

Acquisitive and Organic Growth in Penrose's Theory: A Replication and Extension of Lockett, Wiklund, Davidsson, Girma (2011)

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Abstract

We replicate Lockett, Wiklund, Davidsson, and Girma's (LWDG) (2011) study, which draws on Penrose's theory to explicate how organic and acquisitive growth interact, using data from 128,368 Dutch firms (2011–2016). Our results confirm LWDG's finding that past organic growth negatively affects subsequent organic growth. However, unlike LWDG, reporting a positive association, we find that past acquisitive growth reduces subsequent organic growth. Extending LWDG's framework reveals that this effect turns positive over time, particularly for complementary acquisitions. While our findings align with Penrose's theory, they also provide a more nuanced understanding of the conditions under which acquisitive growth enhances organic growth.

Keywords

Penrose theory, firm growth, organic growth, acquisitions, replication

Introduction

Penrose's seminal work (Penrose, 1959) laid the foundations of the resource-based view and deepened our understanding of firm growth. Penrose explained that firms grow by leveraging resources to pursue new opportunities and enhance their “productive opportunity set” while managing the “adjustment costs” of the growth process. She predicted that organic growth rates slow over time due to limited managerial capacity and difficulties

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adapting administrative structures to support growth, a prediction known as the “Penrose Effect” (Marris, 1964).

While Penrose’s theory has become foundational in strategy and entrepreneurship research (Nason & Wiklund, 2018; Pitelis, 2009; Vidal & Mitchell, 2018), recent scholarship has questioned when and how strongly the Penrose Effect limits firm growth. Rather than viewing it as universally constraining, scholars argue that its impact varies based on managerial factors like attention allocation (Joseph & Wilson, 2018; Tidhar et al., 2025), organizational factors such as resource redeployment capabilities (Hietaniemi et al., 2024; Karim & Capron, 2016), strategic factors such as expansion rate and direction (Bort et al., 2025; Buckley & Casson, 2007), and environmental factors like firm-ecosystem dynamics (Jacobs & Lee, 2025; Pitelis, 2024).

Building on these contingent views, many researchers argue that acquisitive growth offers a way around continuous organic growth constraints. Through acquisitions, firms gain both novel resources and experienced management (Arikan & Stulz, 2016; Karim & Mitchell, 2000; Rios, 2021; Vermeulen & Barkema, 2001), a possibility Penrose herself acknowledged. Thus, acquisitions can help firms overcome internal growth bottlenecks by renewing their resource base.

One of the most systematic examinations of Penrose’s growth predictions was conducted by Lockett et al. (LWDG, 2011). Using data from 11,525 Swedish firms observed during 1987 to 1996, LWDG confirmed that past organic employment growth (henceforth: organic growth) constrains subsequent organic growth, consistent with Penrose’s theory.¹ They also demonstrated that acquisitive employment growth (henceforth: acquisitive growth) enhances subsequent organic growth, suggesting that acquisitions provide a way to escape the “growth deadlock” created by the Penrose Effect. This latter finding addresses an unresolved tension in Penrose’s theory: whether the productive opportunities gained from acquisitions outweigh their adjustment costs and thereby boost subsequent organic growth. Recently, Sivadasan et al. (2025) reported similar employment growth benefits from acquisitions among U.S. firms.

Despite LWDG’s important contribution, questions remain about the robustness and generalizability of these findings across different time periods and contexts (Bettis et al., 2016; Shepherd & Wiklund, 2009). LWDG themselves noted that modern firms face more severe external constraints than post-World War II firms, while acquisition-related adjustment costs may be more manageable than Penrose anticipated.

These insights suggest that Penrose’s theory may be “a product of her time” (LWDG, 2011, p. 49). Penrose’s framework reflected 1950s realities and couldn’t anticipate today’s environment. Contemporary firms operate in more integrated global markets with greater factor mobility. Digital technologies and platform business models have altered entrepreneurial scaling, enabling expansion with less proportional increases in administrative complexity (Amit & Han, 2017; Bort et al., 2025; Volberda et al., 2021). Modern markets for corporate control are more sophisticated (DeLong & DeYoung, 2007; Mirzayev et al., 2025; Schweizer et al., 2022), potentially altering acquisition-related adjustment costs. These structural transformations warrant a systematic examination of whether LWDG’s findings remain robust. Without such research, our knowledge may remain context-specific and fragmented (Bettis et al., 2016; Shepherd & Wiklund, 2009).

We address this need by replicating and extending LWDG’s framework using 144,705 Dutch firms from 2011 to 2019. The Netherlands, like Sweden, is a small, wealthy, open European economy, making it a suitable comparison. However, our context differs institutionally and structurally. Our sample captures firms operating after European integration

deepened and digitalization became widespread. Additionally, our sample captures smaller, younger, and more heterogeneous firms, with organic and acquisitive growth frequently co-occurring. Thus, we test whether LWDG's findings continue to hold in contemporary and different settings.

Our replication yields two key findings. First, we find that past organic growth constrains subsequent organic growth, confirming that the Penrose Effect remains robust across contexts. Second, we diverge from LWDG's finding that acquisitive growth immediately enhances organic growth. We find instead that acquisitions negatively affect subsequent organic growth, though this constraint is weaker than that imposed by past organic growth. Our analysis further suggests that this negative acquisition effect is stronger for smaller and younger firms. Because firms in our sample are, on average, smaller and younger than those in LWDG's and more frequently pursue organic and acquisitive growth simultaneously, we suspect that the negative acquisition effect reflects both the typically weaker acquisition capabilities of such firms and the strain of managing multiple growth trajectories concurrently.

Building on the insights from our replication, we extend LWDG's framework to further explore *when* and *for whom* acquisitive growth may alleviate rather than amplify Penrose Effect constraints. First, we identify a temporal pattern: while acquisitions initially suppress organic growth, acquisitions completed 2 to 4 years earlier significantly boost subsequent organic growth, suggesting that firms eventually overcome adjustment costs and realize an expanded productive opportunity set. Second, we find that moderately related acquisitions are most effective in driving subsequent organic growth, as acquisition targets in these cases bring sufficiently novel resources to expand productive opportunities while remaining similar enough to limit excessive adjustment costs. Finally, post-hoc analysis reveals that firms experiencing sustained growth benefit more from acquisitions, even though they face the same Penrose Effect constraints from past organic growth as other firms. Thus, acquisitive growth and the managerial capabilities it demands appear critical for firms that exhibit sustained high growth.

Our study advances cumulative knowledge on the process of firm growth by replicating LWDG's (2011) systematization of Penrose's theory and examining the interplay between organic and acquisitive growth (Coad et al., 2013; McKelvie & Wiklund, 2010; Moatti et al., 2015; Sivadasan et al., 2025). On the one hand, we confirm that the Penrose Effect remains a remarkably robust constraint on ongoing organic growth across time and institutional contexts: it holds across the settings in which Penrose developed her theory (1950s UK), LWDG tested it (1990s Sweden), and we reexamine it (2010s Netherlands), as well as across different firm groups within our sample. On the other hand, we reveal a highly contingent picture for acquisitive growth. Whereas LWDG found that acquisitions immediately break the "growth deadlock," we find that acquisitions initially suppress organic growth, and only bear fruit 2 to 4 years later. Moreover, the effects of acquisitive growth vary considerably across firms and deals, further illuminating its contingent nature. Together, these findings suggest that although acquisitive growth holds clear potential to revitalize organic growth, it does not universally alleviate the Penrose Effect. Rather, its effectiveness depends on how acquired resources relate to the acquirer and on the managerial capabilities the firm deploys (or lacks) to integrate and convert these resources into renewed productive opportunities.

Organic and Acquisitive Growth: A Summary of LWDG

In their paper, Lockett et al. (2011) propose a theoretical framework about the distinctive mechanisms through which previous organic and acquisitive growth strategies affect subsequent organic growth.

First, LWDG predict that past organic growth negatively relates to subsequent organic growth (Hypothesis 1). Firms growing organically tend to develop increasingly narrow routines (Nelson & Winter, 1982), become myopic in their opportunity search (Levinthal & March, 1993), and repeatedly exploit similar “close-in” resources. This makes them “simple and inert,” creating path-dependence (Sydow et al., 2009) and rigidities that hinder adaptation (Vermeulen & Barkema, 2001). Firms with high past growth rates may have already exploited the lower-hanging opportunities, having to search in more difficult and costly areas. By limiting the pool of opportunities (the “productive opportunity set”) a firm considers and seizes, past organic growth slows down the firm’s capacity to keep growing organically. This negative effect is amplified by putting strain on managerial resources such as the skills, time, and effort required to expand the firm’s management team, employment, and operations (the “adjustment costs”).

Second, while LWDG acknowledge that Penrose “never explicated how [acquisitive growth] would affect the firm’s ability to continue to expand organically” (p. 55), they utilize Penrosean theory to infer a connection between acquisitive and organic growth. They predict that past acquisitive growth positively affects subsequent organic growth because acquisitions expand a firm’s productive opportunity set more than adjustment costs constrain it (Hypothesis 2). Acquisitions bring non-path-dependent resources and knowledge that create new resource-combination possibilities unavailable through organic growth alone (Karim & Mitchell, 2000; Miller, 1993; Vermeulen & Barkema, 2001), particularly benefiting entrepreneurial firms with limited resource bases. For these firms, acquisitions can be seen as a deliberate attempt at entrepreneurial learning, enabling the acceleration of capability development. While acquisitive growth is not immune to adjustment costs,² LWDG argue that its impact on growth is outweighed by benefits stemming from the exploitation of new synergistic and growth opportunities (Geroski, 2005). Additionally, acquisitions can ease the challenge of managing growth by enabling the transfer of valuable managerial resources from the acquired to the acquiring firm (Graebner, 2004; Graebner et al., 2017).

LWDG tested this framework using a panel of 11,525 Swedish firms (1987–1996). The results confirmed their hypotheses: past organic growth constrains future organic growth, while past acquisitions revitalize it. This led LWDG to conclude that acquisitions help firms overcome Penrose Effect constraints because the productive opportunities they create outweigh the adjustment costs Penrose emphasized.

Extension of the LWDG Framework

To deepen our understanding of how acquisitive growth influences subsequent organic growth (LWDG’s Hypothesis 2), we extend LWDG’s framework by exploring *when* acquisitions alleviate versus amplify growth constraints arising from the Penrose Effect. Drawing on recent strategy and entrepreneurship research, developing a contingent view, we examine two aspects of acquisitive growth implicit in Penrose’s theory that LWDG did not formally test: (a) temporal effects and (b) acquisition relatedness. We contend that these factors can influence the balance between adjustment costs and productive opportunities in acquisitive growth.

