result in increased patent applications and number of claims per patent. Additionally, corporations adopting an even-paced rhythm have an increased ability to leverage the possible insights that can be taken from prior experience and apply it to the current situation (Vermeulen & Barkema, 2002). The reason for this is because these corporations spread their activities out over time and hence do not suffer from time compression diseconomies. So, more prior experience and an even-paced rhythm is expected to result in increased innovation performance. Taken together, corporations are better equipped to limit the negative aspects associated with an event-paced rhythm and have an increased ability to leverage the positive aspects of an even-paced rhythm. For the even-event paced rhythm, the negative aspects of both the even-paced and event-paced rhythm are already minimized (Shi & Prescott, 2012). The effect of experience on the even-event paced rhythm is therefore expected to be less pronounced. With prior experience, the difference of the even-paced and event-paced rhythms on innovation performance compared to the even-event paced rhythm is therefore expected to become less prominent. It is therefore expected that the inverted U-shape pattern of the relationship between rhythm and innovation performance will have less steep slopes on both sides of the graph. Taken together, the following hypotheses are formulated:

Hypothesis 3a: Acquisition experience will flatten the inverted U-shaped relationship between acquisition rhythm and patent applications.

Hypothesis 3b: Acquisition experience will flatten the inverted U-shaped relationship between acquisition rhythm and patent quality.

2.5.2 Divestiture experience

Following similar reasoning, divestiture experience is also expected to flatten the inverted U-shape relationship between divestiture rhythms and both innovation performance measures. The following hypotheses are therefore formulated:

Hypothesis 4a: Divestiture experience will flatten the inverted U-shaped relationship between divestiture rhythm and patent applications.

Hypothesis 4b: Divestiture experience will flatten the inverted U-shaped relationship between divestiture rhythm and patent quality.

2.6 Conceptual model

The following conceptual model is depicted to visualise the discussed variables and hypotheses:

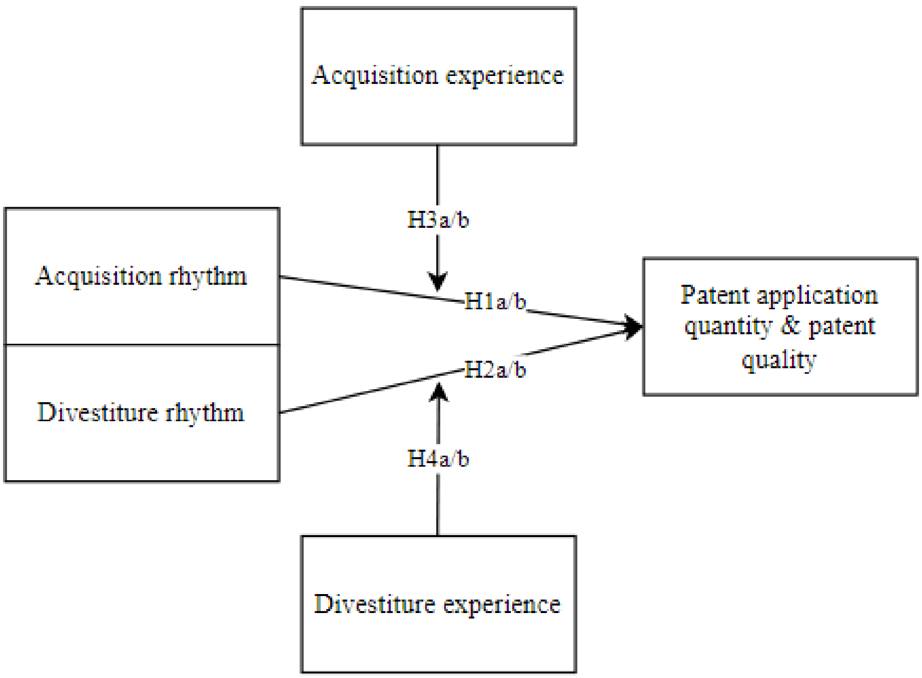

Figure 2: Conceptual model including hypotheses

3. Methodology

The hypotheses will be tested in the high-tech industry context. This industry is characterized by its frequently changing and dynamic environment (D'Aveni et al., 2010; Dibrell et al., 2015). Corporations in this sector also have a high propensity to acquire and divest businesses, but also to patent their patentable innovations (Cloodt et al., 2006; Aalbers et al., 2021; Fontana et al., 2013).

3.1 Sample & data collection

Corporations in the sample are required to have both acquired and divested at least once. Additionally, corporations need to have actively patented in the different years of observation. The corporations also need to be part of the high-tech industry, which is defined according to the different Standard Industrial Classification codes. The following sectors with their respective SIC-codes are included: aerospace and defense (372 & 376), pharmaceuticals (283), electronics and communications (36), and computers (357) (McCarthy & Aalbers, 2022). The window of observation is 2006-2019. The final sample includes 248 corporations who have collectively applied for 5,295,055 patents and have generated a total of 72,873,593 claims.

The database LSEG Workspace will be utilized for the data regarding the acquisition, divestiture, and financial control variables. Orbis Intellectual Property (hereafter Orbis IP) will be utilized for the data regarding the patent application quantity, patent quality, and the control variables related to the knowledge base.

3.2 Variables

3.2.1 Independent variables

Acquisition and divestiture rhythms cover the variance of the frequency of acquisitions or divestitures in a specific time window (Shi & Prescott, 2012). The following formula is adopted:

$$Kurtosis = \{ \frac{\mathrm{n(n+1)}}{\mathrm{(n-1)(n-2)(n-3)}} \sum \left(\frac{\mathrm{xi - xm}}{\mathrm{s}} \right)^4 \} - \frac{3\,\mathrm{(n-1)^2}}{\mathrm{(n-2)(n-3)}}$$

For this formula, n is the number of acquisitions or divestitures, xi is the number of acquisitions or divestitures in year i, and s is the standard deviation of the number of acquisitions or divestitures (Shi & Prescott, 2012). In line with Shi & Prescott (2012), the inverse values will be utilized for consistency, but also to aid in the interpretation process. A low inverse kurtosis indicates an event-paced rhythm, whereas a high inverse kurtosis value indicates an even-paced rhythm. What is found in between is the even-event paced rhythm. Following Shi & Prescott (2012), the entire period up to the year of observation is used to calculate the kurtosis values.

3.2.2 Dependent variables

Patent application quantity is measured by determining the number of patent applications of a corporation at t+1 (McCarthy & Aalbers, 2022). Given the time period and the fact that patent applications can take multiple years before being granted, patent applications is chosen over patents granted (McCarthy & Aalbers, 2022). Patent applications also captures all the innovative activities of a corporation (Belderbos et al., 2010).

As an indication of patent quality, the average number of claims per patent at t+1 will be adopted (Lanjouw & Schankerman, 2004; Trappey et al., 2012). Claim indicate the boundaries of an invention, and therefore define what the invention entails (Tong & Frame, 1994). The number of claims can be considered an indication of patent quality because it defines the scope of protection. This offers corporations legal protection against possible infringement by competitors (Trappey et al., 2012). In addition, it is considered an indication of patent quality because it defines the breadth of the patent (Tong & Frame, 1994; Marco et al., 2019).

3.2.3 Moderator variables

For prior acquisition and divestiture experience, the previous five years of experience were considered (Brauer et al., 2017; Aalbers et al., 2021). In line with Laamanen & Keil (2008), the years of gathered experience is measured prior to the year of observation.

3.2.4 Control variables

A total of eleven control variables will be added. The first control variable is firm size (revenue), because it is positively related to patent activity (Cloodt et al., 2006; McCarthy & Aalbers, 2022). The second variable that is controlled for is R&D intensity, because this is related to increased absorptive capacity and innovation (Cohen & Levinthal, 1990; McCarthy & Aalbers, 2022). Firm age is also controlled for given its relation with innovation performance (Kim et al., 2021). Additionally, financial performance (ROA) is controlled for, because it is related to internal development and innovation (Kim et al., 2021).

The size, age and diversity of the corporations' knowledge bases are also included as control variables, because these factors impact innovation performance (McCarthy & Aalbers, 2022, 2024). The size of the knowledge base is measured by identifying the amount of patents filed in the previous five years (McCarthy & Aalbers, 2022). Knowledge base age is measured according to the average age of the patents owned (McCarthy & Aalbers, 2024). It is included because newer knowledge is expected to result in increased innovation performance. Knowledge base diversity is measured by identifying the distribution of patents among the industries that the corporations are active in (McCarthy & Aalbers, 2022, 2024). This variable is included given that a more diverse and evenly distributed knowledge base can improve a corporation's innovation performance. Knowledge base diversity is measured by identifying the distribution of patents among the different International Patent Classification codes (McCarthy & Aalbers, 2022). This was calculated using the Herfindahl-Hirschman index:

$$Herfindahl\text{-}Hirschman\ index = \sqrt{1 - \sum_{j=1}^{Ni} \left(\frac{Yj}{\sum Yj}\right)^2}$$

For this formula, Yj is the number of patents in IPC sub-class j, and N is the number of IPC sub-classes (Srivastava & Gnyawali, 2011). The values can vary between 0 and close to 1. A value of 0 or close to 0 indicates that the corporation has active patents in only one IPC sub-class or is concentrated in mainly one sub-class. A value close to 1 would indicate that the corporation has patents in many different sub-classes, and that the spread of these is relatively equal.

Acquisition and divestiture relatedness were included and are based on whether the four-digit SIC code of the corporation and the acquired or divested businesses match (McCarthy & Aalbers, 2022).

Industry dummies were included to account for the possible dissimilarities in patenting frequency and to account for other unobserved effects within these different industries (McCarthy & Aalbers, 2016).

Finally, year dummies were included to control for possible fluctuations in patenting propensity and output, as well as other unobserved year effects (Cloodt et al., 2006).

3.3 Data analysis

Given the multiple metrically scaled independent variables, a multivariate statistical technique will be adopted, specifically multiple linear regression analysis (Hair et al., 2019). This method also allows for the inclusion of curvilinear relationships, which is crucial given the hypothesised inverted U-shaped relationships (Hair et al., 2019).

3.4 Research ethics

This research was conducted in conformity with the APA ethical principles (Smith, 2003). In addition, as the utilized data is publicly available, this research does not violate the privacy of corporations. Moreover, the data in this research will not be manipulated nor misrepresented. To guarantee transparency and integrity, all steps taken with regards to data transformation are described in the results section. Additionally, a research integrity form is signed and handed in.

4. Results

Prior to conducting the analyses and presenting the results, specific steps were taking with regards to data examination, data preparation, and assumptions testing (Hair et al., 2019). These steps are described below.

4.1 Data examination & preparation

To conduct a multiple regression analysis, the data must meet specific requirements and needs to be prepared accordingly (Hair et al., 2019).

4.1.1 Missing value analysis

The first step that was taken is an inspection of the frequency table (Appendix A). It can be observed that only the variable ROA has four missing observations. According to Hair et al. (2019), the impact and severity of the missing values needs to be assessed when missing values are present. Given that only 0.1% of one of the variables is missing, the extent and the potential impact of exclusion is low. It was therefore decided to adopt listwise exclusion for these four observations.

