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Riding the Wave: Timing Implications of Divestitures

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Abstract

This study examines divestiture transactions within industry waves and reveals the impact of announcement timing on shareholder wealth. Our findings indicate a causal relationship between divestitures late within a wave and lower abnormal stock returns, relative to firms that divest earlier. This effect remains robust across different configurations, including a varying range of event windows, definitions of early and late movers, event study models, and transaction wave identification models. Strikingly, in contrast to much of the current transaction research, our study identified no discernible early mover advantage. These findings draw attention to the need for astute divestiture timing when implementing restructuring strategies through divestitures. We carefully address potential econometric and sampling issues to ensure the validity of our results and make a notable contribution by presenting a comprehensive framework that adapts the prevailing M&A models used to identify industry waves models to the distinct features of divestitures.

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1. Introduction

The adage goes that the early bird captures the worm, but who catches the return? This study systematically documents the impact of announcement-timing on shareholder wealth, for industry divestiture waves.

The number of divestiture transactions completed globally has more than doubled between 2020 and 2021 (Deloitte, 2022, p. 3). Even preceding this most recent resurgence, divestitures have periodically risen to increased prominence as a corporate restructuring strategy. In the scholarship they are easily overlooked due to the misconception that they are merely reciprocal to M&A transactions. We view this amalgamation as facile and overly reductive and will briefly address this.

The view of divestitures as a unique viable corporate restructuring maneuver, is increasingly being held by both practitioners and academics, making divestitures an emerging topic in fields of finance and strategic management studies. The scholarship has since followed suit, with ample empirical studies documenting motivations behind divestitures, and the implications for shareholder wealth, considering a wide range of mediating factors.

The presence of cyclicality in divestiture transactions is well documented in the literature (Colak & Tekatli, 2010). Empirical studies have shown that divestitures cluster during economic downturns, and the nature and volume of divestiture activity varies significantly across industries (Colak, et al., 2021). Other scholars (Kolev, 2016; Ubl, 2014) find that divestitures are driven by firm-specific or unit-specific characteristics, as supposed to industry environment. These conflicting views on the drivers behind waves can be reconciled with the fact that industries are somewhat homogenous, meaning different firms within the same industry would share common characteristics. Thus, these (endogenous) idiosyncratic firm-characteristics, would be impacted by and respond similarly to (exogenous) macro-economic forces, resulting in an industry wave.

M&A industry waves have been widely studied and are well understood. Antecedents to M&A waves and the valuation effects of transactions within them are well documented. Many studies focus on "entrant position effects", studying how timing shapes abnormal returns at different intervals throughout the wave, or even outside of it. Well-accepted results include an "early-mover" benefit, suggesting that shareholder wealth would be maximized by announcing an M&A deal well before others follow suit. Similarly, "mover effects" have also been studied thoroughly in the light of entering a new market, through asset purchases.

This raises the question: given that divestitures also occur in wave-like distributions, are there similar mover-effects at play? Specifically, does the timing of the divestiture, relative to other divestitures within the same wave, explain variation in post-announcement shareholder wealth?

Understanding the timing implications of divestitures in these waves is critical for both academic research as well as management decision-making, as it provides insights into optimal timing strategies and potential value creation opportunities for companies involved in restructuring activities.

To this end, we draw from a sample of U.S. divestitures covering multiple industries over a 20-year period. We examine the relationship between the timing of asset sales, in industry waves, and their respective stock returns. From previous literature, we derive an extensive list of factors impacting abnormal returns, both within a divestiture wave and in general. We lean on the work of previous scholars and take these factors into account in our analyses. Given that variation in stock returns is what we seek to explain, many of these factors relate to market imperfections. If the timing of the announcement exhibits a significant impact on shareholder wealth, it adds another dimension to the existing literature regarding capital market imperfections. Specifically, in case announcement timing, under equal conditions, positively, or negatively impacts shareholder wealth, it's a potential free lunch or avoidable penalty.

This study contributes significantly to several important topics in the field of corporate finance. Firstly, we uncover both advantages and disadvantages in announcing a divestiture transaction at specific intervals throughout the divestiture wave. This reveals potential early-mover, or late-mover effects, and their implications for shareholder wealth. We lean on real options' theory to provide an explanation for these perceived effects.

Secondly, to the best of our knowledge, we are the first to provide evidence on the accuracy and limitations of different documented methods to identify waves. We adopt the two most common theoretical approaches prevalent in the current finance literature, which are Harford's and Carow's methodology for identifying divestiture waves in the industry (Carow, et al., 2004; Harford, 2005). Carow, et al.'s approach was adjusted and refined for the financial industry by Xu in 2017 (Xu, 2017). While these approaches are employed by many researchers, they were developed for mergers and acquisition (M&A) transactions and therefore need to be adapted to account for the different characteristics of divestitures. By systematically elaborating these adjustments, and validating them with our results, we contribute to the refinement of industry divestiture wave identification procedures and hope to increase the accuracy of future studies examining transaction patterns and industry dynamics.

Thirdly, we shed light on the differences between M&A and divestitures. We find that Carow's (2004) method, due to its low thresholds and heavy reliance on assumptions, is more prone to not capturing "real waves", but mere industry fluctuations. We argue that its inability to accurately identify divestiture waves, despite necessary adjustments, reveals that divestiture waves are fundamentally different in frequency, duration, and transaction concentration.

Finally, we document further evidence of imperfect capital markets, since control variables pertaining to asymmetric information, market conflict and agency problems are studied and included in multivariate regressions. The results hereof reveal how market imperfections shape stock returns. While this has been documented extensively, we include industry-fixed effects (a variable often excluded) in our assessment. We hold that this is necessary for accurate coefficients, since abnormal returns differ substantially across industries, specifically for divestitures.

2. Literature Review

A resource-based view of corporate success propounds that better assets facilitate competitive advantage (Barney, 1991; Wernerfelt & Karnani, 1987) which leads to above-average performance (Amit & Schoemaker, 1993). Contingently, firms continually rearrange their resource base to sustain their competitive advantage (Teece, et al., 1997; Helfat & Peteraf, 2009). The literature has extensively examined how different modes of reconfiguration affect firm performance- including mergers and acquisitions (Ferreira, et al., 2016), internal development (Karim & Mitchell, 2004), and finally, divestitures (Lee & Madhavan, 2010; Miles & Rosenfeld, 1983; Lord & Saito, 2017; Nguyen, 2013; Ofek & John, 1995; Sicherman & Pettway, 1992; Wiersema & Brauer, 2012; Uddin, 2010).

Within the realm of corporate actions, divestitures are a subset of asset sales[1]. What differentiates divestitures from their broader category is the restructuring component. Through divestitures, a firm adjusts its ownership structure or business portfolio scope (Schimmer, 2012, p. 85). To many scholars (Bowman, et al., 1999; Bowman & Singh, 1993) divestitures are more than mere restructuring activities but quintessentially require a dissolution component. They conceptualize divestitures as negative investment, narrowing the firm's lines of business and rearranging their configuration.

These conditions (restructuring and/or dissolution) are generally satisfied by definitionally limiting divestitures to a sell-off, spin-off, split-up or carve-out[2].

2.1 Transaction Types: Ownership Structure and Rationale

Spin-offs and split-ups involve establishing independent entities, while sell-offs and carve-outs involve the transfer of full or partial ownership to third parties.

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[1] Given that we require a minimum transaction threshold of $75 million, asset sales and divestitures encompass similar types of transactions, and the terms are thus used interchangeably.

[2] Some scholars view "targeted stocks' issuance" as a divestiture transaction, which is the distribution of a new class of parent company stock representing the operations of a subsidiary (Lee & Madhavan, 2010, p. 1351). Given the lack of a restructuring and/ or dissolution component, we classify these as equity offerings and not divestitures.

In scholarship, the motivations behind divestitures are broadly categorized as either operational or financial[3]. The former tends to be endogenous and the latter exogenous, with the exception of underperforming assets[4]. This is a reductive theoretical categorization, as in reality, these motivations are often interrelated and exhibit dichotomous characteristics. To substantiate, operationally motivated divestitures still bear immediate financial consequences, and financially motivated divestitures will have implications for operations. This demarcation is also limited to the short term, as long-term motivations converge.

In our paper, the primary focus lies on sell-off transactions. However, it is valuable to gain an understanding of the most common transaction types, along with their rationales and different characteristics, which we outline in the following.

Sell-offs ownership structure and rationale

A sell-off involves the disposal of a business segment or subsidiary to a third party, typically in exchange for cash or stock. Sell-offs tend to be in pursuit of liquidity given that they are the only type of divestiture that can generate direct cash flows to the parent-firm[5] (Frank & Harden, 2003, p. 507). Correspondingly, sell-offs are taxable transactions while spin-offs are not (Cumming & Mallie, 1999, p. 78). While firms facing financial distress sell assets to raise capital, financially healthy firms optimize their return on assets by underperforming assets and allocating the proceeds to more profitable projects (Stouraitis & Kaiser, 2001, p. 321). Further evidence for the financial motivation behind selloffs comes from Palmer and Wiseman (1999) who showed that cash reserves discourage sell-offs. As debt capacity increases, the likelihood of a sell-off decreases (p. 1043). This rationale aligns with the nature of sell-offs, as they enable the divesting firm to generate resources and deploy them in other areas (Frank & Harden, 2003, p. 507).

Chen and Guo (2005) report that firms use selloffs to divest smaller units, operating in the same industry (p. 399). Their finding that sell-offs are “same industry divestments” reveal liquidity as a consideration, since assets are most liquid within their own industry. Secondly,

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[3] An exception would be ESG divestitures which are neither operational nor financial but must be undertaken regardless, on moral and ethical grounds.
[4] An underperforming asset would be an endogenous financial motivation. Typically, financial motivations for divestitures are exogenous, as they involve pressure from external entities/ factors (shareholders, debtholders, macro-economic).
[5] Theoretically, carve-outs generate cash for the newly established subsidiary. Yet, Allen and McConnell (1998) find that in most cases funds are distributed back to the parent (Frank & Harden, 2003, p. 507).

this reveals that sell-offs are not typically focus-increasing pursuits, which would constitute an operational motivation. Corroboratory, Meyer, Milgrom and Roberts (1992) study the cost borne by unfocused multi-unit organizations and find a pattern of sales of poorly performing units to related firms (p. 9).

An alternative definition comes from Benito (2005) who views sell-offs as a form of market-exit through the closure of units in foreign locations (p. 235). This definition aligns best with the term "divestment", which is typically ESG motivated in the short term, but also play a key role in long-term corporate strategy. Common examples include the withdrawal from fossil fuels or from regions with human rights violations.

Spin-off ownership structure and rationale

A spin-off is a divestiture transaction in which a parent company creates a new, legally independent entity, from one of their subsidiaries or business units. The new firm's shares are sold to new or existing shareholders or paid out as a special dividend.

Researchers argue that spin-offs are undertaken for various reasons. Fluck and Lynch (1999), for instance, argue that a spin-off occurs once a project can function as a stand-alone endeavor (p. 325). Alternatively, some argue that spin-offs are undertaken to eliminate the inefficient complexity of broad operations (Linn & Rozeff, 1985, p. 269). The wealth redistribution hypothesis, as first proposed by Myers (1977), argues that spin-offs are used to evade credit constraints, often due to debt overhang. Since debt-obligations remains with the parental unit[6], a spin-off could be a vehicle to solve these agency problems as the subsidiary would undertake all attractive investment opportunities (Miles & Rosenfeld, 1983, p. 1598). Shareholder preferences constitute another financial motivation. Abarbanell et al. (2003) argue that institutional investors prefer to separate high-growth business units from low-growth units (p. 235). Litzenberger and Soisin (1977) claim investors instigate spin-offs when they want to optimize their tax burden and dividend income (Miles & Rosenfeld, 1983, p. 1598).

Split-up ownership structure and rationale

A split-up involves a corporation being broken up into two or more independent entities, each with its own set of shareholders, management, and assets. Many scholars conceptualize a split

[6] Some debt-covenants do not allow for this.

up as a demerger. It differs from the other three types of divestitures in that it results in successor firms, and the original firm ceases to exist (Ramu, 1999, p. 87). Voluntary split-ups are strategic (financial or operational) while involuntary split-ups are a defensive strategy.

Voluntary split-ups aim to eliminate negative synergies and diseconomies of scale, to focus on core business or to address inefficient corporate governance (Ramu, 1999, p. 65). The latter stems from agency problems, which refer to the disconnect between shareholders and management. Fragmentation allows for managers and shareholders to realign.

Defensive split-ups are often an attempt to evade hostile takeover attempts or required by anti-trust regulation. Gibbs (1993) identified the takeover threat as one of three drivers behind split-up restructuring (Ramu, 1999, p. 67). Similarly, anti-trust regulation or the deregulation thereof make business combinations viable or unviable, driving transaction volumes (Weisbach & Kaplan, 1992, p. 108). Anti-trust regulation typically aims at blocking or altering merger transactions that competition authorities deem uncompetitive[7]. The American Federal Trade Commission (FTC) may enforce a pre-merger split-up, in which an entire line of business is sold to a buyer determined in advance and approved by competition authorities (Tenn & Yun, 2011, p. 274).

Carve-out ownership structure and rationale

A carve-out involves the sale of a minority stake in a subsidiary or division to the public or to another firm. The parent enterprise will retain an equity stake, but the new entity is partly owned by outside investors, making it semi-autonomous. Firms with units operating in different industries are more likely to use carve-out as an exit mechanism, which indicates that one of the primary objectives behind carve-outs is to streamline operations (Chen & Guo, 2005, p. 418). Michaely and Shaw (1995) find little evidence that the parent's need for cash or share over- or under- valuation motivate carve-outs (p. 5), however the redistribution of risk does seem to be a motivation behind carve-out transactions. Carve-outs provide a so-called co-insurance effect, where risky subsidiaries are tied to the less risky parent firm (Fuchs, 2003, p. 5). Since carve-outs come with scrutiny and stringent disclosure policies, companies with a

[7] Anti-trust authorities rarely enforce the break-up of a firm that organically grew to an uncompetitive size.

high dividend yield, low-leverage ratios and profitability are more likely to undertake them (Michaely & Shaw, 1995, p. 5).

2.2 Differentiating Divestiture and M&A transactions

Divestitures are often viewed as the mirror images of M&A transactions. From the buyer's perspective, they are reciprocal to an M&A transaction. From the seller's perspective, a sell-off is the multiplicative inverse of an acquisition and a split-up, the inverse of a merger. This misconception stems from the 1980's, when divestiture waves routinely followed M&A waves, and were largely driven by the disposal of unsuccessfully executed diversifying acquisitions (Kaplan & Weisbach, 1992, p. 131).

This is a rather facile interpretation of divestitures, ignoring numerous factors making divestitures fundamentally different in nature. Jensen (1993) argued that divestitures should be considered among the key features of the "third industrial revolution" (p. 834). Brauer (2006) defines divestitures as a "purposeful strategic options for corporate renewal" (p. 753). In this section, we will briefly outline why we agree with Brauer's (2006) conceptualization.

We point to contradictions arising from the amalgamation of the divestiture seller and M&A target. If these parties were one and the same, the roles undertaken and nature of transaction proceedings in the mirroring party would align more coherently.

Firstly, the divestiture seller and the M&A target undertake different roles in the transaction and showcase different levels of agency. The acquirer in an M&A transaction takes an active role and instigates the deal, while the target is often passive and defensive. Contrarily, in divestiture transactions, the seller instigates the asset sale. Divestitures are deliberate decisions made by the management of the divesting firm (Khan & Mehta, 1996, p. 885). Conflating these types of transactions would imply that the M&A target initiates the transaction, which is typically not the case.