Temporal Effects

We first examine how the temporal lag between acquisitive growth and organic growth affects their relationship. Temporal effects are increasingly recognized as crucial when evaluating strategic change events (e.g., Kunisch et al., 2017). We suspect that the balance between adjustment costs and productive opportunities may shift over time in the post-acquisition period. As Penrose herself noted, “integration [...] may potentially retard post-acquisition organic growth” (Penrose, 1959, p. 195). Effective exploitation of new opportunities is contingent upon the integration approach (Barkema & Schijven, 2008; Graebner et al., 2017; Larsson & Finkelstein, 1999; Zollo & Singh, 2004) and the redeployment of the acquired resources (Folta et al., 2016; Moatti et al., 2015). This is a “managerial problem” of resource integration and redeployment, which imposes adjustment costs (Penrose, 1959) on top of the direct costs of acquisitions. Indeed, acquisitive growth can make adjustment costs escalate in the short run because it is likely to add substantially more employees than gradual organic growth, overwhelming the organization’s integration capacity (Bort et al., 2025; Gjerløv-Juel & Guenther, 2019). That is, the organization may initially struggle to manage the substantial human resource integration following an acquisition and to establish new organizational routines.

Thus, we contend that the impact of past acquisitive growth on subsequent organic growth may be initially negative, driven by a surge in adjustment costs, and turn positive once the synergistic benefits set in and expand the productive opportunity (Feldman & Hernandez, 2022; Seth, 1990), more than compensating for the initial costs. To test whether the positive effect of acquisitive growth on subsequent organic growth takes some time to materialize, we leverage the longitudinal dimension of our panel dataset by introducing 2-, 3-, and 4-year lags for organic and acquisitive growth variables.

Relatedness in Acquisitive Growth

Next, we account for the extent of relatedness between the acquiring and acquired firms. Although Penrose recognized that acquisitions can provide an efficient path into new markets by reducing both entry costs and technical challenges, she emphasized that a firm’s existing resources constrain its ability to grow successfully through acquisitions. For example, when analyzing Hercules Powder Company’s growth path, she commented: “the kind of activity [it] moves into is usually related in some way to its existing resources” (Penrose, 1960, p. 2). However, Penrose explained that while expanding into similar markets reduces risk and integration costs, it also offers limited new opportunities to pursue. Therefore, firms may better revamp their growth prospects by acquiring targets that operate in different but related markets.

Since Penrose’s seminal contribution, subsequent research has advanced this work in different directions. Several studies have deepened our understanding of how the extent of relatedness between the acquiring and acquired firms impacts synergy and growth (Agarwal & Helfat, 2009; Vermeulen, 2005; Vermeulen & Barkema, 2001). Relatedness can be understood in two main ways. First, in terms of product markets, where related acquisitions involve buying firms in the same industry (horizontal) or along the supply chain (vertical), while unrelated acquisitions involve diversifying into different industries (Ahuja & Novelli, 2017; Schommer et al., 2019). Second, in terms of resource bases, where related resources are those that are either similar or complementary to each other, while unrelated resources are fundamentally different from each other (Makri et al., 2010; Miozzo et al., 2016; Zaheer et al., 2013).

M&A research shows that moderate relatedness between acquiring and target companies produces the strongest synergies (Feldman & Hernandez, 2022; Makri et al., 2010; Seth, 1990). The diversification literature further supports this finding, demonstrating that related diversification generates the highest performance improvements (Ahuja & Novelli, 2017). LWDG, themselves, argue that “it is complementarities and not similarities that create new opportunities for firms’ improved performance” (p. 54).

To understand more fully how acquisition relatedness affects subsequent organic growth, we must also consider how adjustment costs vary based on the relatedness between the acquiring and target companies. When relatedness is high (acquiring companies in similar markets or with similar resources), acquirers face expensive consolidation of overlapping assets (Zhou, 2011) and must adjust operations to eliminate redundancies (Conyon et al., 2002; Datta et al., 2010; Krishnan et al., 2007; O’Shaughnessy & Flanagan, 1998). When relatedness is low (acquiring companies in different markets or with dissimilar resources), acquirers usually struggle to integrate and redeploy these different assets (Ahuja & Katila, 2001; Makri et al., 2010). This difficulty stems from the acquirer’s limited absorptive capacity (Cohen & Levinthal, 1990; Zahra & George, 2002) and lack of relevant managerial experience for redeploying unfamiliar resources (Hietaniemi et al., 2024; Karim & Williams, 2012; Zaheer et al., 2013). Thus, moderate levels of relatedness enable sufficient understanding for effective resource integration and redeployment.

Therefore, we anticipate that firms benefit most from acquisitive growth when they can balance between expanding their productive opportunities against rising adjustment costs. This typically involves acquiring companies with moderately related rather than identical or completely different resource bases or market positions (Makri et al., 2010; Zaheer et al., 2013). Such acquisitions introduce enough novelty to stimulate learning while maintaining enough relatedness to preserve managerial control.

Methods

Calibration: Data and Sample

To ensure comparability with the original study, we closely follow LWDG’s research design, initially calibrating our analysis to replicate their empirical framework. Subsequent modifications to this initial design are then undertaken systematically and in a stepwise progression, allowing for a clear assessment of potential differences.

Our empirical investigation uses the General Annual Business Register (ABR) data from the Central Bureau of Statistics (CBS) Netherlands. The Register reports annual demographic information on all firms registered in the Netherlands and provides a comprehensive account of any events shaping firms’ life cycles (e.g., exits or acquisitions). These data are directly comparable with the data of LWDG, as they are census data from a European Statistical Office.

In defining the sample from the ABR, we replicate LWDG’s sampling criteria on the population of Dutch firms during the period 2011 to 2019. We consider private, commercially active firms, excluding those operating in the public sector in their last year (SBI 2-digit standard industry codes 84 and 99).³ As in LWDG, we build an unbalanced panel that includes firms that enter and exit during the period (except when they do so within the same year), and excludes those that dissolve. While dissolution is not formally defined by LWDG, we operationalize it as the “break-up” of firms into units continuing as independent firms with new identifiers (IDs). Finally, we drop all surviving firms that do not reach

the threshold of 20 employees in the final year of the panel and impose no other employment-level limit, fully in line with LWDG.

The ABR provides direct IDs for events that change a firm's identity, such as ownership changes, industry reclassifications, or spatial relocations, with event IDs linked to the IDs of firms involved. This feature represents an improvement over LWDG's original dataset, allowing us to consider firms rather than reconstructing firms by tracking portfolios of establishments.

In order to capture the employment growth dynamics of firms in the panel, LWDG combine the employment data available at the establishment level from the Census statistics for all the establishments that are part of a firm at a given time. Because employment data are not available from the ABR at the establishment level, we linked the ABR data to the Employer-Employee databases from the CBS,⁴ which trace the contractual relationship between each individual employee and the firm over time. This approach allows for a more accurate measurement of firm employment over time by aggregating individual-level data and accounting for employee mobility during events such as M&As.

Because the Business Register and the Employer-Employee database do not perfectly match, we exclude firms from the ABR with no employer-employee data. The final unbalanced panel considered in our analysis comprises 144,705 Dutch firms spanning 2011 to 2019.

The Study Context

Both Sweden (1987–1996) and the Netherlands (2011–2019) experienced economic turbulence and recovery during the respective study periods, though with some differences. Sweden experienced significant volatility with boom, crisis, and recovery. After solid growth in the late 1980s, a severe banking crisis hit in the early 1990s. Sweden implemented government intervention under the “Swedish model,” leading to rapid recovery by the mid-1990s and EU membership in 1995. Economic indicators averaged over the period: GDP per capita growth 0.87%, unemployment 4.64%, inflation 4.85%, and interest rates 9.93%.⁵

During 2011 to 2019, the Dutch economy gradually recovered from the 2007 to 2008 financial crisis and the 2010 European debt crisis. By 2019, GDP per capita had returned to 2008 levels after dropping to around 4% in both 2009 and 2013 (CBS, 2018). The recovery showed modest but steady growth with average annual indicators: GDP per capita growth 0.98%, unemployment 6.58%, inflation 1.66%, and interest rates 0.46%.

Both countries are advanced European economies that recovered from international financial crises, though neither period resembles the exceptional post-WWII growth that influenced Penrose's original theory. A key difference between the two countries is the institutional context: Sweden's economy operated relatively independently with its own currency during 1987 to 1996, while the Netherlands was fully EU-integrated using the Euro and benefiting from historically low interest rates. Dutch firms had access to pan-European markets, larger labor pools, and cross-border deal opportunities.

Replication: Variables and Models

Our initial analysis is based on the same variables as LWDG. We measure *Organic growth* as the difference in the log-transformed employment levels between the year-end and the beginning of each year, excluding employees added via acquisition.⁶ *Acquisitive growth* is

the natural logarithm of the number of acquired employees in a given year.⁷ In cases, where a firm performs multiple acquisitions or acquires multiple targets, we pool the number of all acquired employees across the deals. When identifying acquired employees, LWDG distinguish five types of establishments (p. 59): (a) Original; (b) Previously acquired; (c) Previously created; (d) Acquired in the current year; (e) Created in the current year. While we cannot allocate employees to establishments, we replicate this same partition considering employees who are: (a) already employed at the beginning of the year (either previously hired or acquired); (b) acquired during the year; (c) hired during the year (excluding those employees who stop working before the end of the year). Acquisitive growth is thus measured as the number of employees of target firm(s) (group 2) who begin working for the acquirer in the same month as the acquisition event.⁸

All control variables correspond to those of LWDG. *Size* is the number of employees, log-transformed. *Age* is the logarithm of the number of years since entry, truncated at 24 years. *Corporate* ownership is a dummy variable with value 1 when the firm is part of a group. *Foreign* ownership is a dummy variable with value 1 when the firm is in not owned by a Dutch entity. *Size squared* and *Age squared*, *Industry*⁹ and *Year dummies* are also included.

We employ the same model specification as in LWDG to model firm growth, estimated using firm-level fixed-effects OLS panel regression.¹⁰ It is specified as follows:

$$\text{OrganicGr}_{.it} = \alpha + \beta_1 \text{OrganicGr}_{.it-1} + \beta_2 \text{AcquisitiveGr}_{it-1} + \gamma' \text{Controls} + \delta' \text{Dummies} + \varepsilon_{it}$$

where the current rate of organic growth depends on both the organic and acquisitive growth rate in the previous period, plus a set of control variables.

In line with LWDG, we use a two-stage Heckman selection model to account for the selection bias introduced by firm exit (Heckman, 1979; Wooldridge, 1995). The dependent variable of the selection equation is a dummy *survival* with value 1 for surviving firms, and 0 otherwise. Explanatory variables are age, corporate ownership, and industry categorical variables, each with a value of one for a specific sector and zero otherwise. Unlike LWDG, we exclude firm size from the Probit due to high collinearity with the survival status, consistent with prior evidence that Dutch firms typically contract before exit (Cefis et al., 2020) and that firms with negative growth rates have high closure probabilities (Zhou & van der Zwan, 2019).¹¹ To match LWDG's framework as closely as possible, we replaced *size* with a set of categorical variables reporting the *quartiles* of firms' employment levels. This model is estimated for each year separately via Probit regressions. Table A2, Appendix A, reports the estimation results of the first stage. The inverse Mills ratio is then included as an additional covariate in the panel regression models with firm-level fixed effects.