4.1.2 Variable computation & data transformations

Upon inspecting the univariate distribution of the variables, multiple variables did not meet the skewness values (-2 & 2) and the kurtosis values (-7 & 7). This needs to be addressed to prevent issues regarding normality and homoscedasticity (Hair et al., 2019). All these variables were transformed using the natural logarithm, because there were no single outliers resulting in these variables having exceeding values. To conduct log transformations, constants of 1 were added to the variables that included zero values. Additionally, the absolute of the lowest value (-93.48) including a constant of 1 was added to the variable ROA because of some minus values. The other log transformed variables are: revenue, knowledge base size, R&D, the dependent variable measures, the relatedness measures, and the experience measures.

Before creating the interaction terms, the experience and rhythm variables were mean centered to correct for possible multicollinearity and the quadratic terms of the rhythms variables were added (Hair et al., 2019).

Industry and year dummy variables were created, because these were included as control variables. The first year dummy represents the first year of observation (2006) and the last year dummy represents the last year of observation (2019). For the four industry dummies, the order is as follows: aerospace & defense, computers, electronics & communications, and pharmaceuticals.

The variable knowledge base age is inversed to aid in interpretation, because a low age is expected to result in increased innovation output.

4.1.3 Outliers & influential observations

The identification of outliers and influential observations is essential, because these can significantly impact the results of a regression analysis (Hair et al., 2019). Based on this pre-analysis stage, it was observed that the outliers did not originate from data entry errors and that these are representative of the population. Excluding these would therefore bias the results (Hair et al., 2019). Based on generated boxplots, ROA, claims, R&D and revenue had several significant outliers. In line with prior research, winsorization at the .5th and 99.5th percentile was applied (McCarthy & Aalbers, 2016), whereas for claims this was performed at the 2nd and 98th percentile. Any additional outliers were accounted for by validating the results using additional robust regression analyses (Appendix F) (Hair et al., 2019).

4.1.4 Descriptive statistics

The transformed and computed variables were added in a descriptive statistics and correlation matrix table (table 1). It can be observed that firm age has some minus values. The reason for this is because the date of incorporation has been adopted instead of founded year, because the latter had many missing values. As the relative difference between the firms' ages is important and not the actual number itself, this small number of negative values was not seen as problematic. Additionally, some variables have a mean value of 0. The reason for this is because these were mean centered to be included in the interaction terms.

Regarding the correlations, Hair et al. (2019) state that values above 0.7 are strong and values exceeding 0.9 are deemed unacceptable. Knowledge base size has a correlation value of 0.959 with patent applications. It was therefore decided to drop this control variable in the patent quantity analysis. Revenue has a value of 0.733 with patent applications, which is slightly above the threshold. It was decided not to exclude this control variable, because firm size is a crucial control variable in similar research. Total assets was tested as an alternative measure, but had an even higher correlation value than revenue. Additionally, knowledge base size has a correlation of 0.748 with revenue. However, given their importance as control variables and the fact that the assumption of multicollinearity is met (Appendix B), it was decided not to exclude either.

Table 1: Correlations and descriptive statistics.

	Variable	Descriptive Statistics				Correlation Matrix																
		Mean	S.D	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Patent applications	5.5509	1.998	0	10.4914	1																
2	Claims	2.6176	0.3989	0	4.22	0.103	1															
3	ROA	4.5904	0.1011	4.18	4.77	0.159	0.009	1														
4	R&D intensity	2.0361	0.9936	0.1254	6.2442	0.061	0.407	-0.333	1													
5	Revenue	14.5159	1.9962	8.5867	18.6571	0.733	0.067	0.309	-0.291	1												
6	Firm age	41,96	30.549	-5	192	0.17	-0.254	0.087	-0.185	0.266	1											
7	Knowledge base size	7.2248	1.9182	2.4849	12.3092	0.959	0.093	0.128	0.079	0.748	0.183	1										
8	Knowledge base age	5.601	1.5614	0.0114	10.5999	-0.017	-0.125	-0.086	-0.007	-0.207	-0.187	-0.011	1									
9	Knowledge base diversity	0.8265	0.1169	0	0.9835	0.254	-0.089	-0.008	-0.142	0.247	0.162	0.247	-0.066	1								
10	Divestiture rhythm	0	3.8943	-7.92	4.16	0.143	0.037	0.015	-0.041	0.097	-0.069	0.137	0.155	0.044	1							
11	Divestiture rhythm squared	15.1612	18.607	0	62.7	-0.244	-0.104	-0.044	0.008	-0.268	-0.026	-0.24	0.012	-0.094	-0.64	1						
12	Acquisition rhythm	0	3.2756	-8.12	3.96	0.072	0.098	0.086	-0.036	0.091	-0.088	0.078	0.04	0.036	0.193	-0.242	1					
13	Acquisition rhythm squared	10.7267	17.003	0	65.89	-0.164	-0.179	-0.038	0.002	-0.203	0.03	-0.173	0.054	-0.072	-0.098	0.262	-0.67	1				
14	Prior 5 year divestiture experience	0	0.8852	-0.74	3.17	0.45	0.087	0.058	0.039	0.539	0.208	0.47	-0.204	0.189	0.068	-0.387	0.099	-0.205	1			
15	Prior 5 year acquisition experience	0	0.8454	-0.95	3.08	0.41	0.223	0.101	-0.011	0.519	0.01	0.429	-0.169	0.136	0.019	-0.237	0.148	-0.377	0.464	1		
16	Divestiture relatedness	0.093	0.2813	0	2.08	0.185	0.112	0.017	0.109	0.258	0.033	0.207	-0.112	-0.007	0.026	-0.138	0.069	-0.086	0.368	0.23	1	
17	Acquisition relatedness	0.0741	0.2351	0	1.95	0.087	0.121	0.06	0.07	0.111	-0.059	0.095	-0.056	-0.011	0.029	-0.09	0.051	-0.107	0.113	0.17	0.159	1

4.2 Assumptions

After having examined and prepared the data, the following assumptions need to be met prior to conducting the multiple linear regression analysis (Hair et al., 2019).

4.2.1 Normality

The first assumption that was tested was the assumption of normally distributed error terms (Hair et al., 2019). This assumption is met based on a visual inspection of the normal probability plots (P-P plot) (Appendix C).

4.2.2 Independence of error terms

The second assumption to be tested was the assumption of independence of error terms (Hair et al., 2019). Durbin-Watson tests were conducted to check for this assumption. Any value between 1 and 3 is considered sufficient and values close to 2 are considered optimal (Field, 2013). With values of 2.022 and 2.043, this assumption is met (Appendix D).

4.2.3 Linearity

To check if the relation between the independent variables and the dependent variable is linear, the scatterplots incorporating the standardized residuals (ZRESID) and the standardized predicted values (ZPRED) were examined. The residuals need to follow the horizontal line at $y = 0$. This assumption is met (Appendix E).

4.2.4 Homogeneity of variances

To test the assumption of homoscedasticity, the scatterplots including the ZRESID and ZPRED values were examined (Appendix E). Based on the scatterplots the residuals' spread is relatively homogeneous. However, a small number of residuals are further away from the regression line. This is less problematic given the large sample size and the small amount of residuals that are further away from the regression line. However, to account for outliers the results of the regression analysis will validated by conducting additional analyses incorporating robust standard errors (Appendix F) (Hair et al., 2019).

4.2.5 Multicollinearity

The final assumption that was tested was multicollinearity. For each variable, the variance inflation factor (VIF) and the tolerance value was examined. The VIF values should be below 10 and the tolerance values should be above .10 (Hair et al., 2019). As no value came close to these thresholds, this assumption is met (Appendix B).

4.3 Results regression analysis

In order to test the hypotheses, two hierarchical multiple linear regression analyses were conducted. The results related to patent quantity are discussed in the following section, and the subsequent section covers the results for patent quality.

4.3.1 Number of applications

The results of the first analysis are depicted in table 2. Model 1 serves as the base model and includes the control variables. Knowledge base diversity is positively significant ($\beta = 1.118$, $p = <.001$), which indicates that a wide range and equal spread of patents among the different IPC sub-classes results in increased patent applications. Knowledge base age is positively significant as well ($\beta = 0.187$, $p = <.001$). Having more recent knowledge is correlated with number of applications. Furthermore, firm age is also positively significant ($\beta = 0.003$, $p = <.001$), which reveals that older firms generally apply for more patents than newer firms. ROA, R&D intensity, and revenue are also positively significant with the following values respectively ($\beta = 0.910$, $p = <.001$) ($\beta = 0.851$, $p = <.001$) ($\beta = 0.858$, $p = .000$). Corporations with higher values for these variables therefore apply for more patents.

Model 2 includes the variables divestiture rhythm and divestiture rhythm squared. In model 2 only divestiture rhythm is positively significant ($\beta = 0.026$, $p = <.001$), indicating that a more even-paced divestiture rhythm results in more patent applications. The quadratic term of divestiture rhythm is non-significant in model 2 ($\beta = 0.001$, $p = .430$). However, starting from model 5 and 6 this variable becomes statistically significant ($\beta = 0.007$, $p = <.001$). In the final model divestiture rhythm remains significant ($\beta = 0.052$, $p = <.001$). The quadratic term is plotted in figure 3 and shows evidence for a U-shaped relationship. It is important to note that on observing the curve, it closely resembles an exponential function. Based on the figure the even-event paced rhythm therefore results in slightly more applications than the event-paced rhythm (on average 17 patents more). The effect of rhythm on patent quantity becomes more pronounced just before the middle point, and this positive effect increases at an accelerated rate. When exponentiating the natural log value of 6.09 (even-paced) and the value of 5.48 (event-paced), the difference between the two indicates that an even-paced divestiture rhythm results in, on average, 200 more patent applications than the event-paced divestiture rhythm.

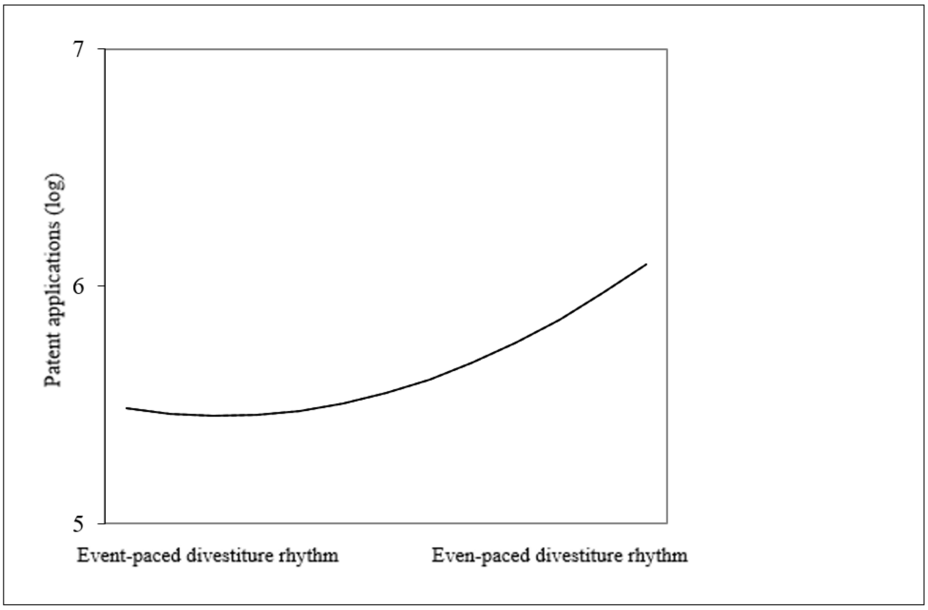

Figure 3: Divestiture rhythm

The acquisition rhythm and the quadratic term of the acquisition rhythm are added in model 3. Both of these are non-significant (β = 0.003, p = .682) (β = 0.001, p = .714). These variables remain non-significant throughout the entire analysis. The rhythm of acquisitions does therefore not directly influence the number of patent applications.