Secondly, descriptive characterizations of the divestiture-seller's and M&A target's behavior cannot easily be reconciled. The divestiture seller, who should act defensively if merely the reciprocal party, has full discretion over the transaction process in a sell-off (Brauer, 2006, p. 754). Divestitures typically do not have a defensive party and have thus been described as much more synergistic and “friendly” transactions compared to takeovers (Datta, et al., 2003, p. 351).

Given this personification of the different agents, and the capacity in which they operate, we can make sense of some empirical observations: The M&A target often experiences negative abnormal returns following the transaction announcement, particularly in the presence of anti-trust regulations or hostile takeovers (Datta, et al., 2003, p. 353). Divestitures are typically associated with positive abnormal returns for both parties (Lee & Madhavan, 2010, p. 1345).

There are also some structural differences between these transactions. Spin-offs and split-ups do not sell to a third-party, which would be a constitutive component of an M&A transaction. Carve-outs' reciprocal parties would be IPO or private investors. Finally, sell-off decisions are of a completely different nature with respect to managers’ cognitions, underlying motivations, and required tolerance for risk (Brauer, 2006, p. 754).

Lastly, as briefly outlined before, divestiture waves occur in entirely different macro-economic conditions compared to M&A waves. Macro-economic cyclicality as an antecedent of divestiture waves suggests that divestitures are motivated by factors very different from the motivations underlying M&A transactions.

2.3 Waves: Formation and Identification

Macro-economic antecedents to transaction waves

Macro-economic cyclicality coinciding with transaction waves, and the causal mechanisms at play, has been extensively studied. Several authors have documented macro-economic upturn and downturn as determinants of M&A and divestiture activity, respectively (Mitchell & Mulherin, 1996; Harford, 2005; Colak & Tekatli, 2010; Haller, 2013; Vencatachellum & Wilson, 2019). Industry merger waves are influenced by economic, regulatory, and technological shocks. This is contingent on there being sufficient overall capital liquidity (Harford, 2005, p. 529). Colak and Tekatli (2010) find that 67.5% of divestiture wave series are driven by the common factors, the industrial production (aggregate output), the inverse of the long-term interest rates (10-year T-bond yields), and the S&P 500 index (stock market levels) (p. 22). These can be summarized as business and credit cycles. Corroboratory, transaction volumes tend to increase during economic expansions due to the availability of credit and optimistic expectations about future earnings (Haller, 2013, p. 327). The latter increases stock valuations, and following Shleifer and Vishny’s (1992) market-timing hypothesis, M&A volumes increase along with stock valuations (Vagenas-Nanos, 2020, p. 91). Cash-financed transactions particularly increase when debt capacity increases (Haller, 2013, p. 327). Inversely, as argued by Nelson (1959) access to equity markets plays a key role in facilitating M&A transactions. When financing becomes more expensive and less accessible, in part due to narrowed profit margins, companies tend to shed unprofitable or non-core assets to retain liquidity (Vencatachellum & Wilson, 2019, p. 29).

Empirically we’ve seen a wave of divestitures in the late 1990s and early 2000s, when American firms divested local operations to outsource them to lower-cost production opportunities in foreign markets (Berry, 2009, p. 392). Although not as self-evident as the credit supply’s impact on divestitures, rising labor costs and deregulation are indeed also external factors which evoke increased divestments.

Idiosyncratic explanations for transaction volumes

Contrary to the prevalent view that transaction volumes are primarily influenced by macroeconomic factors, a growing body of scholarship argues that "firm-related characteristics" provide a better explanation for transaction activity. Ubl's (2014) research aligns with this perspective, as he investigates the relationship between M&A activity and various factors. Specifically, he examines both firm-specific and unit-specific characteristics rather than focusing on the external environment. Ubl's analysis focuses on two key indicators: the average EBITDA multiple and the number of transactions. Surprisingly, his findings show no significant inverse relationship between M&A activity and shocks in monetary policy, which suggests that other factors related to the individual firms and units may be more influential in driving M&A activity (Ubl, 2014, p. 50).

Prominently, Kolev (2016) conducts a meta-analysis of 35 studies on the antecedents of corporate divestitures and develops four broad categories of determinants: corporate governance; firm strategy; performance; and industry environment. He finds that divestitures are mainly driven by past divestment experience, poor unit performance and firm specific factors like size diversification. He finds little evidence of the industry environment as a driving force (Kolev, 2016, p. 189). This does align with prior research on capital allocation, but not divestitures specifically. Arrfelt et al. (2015) proved that managers are not responsive to industry prospects when making strategic decisions (Kolev, 2016, p. 190).

Fluck and Lynch (1999) proposed the "financing synergy hypothesis" to explain the challenges faced by smaller companies in obtaining financing for positive net present value (NPV) projects. According to this hypothesis, agency costs, hierarchy of claimants, and debt overhang problems make it difficult for small firms to secure financing independently. As a solution, small firms may opt to merge with larger counterparts to gain access to the necessary funding. However, as projects progress, coordination costs arise, and the project eventually becomes capable of operating as a stand-alone venture, which leads to a divestiture by the larger firms (Fluck & Lynch, 1999, p. 325). Importantly, this hypothesis highlights that firm size and leverage ratios play crucial roles in determining access to financing, rather than being solely influenced by macroeconomic business or credit cycles.

Harford (2005) on wave formation

Harford (2005) proposes that regulatory and technological shocks are the primary drivers behind industry merger waves. This proposition is extended to aggregate merger waves, which he claims occur due to the accumulation of industry shocks for which mergers facilitate adaptation to the new environment. Waves on industry level only form with the precondition of sufficient capital liquidity, yet the macro-level liquidity component causes industry merger waves to cluster in time even if industry shocks do not (Harford, 2005, p. 529).

Harford views the economic landscape as a network of interconnected industries engaged in trade flows with customers and suppliers. The strength of product-market linkages between industries propagates these mergers in a wave-like pattern, which spreads through the network via customer-supplier connections. This transmission of merger activity occurs rapidly for nearby industries and with some delay also for more distant ones (Ahern & Harford, 2014, p. 527). Therefrom, we extrapolate that Harford (2005; 2014) views divestiture antecedents as both macro-economic and idiosyncratic in nature. Regulatory and technological shocks would be changes to the industry macro-economic environment, with capital liquidity being a macro-economic precondition. Yet the timing and extent to which industry level waves form depend on idiosyncratic qualities such as customer-supplier connections.

2.4 Factors Impacting Divestiture Performance

Divestiture performance is typically measured by market- or accounting-based measures. The former is measured, upon announcement, by calculating the cumulative abnormal return (CAR), which serves as a proxy for investor consensus on future firm performance. Accounting measures typically involve comparing return on assets, EBITDA, or other profitability measures, from before and after the transaction.

One of the most authoritative sources on divestiture performance is Lee and Madhavan (2010) who conducted a meta-analysis on divestitures' effects on firm performance. The authors studied the methodology and results from 94 studies and conclude that divestitures do indeed have a positive impact on subsequent firm performance. The analysis also suggests the type of performance measure, transaction format, transaction intent, and firm's resource level as moderating variables (Lee & Madhavan, 2010, p. 1345). The mechanisms facilitating these moderating factors pertain to market imperfections or strategic inefficiencies. These include the correction of negative synergies, diseconomies of scale, asymmetric information, and agency problems.

Accounting- performance measures

Studies using accounting-performance measures also find significant improvement in operating performance, in the years surrounding a divestiture (Gleason, et al., 2000; Ofek & John, 1995; Montgomery & Thomas, 1988; Hillier, et al., 2009). Divesting firms exhibit lower return on assets and market-to-book ratios before the divestiture and higher values of these performance measures following the divestiture (Hanson & Song, 2003, p. 322).

Theoretical expectation of divestiture performance impact is uniformly positive in the current finance and strategic management literature (Lee & Madhavan, 2010, p. 1348). Studies using accounting measures identify the sources of wealth creation as improved operational or financing arrangements, through synergies, reduced agency costs, more focused management or a better performing asset base.

Market-performance measures

Existing empirical studies have provided mixed and even conflicting results on announcement effects of divestitures (Lee & Madhavan, 2010, p. 1347). Event studies indicate that the market reaction to divestiture announcements is positive and generally larger for sellers than buyers (Gailen, et al., 1987, p. 229) but typically both parties realize some positive return (Jain, 1985, p. 209). Miles and Rosenfeld (1983) show that both spin-off and sell-off public announcements have a positive impact on the stock prices of both parties, but that spin-offs "outperform" the sell-offs on the day of the transaction (p. 1437). The extent of shareholder gains typically differs with deal and market characteristics, with estimates ranging from 1.66% to 9.1% (Hite, et al., 1987, p. 229; Uddin, 2010, p. 43). In studies using market-performance measures, the source of shareholder gain seems to pertain to market imperfections, such as irrational investors, mispricing, the resolution of agency problems or asymmetric information.

To summarize, contradictory empirical results are in part due to different performance measures[8] (market vs accounting). Market performance measures reflect the consensus among market participants, which relies on the interpretation of information and the impact of market imperfections. Consequently, market performance measures can be skewed by potential imperfections, while accounting metrics are less susceptible to imperfections and provide a differing perspective on performance evaluation. This explains why it is easier to reconcile the findings of studies using accounting-performance measures with neo-classical economic theory. Many apparent contradictions and general differences in results across studies can be reconciled by understanding the impact of market imperfections on stock returns. As per Sicherman and Pettway (1992), "even perfect assets trade in imperfect markets" (p. 120).

2.4.1 Divestitures' Sources of Value Creation - Efficient Capital Markets

Synergies/elimination of negative synergies

Empirically, we see that both buyers and sellers realize a positive abnormal return (Jain, 1985, p. 209). In the context of perfect capital markets, the observed market performance measures can be attributed to two main factors. Firstly, it can be attributed to the realization of synergies for the buyer or the elimination of negative synergies for the seller (Ofek & John, 1995). When two entities merge or engage in an acquisition, the combined resources, capabilities, and market positions can create synergy effects that enhance overall performance. On the seller's

[8] Lee and Madhavan (2010) did indeed find "performance measure" to be a statistically significant determinant of divestiture performance (p. 1345).

side, divesting assets or business units can lead to the elimination of negative synergies, allowing the firm to focus on core operations. Secondly, market performance measures can reflect the perception that the acquired asset or business unit generates more value for the buyer than the seller (Hanson & Song, 2003, p. 322). The market's assessment of value is influenced by various factors, including growth prospects, market positioning, competitive advantages, and expected financial returns. Neoclassical theory suggests that restructuring transactions occur to help redeploy corporate assets toward more efficient use (Gort, 1969; Mitchell & Mulherin, 1996).

Indeed, to the seller, often the source of gain in divestitures is the improvement in long-term performance that comes from eliminating negative synergies (Hite, et al., 1987, p. 229; Ofek & John, 1995). A less obvious instance of this is reversing overdiversification or diseconomies of scale. Evidence of improved accounting performance due to synergies comes from Woo et al. (1992) who argue that spin-offs are mechanisms to reduce both monitoring as well as bonding costs (Lee & Madhavan, 2010, p. 1348), resulting in improved margins. Relating to market-performance measures, Berger and Ofek (1999) document average CARs of 7.3% for focusing-related announcements by diversified firms (p. 311).

Similarly, (positive) synergies can also be a source of gain. The "fit hypothesis" predicts that when the divested business or unit has a better fit with the buyer's line of business, the value gains should be passed on to the seller via a stock premium reflected in the seller's abnormal return (Ofek & John, 1995). Aligning well with this hypothesis, past studies have emphasized strategic fit as a major determinant of divestiture returns (Alexander, et al., 1984; Hite & Vetsuypens, 1989).

Improved operational and asset performance

Even in the absence of synergies or increased focus, asset sales can evoke positive stock market reactions and improve accounting performance measures. The most popular contention in divestiture research is that divestitures are used to restore poor firm performance (Dranikoff, et al., 2002; Duhaime & Grant, 1984; Harrigan, 1981; Montgomery & Thomas, 1988; Pashley & Philippatos, 1990).

Reasoning along the same lines of operational improvements, Seward and Walsh (1996) held that more effective internal controls will emerge in the aftermath of a divestiture, particularly if equity claims were altered (Lee & Madhavan, 2010, p. 1348). Using lagged excess returns, Nguyen (2013) shows that the market reaction to divestiture announcements is significantly higher for underperforming firms, since reallocating capital away from underperforming units is expected to improve the return on assets of the seller (p. 1726). Hite, et al. (1987), among others, develop the efficient deployment argument, which suggests that divestitures move assets[9] to higher-valued uses and shareholders capture some of the gains through effective bargaining (Hanson & Song, 2003, p. 323).

2.4.2 Divestitures' Sources of Value Creation - Inefficient Capital Markets

Particularly when employing market-performance measure, value creation effects of divestitures are in part due to capital market imperfections. Proof of this lies in the fact that both buyers and sellers typically earn positive abnormal returns at the announcement of a divestiture (Sicherman & Pettway, 1992, p. 120). In the following, we will briefly address the current state of literature on how asymmetric information and agency problems impact shareholder returns.

Removing negative synergies or operational improvements results in long term improved profitability, but reducing the costs of asymmetric information produces a one-time gain. Nevertheless, shareholders benefit since the announcement reduces information asymmetries and resolves uncertainty about the true value of assets in place (Lang, et al., 1995, p. 4).

Agency problems: managerial discretion and the stated use-of-proceeds

Theory suggests that gains from divesting assets arise from resolving agency problems that exist when internal controls are weak (Jensen, 1993). An agency problem is the disconnect between shareholders and managers' interests, at the cost of shareholder wealth. Agency cost theory would predict that divestitures are value enhancing, as they can potentially mitigate agency costs at the hand of managerial discretion (Xu, 2017, p. 209). Moreover, sell-offs can be an efficient means to raise capital for firms that suffer from a debt overhang[10] problem

[9] Asset illiquidity is a factor that impedes the value-enhancing prospects of divestitures. Firms may want to divest underperforming units and streamline operations but face indirect transaction costs and barriers due to asset illiquidity. This differs greatly between industries. Schlingemann (2002) found that "the segment operating in the least liquid market is less likely to be divested than the best-performing segment, while the worst-performing segment is less likely to be divested than the segment with the most liquid market" (p. 117).
[10] Debt overhang is an instance of agency problems, given the disconnect between parties' interests results in suboptimal actions, such as not investing in a positive NPV project.

(Hanson & Song, 2003, p. 322). Weisbach (1992) demonstrates that divestitures tend to coincide with changes in management compensation schemes (Lang, et al., 1995, p. 4), which is intuitive given that managerial ownership provides strong incentives to improve operations following a divestiture (Hanson & Song, 2003, p. 321). Research on European divestitures shows that stock returns are positively correlated with pre-divestiture changes in block holdings in the divesting firm. The main mechanism for this is the agency costs of managerial discretion (Lang, et al., 1995, p. 6).

Furthermore, the value creation observed in divestitures can also be attributed to the disciplinary role of debt, often referred to as the cost of access to cash. Cash-abundant firms may face a higher risk of investing in negative NPV projects, as managers tend to be more inclined to engage in inefficient allocation of resources. On the other hand, firms operating with looser credit constraints may be more prone to engaging in value-enhancing divestitures (Masulis, et al., 2007, p. 1852).