Extension: Variables and Models

Our extension of LWDG includes the following additional independent variables. First, we account for *temporal dynamics* by introducing up to four lags for both organic and acquisitive growth.¹²

Second, we measure relatedness between acquiring and acquired firms using input-output (IO) trade flows data (see Ahern & Harford, 2014). This approach quantifies how industries are connected by examining the monetary value of products transferred from each supplying industry to each using industry. We use IO tables from the CBS

Table 1. Descriptive Statistics of Selected Variables.

LWDG original results					Replication				
Variable	Mean	Standard deviation	Min	Max	Variable	Mean	Standard deviation	Skewness	Kurtosis
Organic growth	0.054	0.352	-4.060	7.091	Organic growth	0.009	0.314	-0.409	43.216
Acquisitive growth	0.103	0.637	0.000	9.455	Acquisitive growth	0.034	0.303	11.618	164.453
Size	3.740	1.146	0.000	10.331	Size	2.608	1.612	0.532	2.851
Age	12.077	6.984	0.000	24.000	Age	11.347	8.497	0.417	1.632
N. observations	103,136				N. observations	613,336			
Acquisitive/organic growth ratio	1.91				Acquisitive/organic growth ratio	3.78			

Table 2. Cross-Tabulation of Organic and Acquisitive Growth Rates.

LWDG original results			Replication		
	No acquisitive growth year t	Acquisitive growth year t		No acquisitive growth year t	Acquisitive growth year t
No organic growth year t	32,177 (58.11%)	830 (57.60%)	No organic growth year t	228,951 (38.14%)	1,476 (11.32%)
Organic growth year t	23,193 (41.89%)	611 (42.40%)	Organic growth year t	371,320 (61.86%)	11,589 (88.68%)
Total	55,370 (100%)	1,441 (100%)	Total	600,271 (100%)	13,065 (100%)
No organic growth year $t-1$	32,717 (59.09%)	901 (62.53%)	No organic growth year $t-1$	221,965 (36.98%)	1,617 (12.38%)
Organic growth year $t-1$	22,653 (40.91%)	540 (37.47%)	Organic growth year $t-1$	378,306 (63.02%)	11,448 (87.62%)
Total	55,370 (100%)	1,441 (100%)	Total	600,271 (100%)	13,065 (100%)

Netherlands, which classify industries at the 2-digit SIC code level. Our analysis uses 2015 IO data, representing the midpoint of our 2011 to 2019 study period. To standardize the measure, we calculate trade flow values as a proportion of each industry's total output. For firms that acquired multiple targets in a year, we construct a weighted relatedness index, with each acquisition weighted by the share of employees acquired through that deal. We classify acquisitions into three categories based on the distribution of relatedness measures: *Unrelated* acquisitive growth: acquirer-target pairs in the first tertile; *Moderately related* acquisitive growth: pairs in the second tertile; *Highly related* acquisitive growth: pairs in the third tertile.

Results

Replication

Table 1 reports descriptive statistics for LWDG's sample and our study, while Table 2 compares the frequencies of firms experiencing organic and acquisitive growth between the two studies. As shown in Table 1, the samples differ substantially in composition and scale.

LWDG contains 103,136 observations from 11,525 firms (approximately nine observations per firm), while our sample has 613,336 observations from 144,705 firms (approximately 4.2 observations per firm). The shorter average tracking period in our sample partly reflects our 9-year observation window (ending in 2019, before the COVID outbreak) compared to LWDG's 10 years. However, these differences also reflect distinct market dynamics and institutional environments, as discussed below.

First, growth rates and patterns differ substantially. Our sample exhibits lower average growth rates (both organic and acquisitive) than LWDG. Nonetheless, acquisitive growth outpaces organic growth in both samples, though the ratio is higher in our study (3.78 vs. 1.91), indicating that firms in our sample rely more heavily on acquisitions relative to organic expansion. The standard deviation of organic growth is similar across samples, but our sample shows a lower standard deviation in acquisitive growth while simultaneously exhibiting more extreme distributions with high kurtosis. This combination suggests that while most firms pursued modest acquisitions, some firms occasionally engaged in very large acquisitions.

Second, firm characteristics reveal important compositional differences. Our average firm is substantially smaller (approximately 13 employees vs. 42 in LWDG) and younger (11.3 vs. 12.1 years). However, both variables show higher standard deviations in our sample, indicating greater heterogeneity. This broader dispersion captures a more dynamic and diverse population, combining mature incumbents with numerous young and small entrants. Smaller firms typically have fewer resources, face higher exit rates due to liability of newness, and engage in fewer acquisitions, helping explain the observed growth patterns.

Third, the samples reveal fundamentally different growth dynamics. As shown in Table 2, LWDG's sample represents a relatively stagnant population, with 58.1% of non-acquisitive firm-year observations exhibiting no organic growth. Moreover, acquisitive and organic growth appear to be independent: acquisitive observations are no more likely to exhibit organic growth (42.4%) than non-acquisitive observations (41.9%). In contrast, our sample comprises more growth-oriented observations, with organic growth prevalent among both non-acquisitive (61.9%) and acquisitive (88.7%) observations. Importantly, acquisitive and organic growth co-occur frequently in our sample: acquisitive observations are considerably more likely to also exhibit organic growth than non-acquisitive observations, suggesting complementarity rather than independence between growth modes.

These distinct firm growth patterns likely reflect the different macroeconomic environments we discussed earlier. Sweden's relatively high interest rates made financing expensive, favoring larger, established firms with internal resources. Limited market access prior to 1995 EU accession constrained the frequency of organic growth opportunities, explaining why LWDG's sample contains larger, more mature firms and why 58.1% of them exhibited stagnation. Conversely, the Netherlands' lower interest rates and full EU integration enabled smaller, younger firms to access cheap capital and pan-European markets. This combination fostered simultaneous organic and acquisitive expansion, explaining why the two growth modes co-occur so frequently in our sample.

Table 3 presents the results from replicating LWDG estimates. Descriptive statistics and the correlation matrix for variables included in these models are reported in Table A3 of Appendix A. As shown in Model 1, our results confirm LWDG's finding that prior *organic growth* exerts a restraining effect on subsequent organic growth ($\beta = -.440$; $p = .000$). However, contrary to LWDG, we find that past *acquisitive growth* also negatively affects subsequent organic growth ($\beta = -.013$; $p = .000$), although its impact appears smaller than that of organic growth. This result implies that a 10 percentage point increase in

Table 3. Regression Analysis, Replication.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Baseline	Small firms	Large firms	Young firms	Old firms	Squared gr.
Organic gr. [t-1]	-0.440*** (0.005) [0.000]	-0.498*** (0.008) [0.000]	-0.299*** (0.006) [0.000]	-0.539*** (0.007) [0.000]	-0.434*** (0.007) [0.000]	-0.444*** (0.005) [0.000]
Acquisitive gr. [t-1]	-0.013*** (0.002) [0.000]	-0.114*** (0.024) [0.000]	-0.010*** (0.002) [0.000]	-0.029*** (0.003) [0.000]	-0.007*** (0.002) [0.000]	-0.022*** (0.004) [0.000]
Organic gr. [t-1] sq.						0.034*** (0.003) [0.000]
Acquisitive gr. [t-1] sq.						0.003** (0.001) [0.016]
Size [t-1]	-0.424*** (0.009) [0.000]	-0.536*** (0.028) [0.000]	-0.359*** (0.013) [0.000]	-0.498*** (0.017) [0.000]	-0.406*** (0.011) [0.000]	-0.408*** (0.009) [0.000]
Size [t-1] sq.	0.006*** (0.002) [0.000]	0.021** (0.010) [0.027]	0.005*** (0.002) [0.004]	0.002 (0.004) [0.581]	0.008*** (0.002) [0.000]	0.007*** (0.002) [0.000]
Age	-0.064*** (0.007) [0.000]	0.013 (0.010) [0.185]	-0.065*** (0.010) [0.000]	-0.052*** (0.019) [0.006]	-0.017 (0.069) [0.807]	-0.059*** (0.007) [0.000]
Age sq.	0.032*** (0.002) [0.000]	0.034*** (0.005) [0.000]	0.024*** (0.003) [0.000]	0.021 (0.022) [0.351]	0.014 (0.013) [0.281]	0.029*** (0.002) [0.000]
Corporate	0.008 (0.008) [0.298]	-0.107** (0.052) [0.038]	0.011* (0.007) [0.093]	0.024 (0.018) [0.165]	0.003 (0.010) [0.799]	0.007 (0.008) [0.378]
Foreign	0.023*** (0.005) [0.000]	0.000 (0.023) [0.998]	0.020*** (0.004) [0.000]	-0.010 (0.012) [0.404]	0.028*** (0.006) [0.000]	0.022*** (0.005) [0.000]
Selection, survival	0.059*** (0.002) [0.000]	0.057*** (0.001) [0.000]	0.092*** (0.003) [0.000]	0.066*** (0.002) [0.000]	0.055*** (0.002) [0.000]	0.059*** (0.002) [0.000]
Constant	0.940*** (0.013) [0.000]	0.398*** (0.020) [0.000]	1.118*** (0.025) [0.000]	0.940*** (0.018) [0.000]	1.016*** (0.088) [0.000]	0.896*** (0.013) [0.000]
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes
N. observations	613,336	275,158	338,178	274,998	338,338	613,336
N. firms	144,705	97,396	58,669	99,168	70,376	144,705
R ²	0.173	0.164	0.108	0.251	0.143	0.177
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	750.1	52,638	18,410	8,904	18,068	2,218

Note. Robust standard errors in round brackets; *p*-values in squared brackets.

Small firms are firms with size below the median value (2.398), while large firms are firms with size above or equal the median. Young firms are firms with age below the median value (8), while old firms are firms with age above or equal to the median value.