The direct effects of prior five year acquisition and divestiture experience are added in model 4. Divestiture experience is positively significant (β = 0.099, p = <.001), whereas acquisition experience is non-significant (β = 0.009, p = .758). In the following models divestiture experience becomes non-significant as well (β = -0.025, p = .541). Prior divestiture and acquisition experience are not directly related to patent applications.

Model 5 includes the interaction terms of prior five year divestiture experience and the divestiture rhythm (and rhythm squared). Both of these are statistically significant and remain so in the final model (β = 0.048, p = <.001) (β = 0.012, p = <.001). Thus, prior divestiture experience affects the relationship between rhythm and number of applications. Figure 4 is presented to aid in interpretation and visualization. This figure shows that with high experience, the curve is U-shaped, whereas for low experience the curve flips and is inverted U-shaped. In addition, the lines of low and high experience cross twice. Starting before the middle point, high experience results in an accelerated increase in patent applications the more even-paced the rhythm becomes, whilst also resulting in more patent applications than low experience. Low experience does result in more applications when the rhythm is between event-paced and even-event paced. However, when the rhythm is very irregular, high experience results in marginally more patent applications. This indicates that high experience is only beneficial for extreme levels of irregularity. The discussion section will further elaborate on these findings.

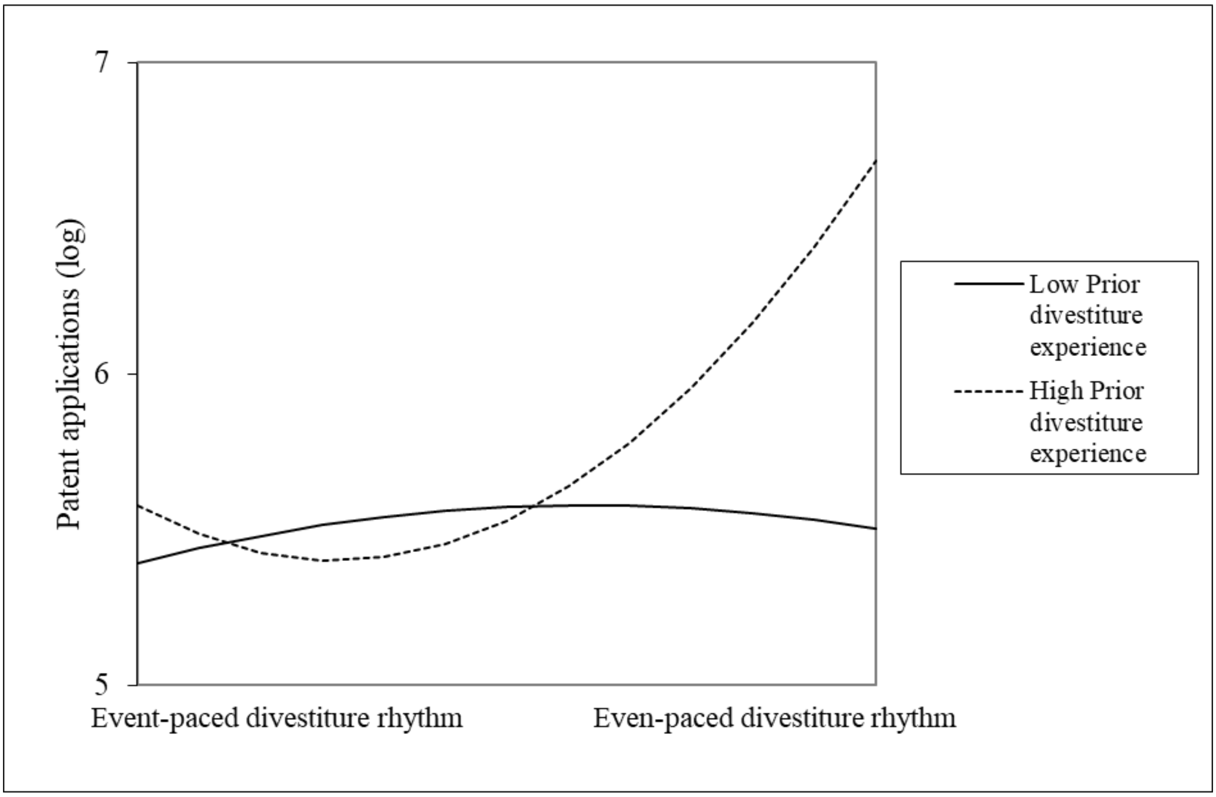

Figure 4: Divestiture rhythm & prior divestiture experience interaction

The final model includes the two interaction terms concerning acquisition experience and acquisition rhythm (and rhythm squared). These are both non-significant (β = -0.018, p = .119) (β = 0.002, p = .503).

Based on the results, hypotheses 1a, 2a, 3a, and 4a are rejected. To validate the results, an additional analysis including robust standard errors using the HC3 method was performed (Appendix F).

The adjusted R^2 of model 1 is .694, which means that the control variables are strong predictors of the dependent variable. The ΔR^2 of the following models is low, which can partially be explained by the large amount of variance captured by the control variables in the base model. This is beneficial to effectively isolate the relationships of interest. Additionally, prior studies have also shown to have similarly low levels of ΔR^2 (McNamara et al., 2008).

4.3.2 Number of claims

Based on the final model (6) of table 3, it can be observed that the results of the variables of interest are somewhat different. Divestiture rhythm and rhythm squared are non-significant with comparable values (β = 0.002, p = .392) (β = -0.001, p = .256). Acquisition rhythm is non-significant and acquisition rhythm squared is significant (β = 0.001, p = .848) (β = -0.004, p = <.001). Divestiture and acquisition experience are significant (β = -0.036, p = .003) (β = 0.056, p = <.001). The interaction term of divestiture experience and divestiture rhythm (and rhythm squared) are non-significant (β = -0.001, p = .855) (β =

0.000, p = .991). As for the interaction term concerning acquisitions, the linear version is significant whereas the quadratic interaction term is not (β = 0.007, p = .038) (β = -0.001, p = .084).

The results of the effect of acquisition experience on the relationship between acquisition rhythm and patent quality is visualized in figure 5. This figure indicates that high acquisition experience results in more claims per patent regardless of the rhythm. Nevertheless, corporations possessing high experience can increase the amount of claims per patent by adopting an even-paced rhythm. Corporations with low experience benefit more from an event-paced rhythm. These findings will also be further explored in the discussion section. To indicate the difference, experienced acquirors adopting an even-paced rhythm produce, on average, 2.2 claims per patent more (difference between the exponentiated values of 2.70 and 2.54) than corporations with low experience.

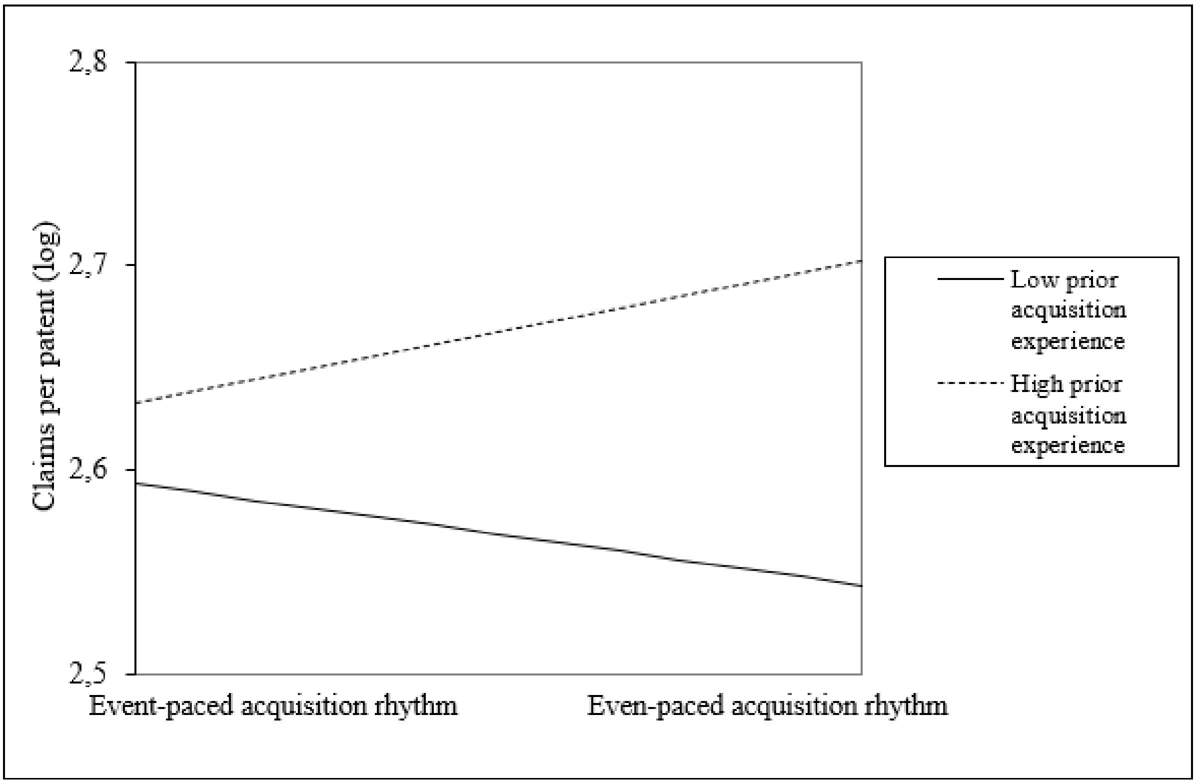

Figure 5: Acquisition rhythm & prior acquisition experience interaction

Based on the results, hypotheses 1b, 2b, 3b, and 4b are rejected. The results were validated by conducting another analysis including the standard errors using the HC3 method (Appendix F).