The stated use-of-proceeds in divestitures plays a significant role in shaping the stock market reaction. Investors draw conclusions about whether management is effectively maximizing shareholder value based on how the proceeds from divestitures are utilized. Hanson and Song (2003) find that stock-price reaction to asset sales is significantly positive for those firms expected to use the proceeds to pay down debt, but negative and insignificant for firms which are expected to keep the proceeds within the firm (Hanson & Song, 2003, p. 323). Similarly, Lang, Poulsen and Stulz (1995) find that the returns depend largely on the stated use of proceeds and the average stock-price reaction to asset sales is positive only when the proceeds are paid out to creditors or shareholders (Lang, et al., 1995, p. 3), as these are the instances that investors are convinced management is acting in shareholders' interests.

Asymmetric information: transaction structure and firm value

Transaction type and details can significantly moderate the performance effect of the transaction (Lee & Madhavan, 2010, p. 1361). Klein (1983) argues that investors can deduce information about overall firm value from the price information associated with the divestiture (Lee & Madhavan, 2010, p. 1354).

Cash-transactions are considered to create more value than common stock-financed transactions for seller shareholders (Amiri, et al., 2019, p. 33; Dogan & Yildrim, 2017, p. 99). This follows the so-called "pecking order theory", which infers that firms' financing choices signal information about the firm to outside investors (Myers S. C., 1984). Given that the management acts in the best interest of existing shareholders, they are most likely to finance the purchase of an asset with stock, if they believe the stock to be overvalued (Baker & Wurgler, 2002; Savor & Lu, 2009, p. 1093). This convinces the seller's shareholders that they did not receive fair payment for the unit and hold overvalued equity among their assets.

Consistent with this concept, divestiture announcements that omit the transaction price evoke no significant change in stock price, as they do not reveal any new information (Sicherman & Pettway, 1992, p. 121). To some investors, the absence of price disclosure could even imply a value-destroying asset sale.

Asymmetric information: financial condition

The returns generated by a transaction are a function of market consensus about whether it was a value-enhancing activity. From the seller's perspective, an asset sold at an undervalued price would be a value-destroying activity, while the opposite can be said about an overpriced asset. Naturally, there is asymmetric information pertaining to the asset's "true value", which is why both parties can realize positive returns.

Shleifer and Vishny (1992) argue an asset will be liquidated below its value in use in the light of diminished debt capacity (p. 1355). Sicherman and Pettway (1992) argue that financial distress taints the seller's negotiation power, resulting in an undervaluation of the asset price (pp. 120-121).

Several studies have provided evidence supporting the notion that divestitures carried out during periods when the parent company is not experiencing financial distress tend to yield more favorable outcomes (Alexander, et al., 1984; Klein, 1983).

Sicherman and Pettway (1992) find that sellers gain most when they have not been downgraded and buyers benefit the most when the price is disclosed (p. 128). This observation can be explained by the prevalent asymmetric information. Another contradictory observation is that sellers rarely negotiate the transaction price, regardless of financial condition (Sicherman & Pettway, 1992, p. 120).

Asymmetric information: early or late mover advantages

Early-mover (late-mover) advantages manifest when incendiary firms earn positive net present value of profits attributable to their timing decision of entry (Lieberman & Montgomery, 1988, p. 51). “Entrant-position advantages” have exclusively been studied in the context of M&A waves and “first mover advantages” have mainly been studied in the light of new market entry or technological innovation. Although these studies serve as a worthwhile point of departure, their conclusions do not necessarily translate well to divestiture waves. We ascertain that, particularly with regards to entrant position, the M&A acquirer is clearly different from the divestiture buyer. For one, the divestiture buyer rarely initiates the transaction (Sicherman & Pettway, 1992, p. 120). Given this passive role, it is difficult to even categorize the divestiture buyer as a “mover”, particularly an “early-mover”, and might be more applicable to the seller in a divestiture transaction. Lieberman and Montgomery (1988) explain that all models on first-mover advantage “assume the existence of some initial asymmetry among competitors that can be exploited by the first-mover firm. This initial asymmetry is critical; without it, first-mover advantages do not arise” (Lieberman & Montgomery, 1988, p. 42). The theory could also hold for late movers if you conceptualize waiting as an action. In this sense, late movers hold some information about future market conditions, conducive to waiting. Similarly, a known knowledge deficit could also imply waiting. One could argue that buyers in divestiture transactions are less passive than they seem, rather they hold superior information conducive to waiting. It would be unconvincing to argue that buyers in divestitures are exploiting the benefit of superior information by moving early, given their passivity. Similarly, given the defensive nature of the M&A target, and the negative stock returns targets experience (Brauer, 2006, p. 775), it is unconvincing to argue that targets are exploiting any type of mover advantage. In conclusion, M&A literature on early movers does not directly apply to the context of divestitures.

2.5 Entrant Position Effects for Divestitures and M&A

The translation difficulty becomes more intuitive when we analyze the sources of early and late mover advantages.

Lieberman and Montgomery (1988), pioneers in the subject field of first mover-theory, explain that first-mover advantages arise from three primary sources: (1) technological leadership, (2) preemption of assets, and (3) buyer switching costs. The first and last mechanism results in a higher market share, which can potentially be exploited to bolster benefits towards a long-lasting competitive advantage[11]. Market share is, by definition, not a consideration for divesting firms, and there is no direct long-lasting competitive advantage to be gained by moving early. This means divesting firms only stand to gain from the preemption of assets by moving early. Preemption of assets in market entry refers to the ability of early movers to buy the best assets at the best price. The benefit is derived from the resource view, which states that superior assets facilitate a competitive advantage (Barney, 1991; Wernerfelt, 1984). In the divestiture context, the benefit of preemption of assets signifies avoiding the losses of peers who divest at a later stage. It's a finite, once-off, loss minimizing endeavor, and won't facilitate a sustained competitive advantage, as we explore in greater detail in the following subsection.

In the sections to follow, we elucidate how early and late mover effects differ across M&A and divestiture transactions by framing these as call options. Asset acquisition (M&A) and asset sales (divestitures) are synonymous with market entry and market exist, respectively.

M&A transactions: early entry into uncertain markets – akin to holding long-call position

If the assets in acquired an M&A transaction appreciate, the buyer stands to achieve potentially limitless gains. Conversely, if the acquiror's market predictions were inaccurate and the assets depreciate, the maximum loss would be capped, realized only if the assets become utterly worthless. In this scenario, the total losses would be finite, encompassing the sum of the initial investment, exit costs, opportunity costs, and any negative cash flows incurred during the period of ownership.

Entering a market is inherently a bullish strategy, as it involves speculating on favorable market conditions, with profits rising as asset prices increase. While the strategy offers the potential for unlimited profit, it also ensures that losses, if any, remain capped and finite.

Divestiture transactions: early exit from an uncertain market - akin to holding short-call position

The objective of a market exit is to mitigate potential losses; losses evaded can be considered as gains. That makes the early movers benefit the equivalent of the losses from falling asset

[11] This involves patents, industry benchmarking, strategies to deter new entrants etc.

prices that were evaded by early exit. The risk in this strategy is to exit prematurely and miss out on subsequently soaring asset prices, thereby incurring a loss defined by foregone asset appreciation. This strategy's maximum gain is finite and corresponds to the maximum loss evaded, equivalent to the total value of the assets. On the other hand, potential losses associated with this strategy are theoretically infinite since asset prices could soar indefinitely, which represents the risk of premature exit.

Market exit is an inherently bearish strategy, as it involves betting on unprofitable future market conditions. Moreover, losses tend to increase as prices rise, while the potential gains are capped.

Our call-option analyses provide insights into how divestiture and M&A waves differ in terms of the potential outcomes under differing market circumstances and for different market entry positions. Early movers in divestiture transactions can evade potential losses, while M&A late movers can also evade such losses. On the other hand, divestiture late movers potentially capture substantial gains, similar to M&A early movers.

Real options' interpretation

We turn to real options to provide an empirical basis for this distribution of early- and late-mover advantages. The answer lies in the real options' dichotomy, which is the cost of waiting relative to the benefit of reduced uncertainty.

Real options theory would argue that firms should delay commitment until uncertainty is resolved (Xu, 2017, p. 208)[12], given that waiting does not come at a cost, and that uncertainty attenuates over time. Sears (2019) develops a real options model of market entry that reduces endogenous uncertainty through experiential learning and exogenous uncertainty through deferral (p. 2). Xu (2017) highlights the role of learning from industry peers as a mechanism through which uncertainty is, at least partially, resolved. She concludes that a late mover advantage is derived from reduced uncertainty as the resolution of market or technological uncertainty happens over the duration of the wave (Xu, 2017, p. 224). Similarly, Folta (1998) holds that endogenous uncertainty can be resolved with organizational learning (p. 1010).

[12] In addition to the market and investment characteristics' impact on a firm's entrant/ exit position, Xu (2017) also provides a firm-specific explanation to entrant-position decisions. She concludes that smaller and younger firms with low leverage and high R&D costs have strong incentives to be first movers (p. 226).

Given that organizational learning is largely a function of time, we conflate exogenous and endogenous uncertainty, as both are resolved through the benefit of more information that the firm can accumulate in due course.

Yet, deferral options come at a cost. Their value is only realized in those instances where the opportunity cost of the investment outweighs the value of the market entry (Sears, 2019, p. 1). Benefits to early market entry, are outlined by Lieberman and Montgomery (1988), but with regards to asset acquisition and asset sales, the most prominent benefit to moving early stems from the preemption of assets (p. 41). This is intuitive if we conceptualize price changes of assets in a specific market to be a function of the viability of that market. Early entry into a viable market would lead to capital appreciation, while early exit from a non-viable market would avoid capital depreciation.

If the cost of waiting is high relative to the benefit of reduced uncertainty, including the benefits of the learning effect, our reasoning leads to an early-mover advantage. Conversely, if the cost of waiting is low relative to the benefit of reduced uncertainty, it implies a late mover advantage. The preceding call-options' analyses reveal that for asset acquisitions (market entry) the cost of waiting is prevalent, whereas for asset sales (market exit), the benefit of reduced uncertainty is relatively higher. Subsequently, options theory would indicate a more pronounced early mover advantage in M&A transactions and a late-mover advantage in divestiture transactions.

Briefly, we synthesize the work of Wernerfelt and Karnani (1987), who studied the effects of uncertainty on the desirability of early versus late market entry. Competitive strategy under uncertainty involves a trade-off between acting early and waiting (Wernerfelt & Karnani, 1987, p. 192). The authors analyzed these trade-offs considering the nature of uncertainty, economics of the industry and competition within the industry. They conclude that commitment can be postponed in "situations without major first mover advantages" (p. 192). Their conclusion aligns with our previous analysis of the dichotomy in options, since a "situation without major first mover advantages" corresponds to a situation with low cost of waiting.

The magnitude of the learning effect

The magnitude of the potential divestiture early mover advantage is straightforward. By selling early, divestiture early movers can evade losses, with the maximum benefit being the total depreciation of all assets. In essence, this can be conceptualized as the maximum cost of waiting.

Assessing the potential magnitude of the learning effect's benefit is less straightforward and beyond the scope of this paper. Studies on the intertemporal effect of divestitures can shed some light on this. Kolev (2016) finds strong support for organizational learning theory and posits that structural characteristics and organizational experiences of a firm's strategy are important determinants of corporate divestitures (Kolev, 2016, p. 182). Furthermore, Kolev (2016) shows that the most influential predictor of divestitures is prior divestiture experience. Experienced managers develop enhanced confidence and skills, enabling them to pursue with further transactions (p. 179). This proves that managers do indeed act according to a perceived learning curve. Similarly, external sell-off experience by advisors and by industry peers is found to positively influence the divestiture–firm performance (Brauer, et al., 2017, p. 1359).

Empirical evidence supporting the value of managerial experience, stems from the findings empirical results that program divestitures generate higher abnormal returns than stand-alone ones (Brauer & Schimmer, 2010, p. 84). Similarly, Bergh and Ngah-Kiing Lim (2008) and Haynes et al. (2002) propose that the inconsistent findings on divestiture returns could be attributed to the lack of studying divestitures as strategically interrelated events (Brauer & Schimmer, 2010, p. 84). An interpretation hereof is that the higher returns from program divestitures are due to the increased learning and expertise of the managers conducting them, as compared to stand-alone divestitures.

2.6 Gaps in Literature

From the preceding literature review, it seems evident that the scholarship possesses a facile understanding of the nature and extent of entrant position effects, specifically regarding divestiture waves. This observation is not surprising, since the study of divestiture waves and the respective entry timing implications associated with them have been largely unexplored in current studies. First-mover advantages have mostly been studied in the context of entering a new market in the consumer goods sector and to a lesser extent within M&A waves. Corporate divestitures fall exclusively in the industrial sector.

The impact of divestiture announcements on shareholder wealth has been well-documented and serves as a useful point of departure. Theoretical expectation of divestiture performance impact is uniformly positive in the current management and finance literatures (Lee & Madhavan, 2010, p. 1348). This aligns well with empirical observations presented by scholars, yet the magnitude of the positive effects presented can vary substantially. This comes as no surprise since the causal explanations offered in the literature rely on vastly different explanatory variables. Furthermore, variation in outcomes can be explained by using market-performance measures as the dependent variable. It follows that shareholder wealth is in part a function of market imperfections, which is why neo-classical economic theory fails to explain variation in announcement outcomes convincingly. Practically, this calls for an exhaustive list of control variables, many of which pertain to market imperfections. We propose that "timing effects within waves" is another potential explanatory variable for the unexplained variation in stock returns, following an announcement. This would add to the list of explanatory variables pertaining to market imperfections, as strategic timing implications indicate a pre-existing information asymmetry.

3. Hypotheses Development

Based on the inconclusive state of financial research on our topic, we formulated the following hypotheses, some of which are mutually exclusive. Below, we provide a brief summary of the theoretical reasoning discovered in the literature review for each hypothesis.

H_0: *The divestiture announcement's timing interval within the industry wave has no effect on the seller's abnormal returns.*

H_1: *There is an early-mover advantage; transaction announcements within the first interval of the industry wave are positively correlated with the seller's abnormal returns.*

H_2: *There is a late-mover advantage; transaction announcements within the last interval of the industry wave are positively correlated with the seller's abnormal returns.*

H_3: *There is an early-mover disadvantage; transaction announcements within the first interval of the industry wave are negatively correlated with the seller's abnormal returns.*

H_4: *There is a late-mover disadvantage; transaction announcements within the last interval of the industry wave are negatively correlated with the seller's abnormal returns.*

We expect to reject H_0, given that timing implications have been documented in prior research on M&A waves.

H_1 is derived from our previous analysis of divestitures as a long-call option, which revealed that the early-mover benefit pertains to loss-evasion or loss-minimalization. Managers quickly divest assets if they anticipate that asset prices will fall in the future, to evade capital depreciation. The view of divestitures as "loss-minimizing" attempts, arguably stems from the notion that divestitures are mainly used to dispose of failed acquisitions, meaning underperforming assets (Amiri, et al., 2019, p. 33). In both these instances, the sooner the firm divests, the better.

There are three potential sources of increased abnormal returns. Firstly, since capital depreciation was evaded by selling assets early on for a fair price, the firm's asset base was not reduced as was the case for non-early mover industry peers. Equity is a claim on the firm's net assets, making a claim in the early mover firm more valuable, relative to others.