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

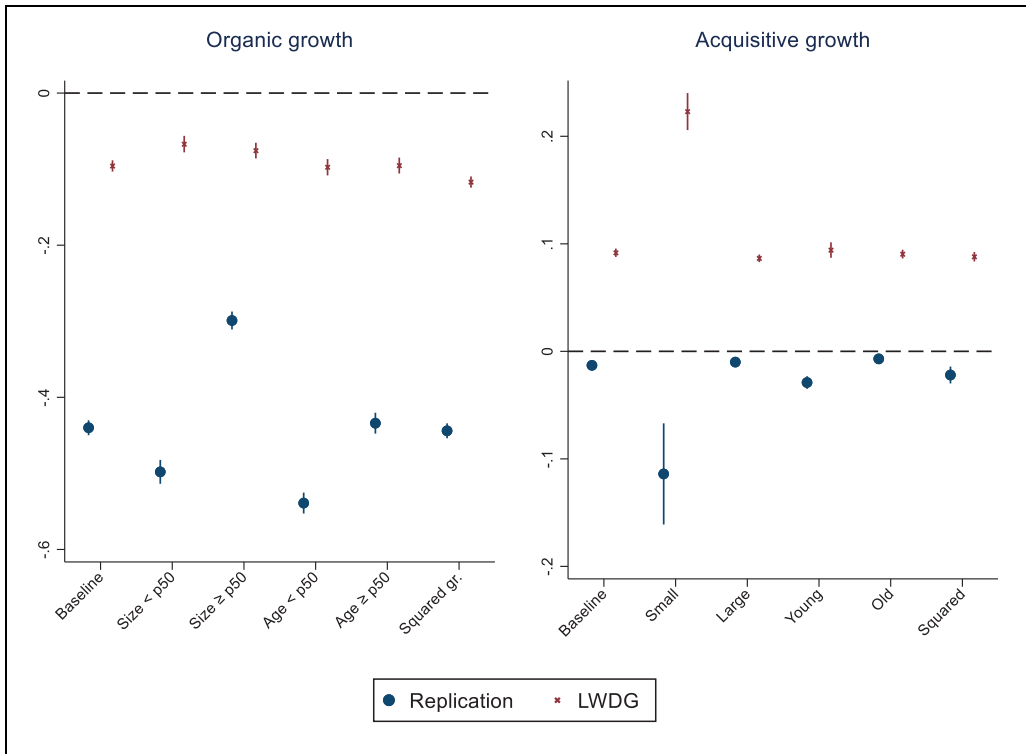


Figure 1. Plot of organic and acquisitive growth coefficients, LWDG original results, and replication.
 Note. LWDG = Lockett, Wiklund, Davidsson, and Girma.

acquisitive growth decreases subsequent organic growth rate by 0.09 percentage points (in contrast to LWDG, where the corresponding effect is an increase of 0.84 percentage points).¹³ Figure 1 displays these results by plotting the coefficients for the two growth variables alongside LWDG's results for comparison.

Next, we replicate LWDG's sensitivity analysis. We observe that the effect of organic growth is fairly stable across different subgroups of firms when firms are split by size (Models 2 and 3) and age (Models 4 and 5). It is noticeable, however, that acquisitive growth has a much stronger negative impact on organic growth for younger firms (Model 4) and a somewhat more negative one for smaller firms (Model 2). Given prior evidence that such firms typically lack the in-house expertise and systematized processes for effective acquisition integration (Graebner et al., 2017; King et al., 2021), the smaller average firm age and size in our sample compared to LWDG's help explain our contrasting finding regarding the effect of acquisitive growth. We also find that both organic and acquisitive growth have curvilinear effects, as indicated by the positive coefficients on the squared terms in Model 6. However, our data captures only the declining portion of the *U*-shaped curve (see Appendix Figures A1 and A2).

Regarding control variables, their coefficients are broadly consistent with LWDG, with minor differences. Unlike in the original paper, the *foreign* and *corporate* ownership variables have significant coefficients. Nonetheless, because of firm-level fixed effects, they capture switches between such categories and, therefore, non-systematic effects.

Robustness Checks

We performed additional analyses to test the robustness of our results and to better understand whether sample differences explain the different results about the effects of acquisitive growth. First, we investigate whether ownership and sectoral differences between samples explain differences in the role of acquisitive growth. We dropped holding companies and public sector firms from our overall sample, and replaced LWDG's sectoral categories with SBI 2-digit codes and technological sectors (see Models 1–4 of Table 4). We also re-estimate our baseline model separately for Manufacturing, Services, and Other sectors subsamples (see Appendix Table A4).

Second, we examine whether our results are robust to differences in firm-level characteristics between our sample and LWDG's. We incrementally expanded the covariates in our baseline model by considering non-truncated firm age and adding number of establishments, limited-liability company status, and whether firms experienced ID-changing events (see Model 5–7 of Table 4).

Third, to account for differences in external growth opportunities faced by firms, we introduced proxies for birth share, capturing the share of greenfield entries; exit share, measured as the share of firm closures; and share of firms introducing new-to-market innovations. These variables are measured for each sector (SBI 2-digit) and each region (NUTS 1-digit) in each year (see Model 8 of Table 4).

Fourth, we investigate whether differences in acquisitive growth's role stem from firms' selection into this strategy. We implemented a double-selection model (Catsiapis & Robinson, 1982) that enabled us to control for acquisition decisions. This approach estimates an additional selection equation with an acquisition dummy as the dependent variable, deriving a second inverse Mills ratio that is added to the panel regression. As an exclusion restriction, we considered the share of acquirers in the same region and industrial sector, arguing that this influences acquisition likelihood through bandwagon effects but doesn't systematically affect focal firm organic growth rates. First-stage probit results (Appendix Table A5) confirm this exclusion restriction's appropriateness. To better capture firms' acquisition strategy, we include three indicators: (a) whether the firm acquires more than two targets within a given year, (b) whether the firm executes more than two acquisition events in the same year, and (c) the firm's acquisition experience, proxied by the cumulative number of acquisitions over the prior 5 years (see Models 9–11 of Table 4). These variables distinguish the scale and frequency of acquisitive activity from accumulated integration experience, which may differentially shape post-acquisition organic growth.

Finally, we vary the measurement intervals for organic and acquisitive growth. Specifically, we examined 1-, 2-, 3-, and 4-year periods rather than annual growth rates alone (results from this analysis are available upon request).

All the results from these analyses confirm that our main findings remain unchanged: both past organic growth and past acquisitive growth are negatively associated with subsequent organic growth.

LWDG Extended Framework

Table 5 presents two extensions of LWDG's framework: a longer lag structure and acquisition relatedness. Models 1 to 4 incrementally extend the lag structure, testing acquisitive growth effects at 1-, 2-, 3-, and 4-year lags. The results consistently support the negative effect of past organic growth. In all multi-year specifications (Models 2–4), lagged organic

Table 4. Regression Analysis, Robustness Checks.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
	No holdings	No public	SBI08 2-digit	Technological sectors	Local units	Legal form	ID event	Environment	>2 targets	>2 acquisition events	Acquisition experience
Organic gr. [t-1]	-0.453*** (0.005)	-0.464*** (0.006)	-0.464*** (0.006)	-0.464*** (0.006)	-0.469*** (0.006)	-0.469*** (0.006)	-0.469*** (0.006)	-0.469*** (0.006)	-0.380*** (0.017)	-0.380*** (0.017)	-0.380*** (0.017)
Acquisitive gr. [t-1]	-0.009*** (0.002)	-0.010*** (0.002)	-0.009*** (0.002)	-0.009*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)	-0.013*** (0.002)	-0.013*** (0.002)	-0.013*** (0.002)
Size [t-1]	-0.429*** (0.009)	-0.431*** (0.009)	-0.429*** (0.009)	-0.429*** (0.009)	-0.426*** (0.009)	-0.427*** (0.009)	-0.427*** (0.009)	-0.428*** (0.009)	-0.297*** (0.020)	-0.297*** (0.020)	-0.297*** (0.020)
Size [t-1] squared	0.006*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	-0.005** (0.003)	-0.005** (0.003)	-0.005** (0.003)
Age	-0.099*** (0.009)	-0.109*** (0.010)	-0.222*** (0.016)	-0.223*** (0.016)	-0.227*** (0.016)	-0.226*** (0.016)	-0.226*** (0.016)	-0.227*** (0.016)	-0.178*** (0.050)	-0.178*** (0.050)	-0.178*** (0.050)
Age ²	0.038*** (0.003)	0.042*** (0.003)	0.094*** (0.006)	0.095*** (0.006)	0.096*** (0.006)	0.096*** (0.006)	0.096*** (0.006)	0.097*** (0.006)	0.073*** (0.018)	0.073*** (0.018)	0.073*** (0.018)
Group	0.011 (0.008)	0.002 (0.009)	0.002 (0.009)	0.002 (0.009)	0.008 (0.009)	0.008 (0.009)	0.009 (0.009)	0.009 (0.009)	0.006 (0.016)	0.006 (0.016)	0.006 (0.016)
Foreign	[0.161] (0.028***)	[0.794] (0.030***)	[0.813] (0.029***)	[0.849] (0.029***)	[0.372] (0.029***)	[0.364] (0.028***)	[0.362] (0.029***)	[0.343] (0.028***)	[0.704] (0.014)	[0.694] (0.014)	[0.707] (0.014)
In(establishments)	(0.005) (0.000)	(0.005) (0.000)	(0.005) (0.000)	(0.005) (0.000)	(0.005) (0.000)	(0.005) (0.000)	(0.005) (0.000)	(0.005) (0.000)	(0.011) (0.218)	(0.011) (0.216)	(0.011) (0.223)
Limited liability					0.140*** (0.006)	0.137*** (0.006)	0.137*** (0.006)	0.138*** (0.006)	0.121*** (0.010)	0.121*** (0.010)	0.120*** (0.010)
					[0.000]	[0.000]	[0.000]	[0.000]	-0.094** (0.037)	-0.094** (0.037)	-0.094** (0.037)
					[0.000]	[0.000]	[0.000]	[0.000]	[0.011]	[0.012]	[0.012]

(continued)

Table 4. (continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
	No holdings	No public	SBI08 2-digit	Technological sectors	Local units	Legal form	ID event	Environment	>2 targets	>2 acquisition events	Acquisition experience
ID event							0.053** (0.026) [0.043]	0.053** (0.026) [0.043]	0.060 (0.074) [0.415]	0.060 (0.074) [0.418]	0.060 (0.074) [0.416]
Births share							0.015 (0.029) [0.600]	0.015 (0.029) [0.600]	-0.018 (0.056) [0.748]	-0.018 (0.056) [0.749]	-0.017 (0.056) [0.756]
Exits share							0.024 (0.026) [0.353]	0.024 (0.026) [0.353]	0.013 (0.067) [0.840]	0.014 (0.067) [0.834]	0.013 (0.067) [0.844]
Share inno, new to market							0.063*** (0.010) [0.000]	0.063*** (0.010) [0.000]	0.041 (0.026) [0.109]	0.041 (0.026) [0.111]	0.041 (0.026) [0.109]
>2 targets [t-1]							-0.003 (0.010) [0.790]	-0.003 (0.010) [0.790]	-0.009 (0.011) [0.390]	-0.009 (0.011) [0.390]	-0.010 (0.011) [0.354]
>2 acquisitions [t-1]									0.034** (0.017) [0.047]	0.034** (0.017) [0.047]	0.032* (0.017) [0.059]
Acquisition experience [t-1]											0.014 (0.009) [0.129]
Selection, survival	0.071*** (0.002) [0.000]	0.078*** (0.002) [0.000]	0.077*** (0.002) [0.000]	0.077*** (0.002) [0.000]	0.076*** (0.002) [0.000]	0.076*** (0.002) [0.000]	0.076*** (0.002) [0.000]	0.076*** (0.002) [0.000]	0.011 (0.011) [0.346]	0.011 (0.012) [0.344]	0.011 (0.012) [0.342]
Selection, acquisition									-0.365*** (0.045) [0.000]	-0.365*** (0.045) [0.000]	-0.361*** (0.045) [0.000]
Constant	1.092*** (0.017) [0.000]	1.099*** (0.018) [0.000]	1.026*** (0.034) [0.000]	0.992*** (0.032) [0.000]	0.879*** (0.033) [0.000]	0.853*** (0.033) [0.000]	0.852*** (0.033) [0.000]	0.816*** (0.034) [0.000]	1.037*** (0.115) [0.000]	1.037*** (0.115) [0.000]	1.039*** (0.115) [0.000]

(continued)

Table 4. (continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
	No holdings	No public	SBI08 2-digit	Technological sectors	Local units	Legal form	ID event	Environment	>2 targets	>2 acquisition events	Acquisition experience
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N observations	506,926	407,407	407,407	407,407	407,407	407,407	407,407	407,181	49,725	49,725	49,725
N firms	110,868	87,896	87,896	87,896	87,896	87,896	87,896	87,885	7,082	7,082	7,082
R ²	0.175	0.180	0.180	0.180	0.184	0.184	0.184	0.184	0.151	0.151	0.151
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-26,661	-29,976	-29,831	-29,908	-29,048	-29,025	-29,010	-28,924	-7,424	-7,422	-7,421

Note. Robust standard errors in round brackets; p-values in squared brackets.