Table 2: Results regression analysis number of applications

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Divestiture rhythm		0.026*** (0.052)	0.026*** (0.051)	0.031*** (0.060)	0.052*** (0.102)	0.052***(0.101)
Divestiture rhythm^2		0.001 (0.010)	0.001 (0.010)	0.003 (0.026)	0.007*** (0.069)	0.007*** (0.069)
Acquisition rhythm			0.003 (0.005)	0.004 (0.007)	0.007 (0.011)	-0.001 (-0.001)
Acquisition rhythm^2			0.001 (0.005)	0.001 (0.008)	0.001 (0.011)	0.003 (0.026)
Prior 5 year divestiture experience				0.099*** (0.044)	-0.025 (-0.011)	-0.025 (-0.011)
Prior 5 year acquisition experience				0.009 (0.004)	0.008 (0.003)	0.011 (0.005)
Div rhythm * div experience					0.047*** (0.065)	0.048*** (0.067)
Div rhythm^2 * div experience					0.012*** (0.084)	0.012*** (0.085)
Acq rhythm * acq experience						-0.018 (-0.024)
Acq rhythm^2 * acq experience						0.002 (0.015)
Return on assets (ROA)	0.910*** (0.046)	0.920*** (0.047)	0.913*** (0.046)	0.962*** (0.049)	0.971*** (0.049)	0.986*** (0.050)
R&D intensity	0.851*** (0.423)	0.851*** (0.424)	0.852*** (0.424)	0.841*** (0.418)	0.843*** (0.419)	0.846*** (0.421)
Revenue	0.858*** (0.857)	0.853*** (0.852)	0.853*** (0.852)	0.833*** (0.832)	0.829*** (0.828)	0.831*** (0.830)
Firm age	0.003*** (0.053)	0.004*** (0.056)	0.004*** (0.056)	0.004*** (0.054)	0.004*** (0.057)	0.004*** (0.058)
Knowledge base age	0.187*** (0.146)	0.180*** (0.141)	0.180*** (0.141)	0.182*** (0.143)	0.184*** (0.144)	0.187*** (0.146)
Knowledge base diversity	1.118*** (0.065)	1.118*** (0.065)	1.116*** (0.065)	1.066*** (0.062)	1.066*** (0.062)	1.056*** (0.062)
Divestiture relatedness	-0.215** (-0.030)	-0.209** (-0.029)	-0.210** (-0.030)	-0.269*** (-0.038)	-0.269*** (-0.038)	-0.273*** (-0.038)
Acquisition relatedness	-0.056 (-0.007)	-0.060 (-0.007)	-0.058 (-0.007)	-0.060 (-0.007)	-0.069 (-0.008)	-0.055 (-0.006)
Industry dummies	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.694	0.696	0.696	0.696	0.698	0.698
Observations	3468	3468	3468	3468	3468	3468

*Significant: *p < .05, ** p< .01, *** p<.001*

Table 3: Results regression analysis number of claims

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Divestiture rhythm		0.001 (0.006)	0.003 (0.025)	0.002 (0.022)	0.002 (0.022)	0.002 (0.021)
Divestiture rhythm^2		-0.001* (-0.049)	0.000 (-0.019)	-0.001 (-0.033)	-0.001 (-0.031)	-0.001 (-0.031)
Acquisition rhythm			-0.004 (-0.032)	-0.002 (-0.018)	-0.002 (-0.018)	0.001 (0.005)
Acquisition rhythm^2			-0.003*** (-0.143)	-0.003*** (-0.108)	-0.003*** (-0.108)	-0.004*** (-0.158)
Prior 5 year divestiture experience				-0.034*** (-0.076)	-0.035** (-0.078)	-0.036** (-0.079)
Prior 5 year acquisition experience				0.053*** (0.113)	0.053*** (0.113)	0.056*** (0.119)
Div rhythm * div experience					0.000 (0.001)	-0.001 (-0.004)
Div rhythm^2 * div experience					0.000 (0.002)	0.000 (0.000)
Acq rhythm * acq experience						0.007* (0.048)
Acq rhythm^2 * acq experience						-0.001 (-0.056)
Return on assets (ROA)	0.411*** (0.104)	0.414*** (0.105)	0.426*** (0.108)	0.415*** (0.105)	0.415*** (0.105)	0.407*** (0.103)
R&D intensity	0.222*** (0.554)	0.222*** (0.553)	0.219*** (0.547)	0.219*** (0.545)	0.219*** (0.545)	0.216*** (0.539)
Revenue	0.081*** (0.403)	0.078*** (0.391)	0.074*** (0.372)	0.070*** (0.352)	0.070*** (0.352)	0.069*** (0.343)
Firm age	-0.003*** (-0.233)	-0.003*** (-0.232)	-0.003*** (-0.225)	-0.003*** (-0.208)	-0.003*** (-0.208)	-0.003*** (-0.212)
Knowledge base age	-0.022*** (-0.085)	-0.021*** (-0.083)	-0.019*** (-0.075)	-0.019*** (-0.074)	-0.019*** (-0.074)	-0.020*** (-0.079)
Knowledge base diversity	-0.169** (-0.049)	-0.173** (-0.051)	-0.173** (-0.051)	-0.163** (-0.048)	-0.163** (-0.048)	-0.159** (-0.047)
Knowledge base size	-0.046*** (-0.223)	-0.047*** (-0.226)	-0.048*** (-0.229)	-0.047*** (-0.227)	-0.047*** (-0.227)	-0.046*** (-0.223)
Divestiture relatedness	-0.010 (-0.007)	-0.012 (-0.009)	-0.011 (-0.008)	-0.002 (-0.001)	-0.002 (-0.001)	0.000 (0.000)
Acquisition relatedness	0.073** (0.043)	0.069** (0.041)	0.054* (0.032)	0.042 (0.025)	0.042 (0.025)	0.036 (0.021)
Industry dummies	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.300	0.302	0.315	0.324	0.323	0.326
Observations	3468	3468	3468	3468	3468	3468

*Significant: *p < .05, ** p< .01, *** p<.001*

4.3.3 Robustness check

To ensure robustness of the interaction effect, prior experience was altered to three years instead of five years. When comparing the results, no significant deviations were observed (Appendix G).

5. Discussion and conclusions

5.1 Findings & theoretical relevance

Based on organizational learning theory, it was expected that both acquisition and divestiture rhythms matter for innovation performance. To be specific, it was hypothesized that even-event paced acquisition and divestiture rhythms would result in increased patent quantity and quality. This means that inverted U-shaped patterns were expected. Furthermore, it was expected that experience would flatten these inverted U-shaped patterns.

5.1.1 Divestiture rhythms

In line with what was anticipated, divestiture rhythms significantly impact innovation performance. However, this only holds for patent quantity and not patent quality. The results indicate that the relationship between divestiture rhythms and patent quantity is curvilinear. Contradictory to hypothesis (2a), this curvilinear relationship does not exhibit an inverted U-shaped pattern, but is U-shaped. As stated in the results section, even though it is U-shaped, it closely resembles an exponential function (figure 3). The graph indicates that an even-event paced divestiture rhythm results in marginally more patent applications than the event-paced rhythm. Starting slightly before the middle point of an even-event paced rhythm the positive effect on patent applications accelerates the more even-paced the rhythm becomes. The highest peak is reached when the rhythm is most even-paced.

One reason for hypothesizing that the even-event paced rhythm was expected to outperform the even-paced rhythm, was because prior research indicates that an even-paced rhythm can result in inertia (Klarner & Raisch, 2013; Shi & Prescott, 2012). As inertia can hinder organizational learning and can result in less innovative output, it was expected that the even-event paced rhythm would result in increased innovation performance (Liao et al., 2008; Shi & Prescott, 2012). However, it can be argued that inertia can be prevented due to the nature of divestitures (Kim et al., 2021). The reason for this is that divestitures generally decrease the chance of being stuck in routines and for corporations to suffer from inertia (Kim et al., 2021). The process of deciding which businesses to divest indicates that corporations are actively looking to optimize the status quo of their operations and prevent inertia by doing so (Kim et al., 2021). Divestitures can therefore minimize one of the main negative aspects associated with an even-paced rhythm. An additional insight that explains why the even-paced rhythm results in increased patent quantity for corporations is because the flexibility associated with an event-paced rhythm might be less crucial for divestitures. Based on research, it is generally beneficial for corporations to be an early-mover with regards to acquisitions. This prevents corporations from potentially paying premiums, from missing opportunities, and from being a late-mover in acquisition waves (Carow et al., 2004; Birkinshaw et al., 2018). Given that acquisitions can be more externally driven, reacting to the environment and being irregular can therefore be more beneficial for acquisitions than divestitures. This would make irregularity or an event-paced divestiture rhythm less essential.

5.1.2 Divestiture rhythms & prior divestiture experience

Given the significant results of the interaction effect, it is appropriate to analyse divestiture rhythms in the context of prior experience rather than viewing divestiture rhythms in isolation. The reason for this is because the effect of divestiture rhythms on patent quantity is contingent upon prior experience. The moderating effect of experience on the relationship between divestiture rhythm and patent quality was non-significant. This means that hypothesis 4b is rejected. Conversely, the moderating effect of divestiture experience on the relationships between divestiture rhythm and patent quantity is significant. This relationship is however different than expected, which means that hypothesis 4a is also rejected.

Based on figure 4 it can be observed that high prior experience results in steeper slopes compared to the direct effect in figure 3. The effect of experience on either the event-paced rhythm or the even-paced rhythm therefore becomes more pronounced, which is in line with the argumentation used for the hypotheses formulation. To elaborate, it was expected that experienced divestors have an enhanced ability to manage the negative aspect of time compression diseconomies associated with an event-paced rhythm (Laamanen & Keil, 2008). Additionally, it was expected that corporations adopting an even-paced rhythm benefit from prior experience (Vermeulen & Barkema, 2002). The reason for this is because low variance in divestiture frequency results in corporations being less affected by time pressure. This provides corporations with an enhanced ability to derive insights from prior experience and to apply it to current situations. Even though the hypotheses are rejected, these findings are in line with the expectations used to formulate the hypotheses.

However, when observing figure 4 it appears that experienced divestors produce less patents with lesser degrees of irregularity. Given the crossing lines, this also holds when comparing it with the patenting output of lesser experienced divestors. Taken together, this indicates that experienced divestors benefit from prior experience when irregularity is more extreme. With lower levels of irregularity, prior experience results in less patent applications and lesser experienced divestors also apply for more patents. This is partially in line with what was expected, but also adds a nuanced understanding on experience and rhythms. As discussed previously, it was expected that prior experience allows corporations to manage the negative aspect of time compression diseconomies associated with an event-paced rhythm. Based on the findings this is only true for more extreme levels of irregularity, because with lower levels of irregularity this does not hold. An explanation for this is that when irregularity is less extreme, corporations might increase their effort to derive insights from prior experience with the belief that this can be done effectively. However, lesser degrees of irregularity can provide corporations with a false sense in their ability to derive insights from prior experiences. In these situations, corporations might attempt to rely on prior experiences to a higher degree, but fail to do so because they are still dealing with time compression diseconomies. This would impede learning and subsequent patent output. Corporations with high levels of irregularity might refrain from more intensive attempts to engage with and derive insights from prior experience and could possibly respond to this irregularity more spontaneously. So, lower levels of irregularity might therefore provide corporations with a false sense in their ability to derive insights from prior experiences, which results in less patent output given that these corporations are still confronted by irregularity.

When observing the curve with low experience, it can be noted that the relationship follows an inverted U-shaped pattern and therefore flips. In line with the expectations from the hypotheses formulation, prior experience allows corporations to manage time compression associated with an event-paced rhythm and enables corporations to leverage the generally beneficial learning conditions associated with an even-paced rhythm (Laamanen & Keil, 2008; Vermeulen & Barkema, 2002). However, corporations are of course unable to do so when prior experience is low. In order to mitigate the negative aspects of the even-paced or event-paced rhythms, lesser experienced corporations can therefore increase their patent output by applying an even-event paced rhythm. Taken together, this means that corporations need experience to manage the negative aspects and to leverage the benefits of either extreme, whereas with low experience corporations rely on a balanced rhythm in order to do so.

Another finding relates to the non-significance of the direct effect of divestiture experience on patent quantity. Given this non-significant direct effect, but a significant moderating effect, this research indicates that divestiture experience alone might not be enough to contribute to increased patent quantity. This means that the experience gathered over time is not as important as organizing these experiences over time to realize increased patent quantity (Shi & Prescott, 2012). Leveraging the divestiture experiences using rhythms is therefore of importance to increase the number of applications.