The second source of gain is related to signaling theory, where pioneers are assumed to have superior resources and capabilities (Lieberman & Montgomery, 1998, p. 1112). The work of Wiersema and Brauer (2012) aligns well with this. They argue that investors face informational uncertainty about the value consequences of a divestiture decision, so they utilize contextual factors to infer the quality of the decision (p. 1473). An alternative interpretation would be that investors value management's proactive evasion of capital depreciation, and their effort to optimize the return on assets by disposing of underperforming units, as this is conducive to long term profitability. It follows that the early mover advantage is derived from reduced agency problems (Morris, 2012).
The third potential source of the early mover benefit could be the impression of superior information. All first mover effects assume a pre-existing information asymmetry, moving early could convince investors that the firm has superior knowledge about future market conditions or prospects (Lieberman & Montgomery, 1988, p. 42). The increase in abnormal returns would constitute how valuable they deem the superior information.

Underlying hypothesis 2, is our real options' theory analysis. This hypothesis assumes that firms evaluate the cost of waiting to be low relative to the benefit of reduced uncertainty. Additionally, it suggests that investors appreciate caution and experience on the part of management. This, in turn, attenuates the likelihood of a value-destroying divestiture and constitutes a better chance of improved operating performance. Following the efficient market hypothesis, these dynamics are reflected in stock returns.

Hypotheses 3 and 4 are derived from the price hypothesis, as explained in the literature review. It holds that stock market reaction is a function of whether investors believe the asset was sold at a competitive price. This hypothesis is an extension of the neo-classical economic theory that views equity as a claim on the firm's assets, meaning an asset sold underpriced would reduce the firm's asset base, making the equity claim less valuable. Generally, investors associate times of increased economic activity with competitive asset prices. As volumes decrease, transactions will be perceived as less competitively priced or even underpriced. This is a bias at play, since sellers rarely negotiate a competitive bid (Sicherman & Pettway, 1992, p. 120).

The dichotomy between the cost of waiting and the benefit of reduced uncertainty is once again applicable. Hypothesis 3 would assume that investors value the learning effect, while hypothesis 4 assumes the cost of waiting to be high.

Following Myers and Majluf's (1984) theory of information asymmetry, firms which divest late in a wave might become subject to adverse selection. Investors could be inclined to interpret the transactions as sellers engaging in herding behavior. Ahern and Harford (2014), among others, show that the actions of peers can have a significant impact on the transaction decisions of a firm (p. 573). This market perception could undermine the strategic rationale of the transaction, thereby diminishing the positive effects of focus-enhancing transactions or synergies. Such an effect would further underline hypothesis 4.

4. Methodology

Industry classification

Transactions were categorized and aggregated based on the initial two digits of the Standard Industrial Classification (SIC) codes. Industry classification facilitated the “industry- fixed effect” variable and the “within-industry” binary variable, which we included in our regressions.

To ensure within-industry comparison, we included an industry-fixed effect variable. This variable was included in our analysis since (Gross & Lindstädt , 2006, p. 23), among others, have found substantial differences in abnormal returns following asset sale announcements across industries.

Secondly, we included a within-industry binary variable to control for narrowed corporate focus. The focal argument posits that a major reason for firms to divest is overly wide corporate diversification, which comes at a cost (Lord & Saito, 2017, p. 71). Divestitures aimed at increasing the corporate focus are associated with higher announcement stock returns (Ofek & John, 1995).

Detailed information concerning the implemented industry variables can be found in the control variables subsection.

Excluding the financial industry

Cornett and De (1991) argue that shareholder reactions in the financial sector are subdued, since seller regulation and the contractual nature of assets’ cash-flows mitigate asymmetric information significantly (Cornett & De , 1991, p. 774). Similarly, Hannan and Wolken (1989) prove that the banking industry’s acquisition announcements’ returns mimic a zero-sum game between bidders and acquirers. Acquisitions announcements result in a wealth transfer from the shareholders of bidding firms to those of target firms, but there is no overall gain. They argue that this is exclusively the case for the financial industry (Hannan & Wolken, 1989, p. 6). Provided that there is no unexplained gain for sellers, there can be no early-mover advantage in the financial industry. Following the work of these authors, and general event-study convention, transaction announcements from the financial industry[13], were excluded.

Transaction threshold justification

The convention in M&A research is to set a threshold for a minimum transaction value of $100 million, but this was adapted to be $75 million for divestitures. The neoclassical explanation for the formation of the corporate waves hold that macroeconomic conditions drive waves. It follows, and can be confirmed empirically, that divestiture waves follow M&A waves due to macro-economic cyclicality[14]. Acquisition activity typically increases as macro-economic conditions become more favourable, while the asset sales, are associated in weakening macro-economic conditions (Tekatli, 2021, p. 23). Theoretical explanations for these empirically observed phenomena rely on different causal mechanisms. For one, favorable macro-economic conditions are conducive to optimistic stock valuations and an increased availability of credit (Fama, 1990, p. 1094). Contingently, the former is considered to drive an increase in M&A transactions involving stock trades, while the latter drives an increase in cash M&A transactions (Travlos, 1987, p. 961). Explanations as to why divestiture activity increases as macro-economic conditions worsen are rather intuitive. First, previously well-performing units could become underperforming and thus be divested. Additionally, cash-constraint businesses may need to sell off assets to enhance their liquidity position (Zhou, et al., 2011, p. 274).

In short, favorable macro-economic conditions, in which M&A waves occur, are conducive to high transaction values. Worsening macro-economic conditions, in which divestiture waves occur, are conducive to lower transaction values. For this reason, we've set the minimum transaction value threshold to $75 million.

Furthermore, the threshold should shape the sample to include all asset sales substantial enough for their announcement to evoke abnormal changes in the respective stock price. Investors are more responsive to negative signals, such as corporate actions during economic

[13] those transactions with a two-digit SIC code between 60-67.

[14] Colak et al. (2021) studied co-movements in corporate waves and found a significant positive dynamic and contemporaneous correlation between M&A waves and divestiture waves (p. 15).

downturn (Yasar, et al., 2020, p. 1309), meaning lower transaction values could evoke substantial abnormal stock price movement.

4.1 Identification of Waves

We are unaware of a single widely accepted approach within the literature used to objectively identify industry transaction waves, which is why we employed two distinctly different methods from previous literature used to identify M&A waves. The methods used were Harford (2005) and Carow et al. (2004). The latter was most notably adjusted to the financial literature by Xu (2017).

Harford (2005)

To assess each industry's potential wave, Harford (2005) computes the maximum 24-month merger bid concentration involving firms in each industry respectively. He then simulates 1000 distributions of the total number of transactions for each industry over a 120-month period, with each event assigned to a month using a random assignment probability of 1/120. Subsequently, he identifies the maximum 24-month concentration of activity from each of the 1000 simulations and compares the actual activity concentration of the potential wave with the empirical distribution of the 1000 highest 24-month concentrations. A period is designated as a wave if the actual concentration surpasses the 95th percentile of the empirical distribution determined by the simulation (Harford, 2005, p. 537).

Adjustments to Harford (2005)

We closely followed Harford's approach, with the adjustment of using the 99th percentile as a threshold as otherwise the assumption of randomness would have led to the identification of waves in almost every industry in the early 2000s, due to the generally increasing level of divestiture activity during that time. Another adjustment was that we excluded industries with a total transaction count of less than 100, which we find reasonable given that the sample covers transactions over a 19-year period and allows for more conclusive results in our later analysis. Employing Harford's methodology, we identified 7 waves over the sample period, including 1,784 transactions throughout 4 industries.

Carow et al. (2004), as per Xu (2017)

Carow, et al's (2004) seminal paper titled "Early Mover Advantages", introduced a methodology to define waves based on transaction count. Specifically, one identifies the year with the highest transaction count as the peak, and the year preceding the peak with the transaction count equal to one-third or less of the peak count is considered the beginning of the wave. The end of the wave is marked by the first year succeeding the peak year, with a transaction count of one third or less relative to the peak. When two subsequent years represent a peak and entail the same transaction count, they jointly form the peak. Carow et al. (2004) counts M&A transactions on a yearly basis and requires a minimum of 10 transactions in the peak year. Assumingly, the reasoning behind a minimum transaction count for the peak year, is to ensure that the authors capture real waves, as supposed to coincidental natural fluctuations over time, although we speculate that the outlined methodology is susceptible to said limitations.

Adjustments to Carow et al. (2004)

We adjusted Carow et al. (2004) to be suitable to identify divestiture waves. Again, we sorted transactions per industry according to the 2-digit SIC code, but on a quarterly basis. We set a minimum transaction count of 5 for the peak and defined the beginning and end of the wave as the first quarter preceding and succeeding the peak, respectively, where the transaction count was less than 50% of that in the peak quarter. Our justification for reducing the minimum transaction count in the peak quarter is the work of Colak (2021), who concluded that M&A waves' transactions follow the standard distribution, while divestiture waves' transaction volumes are entirely non-standard and generally lower in volume (Colak, et al., 2021, p. 15). Additionally, divestiture waves occur in times of economic downturn (Tekatli, 2021, p. 23), which is characterized with reduced economic activity.

Following (the adjusted) Carow et al. (2004) methodology, we identified a total of 30 waves across 7 industries, covering a total of 2,344 transactions. Waves identified with this method, were asymmetrical and often showcased a sudden onset, characterized by a steep increase in quarterly transaction count followed by a slow and steady decline over a longer period.

After considering the characteristics and limitations of both approaches, we decided to focus on Harford's (2005) approach as it is more common in current financial literature and provides a more replicable framework. Moreover, as made evident by the adjustments implemented by scholars, Carow et al.'s (2004) approach is dependent on a greater variety of assumptions and more susceptible to identifying natural market fluctuations instead of "real waves". Nevertheless, we also follow Carow et al.'s (2004) approach further and include the obtained findings as an additional robustness check in the results section.

Early- and late-movers

There is no commonly accepted approach to distinguish early from late movers, Carow et al. (2004) classified the first 20% of transactions as early movers. Given that divestiture waves follow a non-standard distribution, as supposed to M&A waves (Colak, et al., 2021, p. 15) early movers could not be defined in relation to the other transactions within the wave, but rather, had to be defined in relation to a specific time frame within the wave. We divided the waves timespan into quartiles with transactions falling within the first quartile (Q1) being counted as "early movers". "Peak movers" were transactions within the second and third quarters (Q2 and Q3) and "late movers" are transactions within the fourth quartile (Q4).

In this study, the primary independent/explanatory variable is the timing of divestiture transactions, which is operationalized as a dummy variable. Specifically, this variable takes a value of 1 if the transaction occurred within the first or fourth quartile of the identified divestiture wave, respectively, depending on whether we are examining the dataset for an early or late mover effect.

4.2 Event Study Methodology

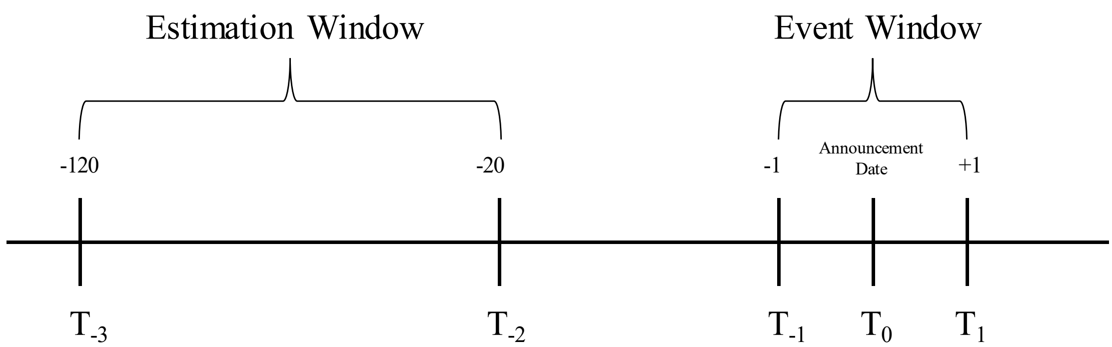
Following common event-study methodology, CAR was used as the dependent variable and represents shareholder wealth, while the announcement is the intervention. Changes in CAR reflect the market consensus on the NPV of the transaction, the financial health of the firm and its management's expertise (Jain, 1985, p. 211). Yet the interpretation of this information could be shaped by when in the wave the asset sale is announced. Abnormal returns are employed to control for the counterfactual, which refers to the expected share price in the absence of the announcement. CARs, in essence, represent the investor's ex-post observable estimate of the value of an event to shareholders (Aktas, et al., 2009, p. 546).

To accurately measure the impact of a divestiture announcement on shareholder wealth, the use of abnormal returns must satisfy two primary conditions. Firstly, stock price responses in event studies must accurately reflect the available public information relevant to the event. Secondly, the selection of an appropriate benchmark model is necessary to ensure accuracy and absence of bias in the measure of abnormal returns. While these conditions are typically assumed to hold true in the study of abnormal returns in finance, it is important to consider potential confounding factors that can impact the interpretation of announcement abnormal returns as a measure of wealth creation. An example of the latter would be if any anticipation of the event results in abnormal returns occurring prior to the event window.

We account for this condition by increasing the robustness of our findings by using (-1, 0), (-1, 1) and (-2, 2) as event windows for the calculation of the CAR.

In conducting the event study, we opt for the market model as the benchmark model, which is the most used in the current financial literature. As additional robustness checks, we also implement the Capital Asset Pricing Model (CAPM), the mean-adjusted model, and the market-adjusted model in the same setting. All parameters for the market model are estimated over a (-120,+6) time interval, while a time interval of (-120; -20) is used for the expected return calculation, which corresponds to the range provided by Peterson (1989, p. 38) of at least 100 days for the period range for daily return studies.

Figure 4.1
Illustrates the key elements of an event study, where T_0 is the divestiture announcement date, with the event window encompassing the time around it. T_{-1} and T_{-2} mark the start and end of the event window, respectively. The estimation window, the period preceding the event window, is marked by T_{-3} and T_{-2} as the start and end, respectively. An event window of (-1;+1) was utilized here for clarity.



Appendix 7.2 contains a detailed discussion of the technical aspects related to the event study methodology. This includes an overview of the characteristics of the various models implemented as well as the calculation of cumulative abnormal returns.

4.3 Regression Methodology

We adopt a classic panel data regression, commonly employed in corporate finance to account for monitoring many entities (cross-sectional data), across time (time-series data). The cross-sectional dimension to our data comprises the different companies that made a divestiture announcement, while the time-series dimension consists of their stock price at specific intervals. Our dependent variable is the abnormal returns following a divestiture announcement, while our main explanatory variable is the divesting firm's time-positioning in the divestiture wave, distinguishing between being an early mover, as supposed to a peak or late mover.

The thesis employs the following OLS regression model to incorporate the control variables in the analysis of CARs:

$$CAR_i = \alpha_i + \beta_1 * Timing + \beta_2 * RelSize + \beta_3 * LogSize + \beta_4 * Focus + \beta_5 * PriorTrans + \beta_6 * DebtRatio + \beta_7 * MarketBook + FixedEffects + \varepsilon_i$$

Where CAR_i is the cumulative abnormal return of security i, the β coefficients represent the respective control variables, γ_i represents the industry fixed effects of security i, $\lambda_t$represents the year fixed effects, and ε_i represents the respective error term.

The subsequent section details the rationale for the inclusion of each respective variable in our analysis.

Time-fixed effects

The weak endogeneity assumption requires that there is no covariance between independent variables and the idiosyncratic error term, which in our case refers to macro-economic conditions. To address the weak endogeneity assumption, we controlled for all macro-economic effects by incorporating a "year-fixed effects" variable in the regression. It is appropriate to control for macro-economic conditions with a time-fixed effects variable, as we assume that macro-economic conditions affect all stock returns equally but differ across time. Our time-fixed effects' regression was done on a yearly basis, which means that every year has its own intercept, denoted by lambda.