ID = identity.

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

Table 5. Regression Analysis, Extension: Temporal Effects and Acquisition Relatedness.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Temporal effects, lag 1	Temporal effects, lag 1-2	Temporal effects, lag 1-3	Temporal effects, lag 1-4	Relatedness, lag 1	Relatedness, lag 1-2	Relatedness, lag 1-3	Relatedness, lag 1-4
Organic gr. [t-1]	-0.440*** (0.005) [0.000]	-0.442*** (0.006) [0.000]	-0.454*** (0.007) [0.000]	-0.466*** (0.008) [0.000]	-0.440*** (0.005) [0.000]	-0.442*** (0.006) [0.000]	-0.454*** (0.007) [0.000]	-0.466*** (0.008) [0.000]
Organic gr. [t-2]		-0.031*** (0.003) [0.000]	-0.064*** (0.005) [0.000]	-0.130*** (0.007) [0.000]		-0.031*** (0.003) [0.000]	-0.064*** (0.005) [0.000]	-0.130*** (0.007) [0.000]
Organic gr. [t-3]			-0.039*** (0.004) [0.000]	-0.092*** (0.006) [0.000]			-0.040*** (0.004) [0.000]	-0.092*** (0.006) [0.000]
Organic gr. [t-4]				-0.051*** (0.004) [0.000]				-0.051*** (0.004) [0.000]
Acquisitive gr. [t-1]	-0.013*** (0.002) [0.000]	-0.008*** (0.002) [0.000]	-0.005** (0.002) [0.016]	-0.003 (0.003) [0.203]				
Acquisitive gr. [t-2]		0.014*** (0.002) [0.000]	0.017*** (0.002) [0.000]	0.018*** (0.003) [0.000]				
Acquisitive gr. [t-3]			0.010*** (0.002) [0.000]	0.011*** (0.003) [0.000]				
Acquisitive gr. [t-4]				0.008*** (0.003) [0.005]				
Unrelated acq. gr [t-1]					-0.010*** (0.002) [0.000]	-0.006** (0.003) [0.019]	-0.006** (0.003) [0.029]	-0.005 (0.003) [0.187]
Unrelated acq. gr [t-2]						0.014*** (0.002) [0.000]	0.016*** (0.003) [0.000]	0.016*** (0.003) [0.000]

(continued)

Table 5. (continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Temporal effects, lag 1	Temporal effects, lag 1-2	Temporal effects, lag 1-3	Temporal effects, lag 1-4	Relatedness, lag 1	Relatedness, lag 1-2	Relatedness, lag 1-3	Relatedness, lag 1-4
Unrelated acq. gr. [t-3]							0.006** (0.003) [0.049]	0.007* (0.004) [0.093]
Unrelated acq. gr. [t-4]								0.008** (0.004) [0.039]
Moderately related acq. gr. [t-1]					-0.019*** (0.004) [0.000]	-0.011** (0.005) [0.031]	-0.004 (0.006) [0.464]	0.000 (0.008) [0.958]
Moderately related acq. gr. [t-2]						0.012*** (0.004) [0.005]	0.017*** (0.005) [0.001]	0.021*** (0.007) [0.003]
Moderately related acq. gr. [t-3]							0.016*** (0.005) [0.004]	0.021** (0.008) [0.011]
Moderately related acq. gr. [t-4]								0.014* (0.007) [0.060]
Highly related acq. gr. [t-1]					-0.013*** (0.003) [0.000]	-0.009*** (0.003) [0.004]	-0.004 (0.003) [0.233]	-0.003 (0.004) [0.355]
Highly related acq. gr. [t-2]						0.015*** (0.003) [0.000]	0.018*** (0.004) [0.000]	0.019*** (0.005) [0.000]
Highly related acq. gr. [t-3]							0.014*** (0.003) [0.000]	0.013*** (0.004) [0.001]
Highly related acq. gr. [t-4]								0.005 (0.004) [0.268]

(continued)

Table 5. (continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Temporal effects, lag 1	Temporal effects, lag 1-2	Temporal effects, lag 1-3	Temporal effects, lag 1-4	Relatedness, lag 1	Relatedness, lag 1-2	Relatedness, lag 1-3	Relatedness, lag 1-4
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection, survival	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N observations	613,336	468,631	354,764	262,425	613,336	468,631	354,764	262,425
N firms	144,705	113,867	92,339	71,387	144,705	113,867	92,339	71,387
R ²	0.173	0.158	0.160	0.164	0.173	0.158	0.160	0.164
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	750.1	15,593	24,675	25,665	753.5	15,594	24,680	25,672

Note. Robust standard errors in round brackets; p-values in squared brackets.

Control variables are the same as in Model 1, Table 3.

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

growth coefficients remain negative and significant. Model 4 illustrates this pattern clearly: organic growth exhibits negative effects that decline over time ($t-1$: $\beta = -.466$; $t-2$: $\beta = -.130$; $t-3$: $\beta = -.092$; $t-4$: $\beta = -.051$; all $p < .001$). These findings reinforce the prediction that past organic growth constrains subsequent organic growth.

A more complex picture emerges with acquisitive growth. Although the coefficient for acquisitive growth in year $t-1$ remains statistically significant and negative, it becomes significantly positive and larger in absolute value in year $t-2$ (Model 2). Similarly, the coefficients of acquisitive growth in years $t-2$ and $t-3$ are positive and statistically significant (Model 3). These relationships are confirmed in the full model (Model 4), where the coefficients of the lags of acquisitive growth after $t-1$, are all positive and significant ($t-2$: $\beta = .018$, $p = .000$; $t-3$: $\beta = .011$, $p = .000$; $t-4$: $\beta = .008$, $p = .005$). Model 4 indicates that, over the 4-year period, a 10 percentage point increase in acquisitive growth raises subsequent organic growth by 0.21 percentage points.¹⁴ This effect remains smaller than LWDG's baseline estimate (0.84), likely because firms in our sample make, on average, much smaller acquisitions than firms in LWDG's sample. This means that a given percentage increase in acquisitive growth corresponds to fewer acquired employees. With fewer new employees integrated, the potential to stimulate subsequent organic growth is correspondingly smaller.

Models 5 to 8 decompose acquisitive growth into unrelated, moderately related, and highly related components, along with the 4-year lag structure. Model 5 shows that all three types of acquisitive growth have immediate negative effects on organic growth (unrelated: $\beta = -.010$, $p = .000$; moderately related: $\beta = -.019$, $p = .000$; highly related: $\beta = -.013$, $p = .000$, respectively). However, this picture changes when we extend the analysis beyond the first year. With a 2-year lag (Model 6), all three acquisitive growth types show comparable positive effects in year $t-2$. As we extend to 3-year lags (Model 7), all three types show positive effects in both year $t-2$ acquisitive growth (unrelated: $\beta = .016$, $p = .000$; moderately related: $\beta = .017$, $p = .001$; highly related: $\beta = .018$, $p = .000$) and $t-3$ acquisitive growth, albeit moderately related acquisitive growth appears to have the most considerable effect (unrelated: $\beta = .006$, $p = .049$; moderately related: $\beta = .016$, $p = .004$; highly related: $\beta = .014$, $p = .000$, respectively). The outperformance of moderately related acquisitive growth among the other two types is confirmed in Model 8, where all four lags are considered ($\beta = .000$, $p = .958$ in $t-1$; $\beta = .021$, $p = .003$ in $t-2$; $\beta = .021$, $p = .011$ in $t-3$; $\beta = .014$, $p = .060$ in $t-4$).

Overall, the results from the extended analysis support our theoretical arguments that acquisitive growth exerts a delayed, positive effect on organic growth. They also confirm that moderately related acquisitive growth is more effective than unrelated or highly related growth in triggering subsequent organic growth.

Additional Robustness Checks

Following our earlier analysis (Appendix Table A5), we investigate whether the results in Table 5 are sensitive to firms' selection into the acquisitive growth strategy. We thus reran the analysis using a double-selection Heckman model that accounts for both survival-related selection and firms' choices between organic and acquisitive growth, as well as additional covariates that capture firm-level characteristics, differences in external growth opportunities, and firms' acquisition strategy. The results, presented in Appendix Table A6, are fully consistent with our main findings.

Next, we examine the sensitivity of the analysis to the specific dependent variable employed. As discussed, we measure firms' organic growth using the number of employees, which is one of the most widely used firm-size proxies (Coad et al., 2013; Josefy et al., 2015). This ensures consistency with LWDG and more direct comparability of results.¹⁵ This is also theoretically appropriate for testing Penrose's predictions, given that Penrose states that her theory concerns the expansion of "human and other resources" (Penrose, 1959). Additionally, using an employee count offers practical measurement advantages in our dataset. It allows for a more precise mapping of post-acquisition combined employee count, and employee data are measured twice annually (at the beginning and end of the year), enabling within-year growth calculations. Nonetheless, we recognize the value of examining whether our findings hold for other outcomes that entrepreneurs and investors may prioritize (Achtenhagen et al., 2010), particularly the effect of (acquisitive) growth on the bottom line. Therefore, we conduct robustness checks using a proxy for profit (net income) growth¹⁶ as an alternative dependent variable (see Appendix Table A7). The results are broadly consistent with our main findings. However, the positive effect of acquisitive growth on profit growth does not emerge until the fourth post-acquisition year. This finding is in line with prior evidence that profit growth lags employment growth (e.g., Coad, 2010).