5.1.3 Acquisition rhythms

As for the direct effect of acquisition rhythm, the results are non-significant. Hypotheses 1a and 1b are therefore rejected. This however does not contradict previous research focussing on acquisition rhythms (Shi & Prescott, 2012; Laamanen & Keil, 2008). One possible explanation for the difference in findings is that these two mentioned studies investigated the effect on financial performance measures. The former adopted Tobin’s Q, whereas the latter adopted excess market returns. In general, stock markets are updated relatively quickly in response to acquisitions and are less prone to time effects (Aalbers et al., 2021). It can be argued that innovation performance is more prone to time lag and confounding time effects. Additionally, it is important to note that previous research indicates that the relationship between acquisitions and innovation is complicated (McCarthy & Aalbers, 2016). McCarthy & Aalbers (2024) state that only 21% of the innovation-based acquisitions are successful. In their literature review, Barkema & Schijven (2008) state that the success of acquisitions significantly depends on aspects such as target selection, synergy realization, and post-integration. These aspects highlight the complexity of the topic being researched and that an acquisition rhythm might not operate in isolation. This is confirmed by the significant moderation effect of prior acquisition experience. In other words, the relationship between acquisition rhythm and patent quality is more complex, because it is contingent upon prior acquisition experience.

5.1.4 Acquisition rhythms & prior acquisition experience

The results suggest that prior experience moderates the relationship between acquisition rhythms and patent quality. However, the previous curvilinear direct effects were non-significant, which results in hypotheses 3a and 3b to also be rejected. In line with what was expected, experienced acquirors can more effectively manage the negative aspects of time compression diseconomies associated with an event-paced rhythm (Laamanen & Keil, 2008). In doing so, experienced acquirors can mitigate its negative constraint on organizational learning and therefore generate more claims per patent. Similarly to divestitures, experienced acquirors also have an increased ability to leverage the positive aspects of an even-paced rhythm (Vermeulen & Barkema, 2002). Regardless of the rhythm, experienced acquirors therefore generate more claims per patent than lesser experienced acquirors.

Based on figure 5, it can be observed that corporations possessing high levels of experience generate more claims per patent when adopting an even-paced rhythm. This finding is similar to that of divestitures and patent quantity. Experienced acquirors have an enhanced ability to derive insights from their acquisition experience when the variance in acquisition frequency is low (Vermeulen & Barkema, 2002). In other words, without the limitation of time compression diseconomies resulting from irregularity, corporations can enhance their capability to leverage prior experiences. Conversely, for lesser experienced acquirors, an event-paced acquisition rhythm results in more claims per patent than for an even-paced rhythm. As stated in the section on divestiture rhythms, acquisitions possibly derive greater advantage from flexibility and responsiveness to the external environment (Carow et al., 2004; Birkinshaw et al., 2018). This might particularly be true in dynamic environments where innovations and business models change frequently. Without the ability to leverage acquisition experience, less experienced acquirors therefore appear to benefit more from being flexible when considering the amount of claims per patent as a quality measure.

5.2 Theoretical contributions

Even though the hypotheses are rejected, plenty meaningful insights can be derived from the results which contribute to the existing body of research on the temporal perspective, rhythms, organizational learning theory, acquisitions, divestitures, experience, and innovation.

First of all, this research specifically enriches the limited literature on rhythms. It fills a gap in the rhythm literature by finding evidence for a relationship between business divestiture rhythm and patent applications. It is the first study to investigate the effect of business divestiture rhythms. One previous study has focussed on divestiture rhythms, but incorporated technological patent divestitures (Kim et al., 2021). Additionally, this research confirms the underlying mechanisms that explains why an even-paced rhythm is potentially more beneficial for divestitures. With an even-paced divestiture rhythm not only learning is optimized, but the negative aspect of inertia is tackled due to the nature of divestitures (Kim et al., 2021). Moreover, this research adds a nuanced understanding to this by finding evidence for a curvilinear relationship. With a more even-paced divestiture rhythm the positive effect on patent applications increases at an accelerate rate.

Second, it was found that divestiture experience influences the relationship of divesture rhythms and patent applications. The findings therefore further enrich the research on rhythms, but also on prior divestiture experience (Bergh & Lim, 2008; Lee & Roh, 2020; Humphery-Jenner et al., 2019). Even though experience has been widely studied, its application as a variable to the context of rhythms is limited to one research (Laamanen & Keil, 2008). In line with Laamanen & Keil (2008), prior divestiture experience allows corporations to mitigate the negative aspect of time compression diseconomies associated with irregularity. This research however adds a nuanced understanding to this by finding that it is contingent upon the level of irregularity. The findings indicate that this only holds for more extreme levels of irregularity. Furthermore, when moderating for divestiture experience, it was found that high divestiture experience strengthens the U-shaped relationship between divesture rhythm and patent applications. However, with low levels of divestiture experience, this relationship transforms into an inverted U-shaped curve. These findings add to the literature by confirming that the relationship between divestiture rhythm and patent applications is contingent upon experience.

Third, this study enriches the literature on acquisition rhythms and acquisition experience by finding no direct relationship between acquisition rhythms and patent quantity nor quality. Moreover, it contributes to the literature on these topics, because the findings indicate that relationship between acquisition rhythms and the subsequent number of claims per patent is contingent upon prior acquisition experience. Even though research on acquisition experience presents contradictory findings (Argote et al., 2021), this research indicates that acquisition experience is beneficial for increasing the number of claims per patent regardless of the rhythm.

Fourth, this research enriches the acquisition rhythm and experience literature by finding that the rhythm resulting in the most claims per patent depends on prior experience. Experienced acquirors derive greater advantage from an even-paced acquisition rhythm, whereas less experienced acquirors generate more claims per patent when adopting an event-paced rhythm. The latter is somewhat contradictory to the findings of Shi & Prescott (2012) and Laamanen & Keil (2002). However, in their studies prior experience was not moderated for. Additionally, it captured a different context and the performance measures were non-innovation related. The finding that flexibility is crucial for less experienced acquirors, possibly to be responsive to external innovations and knowledge in a dynamic industry, adds a nuanced understanding to the acquisition rhythm and experience literature.

Fifth, the findings also enrich the rhythm and experience literature by testing for curvilinear relationships. Prior research has mostly focused on linear relationships (Klarner & Raisch, 2013, Vermeulen & Barkema, 2002; Kim et al., 2021; Laamanen & Keil, 2008), whereas very limited studies have focussed on curvilinear relationships (Shi & Prescott, 2012).

Sixth, this study adds to the rhythm literature by focussing on innovation performance measures instead of the generally adopted financial or accounting based performance measures (Klarner & Raisch, 2013, Vermeulen & Barkema, 2002; Laamanen & Keil, 2008; Shi & Prescott, 2012).

Finally, this research enriches the literature on organizational learning theory by explicitly incorporating it to aid in explaining the underlying mechanisms of the variables and their relationships.

5.3 Managerial implications

The findings of this study are crucial for managers and other professionals involved with corporations managing a portfolio of businesses. The findings are especially important for corporations that operate in dynamic and fast-changing contexts where innovation is critical for gaining a sustained, competitive advantage. Acquisitions and divestitures are essential for corporations to navigate in this context and to realise innovation performance. The ability to leverage these in order to maximize their outcomes is therefore crucial. This can be done through the use of rhythms.

Specifically, divestiture rhythms can be leveraged to significantly increase subsequent patent application output. Corporations possessing higher levels of divestiture experience can do so by adopting an even-paced divestiture rhythm. Conversely, lesser experienced divestors can maximize their patent application output by adopting an even-event paced divestiture rhythm. However, it is advisable for these lesser experienced divestors to increase their divestiture experience. By doing so they can eventually transition to an even-paced divestiture rhythm. This is advantageous because experienced divestors adopting an even-paced divestiture rhythm realize the highest level of patent application output.

Acquisition rhythms can be utilized to enhance the average amount of claims per patent. More specifically, experienced acquirors adopting an even-paced acquisition rhythm can increase the average number of claims per patent. An even-paced acquisition rhythm enhances a corporation's ability to derive insights from prior experience and therefore to maximally leverage this. Conversely, corporations possessing less acquisition experience are advised to adopt an event-paced acquisition rhythm. Without the ability to leverage prior acquisition experience, corporations benefit from being flexible. This flexibility and responsiveness enables corporations to react promptly to external changes and capture innovation related opportunities using acquisitions. Similar to divestitures, corporations would benefit from gathering acquisition experience to ultimately leverage the even-paced divestiture rhythm.

5.4 Limitations & future research

One limitation of this research is that the knowledge base size, age, and diversity for the acquired and divested businesses were not controlled for (McCarthy & Aalbers, 2022). Gathering and aggregating this data for the thousands of acquired and divested businesses was out of the scope of this research. A significant amount of the acquired and divested businesses are also not public, which makes it impossible to gather the needed patent data. Deal value was considered as an alternative to knowledge base size. However one third of the acquisitions and half of the divestitures had missing deal values. The ability to obtain this data was therefore limited by the available databases. In line with prior research, it was therefore decided to not control for deal size (Humphery-Jenner et al., 2019).

Additionally, this research only focusses on patent applications and claims. However, not all innovations are patented and additional patent measures can be investigated (e.g. forward citations) (McCarthy & Aalbers, 2022). Additionally, the narrowness of patent claims and the amount of words per claim as quality indicators were also not adopted in this research (Marco et al., 2019). Besides innovation performance, financial or accounting performance measures can also be further explored. Shi & Prescott (2012) adopted Tobin's Q as a financial performance measure, which was lagged by one year. Future research could investigate financial performance measures with less time lag, such as cumulative abnormal returns (Aalbers et al., 2021).

Future research could focus on alliance rhythms and investigate how these affect innovation performance. Additionally, future research could explore the effect of internal development related rhythms (e.g. R&D) on innovation performance.

Moreover, this research only accounted for the total amount of acquisition and divestiture experience. It therefore does not include experience-specific measures, such as heterogeneity of prior experience or size-related aspects of experience (Brauer et al., 2017; Ellis et al., 2011). Future research could distinguish between these different types of experience.

Generalizability is another limitation, because the corporations are all part of the high-tech industry. Different industries might favour different strategies with regards to – the timing of – acquisitions and divestitures, and can therefore result in different findings.

Given the scope, this research is also limited with regards to the different tests and robustness checks that can be considered for curvilinear relationships and subsequent moderation effects (Haans et al., 2016).

Based on the findings, this research proposes additional possibilities for future research. Future research can investigate what the underlying mechanisms are for explaining the difference in patenting output for experienced divestors when comparing extreme levels of irregularity with lesser levels of irregularity. Additionally, future research could focus on refining and adding to the understanding of why lesser experienced acquirors generate more claims per patent by adopting an event-paced acquisition rhythm. This research has provided possible explanations for both recommendations. However, future research is warranted to explore the intricacies in more detail.

5.5 Conclusions

The main research question of this study aims to discover whether even-event paced acquisition and divestiture rhythms result in increased innovation performance compared to even-paced and event-paced rhythms. Two additional questions were posed to examine how prior experience influences the relationship between the rhythms and innovation performance. Based on the findings, an even-paced divestiture rhythm generally results in more patent applications. It is argued that the underlying reason for this is because divestitures counteract the negative aspect of inertia associated with an even-paced rhythm. Additionally, given their internal focus, flexibility might be less important for divestitures than for acquisitions.

However, the relationship between divestiture rhythms and subsequent patent applications is contingent upon prior divestiture experience and should therefore be included in the interpretation. When incorporating divestiture experience, the findings suggest that corporations having low divestiture experience can maximize their patent application quantity by adopting an even-event paced divestiture rhythm. Without experience to leverage the benefits of the even-paced or event-paced divestiture rhythm, corporations need an even-event paced rhythm to balance the positive aspects and minimize the negative aspects associated with both. On the other hand, experienced divestors can maximize their patenting output by adopting an even-paced divestiture rhythm. This rhythm provides corporations with an enhanced ability to derive insights from prior experience, because this rhythm is not constraint by time compression diseconomies.