Entity-fixed effects

As mentioned earlier, we incorporated an "industry-fixed effects" variable, to control for industry variation; abnormal returns differ substantially across industries (Gross & Lindstädt, 2006, p. 23). It is important to keep in mind that while industries can show different responses, these differences remain constant over time.

Control Variables

Our control variables consist of a set of well-established variables commonly employed in the current financial literature. These have become somewhat standardized in literature that incorporates event-studies analyses, with stock returns as the dependent variable and include all variables known to impact stock returns in the presence or absence of any corporate action. Including them isolates the effect that the position in a divestiture wave has on stock returns.

Control variables also serve to address the omitted variable bias. Two fixed-effects variables were included specifically to address unexplained variation across industries and time.

Focus-increasing effects

In our regression analysis, we include a same-industry binary variable based on SIC codes[15]. We define a cross-industry transaction as one in which the seller divests a subunit with a two-digit SIC code that differs from its primary two-digit SIC code. Such cross industry-divestitures are considered focus-increasing as they involve the seller narrowing down its operating areas and concentrating on its primary line of business. As outlined in the literature review, there is a wealth of evidence indicating that focus-enhancing transactions exhibit a positive impact on firm performance and stock returns (Meyer, et al., 1992; Ramu, 1999, p. 65).

Deal size

Asquith, Bruner, and Mullins (1983) argue that the relative size of the asset[8] dictates the announcement's effect on abnormal returns (Cornett & De , 1991, p. 773). Similarly, Klein

[15] The binary variable used to identify cross-industry transactions takes a value of 1 if the primary SIC code of the parent company differs from the two-digit SIC code of the divested subsidiary, and a value of 0 otherwise.

(1986) proved that the relative size of divestitures is positively correlated to abnormal returns, however only if the transaction price is included in the announcement (Sicherman & Pettway, 1992, p. 120). This control variable was defined as the transaction value divided by the book value of the seller's total assets.

Size of the seller

Keim (1983) studied size-related anomalies, in relation to stock return and seasonality. Perhaps surprising to some, he found a negative but significant correlation between seller size and abnormal returns following an announcement. This implies that larger sellers' announcements evoke a relatively[16] smaller reaction, which cannot be explained by relative transaction value (Keim, 1983, p. 13). Keim's (1983) finding that the correlation between abnormal returns and firm size becomes stronger during times of increased activity[17], convinced us to include "seller size" as a control variable, even at the risk of multicollinearity[18], given that our main explanatory variable comes down to seasonality. The seller's size was defined as the logarithm of the seller's book value of total assets. Log transformation is common practice, as it stabilizes the variance and diminishes the effect of outliers.

Anticipated growth rate

The Price-to-book value (P/B) is defined as the market value divided by the book value of the seller's assets and represents investor consensus on the seller's future growth prospects. Investors value assets based on their expected cash flows; thus, the expectation of increased future cash flows would result in a positive stock return. In the context of a divestiture announcement, where the market perceived the divested unit as underperforming, investors would be inclined to expect an improved return on investment, as the divesting firm is expected to utilize the generated cash flow more efficiently, thereby increasing its growth rate. An increased return on investment is synonymous with growth. Daley et al. (1997) refer to this effect as "bonding benefits", which refers to the management's commitment to avoid cross-subsidization of underperforming units (p. 257).

[16] Keim argues in relative not absolute terms, meaning larger sellers' corporate actions do evoke substantial abnormal returns but these are negatively proportional to their size.
[17] Precisely, Keim finds that the "size-effect" (that larger firms' announcements' reactions are relatively understated) becomes more severe during times of increased activity, such as January.
[18] Seller size could potentially be correlated with deal size.

Including this variable thus indirectly controls for both the performance of the divested asset, and a potentially confounding variable. The latter would be growth from unrelated business activities, coincidentally occurring at the same time as the divestiture announcement and bolstering stock returns.

Financial condition

We control for the financial condition of the seller by incorporating a variable defined as the ratio of net debt to the total book value of assets. “Financial condition” serves as a proxy for potential insolvency or illiquidity problems. The impression of either would attenuate abnormal returns, in itself[19].

It's been theorized that the level of abnormal returns, following an announcement, is contingent upon the market’s perception of whether the asset was sold at a fair price (Sicherman & Pettway, 1992, p. 120). The presence or absence of financial distress plays a role in determining the fairness of the price. Investors tend to believe that firms facing financial distress are less likely to seek a competitive price and may be forced to accept a lower one. This could be due to urgency or as Sicherman & Pettway (1992) would argue the lost negotiating power (p. 120)[20]. When the seller is financially healthy, shareholders are inclined to interpret the transaction price as competitive and the rationale for the divestiture to be growth or an attempt to optimize performance (Afshar, et al., 1992, p. 117).

Contrary to the aforementioned theory, empirical results show that asset sale announcements from firms in financial distress almost always evoke a substantial positive stockholder reaction. These can be reconciled with the “bankruptcy avoidance hypothesis”[21]. Should investors estimate bankruptcy imminent and its costs to be substantial, an asset sold underpriced, could still result in positive abnormal returns[16] since bankruptcy was evaded (Afshar, et al., 1992, p. 115). This hypothesis is also more in line with the previously explained “bonding benefits” (Daley, et al., 1997, p. 257).

[19] Unrelated to the divestiture announcement.
[20] They explain abnormal returns (following an announcement) as a function of the perceived negotiating power. Specifically, a perceived lack of negotiating power evokes an exaggerated (negative) reaction from shareholders, since they are convinced that the asset was sold underpriced.
[21] Specifically, this posits that abnormal returns, following an asset sale announcement, increase with leverage as the probability of bankruptcy is lowered by the asset sale, even though the divestiture reveals financial distress.

In short, it is difficult to accurately predict how an announcement associated with or stemming from financial distress affects stock returns[22], due to the contradicting findings in current financial literature. Yet, it's evident that financial condition impacts stock returns, which is why it's included as a control variable.

Prior Transaction Experience

Prior transaction experience, earlier eluded to as inter-temporal effects, can significantly influence a firm's ability to effectively manage and execute subsequent deals, consequently impacting the seller's stock returns (Aktas, et al., 2011, p. 19). Empirical evidence suggests that firms that conducted prior divestitures in the past tend to achieve larger returns due to accumulated knowledge and expertise. This can lead to more efficient decision-making, reduced information asymmetry, and lower agency costs (2019, p. 10).

Finally, as per econometric standards in the social sciences, we used robust standard errors to ensure unbiased standard errors under heteroscedasticity. Heteroscedasticity is non-constant variance, meaning the standard deviations of predicted abnormal returns, monitored at different wave intervals, or/and related to prior time periods, are non-constant. This is the result of residuals being time-series dependent within a given firm or cross-sectionally dependent across firms.

4.4 Econometric Specifications and Limitations

We adopt a classic panel regression, widely employed in corporate finance. While simple regression models can be effective, they often suffer from the omission of important variables, resulting in biased coefficients. Given the high degree of unexplained variation in our model, indicated by low adjusted R-squared figures, this bias could be substantial, and the true coefficient values could differ significantly from the initial estimates. Nevertheless, while R-squared is a widely used measure for how well a model fits the data, its informational value is highly context-dependent and requires careful consideration of the specific application context and the comparison of different models (Camerin & Windmeijer, 1997, p. 330).

[22] We're studying imperfect markets, with interrelated market frictions and causal mechanisms.

In addition to biased estimators, we have to consider the complex dependencies of the residuals, which can violate the independent and identically distributed (i.i.d.) random variables assumption of ordinary least squares and lead to biased standard errors. With biased OLS standard errors, the statistical significance of our estimated regression coefficients cannot be reliably interpreted.

In our setting, the residuals may exhibit time-series dependence within a given firm or cross-sectional dependence across different firms. To address these issues, we employ clustered standard errors, which is a widely used approach for dealing with such dependence (Petersen, 2009, p. 460). Clustering ensures that the correlation of residuals within a cluster can take any form. As the number of clusters increases, the cluster-robust standard errors become consistent (Donald & Lang, 2007, p. 221).

5. Results and Data

5.1 Sample Construction

Since this study focuses specifically on divestitures in the U.S., Thomson Reuters' Platinum Securities Data Company (SDC) Mergers and Acquisitions database was used to compile the data of the transactions. Our initial dataset entails all transacrions which were classified as divestitures by SDC, occurred between January 1, 2000, and December 31, 2019, were conducted by U.S. public sellers, and had a transaction value of at least $75 million. Following these steps, we receive a total of 8,800 transactions.

The figure below illustrates the annual coverage of our transaction volume in relation to the total transaction volume of divestitures documented by Thomson's SDC database for each year.

Figure 5.1

Initial sample breakdown -the figure relates the total value of our original sample to the value of all divestitures within the observed period. The total sample consists of all transactions identified by the SDC database as a divestiture over the period 2000–2019. A detailed depiction of the yearly coverage can be found in table 8.1 in the appendices.

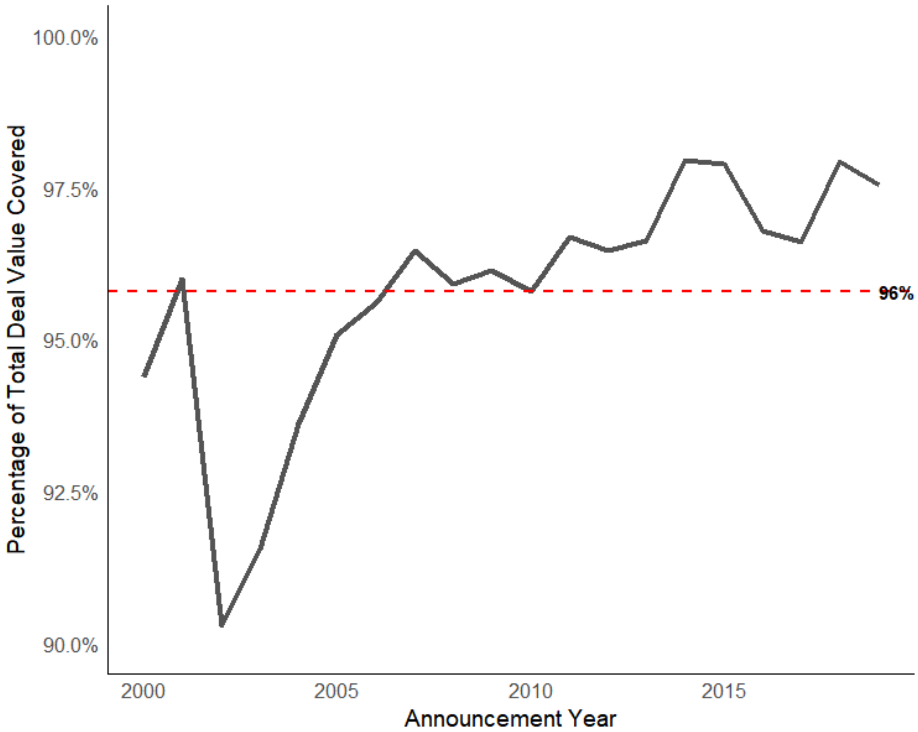


Figure 1 illustrates that our analysis encompasses over 90% of the total deal value of all recorded divestitures across each year. The dotted red line represents the mean percentage value, and lies marginally above 96%. The consistently high coverage level indicates that our study does not suffer from inferential validity, and that we can confidently infer that the findings, which are based on this sample, apply to the entire divestiture population.

After identifying the relevant waves of divestitures using Harford's (2005) method and limiting the sample to those transactions within waves, our dataset was reduced to 5,323 divestitures. To further enhance the comparability of transactions within the sample, a criterion was applied to only include transactions in which the buyer held 100% ownership after the divestiture. This ensures that the dataset is limited to asset sales by which complete control of the divested assets was transferred to the buyer, thereby eliminating any ambiguity or partial ownership scenarios, and controlling for the substantial difference in asset sale types, outlined in detail in the beginning of our literature review section.

To ensure the integrity in our subsequent event study, we implemented another filtering step, which consisted of excluding all instances where companies had undergone more than divestitures within the estimation period (120 days prior to announcement). This exclusion helped mitigate any confounding factors that could negatively affect the accuracy and reliability of our CAR estimates.

After applying these selection criteria, the dataset was further refined, excluding industries with a total divestiture count of less than 30 as well as sellers from the financial industry, as outlined in the methodology section. This results in a final sample size of 1,784 transactions.

Subsequently, we proceeded to extract firm-specific stock information from the Center for Research in Security Prices (CRSP) database. For the financial benchmark we used the provided quarterly data from the CRSP/COMPUSTAT Merged database. Barnes et al. (2014) have outlined the potential for inaccuracies in the SDC data, particularly concerning smaller acquirers characterized by higher book-to-market ratios and weaker market responses during the announcement period (p. 817). However, the scope of this research thesis is limited to divestitures involving publicly traded firms and transactions which exceed $75 million in value, which implies a relative large size of the divesting firms. Thus, we anticipate only minimal inaccuracies in the SDC data for our analysis.

Data Limitations

In this research thesis, variables pertaining to corporate assets, financial performance, and capital structure were obtained from the COMPUSTAT and the CRSP database. It is important to note that we encountered missing observations in the dataset, which could potentially skew the analysis and thereby introduce bias to our sample. To address this issue, we made certain assumptions regarding the missing observations for long-term debt and cash variables. In particular, we treated missing observations as an indicator of the absence of the respective balance sheet position, i.e., interpreted them like values of zero. We acknowledge the daring nature of these assumptions and are aware of the potential limitations they may entail but recognize that such an approach is common in the financial scholarship and point towards the need of future research to refine data collection methods in future studies.

Moreover, a substantial amount of information was lost, transferring the relevant firm data across different databases. Many divesting firms of which we derived data through SDC were not included in the CRSP or COMPUSTAT databases, or at least lacked the necessary identifiers to be able to collect the data. Consequently, after carefully cleaning the dataset to exclude firms with insufficient information for meaningful analysis, we were left with a reliable final sample size of 701 observations stemming from four industries, which served as the basis for conducting our subsequent quantitative analyses.

Identified Waves

The table below depicts the waves identified following Harford`s (2005) approach.

Table 5.1

Industry divestiture waves identified using Harford's (2005) approach to identify the maximum merger bid concentration. A period is designated as a wave if the actual peak concentration surpasses the 99th percentile of the empirical distribution.