Post-hoc Analysis

We conduct a post-hoc analysis of high-growth firms in our sample to better understand whether their high organic growth rates are associated with prior acquisitive growth. This is an important question because, unlike firms in Penrose's era that grew gradually over decades, many contemporary firms demonstrate sustained, extraordinary growth rates since their early years. These modern firms can exploit mechanisms unavailable in Penrose's era: digital platforms enable instant global reach, cloud computing eliminates infrastructure bottlenecks, global talent markets provide skilled workers, and readily available risk capital supports rapid scaling (Hanelt et al., 2021; Warner & Wäger, 2019).

These environmental shifts may have relaxed Penrose's growth constraints, particularly regarding acquisitive growth, given the increasing sophistication of modern markets for corporate control (DeLong & DeYoung, 2007; Mirzayev et al., 2025; Schweizer et al., 2022). While short-term adjustment costs likely persist, high-growth firms (HGFs) may be better positioned to leverage acquisitive growth to generate subsequent organic growth. Therefore, we examine the extent to which the observed extraordinary growth rates of some firms are systematically associated with past acquisitive growth.

To identify HGFs, we follow closely the Eurostat-OECD definition and consider firms with an average annualized growth rate of at least 20% over three consecutive years in either employees or turnover, and with at least 10 employees in the first year (Eurostat-OECD, 2007, p. 61).

Table 6 reports regression results from re-estimating our baseline model separately for HGFs (Models 1–4) and non-HGFs (Models 5–8) to examine whether HGFs benefit more from acquisitions. For HGFs, the coefficient for acquisitive growth is negative and significant only at $t-1$ in Model 1. Models 2 to 4, which introduce time lags incrementally, reveal that HGFs experience a significantly positive effect of acquisitive growth on subsequent organic growth. In the full model (Model 4), the coefficients are $\beta = -.005$ ($p = .137$) in $t-1$; $\beta = .031$ ($p = .000$) in $t-2$; $\beta = .015$ ($p = .003$) in $t-3$; and $\beta = .012$ ($p = .019$) in

Table 6. Regression Analysis, Post-Hoc: Firm Growth Dynamics.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	HGF, lag 1	HGF, lag 1-2	HGF, lag 1-3	HGF, lag 1-4	No-HGF, lag 1	No-HGF, lag 1-2	No-HGF, lag 1-3	No-HGF, lag 1-4
Organic gr. [t-1]	-0.406*** (0.009) [0.000]	-0.413*** (0.011) [0.000]	-0.441*** (0.012) [0.000]	-0.458*** (0.014) [0.000]	-0.498*** (0.006) [0.000]	-0.496*** (0.008) [0.000]	-0.502*** (0.009) [0.000]	-0.504*** (0.011) [0.000]
Organic gr. [t-2]		-0.007 (0.005) [0.179]	-0.039*** (0.007) [0.000]	-0.096*** (0.010) [0.000]		-0.026*** (0.005) [0.000]	-0.057*** (0.007) [0.000]	-0.130*** (0.011) [0.000]
Organic gr. [t-3]			-0.027*** (0.005) [0.000]	-0.072*** (0.008) [0.000]			-0.031*** (0.006) [0.000]	-0.088*** (0.009) [0.000]
Organic gr. [t-4]				-0.039*** (0.006) [0.000]				-0.048*** (0.007) [0.000]
Acquisitive gr. [t-1]	-0.013*** (0.003) [0.000]	-0.008*** (0.003) [0.003]	-0.006** (0.003) [0.035]	-0.005 (0.003) [0.137]	-0.034*** (0.003) [0.000]	-0.027*** (0.004) [0.000]	-0.021*** (0.004) [0.000]	-0.015*** (0.004) [0.001]
Acquisitive gr. [t-2]		0.024*** (0.003) [0.000]	0.028*** (0.003) [0.000]	0.031*** (0.004) [0.000]		0.009*** (0.003) [0.003]	0.010*** (0.003) [0.003]	0.008* (0.004) [0.051]
Acquisitive gr. [t-3]			0.013*** (0.004) [0.001]	0.015*** (0.005) [0.003]			0.007** (0.003) [0.039]	0.008* (0.004) [0.062]
Acquisitive gr. [t-4]				0.012** (0.005) [0.019]				0.012*** (0.004) [0.001]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection, survival	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N observations	115,597	99,394	83,191	67,275	451,479	330,710	240,018	169,950
N firms	16,203	16,203	15,916	15,299	120,769	90,692	70,068	50,269
R ²	0.216	0.196	0.204	0.204	0.192	0.176	0.173	0.174
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-24,281	-15,640	-8,293	-3,244	45,179	44,710	41,872	35,065

Note. Robust standard errors in round brackets; *p*-values in squared brackets.

Control variables are the same as in Model 1, Table 3.

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

t-4. These coefficients are consistently larger and positive than the corresponding coefficients for non-HGFs across all the lags beyond *t*-1.

Overall, these results imply that HGFs may possess superior acquisitive growth capabilities, enabling them to leverage acquisitive growth more effectively than other firms to drive subsequent organic growth. Table 7 summarizes the predictions of the original and extended theoretical frameworks, along with a comparison of the corresponding empirical findings.

Table 7. Summary of Predictions and Empirical Findings.

Replication: Testing LWDG hypotheses				
Hypotheses	Estimates		Results	
	LWDG	Our study		
H1: The greater the rate of organic growth in previous periods, the lower the rate of organic growth in the current period	$\beta_{lag1} = -0.096^{***}$	$\beta_{lag1} = -0.440^{***}$	H1 is supported in both studies with evidence of a stronger effect in our study.	
H2: The greater the rate of acquisitive growth in previous periods, the lower the rate of organic growth in the current period	$\beta_{lag1} = 0.092^{***}$	$\beta_{lag1} = -0.013^{***}$	H2 is supported in LWDG but is not supported in our study, finding an effect of opposite sign than LWDG.	
Extension: Exploring boundary conditions to the assumption underpinning LWDG's H2 that the (positive) effect of an expanded POS through acquisitive growth is greater than the (negative) effect of the increased AC, i.e., $ AC < POS $				
<i>Temporal dynamics</i> $ AC < POS $ only after a certain period after acquisitive growth		$\beta_{lag1} = -0.003$ $\beta_{lag2} = 0.018^{***}$ $\beta_{lag3} = 0.011^{***}$ $\beta_{lag4} = 0.008^{***}$	H2 is supported for longer than 1-year delayed effect	
<i>Relatedness</i> $ AC < POS $ conditionally on the relatedness of acquisitive growth	Unrelated $\beta_{lag1} = -0.005$ $\beta_{lag2} = 0.016^{***}$ $\beta_{lag3} = 0.007^*$ $\beta_{lag4} = 0.008^{**}$	Moderately related $\beta_{lag1} = 0.000$ $\beta_{lag2} = 0.021^{***}$ $\beta_{lag3} = 0.021^{**}$ $\beta_{lag4} = 0.014^*$	Highly related $\beta_{lag1} = -0.003$ $\beta_{lag2} = 0.019^{***}$ $\beta_{lag3} = 0.013^{***}$ $\beta_{lag4} = 0.005$	H2 is supported more strongly when acquisitive growth is moderately related
<i>Post-hoc analysis:</i> <i>Firm growth dynamics</i> $ AC < POS $ conditionally on firm-specific growth capabilities	High-growth $\beta_{lag1} = -0.005$ $\beta_{lag2} = 0.031^{***}$ $\beta_{lag3} = 0.015^{***}$ $\beta_{lag4} = 0.012^{**}$	Non-high-growth $\beta_{lag1} = -0.015^{***}$ $\beta_{lag2} = 0.008^*$ $\beta_{lag3} = 0.008^*$ $\beta_{lag4} = 0.012^{***}$	H2 is supported more strongly for high-growth firms	

Note. AC = adjustment costs; LWDG = Lockett, Wiklund, Davidsson, and Girma; POS = productive opportunity set.
 $^{***}p < .01$. $^{**}p < .05$. $^*p < .1$.

Discussion

This study contributes to research on the process of firm growth by explicating how the interplay between organic and acquisitive growth shapes firms' future growth trajectories. Our research advances cumulative knowledge by replicating and extending LWDG's (2011) systematization of Penrose's growth theory across different time periods and institutional contexts, thereby testing the robustness and generalizability of their framework (Bettis et al., 2016; Shepherd & Wiklund, 2009).

Regarding organic growth, we confirm Penrose's core prediction by demonstrating that the Penrose Effect remains a fundamental constraint on continuous organic growth: as firms expand, organizational efficiency deteriorates because management cannot address emerging problems quickly enough, creating a natural ceiling on sustainable growth rates. This finding is particularly notable given the considerably different contexts in which

Penrose developed her theory (1950s UK), LWDG tested it (1990s Sweden), and we reexamine it (2010s Netherlands), and it holds across different firm groups within our sample. Nevertheless, this consistency should not be interpreted as evidence that little has changed over time. Instead, it likely reflects the co-evolution of countervailing forces. On the one hand, significant advances in organizational practices and information-processing technologies have likely reduced the adjustment costs of growth in modern firms (Hanelt et al., 2021). On the other hand, hypercompetitive market conditions may have simultaneously restricted the growth opportunities available to firms (D'Aveni & Gunther, 1994; Rindova & Kotha, 2001), maintaining the fundamental constraint on growth rates—particularly in employment (Barkai & Panageas, 2025)—as LWDG also argued.

Regarding acquisitive growth, our findings reveal a more nuanced picture than LWDG reported. While LWDG found that acquisitions immediately enhance subsequent organic growth, we observe that recent acquisitions initially suppress subsequent organic growth, though less severely than past organic growth did. This finding aligns with Penrose's emphasis on acquisition-related adjustment costs: "Consistent general policies must be worked out, financial and accounting procedures co-ordinated, personnel policies and the numerous other problems handled by the 'staff service' departments must be integrated" (Penrose, 1959, p. 113). This divergence from LWDG can be explained, at least partly, by differences in sample composition that reflect the heterogeneity of growth patterns among firms with different capabilities. Our sample comprises firms that are, on average, smaller and younger than those in LWDG's sample. Our analysis shows that the negative effect of prior acquisitive growth is more pronounced for small and young firms than for large and established ones. Smaller and younger firms typically lack the managerial capabilities and systematized processes needed to effectively integrate acquired employees, resources, and operations (Bodner & Capron, 2018; Graebner et al., 2017; King et al., 2021). In contrast, larger and more established firms are more likely to possess the organizational infrastructure to manage integration challenges and contain adjustment costs (Abravanel et al., 2025).

An additional explanation lies in the observation that organic and acquisitive growth co-occur much more frequently in our sample than in LWDG's. When firms deploy limited managerial resources simultaneously for organic expansion and the integration of acquisitions, they risk straining their capacity and creating conflicting priorities (Strobl et al., 2025; Symeonidou et al., 2022), which diminishes their ability to integrate acquired resources efficiently and convert them into renewed productive opportunities. Both explanations imply that acquisitive growth does not universally alleviate the Penrose Effect; instead, its effectiveness depends on firms' managerial capabilities to pursue acquisitions alongside ongoing organic growth.