As for acquisition rhythms, its relationship with the patent quality measure (i.e., average number of claims per patent) depends on prior acquisition experience. The findings suggest that experienced acquirors produce more claims per patent than lesser experienced acquirors regardless of the rhythm. Additionally, experienced acquirors generate more claims per patent when adopting an even-paced acquisition rhythm. In line with the reasoning for divestitures, this rhythm allows corporations to maximally leverage the insights that can be derived from prior experience. For lesser experienced acquirors, it is not optional to leverage prior experience using an even-paced rhythm. Instead, corporations can increase their patent quality by adopting an event-paced acquisition rhythm. The findings suggest that without prior acquisition experience, leveraging flexibility to access external opportunities is essential to enhance the amount of claims per patent.

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Appendices

Appendix A

Univariate Statistics Variable	N	Missing Count	Percent
Knowledge base age	3472	0	0
Knowledge base diversity	3472	0	0
Knowledge base size	3472	0	0
Number of applications	3472	0	0
Firm age	3472	0	0
ROA	3468	4	0.1
R&D intensity	3472	0	0
Revenue	3472	0	0
Number of claims	3472	0	0
Prior 5 year acquisition experience	3472	0	0
Prior 5 year divestiture experience	3472	0	0
Acquisition rhythm	3472	0	0
Divestiture rhythm	3472	0	0
Acquisition relatedness	3472	0	0
Divestiture relatedness	3472	0	0

Appendix B

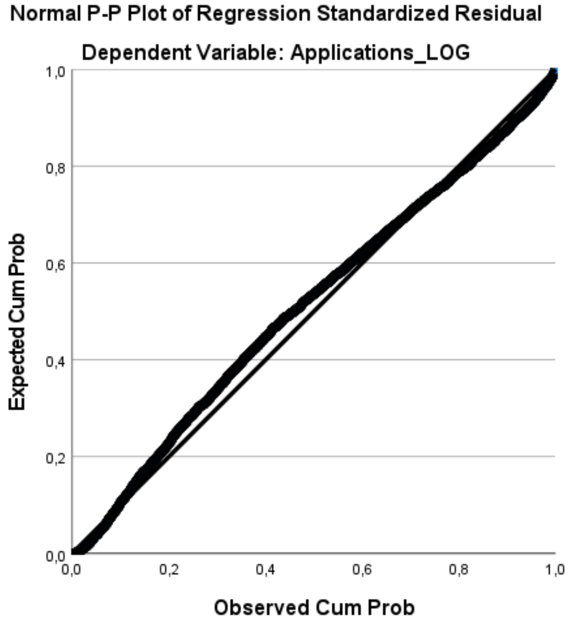
Variable	Tolerance	VIF
ROA	0.785	1.274
R&D intensity	0.626	1.597
Revenue	0.441	2.267
Firm age	0.798	1.253
Knowledge base age	0.817	1.224
Knowledge base diversity	0.799	1.252
Divestiture relatedness	0.793	1.26
Acquisition relatedness	0.923	1.084
Industry=Computers	0.44	2.275
Industry=Electronics & communications	0.241	4.146
Industry=Pharmaceuticals	0.237	4.224
year=2007.0	0.537	1.864
year=2008.0	0.53	1.885
year=2009.0	0.522	1.916
year=2010.0	0.523	1.911
year=2011.0	0.517	1.934
year=2012.0	0.508	1.967
year=2013.0	0.503	1.988
year=2014.0	0.493	2.03
year=2015.0	0.492	2.034
year=2016.0	0.487	2.055
year=2017.0	0.49	2.04
year=2018.0	0.487	2.055
year=2019.0	0.484	2.067
Divestiture rhythm	0.326	3.071
Divestiture rhythm^2	0.265	3.776
Acquisition rhythm	0.328	3.049
Acquisition rhythm^2	0.214	4.678
Prior 5 year divestiture experience	0.271	3.685
Prior 5 year acquisition experience	0.348	2.871
Div rhythm * div experience	0.336	2.979
Div rhythm^2 * div experience	0.212	4.725
Acq rhythm * acq experience	0.367	2.723
Acq rhythm^2 * acq experience	0.185	5.409

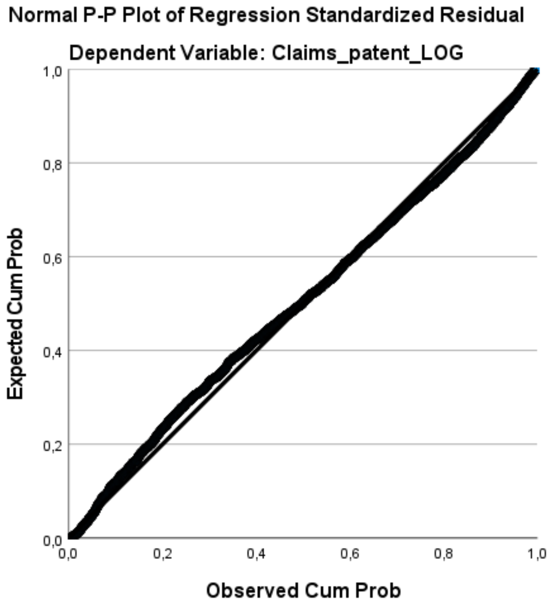
Dependent variable: Number of applications

Variable	Tolerance	VIF
Industry=Computers	0.43	2.326
Industry=Electronics & communications	0.231	4.336
Industry=Pharmaceuticals	0.237	4.224
year=2007.0	0.537	1.864
year=2008.0	0.53	1.885
year=2009.0	0.522	1.917
year=2010.0	0.523	1.911
year=2011.0	0.517	1.934
year=2012.0	0.508	1.967
year=2013.0	0.503	1.989
year=2014.0	0.493	2.03
year=2015.0	0.491	2.035
year=2016.0	0.487	2.055
year=2017.0	0.49	2.04
year=2018.0	0.486	2.056
year=2019.0	0.484	2.067
Acquisition relatedness	0.923	1.084
Divestiture relatedness	0.792	1.263
ROA	0.784	1.275
R&D intensity	0.439	2.279
Revenue	0.201	4.966
Firm age	0.786	1.272
Knowledge base age	0.752	1.329
Knowledge base diversity	0.792	1.263
Knowledge base size	0.265	3.772
Divestiture rhythm	0.321	3.118
Divestiture rhythm^2	0.263	3.796
Acquisition rhythm	0.328	3.049
Acquisition rhythm^2	0.214	4.681
Prior 5 year divestiture experience	0.271	3.685
Prior 5 year acquisition experience	0.348	2.872
Div rhythm * div experience	0.333	3.002
Div rhythm^2 * div experience	0.211	4.746
Acq rhythm * acq experience	0.367	2.725
Acq rhythm^2 * acq experience	0.185	5.41

Dependent variable: Number of claims

Appendix C





Appendix D

Model Summary[g]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,834[a]	,696	,694	1,1046748541	,696	328,708	24	3443	,000	
2	,835[b]	,698	,696	1,1016322535	,002	10,522	2	3441	<,001	
3	,835[c]	,698	,696	1,1019228361	,000	,093	2	3439	,911	
4	,836[d]	,699	,696	1,1003381100	,001	5,956	2	3437	,003	
5	,837[e]	,701	,698	1,0972804243	,002	10,591	2	3435	<,001	
6	,837[f]	,701	,698	1,0967252961	,000	2,739	2	3433	,065	2,022

a. Predictors: (Constant), year=2019.0, Industry=Pharmaceuticals, ROA_WINS, year=2016.0, FIRM_AGE, year=2014.0, ACQ_EXP_R_LOG, year=2010.0, year=2013.0, year=2015.0, Industry=Computers, year=2008.0, DIV_EXP_R_LOG, year=2011.0, KNBASE_AGE_INV, year=2012.0, KNBASE_DIV, year=2007.0, year=2017.0, year=2009.0, REV_WINS, RD_WINS, year=2018.0, Industry=Electronics & communications

b. Predictors: (Constant), year=2019.0, Industry=Pharmaceuticals, ROA_WINS, year=2016.0, FIRM_AGE, year=2014.0, ACQ_EXP_R_LOG, year=2010.0, year=2013.0, year=2015.0, Industry=Computers, year=2008.0, DIV_EXP_R_LOG, year=2011.0, KNBASE_AGE_INV, year=2012.0, KNBASE_DIV, year=2007.0, year=2017.0, year=2009.0, REV_WINS, RD_WINS, year=2018.0, Industry=Electronics & communications, DIV_Rhythm, DIV_Rhythm_squared

c. Predictors: (Constant), year=2019.0, Industry=Pharmaceuticals, ROA_WINS, year=2016.0, FIRM_AGE, year=2014.0, ACQ_EXP_R_LOG, year=2010.0, year=2013.0, year=2015.0, Industry=Computers, year=2008.0, DIV_EXP_R_LOG, year=2011.0, KNBASE_AGE_INV, year=2012.0, KNBASE_DIV, year=2007.0, year=2017.0, year=2009.0, REV_WINS, RD_WINS, year=2018.0, Industry=Electronics & communications, DIV_Rhythm, DIV_Rhythm_squared, ACQ_Rhythm_squared, ACQ_Rhythm

d. Predictors: (Constant), year=2019.0, Industry=Pharmaceuticals, ROA_WINS, year=2016.0, FIRM_AGE, year=2014.0, ACQ_EXP_R_LOG, year=2010.0, year=2013.0, year=2015.0, Industry=Computers, year=2008.0, DIV_EXP_R_LOG, year=2011.0, KNBASE_AGE_INV, year=2012.0, KNBASE_DIV, year=2007.0, year=2017.0, year=2009.0, REV_WINS, RD_WINS, year=2018.0, Industry=Electronics & communications, DIV_Rhythm, DIV_Rhythm_squared, ACQ_Rhythm_squared, ACQ_Rhythm, ACQ_EXP_LOGMC_5YLAG, DIV_EXP_LOGMC_5YLAG

e. Predictors: (Constant), year=2019.0, Industry=Pharmaceuticals, ROA_WINS, year=2016.0, FIRM_AGE, year=2014.0, ACQ_EXP_R_LOG, year=2010.0, year=2013.0, year=2015.0, Industry=Computers, year=2008.0, DIV_EXP_R_LOG, year=2011.0, KNBASE_AGE_INV, year=2012.0, KNBASE_DIV, year=2007.0, year=2017.0, year=2009.0, REV_WINS, RD_WINS, year=2018.0, Industry=Electronics & communications, DIV_Rhythm, DIV_Rhythm_squared, ACQ_Rhythm_squared, ACQ_Rhythm, ACQ_EXP_LOGMC_5YLAG, DIV_EXP_LOGMC_5YLAG, DIV_Interaction, DIV_SQ_Interaction

f. Predictors: (Constant), year=2019.0, Industry=Pharmaceuticals, ROA_WINS, year=2016.0, FIRM_AGE, year=2014.0, ACQ_EXP_R_LOG, year=2010.0, year=2013.0, year=2015.0, Industry=Computers, year=2008.0, DIV_EXP_R_LOG, year=2011.0, KNBASE_AGE_INV, year=2012.0, KNBASE_DIV, year=2007.0, year=2017.0, year=2009.0, REV_WINS, RD_WINS, year=2018.0, Industry=Electronics & communications, DIV_Rhythm, DIV_Rhythm_squared, ACQ_Rhythm_squared, ACQ_Rhythm, ACQ_EXP_LOGMC_5YLAG, DIV_EXP_LOGMC_5YLAG, DIV_Interaction, DIV_SQ_Interaction, ACQ_Interaction, ACQ_SQ_Interaction