Start of Wave	End of Wave	Industry
2011-01-01	2019-04-01	Mining
2000-01-01	2002-05-01	Manufacturing
2004-11-01	2008-11-01	Manufacturing
2012-04-01	2016-09-01	Manufacturing
2000-01-01	2007-09-01	Transportation
2003-11-01	2008-01-01	Service

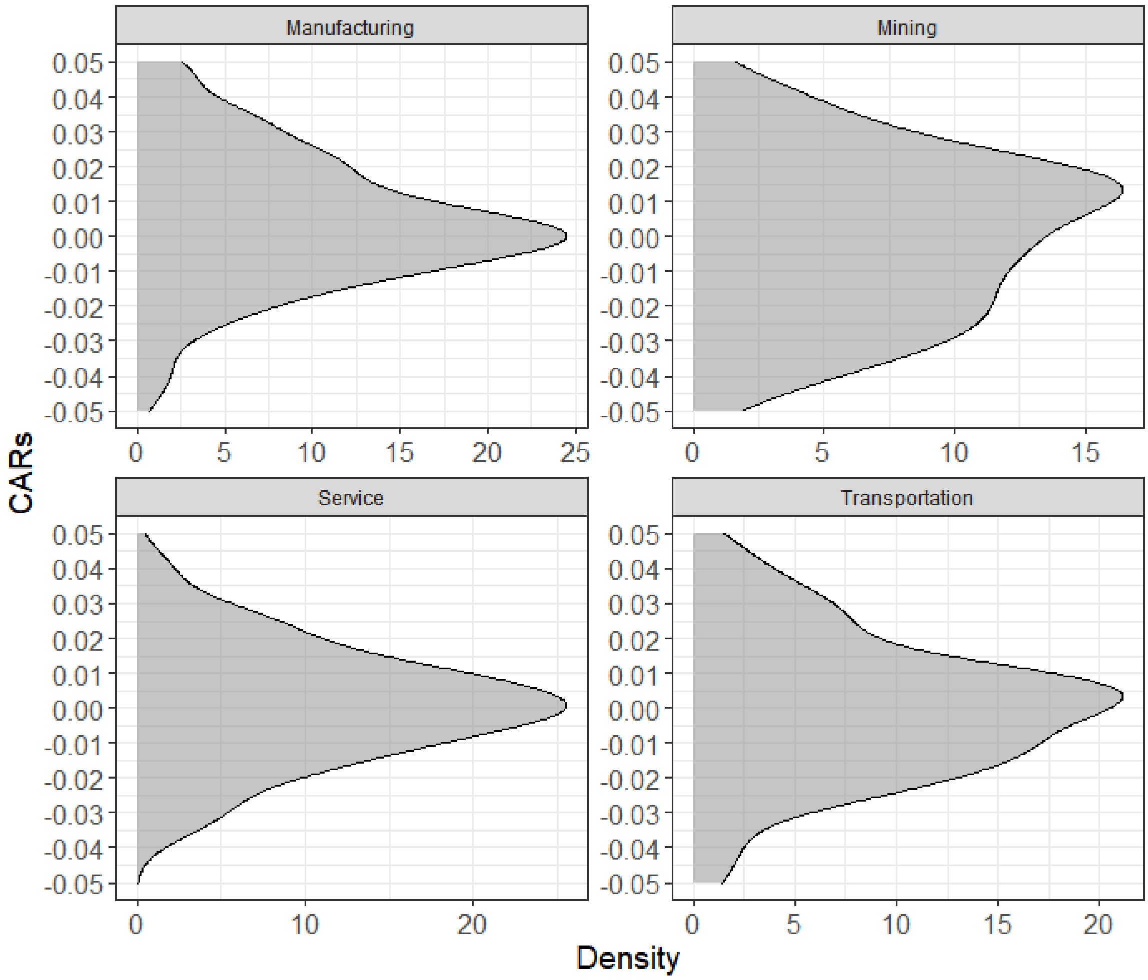
Table 5.1 presents the remaining industry divestiture waves following the data cleaning procedures outline previously. It illustrates six distinct divestiture waves observed across four industries, with each wave spanning over a distinct time period.

5.2 Event Study Results

Transactions that were announced within one of our industry divestiture waves are added to our filtered sample and are subject to an event study to determine the CAR estimates in relation to their announcement date. Due to the financial framework of Harford's (2005) approach, which includes a simulation distribution and rolling 24 months wave-period, it could be the case that certain divestitures were initially included in more than one wave. However, we implemented filters which ensure no double counting, and that each transaction is included in the specific divestiture wave that first recorded the transaction.

Figure 5.2

The density plots depict the probability density function of cumulative abnormal returns (CARs) across different industries. CAR values ranging from -0.05 to 0.05 are plotted on the x-axis. The y-axis represents the density, which reflects the relative likelihood of observing CARs at specific values.



Our analysis in figure 5.2 demonstrates that the highest density values in each industry, with the exception of the mining industry, are centred around or slightly above zero, indicating that, overall, investors appear to respond efficiently to the information conveyed by the divestiture announcements by adjusting their investment decisions. Nevertheless, we expect to observe positive average abnormal returns for each industry. This observation appears to, at least partly, align with the efficient market hypothesis, which posits that market prices incorporate and reflect all available information. Nevertheless, to make more precise statements on the capital market efficiency, further analyses are required.

Table 5.2

Cumulative average abnormal returns (CAARs) for each industry and quartile in event study analysis.

Industry	CAARs	Q1	Q2	Q3	Q4
Manufacturing	*0.0150*	*99*	*0*	*0*	*0*
Manufacturing	*0.0139*	*0*	*120*	*0*	*0*
Manufacturing	*0.0046*	*0*	*0*	*102*	*0*
Manufacturing	*0.0179*	*0*	*0*	*0*	*89*
Mining	*0.0070*	*28*	*0*	*0*	*0*
Mining	*0.0039*	*0*	*28*	*0*	*0*
Mining	*0.0102*	*0*	*0*	*31*	*0*
Mining	*0.0080*	*0*	*0*	*0*	*25*
Service	*0.0378*	*14*	*0*	*0*	*0*
Service	*0.0019*	*0*	*16*	*0*	*0*
Service	*0.0202*	*0*	*0*	*6*	*0*
Service	*-0.0038*	*0*	*0*	*0*	*7*
Transportation	*0.0104*	*33*	*0*	*0*	*0*
Transportation	*0.1568*	*0*	*33*	*0*	*0*
Transportation	*0.0102*	*0*	*0*	*35*	*0*
Transportation	*0.0018*	*0*	*0*	*0*	*35*

Upon examining the results in table 5.2, we conclude that the great majority of CAR estimations display positive values, indicating a favourable market reaction for most divestitures in industries and quartiles. This finding is consistent with the prevailing consensus of scholars such as Hite et al. (1987), Jain (1985) or Lee and Madhavan (2010), which support the notion of a positive market reaction to the announcement of divestitures.

Notably, there is an exception in the service industry where the CARs for the fourth quartile depict negative returns. The deviation from the overall trend could be attributed to specific factors unique to that industry or quartile. Further investigation might be warranted to gain insights into the underlying reasons for this observation.

Already, the data could be interpreted as hinting towards a potential late mover disadvantage, as there appears to be a negative correlation between the last quartile and abnormal returns. This would imply that firms divesting later in the event study period may experience comparatively low returns compared to those transaction which were conducted earlier. However, our analysis is so far descriptive in nature and does not establish a causal relationship. The further analyses of the upcoming sections are designed to assess the significance of timing implications on CARs and allows us to conduct a more conclusive interpretation of the results.

5.3 Regression Results

The previous analyses served an explanatory purpose, providing a first understanding of the relationships between timing implications and CARs. Rigorous multivariate regression follows to establish the causal relationship between within wave-interval and shareholder wealth, all else held constant.

To provide a comprehensive overview, we present descriptive statistics to outline the key characteristics of the divestiture transactions in our dataset. These statistics offer insights into the distribution and variability of variables relevant to our analysis, such as relative size, log size, (net) debt/assets, market/book ratio, and transaction value. The objective of presenting these statistics is to further enhance the clarity and comprehensibility of our subsequent analyses and make the study easily replicable.

Building upon the descriptive analysis, we proceed to conduct an OLS regression analysis, in which employ various modelling techniques to isolate and assess the specific effects of divestiture timing within waves on shareholder returns.

Finally, we confirm the robustness of our results by running multiple different variations of the experiment. Specifically, we replicate the model with alternative approaches techniques for each technical factor. This ensures that our findings are not contingent to our model specifications, but that causal effects are indeed present, regardless of our choices of inputs. Different versions of the same experiment validating the same conclusion, provide us with the confidence to ascertain key findings.

Descriptive Statistics

Table 5.3

Descriptive Statistics on dataset which was used for regression analysis. See appendix 8.1. for the variable explanation and section 4.3 for the rationale behind including them as dependent variables.

Variable	N	Mean	Median	Std. Dev.	Min	Pctl. 25	Pctl.75
Relative Size	701	0.18	0.044	1.3	0.00032	0.015	0.14
Log Size	701	9	9.1	1.7	2.8	7.8	10
(Net)Debt Ratio	701	0.23	0.23	0.19	-0.43	0.11	0.33
Market Cap	699	28,028	6,192	59,834	3.6	1,884	21,846
Market/Book	699	1.2	0.85	1.4	0.0067	0.48	1.4
Transaction Value	701	814	270	1,915	75	135	630

Table 5.3 provides insights into the dataset under investigation. It offers information on the characteristics of some of the main variables included in the latter regression analyses.

From the table we can deduce that on average the transaction volume makes up for about 20% of the total book value of the respective divesting firm. Moreover, the relatively low values of the median as well as the 75th percentile imply that the asset sales covered in the dataset have a large range of relative sizes, with some being significantly larger than others.

In terms of log size, the mean and median values of about 9 and 9.1, respectively, suggest considerable log size in the sample, which is to be expected given the minimum transaction value requirements discussed above. The relatively high standard deviation of 1.7 further emphasizes the considerable dispersion within the dataset and highlights the heterogeneity of firm sizes.

As for the debt ratio, the mean and median values of 0.23, respectively, indicate a relatively stable debt ratio among the divesting firms. Moreover, it signals that, on average, divesting companies have moderate debt levels relative to their total assets. The relatively low standard deviation of 0.19 also underscores this assumption.

The analysis of the market-to-book variable shows a considerable range in ratios, with values of 1.2 and 0.85 for the mean and median, respectively, which reflects the wide disparity in market forecasts for future growth among firms within the sample.

Finally, in terms of transaction value, the data implies a wide range of values, as indicated by the large standard deviation of 1,915. The mean transaction value of $814 and the median value of $270 demonstrate the skewed distribution.

Overall, the descriptive statistics suggest that there are substantial differences in the scale of divestment transactions, which could potentially arise from differences in the strategic importance or market value of the assets divested.

Correlation Analysis

The table below presents correlation estimates between the individual variables used in our regression analyses. In the context of a cross-sectional regression analysis, a high correlation between independent variables can indicate the potential presence of incomplete multicollinearity, which can potentially lead to two primary issues: coefficients may be measured inaccurately, and estimates may be sensitive to minor changes in the model.

Interpreting the results of our table reveals a varying degree of correlation among the regression variables. In particular, the variables related to prior transactions, corporate debt-to-assets and market-to-book ratios depict high correlation values with several other variables. However, the high correlation levels of these variables do not pose a major concern as we have conducted regression analyses without the inclusion of those variables in our regression analysis in Table 5.5. The results demonstrate only a slight difference in results when the additional controlling variables are introduced and reveal no variations in the significance level of the coefficient estimates for CARs. Moreover, we conducted a variance inflation factor (VIF) analysis, which resulted in a value of less than 1.44 for each of the explaining variables. Hence, multicollinearity does not seem to present an issue.

The correlation analysis shows that announcements within the late mover interval are negatively correlated with abnormal returns. The lack of statistically significance of this relationship, could be the exclusion of control variables, which potentially biases the underlying relationship between these variables. Therefore, to further investigate our assumption, a thorough regression analysis follows.

Table 5.4
Summary of the pairwise correlations among the variables considered in our study. Values close to an absolute value of 1 signify strong correlation, while a value close to 0 indicates no linear relationship. The coefficients were calculated using the Pearson correlation method with listwise deletion.

	Same SIC	*Late mover*	*Rel. size*	*Log size*	*Debt ratio*	*Market-Book*	*Prior Trans*	*CARs*
Same SIC								
Late mover	0.078*							
Rel. size	0.049	-0.015						
Log size	-0.110**	0.027	-0.169***					
Debt ratio	0.185***	-0.017	-0.063	-0.071				
Market-Book ratio	-0.001	0.045	0.507***	-0.093*	-0.238***			
Prior Transactions	-0.012	0.159***	-0.074*	0.454***	0.005	-0.060		
CARs	0.035	-0.019	0.054	-0.147***	-0.056	-0.044	-0.040	

Cross Sectional Regression Analysis

In Table 5.5 below, we estimate the regression of announcement abnormal returns while controlling for measures of firm size as well as transaction-specific characteristics that were introduced in the methodology section and are commonly examined in existing financial literature.

Table 5.5
Cross sectional regression analysis of cumulative abnormal returns on firm as well as deal characteristics. A dot, one, two and three stars represent a 10%, 5%, 1% and 0.1% significance level, respectively. Numbers in parentheses indicate the respective standard error of the coefficient.

Variables	**(1)**	**(2)**	**(3)**
Dependent Var.:	CARs	CARs	CARs
Constant	0.142 (0.125)		
Late mover	-0.008 (0.013)	-0.026** (0.003)	-0.025** (0.003)
Rel. size	0.003 (0.006)	0.003 (0.006)	0.009 (0.009)
Log size	-0.014 (0.013)	-0.016 (0.015)	-0.020 (0.019)
Same SIC	0.008 (0.008)	0.005 (0.007)	0.011 (0.011)
Prior Transaction			-0.109 (0.121)
Debt ratio			-0.012 (0.009)
Market/Book			0.021 (0.021)
Fixed-Effects:	--------------	----------------	----------------
Industry	No	Yes	Yes
Announcement Year	No	Yes	Yes
S.E.: Clustered	by: Industry	by: Industry	by: Industry
Observations	696	696	694
R2	0.02232	0.06504	0.08370
Within R2	--	0.02812	0.04753

In regression model (1), we restrict our analysis to the three control variables most prevalent in the current financial literature as well as the explaining variable of timing implications, introduced by us. This model presents our most simplistic approach as we refrain from introducing fixed effects. The estimated coefficient for the late mover variable amounts -0.008 and is not significant at the 10% level.

In regression (2) fixed effects for industry and the announcement year are introduced. In this instance the late mover variable shows a statistically significant negative association with CARs at the 1% level. The economic interpretation of coefficient, which is estimated as -0.026, indicates that late movers experience on average 2.6% lower announcement abnormal returns compared to firms that divest at an earlier point within the wave. Upon incorporating fixed industry and year-specific fixed effects, we observe a highly significant coefficient for the timing implication variable, which emphasizes that controlling for unobserved heterogeneity and time-specific factors, including potential macro-economic effects, is crucial in deciphering the relationship between the variables of interest and divestiture activities. The inclusion of fixed effects helps us mitigate the impact of confounding factors and provides a more accurate assessment of the specific effects of the variables under investigation.

Regression (3) differs from (2) in that it includes additional control variables. In line with our expectations, regression (3) depicts a similar coefficient of -0.025, significant at the 1% level, implying on average 2.5% lower announcement abnormal returns for late movers compared to their earlier moving peers. We find that the inclusion of the additional control variables has little effect the coefficient of our explanatory variable, which is intuitive as those variables also take a subordinate role in many prominent studies of financial scholars.
To determine the economic significance of the coefficients, we scaled the change in the explanatory variable by the sample mean of the explanatory variable. Our findings indicate that scaling the late mover coefficient by its standard error (0.003) results in a substantial decrease of 40.52% in the CARs variable. This suggests a pronounced practical significant impact of the late mover variable on the observed changes in CARs.

The regression results suggest that the timing of being a late mover has a highly significant negative effect on market reactions to announcements, indicating that investors perceive transactions towards the end of a divestiture wave less favorably than those conducted prior.

In appendix 8.5 regression tables concerning early movers (first quartile) as well as firms divesting in the second and third quartile ("peak movers"), are provided. Our findings indicate that, while divesting late within the wave seems to have a significantly negative impact on shareholder returns, there is no significant indication of other timing implications. Neither the table depicting early mover effects nor the one concerning peak movers show statistically significant results. Divesting in the second quartile of the wave reports a coefficient of 0.02, which lies just slightly above the marginal significance threshold of 10%.