Building on insights from our replication of heterogeneous acquisition effects across firms, our extended analyses identify three contingencies illuminating *when* and *for whom* acquisitive growth helps overcome the Penrose Effect. First, we identify a clear temporal pattern in how acquisitions affect organic growth. Although acquisitions initially suppress organic growth as firms grapple with integration disruption and adjustment costs (Capron et al., 1998; Karim, 2006; Karim & Mitchell, 2000), acquisitions made 2 to 4 years earlier significantly boost subsequent organic growth. This pattern indicates that adjustment costs are concentrated in the immediate post-acquisition period rather than constituting enduring constraints. Once firms overcome these initial challenges, they realize the benefits of an expanded productive opportunity set. These findings support LWDG's claim that while

Penrose correctly identified adjustment costs, she overestimated their magnitude and, as we demonstrate, their persistence.

Second, our study validates Penrose's theoretical predictions about the strategic advantages of related diversification, finding that moderate relatedness represents an optimal balance. Acquisitions that are too similar seem to provide limited new productive opportunities, while those that are too different impose excessive adjustment costs. This finding corroborates recent diversification literature (Ahuja & Novelli, 2017; Schommer et al., 2019) and aligns with M&A research showing that firms achieve better outcomes by acquiring targets that expand their capabilities in complementary areas (Ahuja & Katila, 2001; Makri et al., 2010; Miozzo et al., 2016; Zaheer et al., 2013), thereby providing both learning opportunities and adequate absorptive capacity.

Finally, our post-hoc analysis provides additional evidence consistent with a capability-based perspective on growth. Firms with sustained high growth derive significantly greater returns from acquisitive growth than other firms, despite facing comparable constraints from prior organic growth. This suggests that some firms possess superior managerial capabilities for integrating and recombining acquired resources to reignite organic growth (Graebner et al., 2017; Welch et al., 2020), enabling them to experience lower adjustment costs and realize greater productive opportunities from their acquisitions.

Taken together, our findings suggest that firms vary more widely in their capabilities to manage acquisitions than in their capabilities to manage organic growth. This is consistent with prior research showing that, because acquisitions are relatively rare and path-dependent corporate activities, firms differ considerably in their ability to execute such complex transactions (Haspeslagh & Jemison, 1991; Rios, 2021; Trichterborn et al., 2016). Thus, although acquisitive growth holds promise for overcoming the Penrose Effect, its effectiveness depends on how acquired resources relate to the acquirer and on the managerial capabilities the firm deploys to integrate and convert them into renewed productive opportunities.

Limitations and Future Research

As with most studies, the findings and contributions of this study should be considered in light of its limitations. Both LWDG's research and our study examine two of Europe's wealthiest nations: the Netherlands (ranked third in GDP per capita in 2023) and Sweden (ranked eighth). Assessing whether these patterns hold in other parts of the world, especially emerging and institutionally diverse contexts, would strengthen the generalizability of our theoretical framework.

Beyond addressing this geographic limitation, future research could leverage temporal variation to extend our understanding of the growth process. The temporal progression from Penrose's observations of English industrial firms in the 1950s to LWDG's study of Swedish firms in the 1990s to our examination of Dutch firms in the 2010s reveals that, while Penrose's core predictions remain remarkably robust, the specific mechanisms through which they operate may be evolving. Specifically, our findings highlight the existence of heterogeneous capabilities across firms (small vs. large, young vs. old, and high-growth vs. non-high-growth) in managing, especially acquisitive, growth. These capabilities are likely shaped by the profound transformations in how firms organize, grow, and integrate acquisitions since Penrose's original theorization.

These transformations create opportunities to explore how Penrose's predictions operate under contemporary conditions. For instance, the penetration of artificial intelligence

(AI) technologies across all business functions will likely alter the managerial capacity bottleneck that Penrose identified by expanding managers' problem-solving capacity or alleviating coordination challenges within the firm. Simultaneously, AI may enhance the scope and efficiency of firms' acquisition target searches and improve post-acquisition integration practices (Benitez et al., 2018; Korotana et al., 2019). Together, these developments could shift the interplay between organic and acquisitive growth and the temporal dynamics we observed by relaxing the managerial constraints that Penrose saw as limiting organic expansion while also making M&A processes more sophisticated through AI-enabled playbooks and tools. Additionally, the "sweet spot" we identified for moderately related acquisitions may shift as organizational boundaries become increasingly fluid with the rise of platform businesses, digital ecosystems, and network organizations. Exploring these questions would position Penrose's enduring theory as a bridge between historical organizational realities and emerging forms of firm growth and transformation.

Finally, future research could leverage recent methodological advances in causal machine learning (Athey & Imbens, 2019) to examine the complex, heterogeneous effects that characterize firm growth processes. Techniques such as causal forests (Davis & Heller, 2017) or generalized random forests (Wager & Athey, 2018) could identify how acquisitions affect subsequent organic growth across firms with different managerial capacities, resource bases, or strategic orientations. By estimating treatment heterogeneity without imposing rigid functional forms, these approaches could complement traditional econometric models and generate new insights into the contextual and firm-specific contingencies underlying the Penrose Effect.

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Data Availability Statement

This study utilizes microdata from Statistics Netherlands (CBS), which was accessed securely through an authorized research project. Only aggregate statistics suitable for disclosure, as checked by CBS, are published from this secure environment.

Supplemental Material

Supplemental material for this article is available online.

Notes

1. LWDG's study focuses on organic and acquisitive growth in employment. This dimension is particularly relevant for testing Penrose's growth theory, which conceptualizes firms as bundles of human and non-human resources. Among these, human resources (encompassing unskilled labor, skilled labor, and managerial capabilities) are especially central, as hiring decisions involve substantial investment commitments.
2. Adjustment costs do not include direct acquisition-related costs (i.e., transaction value), as also specified by LWDG: "We define the ACs of growth, consistent with Penrose (1959) and Geroski (2005), as the costs of managing the growth process, i.e. the time and effort required to integrate new people into the firm, not the direct costs of acquisition." (p. 51). They do however include integration costs emerging post-acquisition.
3. We consider the Standard Industrial Classification of the Dutch Statistical Office (Standaard Bedrijfsindeling, SBI), version 2008. It coincides at the 4-digit level with the European NACE Rev.2 classification (with few exceptions) and at the 2-digit level with the international ISIC Rev.4 classification.
4. In particular, we considered the Baankenmerkenbus database for years 2011–2016 and the Spolisbus database for years 2017–2019, since the Baankenmerkenbus was discontinued from 2017 onwards.
5. Authors' calculations using data from the World Bank, OECD, and Bank of International Settlements archives. Interest rates refer to the Central Bank's policy rates. Annual averages are reported.
6. Exploiting the availability of monthly information from the datasets, we consider firms' employment at two time points in each year: at the beginning of January and at the end of December. Organic growth is defined by LWDG as "total employment (t)—total employment (t-1): the change in employment in associated establishments acquired in the current year, i.e. acquisition growth(t)" at p. 59 and as "change in the log of organic employment" in Table 1. The definition most likely contains a typo. The operationalization we adopted is in line with the fact that the other employment variables are log-transformed and with extant literature (e.g., as in Bird & Zellweger, 2018, or Coad, 2021).
7. We focus on acquisitions, excluding the small number of mergers in our sample (12% of initially selected M&A events). Although often treated as comparable, mergers and acquisitions differ fundamentally: mergers create a new entity from the disappearance of the merging firms, while acquisitions involve one entity (the acquirer) continuing while the target firm exits. To include mergers, we would need to arbitrarily decide which firm's ID the merged entity retains, complicating the analysis.
8. Not all target firms are not included in the employer–employee dataset. In this case, we considered as acquired those employees that were not part of the acquiring firm in the year prior the acquisition and who started a job position at the acquiring firm on the very same month of the acquisition event, as other acquired employees are registered in the data.
9. We linked LWDG's sectoral categories to 2-digit SBI codes to the best of our knowledge, since they do not directly match formal SBI definitions. Further details are available in Table A1 in the Appendix. In robustness checks, we consider different sets of industrial dummies. To rule out

- potential sectoral differences, we also re-estimated our models on sub-samples based on macro-sectors, as discussed in the Robustness checks section.
10. Hausman's and robust Hausman's specification tests confirm the need of firm-level fixed- over random-effects.
 11. While exits can assume different forms such as exit by M&A, about 66% of exits in our sample are by closure.
 12. We also reran the analysis after extending our lag structure to 5 years and the results remained broadly comparable with the results reported here. However, this specification resulted in a loss of over two-thirds of the observations from the baseline model due to data attrition, and hence, results are not reported here.
 13. In the presence of lagged values of the dependent variable (organic growth) among the regressors, we follow Chudik et al. (2016) and Wooldridge (2013: p.637) to compute the effect of acquisitive growth on subsequent organic growth: the total effect equals the sum of all significant coefficients on the lagged values of the independent variable of interest (acquisitive growth), divided by one minus the sum of all significant coefficients on the lagged values of the dependent variable (organic growth). Since subsequent organic growth is expressed as a percentage growth rate, and acquisitive growth is also a percentage growth rate, the coefficients represent changes in percentage points. That is, here the effect is computed as $(-0.013)/[1 - (-0.44)]$. The corresponding effect by LWDG is $(0.0917/1 - (-0.0958))$.
 14. The computation of the total effect is as follows (Chudik et al., 2016; Wooldridge, 2013): $[0.018 + 0.011 + 0.008]/[1 - (-0.466 + (-0.130) + (-0.092) + (-0.051))]$.
 15. There are many advantages from using employment growth in replicating LWDG. First, it captures a particular dimension of firm growth that may not be directly comparable to alternative measures. Prior research suggests that different growth dimensions, while correlated, are conceptually distinct (Bort et al., 2025). Moreover, correlations between different size measures have weakened over time, and conflating them can lead to confusion (Josefy et al., 2015; Shepherd & Wiklund, 2009).
 16. Net income is calculated as turnover minus all costs and expenses, including financial ones, taxes, and third-party shares.

References

- Abravanel, I., Biron, M., & Brueller, N. N. (2025). How do organizations refine their post-merger integration routines over consecutive acquisitions? *European Management Review*, 22(3), 706–721.
- Achtenhagen, L., Naldi, L., & Melin, L. (2010). “Business growth”—Do practitioners and scholars really talk about the same thing? *Entrepreneurship Theory and Practice*, 34(2), 289–316.
- Agarwal, R., & Helfat, C. E. (2009). Strategic renewal of organizations. *Organization Science*, 20(2), 281–293.
- Ahern, K. R., & Harford, J. (2014). The importance of industry links in merger waves. *The Journal of Finance*, 69(2), 527–576.
- Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, 22(3), 197–220.
- Ahuja, G., & Novelli, E. (2017). Redirecting research efforts on the diversification–performance linkage: The search for synergy. *Academy of Management Annals*, 11(1), 342–390.
- Amit, R., & Han, X. (2017). Value creation through novel resource configurations in a digitally enabled world. *Strategic Entrepreneurship Journal*, 11(3), 228–242.
- Arikan, A. M., & Stulz, R. M. (2016). Corporate acquisitions, diversification, and the firm's life cycle. *The Journal of Finance*, 71(1), 139–194.
- Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics*, 11(1), 685–725.
- Barkai, S., & Panageas, S. (2025). Value without employment. *Journal of Finance*, 80(6), 3725–3770.
- Barkema, H. G., & Schijven, M. (2008). Toward unlocking the full potential of acquisitions: The role of organizational restructuring. *Academy of Management Journal*, 51(4), 696–722.