g. Dependent Variable: Applications_LOG

Model Summary[g]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,553[a]	,305	,300	,33348	,305	60,528	25	3442	<,001	
2	,555[b]	,308	,302	,33303	,002	5,684	2	3440	,003	
3	,567[c]	,321	,315	,32989	,013	33,806	2	3438	<,001	
4	,574[d]	,330	,324	,32786	,009	22,443	2	3436	<,001	
5	,574[e]	,330	,323	,32795	,000	,003	2	3434	,997	
6	,577[f]	,333	,326	,32732	,003	7,606	2	3432	<,001	2,043

a. Predictors: (Constant), KNBASE_SIZE_LOG, year=2013.0, Industry=Electronics & communications, KNBASE_AGE_INV, year=2012.0, year=2011.0, ACQ_EXP_R_LOG, year=2010.0, ROA_WINS, year=2014.0, year=2015.0, year=2016.0, FIRM_AGE, year=2008.0, DIV_EXP_R_LOG, KNBASE_DIV, year=2017.0, year=2007.0, year=2019.0, Industry=Computers, year=2009.0, RD_WINS, year=2018.0, Industry=Pharmaceuticals, REV_WINS

b. Predictors: (Constant), KNBASE_SIZE_LOG, year=2013.0, Industry=Electronics & communications, KNBASE_AGE_INV, year=2012.0, year=2011.0, ACQ_EXP_R_LOG, year=2010.0, ROA_WINS, year=2014.0, year=2015.0, year=2016.0, FIRM_AGE, year=2008.0, DIV_EXP_R_LOG, KNBASE_DIV, year=2017.0, year=2007.0, year=2019.0, Industry=Computers, year=2009.0, RD_WINS, year=2018.0, Industry=Pharmaceuticals, REV_WINS, DIV_Rhythm, DIV_Rhythm_squared

c. Predictors: (Constant), KNBASE_SIZE_LOG, year=2013.0, Industry=Electronics & communications, KNBASE_AGE_INV, year=2012.0, year=2011.0, ACQ_EXP_R_LOG, year=2010.0, ROA_WINS, year=2014.0, year=2015.0, year=2016.0, FIRM_AGE, year=2008.0, DIV_EXP_R_LOG, KNBASE_DIV, year=2017.0, year=2007.0, year=2019.0, Industry=Computers, year=2009.0, RD_WINS, year=2018.0, Industry=Pharmaceuticals, REV_WINS, DIV_Rhythm, DIV_Rhythm_squared, ACQ_Rhythm_squared, ACQ_Rhythm

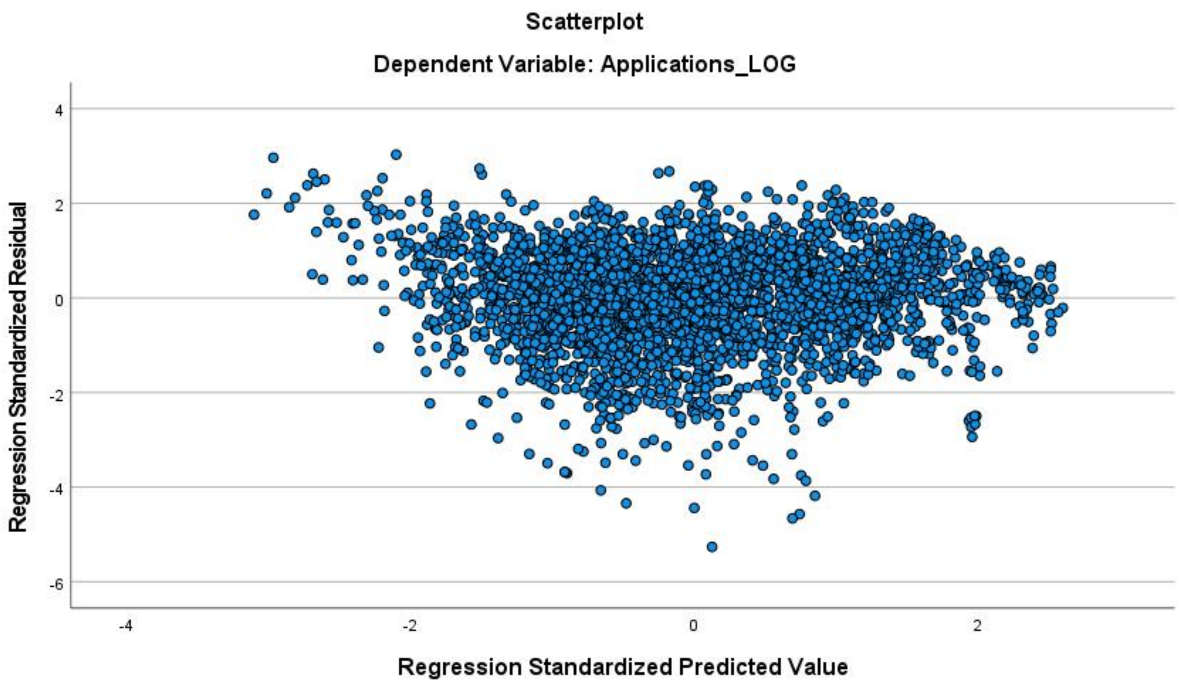
d. Predictors: (Constant), KNBASE_SIZE_LOG, year=2013.0, Industry=Electronics & communications, KNBASE_AGE_INV, year=2012.0, year=2011.0, ACQ_EXP_R_LOG, year=2010.0, ROA_WINS, year=2014.0, year=2015.0, year=2016.0, FIRM_AGE, year=2008.0, DIV_EXP_R_LOG, KNBASE_DIV, year=2017.0, year=2007.0, year=2019.0, Industry=Computers, year=2009.0, RD_WINS, year=2018.0, Industry=Pharmaceuticals, REV_WINS, DIV_Rhythm, DIV_Rhythm_squared, ACQ_Rhythm_squared, ACQ_Rhythm, ACQ_EXP_LOGMC_5YLAG, DIV_EXP_LOGMC_5YLAG

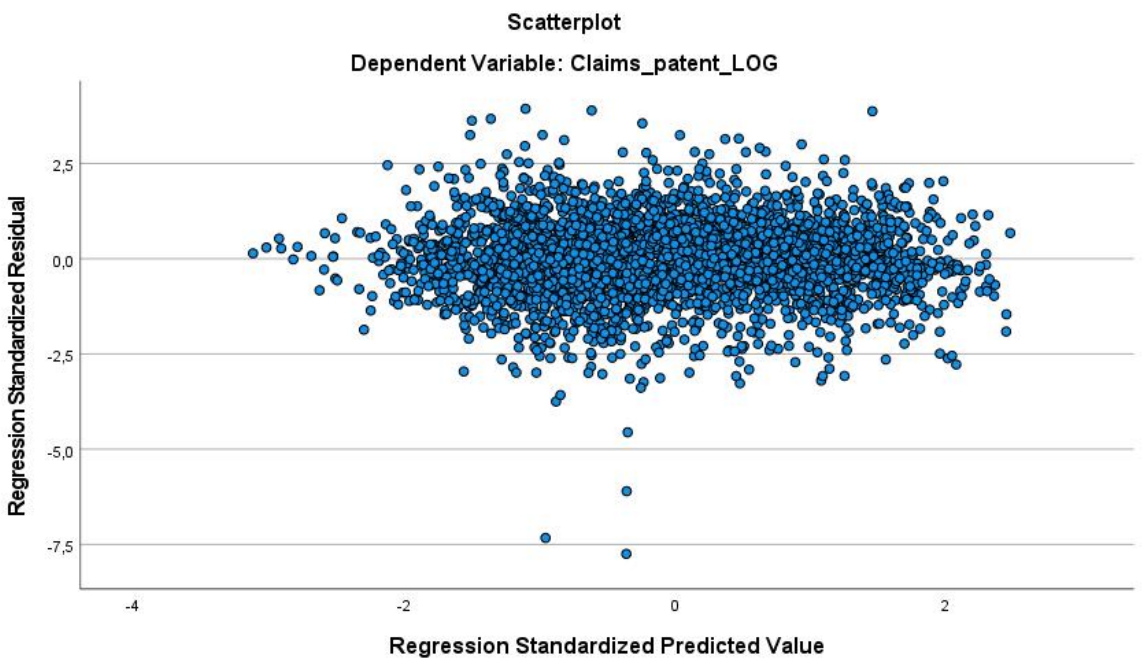
e. Predictors: (Constant), KNBASE_SIZE_LOG, year=2013.0, Industry=Electronics & communications, KNBASE_AGE_INV, year=2012.0, year=2011.0, ACQ_EXP_R_LOG, year=2010.0, ROA_WINS, year=2014.0, year=2015.0, year=2016.0, FIRM_AGE, year=2008.0, DIV_EXP_R_LOG, KNBASE_DIV, year=2017.0, year=2007.0, year=2019.0, Industry=Computers, year=2009.0, RD_WINS, year=2018.0, Industry=Pharmaceuticals, REV_WINS, DIV_Rhythm, DIV_Rhythm_squared, ACQ_Rhythm_squared, ACQ_Rhythm, ACQ_EXP_LOGMC_5YLAG, DIV_EXP_LOGMC_5YLAG, DIV_Interaction, DIV_SQ_Interaction

f. Predictors: (Constant), KNBASE_SIZE_LOG, year=2013.0, Industry=Electronics & communications, KNBASE_AGE_INV, year=2012.0, year=2011.0, ACQ_EXP_R_LOG, year=2010.0, ROA_WINS, year=2014.0, year=2015.0, year=2016.0, FIRM_AGE, year=2008.0, DIV_EXP_R_LOG, KNBASE_DIV, year=2017.0, year=2007.0, year=2019.0, Industry=Computers, year=2009.0, RD_WINS, year=2018.0, Industry=Pharmaceuticals, REV_WINS, DIV_Rhythm, DIV_Rhythm_squared, ACQ_Rhythm_squared, ACQ_Rhythm, ACQ_EXP_LOGMC_5YLAG, DIV_EXP_LOGMC_5YLAG, DIV_Interaction, DIV_SQ_Interaction, ACQ_Interaction, ACQ_SQ_Interaction

g. Dependent Variable: Claims_patent_WINS

Appendix E




Scatterplot
Dependent Variable: Claims_patent_LOG
Regression Standardized Residual
2,5
0,0
-2,5
-5,0
-7,5
-4
-2
0
2
Regression Standardized Predicted Value