5.4 Robustness Checks

In this section, we investigate the robustness of our regression results by addressing four potential concerns: (1) variations in the event window used in event study, (2) alternative definitions of early and late movers, (3) alternative financial models to compute CARs, and (4) an alternative method for identifying industry transaction waves. These factors have been identified as potential sources of variation and may substantially alter our findings of timing implications on CAR estimates.

Variations in Event Window

As indicated in table 5.6, we incorporated a variable event window in our event study analysis to assess the robustness of our findings. Implementing this approach allows us to examine the sensitivity of our discovered coefficients to different time periods around the event date in question. Moreover, it enables capturing potential variations in the impact of the event across different observation periods. Thereby, we also control for potential event anticipations by the market or an inefficient rapid response that could lead to a premature/postponed stock return response. Overall, robustness checks are useful measures to mitigate potential biases and ensures the reliability of our conclusions in different time contexts.

Table 5.6
Cross sectional regression analysis of CARS on firm as well as deal characteristics. Regressions (1), (2), and (3) represent event windows of (-1;0), (-1;+1), and (-2;+2), respectively. A dot, one, two and three stars represent a 10%, 5%, 1% and 0.1% significance level, respectively. Numbers in parentheses indicate the respective standard error of the coefficient.

Variables	(1)	(2)	(3)
Dependent Var.:	CARs	CARs	CARs
Late mover	-0.025** (0.003)	-0.025** (0.003)	-0.026** (0.003)
Rel. size	0.009 (0.009)	0.019 (0.009)	0.025 (0.013)
Log size	-0.020 (0.019)	-0.024 (0.019)	-0.022 (0.017)
Same SIC	-0.109 (0.121)	-0.115 (0.119)	-0.107 (0.106)
Prior Transaction	-0.012 (0.009)	-0.013 (0.008)	-0.014 (0.010)
Debt ratio	0.011 (0.011)	0.009 (0.014)	0.004 (0.014)
Market/Book	0.021 (0.021)	0.023 (0.020)	0.018 (0.019)
Fixed-Effects:	----------------	----------------	----------------
Industry	Yes	Yes	Yes
Announcement Year	Yes	Yes	Yes
S.E.: Clustered	by: Industry	by: Industry	by: Industry
Observations	694	701	702
R2	0.08370	0.09602	0.10342
Within R2	0.04753	0.06583	0.07146

We can see that all three regression models depict very similar results and indicate a late mover disadvantage, significant at the 1% level. These findings highlight a consistent pattern wherein late movers on average experience a significantly lower announcement abnormal return, consistently exceeding the 2.5% mark. These outcomes emphasize the robustness of the observed late mover effect, further substantiating its economic implications.

Moreover, none of the control variable coefficients indicate a statistically significant impact on stock returns. This finding is surprising considering that they are documented to exhibit substantial effects and their algebraic signs overall align with the expected directions based on the existing literature.

Alternative Early and Late Mover Definitions

Appendix 8.6.1. summarizes the regression results for a variety of early and late mover definitions. As stated before, in the initial regression model we divided the transactions up into quartiles. In our robustness check analysis, we categorize them by quantiles, thirds and halves. All analyses show results with very similar economic implications, i.e., a late mover disadvantage that suggests a loss in shareholder value of at least 1.45% compared to the expected level. Nevertheless, significance levels differ, as model (3), with a p-value of slightly above the 10% mark, does not indicate a significant correlation between late movers and abnormal returns, while models (2) and (4) do so at marginal significance levels of 5% and 10%, respectively. The significant negative effect of being a late mover in models (1), (2) and (4) underlines our previously adopted conjecture that delayed market entry might have adverse implications for firm performance.

Alternative Financial Model to compute CARs

While the market model is the most employed in the finance literature to calculate abnormal returns in event studies, there also exist other prominent benchmark models to determine CARs. The CAPM, the mean-adjusted model, and the market-adjusted model are among the most frequently used alternatives. These models differ slightly in their calculation approaches, allowing researchers to choose the most appropriate approach based on their specific research objectives. To enhance the robustness of our findings, we decided to incorporate them all in our analysis. Appendix 8.6.2 provides a short overview of the respective model characteristics and their practical implications.

Table 8.7 in the appendices depicts the OLS regression results received following the models' approaches. As expected, we obtain very similar results to those of the market model. All results are highly statistically significant and indicate a late mover disadvantage. The absolute value of all estiamted coefficients lies above 0.026, implying a substantial decrease in announcement abnormal returns for late movers compared to their earlier moving peers, after controlling for key characteristics. Upon examining the economic significance of the results, we observe that scaling the coefficient of the late mover variable obtained from the CAPM analysis results in a substantial change of approximately 30.66% in our dependent CAR variable, which is corroborated by the other implemented models.

Alternative method to identify industry transaction waves

As discussed in previous sections, our research primarily focuses on Harford's approach for identifying industry transaction waves due to its prevalence in current financial literature and less restrictive underlying assumptions. Nevertheless, we acknowledge that there is no consensus on an objective identification and definition of what constitutes an industry transaction wave. Therefore, we also conduct comprehensive analyses following Carow's (2004) approach, which has been employed in the finance literature before, most notably by the Xu (2017). Appendix 8.6.3 presents the details of this approach.

Following Carow's (2004) framework, we identified a total of 28 waves across 6 industries. The approach yielded a higher number of significantly shorter waves, compared to the waves identified implementing Harford's (2005) approach. This finding can be attributed to the implementation of lower thresholds for considering market fluctuations as waves following Carow's (2004) approach. Consistent with our findings following Harford and current research, we also find on average positive abnormal returns for all industries (Lee & Madhavan, 2010).

Tables 8.10. and 8.11. in the appendices section present our regression results, showcasing the findings obtained when employing different definitions of early/late movers as well as varying event windows. In the first analysis, we observe that with an early/late mover definition based on the first/last 25%, we find significant evidence of a late mover advantage at the 5% significance level. However, as we expand the definition to 50%, the coefficient switches to a negative value and the results become more aligned with those obtained using the Harford's (2005) approach, albeit not statistically significant. Given the substantially shorter duration of these identified waves, we consider it reasonable to extend the timing assumptions and thereby enhance the comparability between our two approaches.

In the second table, we observe a similar trend, where an event window of (-1;0) indicates a late mover advantage, while a larger event window of (-2;+2) suggests a late mover disadvantage. None of these results prove statistically significant, and therefore hold limited explanatory value.

6. Conclusion

While M&A waves have been studied extensively, the same cannot be said about divestitures nor about divestiture waves. The recent soar in divestiture transactions has brought restructuring asset sales to prominence for practitioners and scholars alike. Responding to this, we examined divestiture transactions within industry waves to determine the impact of announcement timing on shareholder wealth.

From Thomson's M&A SDC database, we collected all divestiture announcements between 2000 and 2019, specifying transaction characteristics aligning with convention. Following Harford's method, we determined the duration of divestiture waves for each industry and delineated them into distinct time periods. These were defined as waves, and all transactions within these periods formed part of our sample.

Using data from the CRSP database, we calculated the average abnormal returns for different timing-intervals, within every wave. As an intermediary step we presented descriptive results. These revealed a correlation between late announcements and lower stock returns but lacked the control variables necessary to confidently prove causal effects. To do this we implemented OLS regression analyses to isolate the effect of within-wave timing on observed stock returns. This called for an extensive list of control variables, many of which have become standardized in M&A and event-study methodology. We derived further control variables from the literature on divestitures' sources of value creation. The necessary data was sourced from COMPUSTAT.

Consistent with previous research, our event study analysis discovers positive average abnormal returns across all industry waves, regardless of the identification model implemented. Moreover, our findings indicate a causal relationship between divestiture announcements being announced late in the wave and lower abnormal stock returns. Given that this effect was statistically significant at the 1% level, we reject the null hypothesis and accept H_4. The results hold significance across different event windows, various corporate financial models, and different definitions of early and late movers, corroborating the robustness of our findings.

This stands in contrast to scholarship on M&A entrant-position effects, indicate a first-mover advantage (Bergen & Dick, 2007; Carow, et al., 2004; Mcnamara,et al., 2008) which is to be expected given that the differences between M&A and divestiture transactions extend far beyond mere multiplicative inverses. Moreover, our finding reveals yet another aspect in which M&A and divestitures are fundamentally different. In a real options context, our finding indicates that for divestitures the cost of waiting is larger than the benefit of reduced uncertainty. Alternatively, asymmetric information does not clear over the duration of the wave, or the learning effect is not valued by investors.

On average, shareholders of firms divesting in the last quarter of a wave experience significantly 2.48% lower abnormal returns, compared to sellers which divested earlier within that wave. This reduction in abnormal returns, expressed as a percentage of the median market capitalization of all divesting firms, amounts to $154 million. Digging deeper into the practical significance of our results, we found that scaling our late mover variable by one-times its standard error leads to a fluctuation of over 40% in the respective CAR variable. This implies yet another market imperfection pertaining to stock returns, calling for astute announcement timing on the part of corporate management.

To answer the initially posed question, it remains unclear whether the early bird will catch the return, but we are certain that the late bird won’t.

7. Bibliography

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8. Appendices

8.1 Variable Description

Variable	Explanation	Calculation	Original Source
Response Variable			
Cumulative Abnormal Return	We employed Cumulative Abnormal Returns (CARs) as the dependent variable. The event window was defined as (-1, 0), and was calculated using the market model. The estimation of event alpha and beta involved using daily stock returns over a 100-day period, concluding 20 days prior to the event date. For the market return, we used the CRSP value weighted worldwide index. To further ensure the robustness of our results, we conducted additional analyses with event windows of (-1, 1) and (-2, 2).	$CAR_{it} = a_{it} - r_{it}$ where a_{it} is security i's actual share return of the divesting firm on day t and r_{it} is the security i's expected share return of the divesting firm on day t	Center for Research in Security Prices (CRSP)
Explanatory Variable			
Timing of Divestiture	We categorized divestitures into early, peak, and late movers based on their position within the industry divestiture wave. The division was determined by allocating divestitures into brackets using a 25% threshold. To ensure the robustness of our findings, we conducted additional analyses using alternative definitions of timing brackets.		Thomsons's Securities Data Company (SDC)
Control Variable			
Deal Size	Monetary amount involved in the transaction. Represents the consideration paid by the buyer to acquire the target company from the seller. It reflects the total financial value exchanged between the involved parties as part of the deal.	Σ of total financial consideration involved in transaction	COMPUSTAT
Size of Seller	Log of total book value of assets recorded on announcement date. Provides a transformed representation of the asset value.	Natural logarithm of the total financial value of the seller's assets	COMPUSTAT
Price-to-Book Value	Financial metric used to evaluate the growth prospects of a company. It compares the market price per share of a company's stock to its book value per share.	$PB_{it} = \frac{M_{it}}{A_{it}}$ where M_{it} denotes security i's market capitalization on day t and Ait is the re$_{sp}$ective total book value of assets	COMPUSTAT
(Net) Debt Ratio	Financial ratio that measures the relationship between a company's total (net) debt and its total assets. Provides an insight into the composition of the seller's capital structure.	$DR_{it} = \frac{D_{it}}{A_{it}}$ where D_{it} denotes the sellers i'th long term net debt on day t and A_{it} is the respective total book value of assets	COMPUSTAT
Fixed Effects			
Industry Fixed Effects	Selling firms were divided into industry brackets, according to their two digits standardized identification codes (SIC)		Thomsons's Securities Data Company (SDC)
Year Fixed Effects	The year of announcement for the respective seller's divestitures was utilized to categorize them into brackets		Thomsons's Securities Data Company (SDC)

8.2 Event Study Methodology

In our event study analysis, we primarily utilize the market model, as it is the most widely adopted in the current financial literature. However, to ensure the robustness of our regression results, we also employ the CAPM, the mean-adjusted model, and the market-adjusted model as supplementary analyses. In the following sections, we will summarize the key characteristics of the financial models implemented in our event study. In our mathematical notations we follow established standards of (financial) econometrics, such as those provided by Stock and Watson (2003) or Campbell et al. (1997).

Market Model

The market model, also known as the single-index model, is an approach widely implemented in event study literature. The model's findings are based on the assumption that a company's share returns are linearly related to market returns. Moreover, it assumes a company's stock price to be affected by both company-specific as well as market-wide factors. Brown and Warner (1985) describe the market model as *"well-specified under a variety of conditions"* (p. 25).

The market model is defined as:

$$r_{it} = \alpha_i + \beta_i \times r_{mt} + e_{it}$$

where α_i is denoted as security i's regression intercept representing the abnormal return, i.e., the return of security i which exceeds the mean market return multiplied with the security's β_i, β_i is representing security i's regression slope and volatility measure of systematic risk, r_{mt} is the market return on day t and e represents the security i's residual value on day t. The subsequent r_{it} represents security i's expected return based on the company's systematic risk and the general market conditions. α_i and β_i are mathematically defined as follows:

$$\alpha_i = \mu_i - \beta_i * \mu_m$$

$$\beta_i = \frac{\sum_{T_{-2}}^{T-3}(r_{it} - \mu_i) * (r_{mt} - \mu_{mt})}{\sum_{T_{-2}}^{T-3}(r_{mt} - \mu_{mt})^2}$$

where T_{-3} and T_{-2} denote the beginning and end of the estimation window, respectively, which in our case corresponds to 120 and 20 days prior to the announcement date.

CAPM

In contrast to the market model, the CAPM incorporates additional factors such as the risk-free rate and the excess market return. It provides a framework for estimating returns based on the relationship between systematic risk and (market) risk premium (Sharpe, 1964).

The CAPM is defined as:

$$r_{it} = rf_t + \beta_i \times R_{mt} + e_{it}$$

where rf_t is denoted as the risk-free rate on day t, β_i represents security i's regression slope and volatility measure of industry wide risk, R_{mt} is the excess market return, also called market risk premium, which is calculated as the residual between the market return on day t and the respective risk-free rate. e represents security i's residual value on day t. R_{mt} is defined as the residual of the market return on day t and the risk-free rate on day t.

Mean-adjusted model

The rationale behind the mean-adjusted model is to assume that the event does not have a significant impact on the systematic risk of the asset but influences the return of the asset due to temporary or idiosyncratic factors. By using the "historical mean return" as the basis for the estimated returns, the model aims to capture the underlying performance of the asset and thereby isolate the impact of the event on abnormal returns. The mean-adjusted model is simple and easy to implement as it relies solely on historical data and does not require additional inputs such as market indices or specific risk factors (Tsay, 2005).

The expected return following the mean-adjusted model is defined as:

$$r_{it} = \bar{r}_i$$

where $\bar{r}_I$ is denoted as the i'th security's historical return rate.

Market-adjusted model

The market-adjusted model aims to capture the impact of an event on the stock return of a firm by adjusting for the general market fluctuations during the event period. The basic idea behind the market-adjusted model is to isolate the impact of an event by removing the general market shifts which affect all assets. By comparing an asset's return to overall market performance, we can determine if the return deviates from what would be expected based on market movements alone (Brown & Warner, 1985). According to Brown (1985), the market model and market-adjusted model entail a similar level of validity (pp. 25-26).

The expected return following the market-adjusted model is defined as:

$$r_{it} = r_{mt}$$

where r_{mt} is the market return on day t.

For the risk-free rate, we used the 10-year US Treasury rate, and for the market return, we employed the value-weighted CRSP index. We used historical stock return data to estimate hypothetical stock alpha and beta. To estimate the abnormal returns, we utilized daily historical stock return data to calculate a hypothetical stock alpha and beta. The difference between the actual stock price return and the estimated counterfactual constitutes the abnormal return.