Appendix F

Parameter	B	Robust Std. Error	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
year=2007	-0.05	0.101	-0.499	0.618	-0.248	0.147
year=2008	-0.203	0.103	-1.968	0.049	-0.405	-0.001
year=2009	-0.062	0.101	-0.617	0.537	-0.259	0.135
year=2010	-0.117	0.102	-1.157	0.247	-0.316	0.082
year=2011	-0.124	0.101	-1.228	0.219	-0.323	0.074
year=2012	0.018	0.104	0.173	0.863	-0.186	0.222
year=2013	0.015	0.104	0.139	0.889	-0.19	0.219
year=2014	-0.085	0.11	-0.772	0.44	-0.3	0.13
year=2015	-0.067	0.108	-0.616	0.538	-0.279	0.145
year=2016	-0.099	0.107	-0.922	0.357	-0.309	0.111
year=2017	-0.195	0.106	-1.834	0.067	-0.403	0.013
year=2018	-0.314	0.108	-2.912	0.004	-0.526	-0.103
year=2019	-0.511	0.11	-4.624	<.001	-0.727	-0.294
Industry=Computers	0.711	0.09	7.887	<.001	0.534	0.888
Industry=Electronics & communications	0.844	0.071	11.893	<.001	0.705	0.983
Industry=Pharmaceuticals	-0.097	0.084	-1.146	0.252	-0.262	0.069
Divestiture relatedness	-0.273	0.068	-3.98	<.001	-0.407	-0.138
Acquisition relatedness	-0.055	0.074	-0.738	0.46	-0.2	0.091
ROA	0.986	0.207	4.759	<.001	0.58	1.392
R&D	0.846	0.026	33.016	<.001	0.796	0.897
Revenue	0.831	0.016	52.478	0	0.8	0.862
Firm age	0.004	0.001	5.162	<.001	0.002	0.005
Knowledge base age	0.187	0.015	12.686	<.001	0.158	0.215
Knowledge base diversity	1.056	0.169	6.241	<.001	0.724	1.388
Acquisition rhythm	-0.001	0.01	-0.094	0.925	-0.02	0.018
Acquisition rhythm^2	0.003	0.003	1.234	0.217	-0.002	0.008
Divestiture rhythm	0.052	0.008	6.254	<.001	0.036	0.068
Divestiture rhythm^2	0.007	0.002	3.662	<.001	0.003	0.011
Acquisition experience 5Y	0.011	0.037	0.3	0.764	-0.062	0.084
Divestiture experience 5Y	-0.025	0.042	-0.586	0.558	-0.107	0.058
Acq rhythm * acq experience	-0.018	0.011	-1.594	0.111	-0.04	0.004
Acq rhythm^2 * acq experience	0.002	0.003	0.63	0.529	-0.004	0.008
Div rhythm * div experience	0.048	0.011	4.294	<.001	0.026	0.07
Div rhythm^2 * div experience	0.012	0.003	4.103	<.001	0.006	0.018

a HC3 method

Dependent variable: Number of applications

Parameter	B	Robust Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
year=2007	-0.022	0.034	-0.632	0.527	-0.089	0.046
year=2008	-0.025	0.034	-0.718	0.473	-0.092	0.043
year=2009	-0.04	0.035	-1.163	0.245	-0.109	0.028
year=2010	-0.049	0.034	-1.434	0.152	-0.116	0.018
year=2011	-0.061	0.034	-1.792	0.073	-0.128	0.006
year=2012	-0.033	0.033	-0.984	0.325	-0.098	0.032
year=2013	-0.04	0.034	-1.166	0.244	-0.106	0.027
year=2014	-0.062	0.035	-1.787	0.074	-0.131	0.006
year=2015	-0.034	0.034	-0.989	0.323	-0.102	0.034
year=2016	-0.015	0.034	-0.426	0.67	-0.082	0.053
year=2017	-0.019	0.035	-0.558	0.577	-0.087	0.049
year=2018	-0.01	0.035	-0.289	0.773	-0.079	0.059
year=2019	-0.025	0.036	-0.701	0.483	-0.095	0.045
Industry=Computers	-0.051	0.025	-2.012	0.044	-0.1	-0.001
Industry=Electronics & communications	-0.05	0.021	-2.367	0.018	-0.091	-0.009
Industry=Pharmaceuticals	-0.088	0.026	-3.403	<.001	-0.138	-0.037
Divestiture relatedness	0	0.019	0.008	0.994	-0.038	0.038
Acquisition relatedness	0.036	0.023	1.553	0.12	-0.009	0.081
ROA	0.407	0.063	6.511	<.001	0.285	0.53
R&D	0.216	0.01	22.662	<.001	0.198	0.235
Revenue	0.069	0.007	10.49	<.001	0.056	0.081
Firm age	-0.003	0	-11.245	<.001	-0.003	-0.002
Knowledge base age	-0.02	0.004	-5.018	<.001	-0.028	-0.012
Knowledge base diversity	-0.159	0.082	-1.934	0.053	-0.32	0.002
Knowledge base size	-0.046	0.006	-7.469	<.001	-0.059	-0.034
Acquisition rhythm	0.001	0.003	0.199	0.842	-0.005	0.006
Acquisition rhythm^2	-0.004	0.001	-5.72	<.001	-0.005	-0.002
Divestiture rhythm	0.002	0.002	0.886	0.376	-0.003	0.007
Divestiture rhythm^2	-0.001	0.001	-1.246	0.213	-0.002	0
Acquisition experience 5Y	0.056	0.01	5.438	<.001	0.036	0.076
Divestiture experience 5Y	-0.036	0.011	-3.321	<.001	-0.057	-0.015
Acq rhythm * acq experience	0.007	0.003	2.235	0.026	0.001	0.013
Acq rhythm^2 * acq experience	-0.001	0.001	-1.831	0.067	-0.003	0
Div rhythm * div experience	-0.001	0.003	-0.197	0.844	-0.007	0.006
Div rhythm^2 * div experience	-0.0001	0.001	-0.012	0.99	-0.002	0.002

a HC3 method

Dependent variable: Number of claims

Appendix G

Results regression analysis patent applications (robustness check three years prior experience)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Divestiture rhythm		0.026*** (0.052)	0.026*** (0.051)	0.029*** (0.056)	0.049*** (0.095)	0.049***(0.095)
Divestiture rhythm^2		0.001 (0.010)	0.001 (0.010)	0.002 (0.020)	0.006*** (0.060)	0.006*** (0.060)
Acquisition rhythm			0.003 (0.005)	0.004 (0.007)	0.007 (0.011)	0.004 (0.006)
Acquisition rhythm^2			0.001 (0.005)	0.001 (0.009)	0.001 (0.012)	0.003 (0.030)
Prior 3 year divestiture experience				0.091** (0.034)	-0.042 (-0.016)	-0.039 (-0.015)
Prior 3 year acquisition experience				0.031 (0.012)	0.028 (0.010)	0.014 (0.005)
Div rhythm * div experience					0.057*** (0.063)	0.058*** (0.065)
Div rhythm^2 * div experience					0.014*** (0.079)	0.014*** (0.080)
Acq rhythm * acq experience						-0.011 (-0.012)
Acq rhythm^2 * acq experience						0.004 (0.022)
Return on assets (ROA)	0.910*** (0.046)	0.920*** (0.047)	0.913*** (0.046)	0.959*** (0.049)	0.960*** (0.049)	0.978*** (0.050)
R&D intensity	0.851*** (0.423)	0.851*** (0.424)	0.852*** (0.424)	0.842*** (0.419)	0.842*** (0.419)	0.846*** (0.421)
Revenue	0.858*** (0.857)	0.853*** (0.852)	0.853*** (0.852)	0.834*** (0.833)	0.829*** (0.828)	0.830*** (0.829)
Firm age	0.003*** (0.053)	0.004*** (0.056)	0.004*** (0.056)	0.004*** (0.055)	0.004*** (0.057)	0.004*** (0.058)
Knowledge base age	0.187*** (0.146)	0.180*** (0.141)	0.180*** (0.141)	0.182*** (0.142)	0.183*** (0.143)	0.186*** (0.145)
Knowledge base diversity	1.118*** (0.065)	1.118*** (0.065)	1.116*** (0.065)	1.079*** (0.063)	1.072*** (0.063)	1.071*** (0.063)
Divestiture relatedness	-0.215** (-0.030)	-0.209** (-0.029)	-0.210** (-0.030)	-0.266*** (-0.038)	-0.268*** (-0.038)	-0.274*** (-0.039)
Acquisition relatedness	-0.056 (-0.007)	-0.060 (-0.007)	-0.058 (-0.007)	-0.063 (-0.007)	-0.070 (-0.008)	-0.060 (-0.007)
Industry dummies	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.694	0.696	0.696	0.696	0.698	0.698
Observations	3468	3468	3468	3468	3468	3468

*Significant: *p < .05, ** p< .01, *** p<.001*

Results regression analysis number of claims (robustness check three years prior experience)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Divestiture rhythm		0.001 (0.006)	0.003 (0.025)	0.002 (0.023)	0.002 (0.017)	0.002 (0.020)
Divestiture rhythm^2		-0.001* (-0.049)	0.000 (-0.019)	-0.001 (-0.028)	-0.001 (-0.033)	-0.001 (-0.031)
Acquisition rhythm			-0.004 (-0.032)	-0.003 (-0.026)	-0.003 (-0.026)	0.000 (0.000)
Acquisition rhythm^2			-0.003*** (-0.143)	-0.003*** (-0.124)	-0.003*** (-0.125)	-0.004*** (-0.151)
Prior 3 year divestiture experience				-0.030** (-0.056)	-0.026* (-0.049)	-0.027* (-0.050)
Prior 3 year acquisition experience				0.043*** (0.080)	0.044*** (0.080)	0.042*** (0.078)
Div rhythm * div experience					-0.002 (-0.009)	-0.002 (-0.013)
Div rhythm^2 * div experience					0.000 (-0.010)	0.000 (-0.013)
Acq rhythm * acq experience						0.010* (0.053)
Acq rhythm^2 * acq experience						-0.001 (-0.026)
Return on assets (ROA)	0.411*** (0.104)	0.414*** (0.105)	0.426*** (0.108)	0.413*** (0.105)	0.413*** (0.105)	0.403*** (0.102)
R&D intensity	0.222*** (0.554)	0.222*** (0.553)	0.219*** (0.547)	0.219*** (0.545)	0.218*** (0.544)	0.216*** (0.539)
Revenue	0.081*** (0.403)	0.078*** (0.391)	0.074*** (0.372)	0.072*** (0.361)	0.072*** (0.361)	0.071*** (0.353)
Firm age	-0.003*** (-0.233)	-0.003*** (-0.232)	-0.003*** (-0.225)	-0.003*** (-0.215)	-0.003*** (-0.215)	-0.003*** (-0.217)
Knowledge base age	-0.022*** (-0.085)	-0.021*** (-0.083)	-0.019*** (-0.075)	-0.019*** (-0.074)	-0.019*** (-0.074)	-0.020*** (-0.079)
Knowledge base diversity	-0.169** (-0.049)	-0.173** (-0.051)	-0.173** (-0.051)	-0.166** (-0.049)	-0.166** (-0.049)	-0.165** (-0.048)
Knowledge base size	-0.046*** (-0.223)	-0.047*** (-0.226)	-0.048*** (-0.229)	-0.048*** (-0.229)	-0.047*** (-0.228)	-0.047*** (-0.226)
Divestiture relatedness	-0.010 (-0.007)	-0.012 (-0.009)	-0.011 (-0.008)	-0.002 (-0.001)	-0.002 (-0.001)	0.001 (0.001)
Acquisition relatedness	0.073** (0.043)	0.069** (0.041)	0.054* (0.032)	0.042 (0.025)	0.042 (0.025)	0.035 (0.021)
Industry dummies	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included
Adjusted R^2	0.300	0.302	0.315	0.320	0.320	0.322
Observations	3468	3468	3468	3468	3468	3468

*Significant: *p < .05, ** p< .01, *** p<.001*