Abnormal return calculation

Abnormal returns are defined as the difference between the actual return observed in the market and the expected return, which was estimated using one of the respective benchmark models. We calculate the abnormal return of each day of our defined event window, in our case denoted as $(-1; 0)$.

$$AR_{it} = r_{it} - \widehat{r_{it}}$$

where AR_{it} is the abnormal return for security i on day τ within the event window, $r_{i\tau}$ is the actual return of security i recorded on day t within the event window, $\widehat{r_{it}}$ is the expected return of security i estimated for day t within the event window and depends on the respective financial model.

The respective variance is defined as:

$$\widehat{\sigma_i}^2(AR_{it}) = \frac{1}{L-2} * \sum_{T_{-3}}^{T_{-2}} \hat{e}_{it} \text{, where } \quad AR_{it} \sim N(0, \widehat{\sigma_i}^2(AR_{it}))$$

where L is defined as the length of the estimation window ($T_{-3} - T_{-2}$).

Subsequently, we aggregate the individual abnormal returns to calculate the cumulative abnormal returns for the entire event window of interest.

$$CAR_{i(T_{-1},T_1)} = \sum_{T_{-1}}^{T_1} AR_{it}$$

where T_{-1} and T_1 denote the start and end of the event window, respectively, $CAR_{i(T_{-1},T_1)}$ is the cumulative abnormal return for security i within the event window period, AR_{iT_0} is the abnormal return for security i on day t within the event window.

Subsequently, the variance of CARs is defined as:

$$\hat{\sigma}_i^2\left(CAR_{i(T_{-1},T_1)}\right) = (T_1 - T_{-1} + 1) * \hat{\sigma_i}^2(AR_{it})$$

which, in essence, represents the sum of the daily variances over the event window.

8.3 Transaction Value Coverage

Table 8.1
Summary of divestiture transactions, displaying key information related to the announcement year, total value of deals, value of selected deals, and the percentage of total deal value covered. Offers a comprehensive overview of the aggregated values and coverage percentages, allowing for comparison and analysis of divestiture activity.

Announcement Year	All Deals	Selected Deals	Coverage Ratio
2000	305,466.94	288,312.55	94.38%
2001	317,411.93	304,679.99	95.99%
2002	144,917.27	130,862.16	90.30%
2003	182,358.08	166,956.52	91.55%
2004	212,514.38	198,938.62	93.61%

Announcement Year	All Deals	Selected Deals	Coverage Ratio
2005	305,813.47	290,735.32	95.07%
2006	356,054.01	340,409.31	95.61%
2007	455,857.81	439,712.55	96.46%
2008	292,217.41	280,259.67	95.91%
2009	244,227.87	234,792.53	96.14%
2010	242,231.00	232,021.32	95.79%
2011	318,635.86	308,066.38	96.68%
2012	309,409.32	298,490.33	96.47%
2013	338,634.06	327,205.98	96.63%
2014	542,759.69	531,644.95	97.95%
2015	500,710.55	490,094.44	97.88%
2016	384,663.10	372,272.88	96.78%
2017	391,547.49	378,288.44	96.61%
2018	542,941.93	531,674.52	97.92%
2019	434,678.66	424,012.69	97.55%

Announcement Year	All Deals	Selected Deals	Coverage Ratio
	6,823,050.83	**6,569,431.18**	**96.28%**

8.4 Waves identified using Harford's (2005) approach

Table 8.2
Mean cumulative abnormal returns and observations per industry.

Industry	Mean CARs per Industry	Observations per Industry
Manufacturing	0.0127	410
Mining	0.0073	112
Service	0.0152	43
Transportation	0.0437	136

8.5 Timing implications within divestiture waves

Table 8.3
Cross sectional regression analysis of cumulative abnormal returns on firm as well as deal characteristics. A dot, one, two and three stars represent a 10%, 5%, 1% and 0.1% significance level, respectively. Numbers in parentheses indicate the respective standard error of the coefficient.

Variables	**(1)**	**(2)**	**(3)**
Dependent Var.:	CARs	CARs	CARs
Constant	0.143 (0.128)		
Early mover	-0.006 (0.013)	-0.002 (0.006)	-0.002 (0.005)
Rel. size	0.004 (0.006)	0.003 (0.006)	0.009 (0.009)
Log size	-0.014 (0.013)	-0.016 (0.015)	-0.020 (0.019)
Same SIC	0.007 (0.006)	0.005 (0.007)	0.010 (0.011)
Prior Transaction			-0.110 (0.122)
Debt ratio			-0.012 (0.009)
Market/Book			0.020 (0.020)
Fixed-Effects:	--------------	--------------	--------------
Industry	No	Yes	Yes
Announcement Year	No	Yes	Yes
S.E.: Clustered	by: Industry	by: Industry	by: Industry
Observations	696	696	694
R2	0.02218	0.06315	0.08204
Within R2	--	0.02615	0.04580

Table 8.4
Cross sectional regression analysis of cumulative abnormal returns on firm as well as deal characteristics. A dot, one, two and three stars represent a 10%, 5%, 1% and 0.1% significance level, respectively. Numbers in parentheses indicate the respective standard error of the coefficient.

Variables	**(1)**	**(2)**	**(3)**
Dependent Var.:	CARs	CARs	CARs
Constant	0.144 (0.125)		
Q2 mover	-0.012 (0.006)	-0.0003 (0.006)	-0.0006 (0.005)
Rel. size	0.003 (0.006)	0.003 (0.006)	0.009 (0.009)
Log size	-0.014 (0.013)	-0.016 (0.015)	-0.020 (0.019)
Same SIC	0.007 (0.007)	0.005 (0.007)	0.010 (0.011)
Prior Transaction			-0.110 (0.122)
Debt ratio			-0.012 (0.009)
Market/Book			0.020 (0.021)
Fixed-Effects:	--------------	---------------	---------------
Industry	No	Yes	Yes
Announcement Year	No	Yes	Yes
S.E.: Clustered	by: Industry	by: Industry	by: Industry
Observations	696	696	694
R2	0.02294	0.06314	0.08203
Within R2	--	0.02615	0.04579

Table 8.5
Cross sectional regression analysis of cumulative abnormal returns on firm as well as deal characteristics. A dot, one, two and three stars represent a 10%, 5%, 1% and 0.1% significance level, respectively. Numbers in parentheses indicate the respective standard error of the coefficient.

Variables	**(1)**	**(2)**	**(3)**
Dependent Var.:	CARs	CARs	CARs
Constant	0.132 (0.111)		
Q3 mover	0.024 (0.028)	0.019 (0.009)	0.019 (0.008)
Rel. size	0.004 (0.006)	0.003 (0.006)	0.010 (0.009)
Log size	-0.014 (0.013)	-0.016 (0.015)	-0.020 (0.019)
Same SIC	0.008 (0.008)	0.005 (0.007)	0.010 (0.011)
Prior Transaction			-0.110 (0.122)
Debt ratio			-0.013 (0.009)
Market/Book			0.019 (0.021)
Fixed-Effects:	--------------	--------------	--------------
Industry	No	Yes	Yes
Announcement Year	No	Yes	Yes
S.E.: Clustered	by: Industry	by: Industry	by: Industry
Observations	696	696	694
R2	0.02576	0.06467	0.08347
Within R2	--	0.02774	0.04729

8.6 Robustness Check – Differing Event Window

8.6.1 Differing Entrant Position Definitions

Table 8.6

Cross sectional regression analysis of CARs on firm as well as deal characteristics. Regressions (1), (2), (3), and (4) represent the definition of early movers as the first 25%, 20%, 33%, and 50%, respectively, and vice versa for late movers. A dot, one, two and three stars represent a 10%, 5%, 1% and 0.1% significance level, respectively. Numbers in parentheses indicate the respective standard error of the coefficient.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Dependent Var.:	CARs	CARs	CARs	CARs
Late mover	-0.025** (0.003)	-0.039* (0.011)	-0.016 (0.007)	-0.021* (0.006)
Rel. size	0.009 (0.009)	0.008 (0.009)	0.008 (0.009)	0.008 (0.009)
Log size	-0.020 (0.019)	-0.021 (0.019)	-0.021 (0.019)	-0.021 (0.019)
Same SIC	-0.109 (0.121)	0.0002 (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)
Prior Transaction	-0.012 (0.009)	-0.008 (0.005)	-0.008 (0.005)	-0.008 (0.005)
Debt ratio	0.011 (0.011)	0.003 (0.005)	0.003 (0.005)	0.003 (0.005)
Market/Book	0.021 (0.021)	0.018 (0.019)	0.018 (0.019)	0.018 (0.020)
Fixed-Effects:	----------------	---------------	---------------	---------------
Industry	Yes	Yes	Yes	Yes
Announcement Year	Yes	Yes	Yes	Yes
S.E.: Clustered	by: Industry	by: Industry	by: Industry	by: Industry
Observations	694	694	694	694
R2	0.08370	0.07658	0.07420	0.07493
Within R2	0.04753	0.04012	0.03766	0.03841

8.6.2 Differing Financial Models implemented to estimate CARs

Table 8.7
Cross sectional regression analysis of CARs on firm as well as deal characteristics. Regressions (1), (2), and (3) represent CARs calculated following the CAPM, mean-adjusted model, and market-adjusted model respectively. A dot, one, two and three stars represent a 10%, 5%, 1% and 0.1% significance level, respectively. Numbers in parentheses indicate the respective standard error of the coefficient.

Variables	**(1)**	**(2)**	**(3)**
Dependent Var.:	CARs	CARs	CARs
Late mover	-0.029*** (0.002)	-0.026** (0.002)	-0.027** (0.002)
Rel. size	0.011 (0.010)	0.010 (0.010)	0.010 (0.010)
Log size	-0.022 (0.020)	-0.021 (0.019)	-0.020 (0.020)
Same SIC	-0.109 (0.125)	-0.112 (0.124)	-0.107 (0.123)
Prior Transaction	-0.013 (0.010)	-0.012 (0.009)	-0.012 (0.010)
Debt ratio	0.012 (0.008)	0.009 (0.011)	0.012 (0.009)
Market/Book	0.020 (0.023)	0.018 (0.021)	0.019 (0.022)
Fixed-Effects:	-----------------	----------------	----------------
Industry	Yes	Yes	Yes
Announcement Year	Yes	Yes	Yes
S.E.: Clustered	by: Industry	by: Industry	by: Industry
Observations	692	692	692
R2	0.08946	0.08883	0.08503
Within R2	0.04988	0.04932	0.04640

8.6.3 Results following Carow Approach

Table 8.8
Industry divestiture waves identified using Carow et al.'s (2004) approach

Industry	Start of Wave	End of Wave
Mining	2000-01-01	2000-10-01
Mining	2001-04-01	2002-07-01
Mining	2003-07-01	2005-04-01
Mining	2006-01-01	2008-04-01
Mining	2008-01-01	2008-12-31
Mining	2009-10-01	2012-04-01
Mining	2012-07-01	2013-04-01
Mining	2013-01-01	2015-04-01
Mining	2016-01-01	2017-07-01
Manufacturing	2004-10-01	2008-07-01
Manufacturing	2013-04-01	2015-12-31
Transportation	2001-07-01	2006-10-01
Transportation	2009-01-01	2009-10-01
Transportation	2010-04-01	2011-12-31
Transportation	2012-07-01	2013-07-01
Transportation	2014-01-01	2015-04-01
Transportation	2016-01-01	2016-12-31
Retail	2000-04-01	2001-07-01
Retail	2002-07-01	2004-04-01
Retail	2005-01-01	2005-10-01
Retail	2006-01-01	2007-10-01
Retail	2011-07-01	2012-12-31
Retail	2015-01-01	2015-10-01
Service	2005-04-01	2007-10-01
Service	2009-01-01	2009-12-31
Service	2011-01-01	2011-12-31
Service	2013-01-01	2015-07-01
Service	2015-04-01	2018-04-01

Table 8.9
Mean cumulative abnormal returns and observations per industry, identified following Carow et al.'s (2004) approach

Industry	Mean CARs per Industry	Observations per Industry
Manufacturing	0.0125	274
Mining	0.0071	153
Retail	0.0295	39
Service	0.0196	98
Transportation	0.0092	151

Table 8.10
Cross sectional regression analysis of cumulative abnormal returns on firm as well as deal characteristics. Waves were determined following Carow et al.'s (2004) approach. Regressions (1), (2), and (3) represent the definition of early movers as the first 25%, 33%, and 50%, respectively, and vice versa for late movers. A dot, one, two and three stars represent a 10%, 5%, 1% and 0.1% significance level, respectively. Numbers in parentheses indicate the respective standard error of the coefficient.

Variables	**(1)**	**(2)**	**(3)**
Dependent Var.:	CARs	CARs	CARs
Late mover	0.009. (0.004)	0.007 (0.006)	-0.005 (0.005)
Rel. size	-6.48e-5 (0.0002)	-5.59e-5 (0.0002)	-7.35e-5 (0.0002)
Log size	-0.003* (0.0010)	-0.003* (0.0010)	-0.003* (0.0009)
Same SIC	-0.0001 (5.66e-5)	-0.0001 (6e-5)	-0.0001 (5.74e-5)
Prior Transaction	-3.41e-5 (3.89e-5)	-3.57e-5 (3.93e-5)	-3.27e-5 (3.88e-5)
Debt ratio	-0.004 (0.005)	-0.004 (0.005)	-0.003 (0.005)
Market/Book	-0.001 (0.005)	-0.001 (0.005)	-0.001 (0.005)
Fixed-Effects:	------------------	------------------	------------------
Industry	Yes	Yes	Yes
Announcement Year	Yes	Yes	Yes
S.E.: Clustered	by: Industry	by: Industry	by: Industry
Observations	700	700	700
R2	0.08019	0.07920	0.07808
Within R2	0.02092	0.01987	0.01868

Table 8.11
Cross sectional regression analysis of cumulative abnormal returns on firm as well as deal characteristics. Waves were determined following Carow et al.'s (2004) approach. Regressions (1), (2), and (3) represent event windows of (-1;0), (-1;+1), and (-2;+2), respectively. A dot, one, two and three stars represent a 10%, 5%, 1% and 0.1% significance level, respectively. Numbers in parentheses indicate the respective standard error of the coefficient. Numbers in parentheses indicate the respective standard error of the coefficient.

Variables	**(1)**	**(2)**	**(3)**
Dependent Var.:	CARs	CARs	CARs
Late mover	0.009 (0.008)	0.002 (0.002)	-0.0009 (0.003)
Rel. size	-6.48e-5 (0.0003)	0.0007* (0.0002)	0.0007* (0.0002)
Log size	-0.003 (0.002)	-0.005* (0.001)	-0.005* (0.001)
Same SIC	-0.0001 (0.0001)	0.0002. (8.4e-5)	0.0002 (0.0001)
Prior Transaction	-3.41e-5 (4.82e-5)	-0.0002* (3.62e-5)	-0.0002** (3.44e-5)
Debt ratio	-0.004 (0.005)	-0.003 (0.007)	-0.005 (0.008)
Market/Book	-0.001 (0.006)	-0.001 (0.008)	-0.003 (0.007)
Fixed-Effects:	------------------	------------------	-------------------
Industry	Yes	Yes	Yes
Announcement Year	Yes	Yes	Yes
S.E.: Clustered	by: Industry	by: Industry	by: Industry
Observations	700	707	707
R2	0.08019	0.07556	0.08840
Within R2	0.02092	0.03612	0.03529