- Benitez, J., Ray, G., & Henseler, J. (2018). Impact of information technology infrastructure flexibility on mergers and acquisitions. *MIS Quarterly*, 42(1), 25-A12.
- Bettis, R. A., Helfat, C. E., & Shaver, J. M. (2016). The necessity, logic, and forms of replication. *Strategic Management Journal*, 37(11), 2193–2203.
- Bird, M., & Zellweger, T. (2018). Relational embeddedness and firm growth: Comparing spousal and sibling entrepreneurs. *Organization Science*, 29(2), 264–283.
- Bodner, J., & Capron, L. (2018). Post-merger integration. *Journal of Organization Design*, 7(1), 3.
- Bort, J., Wiklund, J., & Yu, W. (2025). Firm growth and the job satisfaction of the startup workforce. *Strategic Management Journal*, 46(10), 2535–2572.
- Buckley, P. J., & Casson, M. (2007). Edith Penrose's theory of the growth of the firm and the strategic management of multinational enterprises. In *Foreign Direct Investment, China and the World Economy* (pp. 53–77). Springer.
- Capron, L., Dussauge, P., & Mitchell, W. (1998). Resource redeployment following horizontal acquisitions in Europe and North America, 1988–1992. *Strategic Management Journal*, 19(7), 631–661.
- Catsiapis, G., & Robinson, C. (1982). Sample selection bias with multiple selection rules: An application to student aid grants. *Journal of Econometrics*, 18(3), 351–368.
- CBS. (2018). *The Netherlands 10 years after Lehman Brothers*. <https://www.cbs.nl/en-gb/news/2018/37/the-netherlands-10-years-after-lehman-brothers>
- Cefis, E., Malerba, F., Marsili, O., & Orsenigo, L. (2020). Time to exit: “revolving door effect” or “Schumpeterian gale of creative destruction”? *Journal of Evolutionary Economics*, 31, 1465–1494.
- Chudik, A., Mohaddes, K., Pesaran, M. H., & Raissi, M. (2016). Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors. In *Essays in Honor of man Ullah* (pp. 85–135). Emerald Group Publishing Limited.
- Coad, A. (2010). Exploring the processes of firm growth: evidence from a vector auto-regression. *Industrial and Corporate Change*, 19(6), 1677–1703.
- Coad, A. (2021). Econometrics and the growth of firms: Perspectives from evolutionary economics. *Strategy Science*, 6(4), 338–352.
- Coad, A., Frankish, J., Roberts, R. G., & Storey, D. J. (2013). Growth paths and survival chances: An application of Gambler's Ruin theory. *Journal of Business Venturing*, 28(5), 615–632.
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152.
- Conyon, M. J., Girma, S., Thompson, S., & Wright, P. W. (2002). The impact of mergers and acquisitions on company employment in the United Kingdom. *European Economic Review*, 46(1), 31–49.
- Datta, D. K., Guthrie, J. P., Basuil, D., & Pandey, A. (2010). Causes and effects of employee downsizing: A review and synthesis. *Journal of Management*, 36(1), 281–348.
- D'Aveni, R. A., & Gunther, R. (1994). *Hypercompetition: Managing the Dynamics of Strategic Manuevering*. The Free Press.
- Davis, J. M., & Heller, S. B. (2017). Using causal forests to predict treatment heterogeneity: An application to summer jobs. *American Economic Review*, 107(5), 546–550.
- DeLong, G., & DeYoung, R. (2007). Learning by observing: Information spillovers in the execution and valuation of commercial bank M&As. *The Journal of Finance*, 62(1), 181–216.
- Eurostat-OECD. (2007). *Eurostat-OECD Manual on Business Demography Statistics* (Eurostat Methodologies and working papers). Issue.
- Feldman, E. R., & Hernandez, E. (2022). Synergy in mergers and acquisitions: Typology, life cycles, and value. *Academy of Management Review*, 47(4), 549–578.
- Folta, T. B., Helfat, C. E., & Karim, S. (2016). Examining resource redeployment in multi-business firms. In *Resource redeployment and corporate strategy* (pp. 1–17). Emerald Group Publishing Limited.
- Geroski, P. A. (2005). Understanding the implications of empirical work on corporate growth rates. *Managerial and Decision Economics*, 26(2), 129–138.
- Gjerløv-Juel, P., & Guenther, C. (2019). Early employment expansion and long-run survival. *Journal of Business Venturing*, 34(1), 80–102.

- Graebner, M. E. (2004). Momentum and serendipity: How acquired leaders create value in the integration of technology firms. *Strategic Management Journal*, 25(8–9), 751–777.
- Graebner, M. E., Heimeriks, K. H., Huy, Q. N., & Vaara, E. (2017). The process of postmerger integration: A review and agenda for future research. *Academy of Management Annals*, 11(1), 1–32.
- Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2021). A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. *Journal of Management Studies*, 58(5), 1159–1197.
- Haspeslagh, P. C., & Jemison, D. B. (1991). *Managing acquisitions: Creating value through corporate renewal (Vol. 416)*. Free Press New York.
- Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the Econometric Society*, 47(1), 153–161.
- Hietaniemi, L., Santamaria, S., Kacperczyk, A., & Peltonen, J. (2024). Human resource redeployability and entrepreneurial hiring strategy. *Strategic Management Journal*, 45(2), 272–300.
- Jacobs, C., & Lee, G. K. (2025). Endogenous shaping as an evolutionary process: An empirical demonstration with the photovoltaic cell industry, 1976–2010. *Strategic Management Journal*, 46(7), 1666–1699.
- Josefy, M., Kuban, S., Ireland, R. D., & Hitt, M. A. (2015). All things great and small: Organizational size, boundaries of the firm, and a changing environment. *Academy of Management Annals*, 9(1), 715–802.
- Joseph, J., & Wilson, A. J. (2018). The growth of the firm: An attention-based view. *Strategic Management Journal*, 39(6), 1779–1800.
- Karim, S. (2006). Modularity in organizational structure: The reconfiguration of internally developed and acquired business units. *Strategic Management Journal*, 27(9):799–823.
- Karim, S., & Capron, L. (2016). Reconfiguration: Adding, redeploying, recombining and divesting resources and business units. *Strategic Management Journal*, 37(13), 54–62.
- Karim, S., & Mitchell, W. (2000). Path-dependent and path-breaking change: Reconfiguring business resources following acquisitions in the US medical sector, 1978–1995. *Strategic Management Journal*, 21(10–11), 1061–1081.
- Karim, S., & Williams, C. (2012). Structural knowledge: How executive experience with structural composition affects intrafirm mobility and unit reconfiguration. *Strategic Management Journal*, 33(6), 681–709.
- King, D. R., Wang, G., Samimi, M., & Cortes, A. F. (2021). A meta-analytic integration of acquisition performance prediction. *Journal of Management Studies*, 58(5), 1198–1236.
- Korotana, A., McLetchie, J., & Ingelgem, K. V. (2019). *M&A success, powered by advanced analytics*. <https://www.mckinsey.com/~media/McKinsey/Business%20Functions/Strategy%20and%20Corporate%20Finance/Our%20Insights/M%20and%20A%20success%20powered%20by%20advanced%20analytics/M-and-A-success-powered-by-advanced-analytics-vF.pdf>
- Krishnan, H. A., Hitt, M. A., & Park, D. (2007). Acquisition premiums, subsequent workforce reductions and post-acquisition performance. *Journal of Management Studies*, 44(5), 709–732.
- Kunisch, S., Bartunek, J. M., Mueller, J., & Huy, Q. N. (2017). Time in strategic change research. *Academy of Management Annals*, 11(2), 1005–1064.
- Larsson, R., & Finkelstein, S. (1999). Integrating strategic, organizational, and human resource perspectives on mergers and acquisitions: A case survey of synergy realization. *Organization Science*, 10(1), 1–26.
- Levinthal, D. A., & March, J. G. (1993). The myopia of learning. *Strategic Management Journal*, 14(S2), 95–112.
- Lockett, A., Wiklund, J., Davidsson, P., & Girma, S. (2011). Organic and acquisitive growth: Re-examining, testing and extending Penrose's growth theory. *Journal of Management Studies*, 48(1), 48–74.
- Makri, M., Hitt, M. A., & Lane, P. J. (2010). Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic Management Journal*, 31(6), 602–628.
- Marris, R. (1964). *The economic theory of managerial capitalism*. Macmillan.

- McKelvie, A., & Wiklund, J. (2010). Advancing firm growth research: A focus on growth mode instead of growth rate. *Entrepreneurship Theory and Practice*, 34(2), 261–288.
- Miller, D. (1993). The architecture of simplicity. *Academy of Management Review*, 18(1), 116–138.
- Miozzo, M., DiVito, L., & Desyllas, P. (2016). When do acquirers invest in the R&D assets of acquired science-based firms in cross-border acquisitions? The role of technology and capabilities similarity and complementarity. *Long Range Planning*, 49(2), 221–240.
- Mirzayev, E., Vanneste, B., & Testoni, M. (2025). *Artificial Agents and the Evaluation of M&As*. Available at SSRN.
- Moatti, V., Ren, C. R., Anand, J., & Dussauge, P. (2015). Disentangling the performance effects of efficiency and bargaining power in horizontal growth strategies: An empirical investigation in the global retail industry. *Strategic Management Journal*, 36(5), 745–757.
- Nason, R. S., & Wiklund, J. (2018). An assessment of resource-based theorizing on firm growth and suggestions for the future. *Journal of Management*, 44(1), 32–60.
- Nelson, R., & Winter, S. (1982). *An evolutionary theory of economic change*. The Belknap of Harvard University Press, Cambridge Mass.
- O’Shaughnessy, K. C., & Flanagan, D. J. (1998). Determinants of layoff announcements following M&As: An empirical investigation. *Strategic Management Journal*, 19(10), 989–999.
- Penrose, E. T. (1959). *The theory of growth of the firm*. Blackwell.
- Penrose, E. T. (1960). The growth of the firm—A case study: The Hercules Powder Company. *Business History Review*, 34(1), 1–23.
- Pitelis, C. N. (2009). *Edith Penrose’s “The theory of the growth of the firm” fifty years later*. Available at SSRN 1477885.
- Pitelis, C. N. (2024). Why unicorns exist? On Penrose, Hymer, and prediction. *Strategic Management Review*, 5(1), 91–112.
- Rindova, V. P., & Kotha, S. (2001). Continuous “morphing”: Competing through dynamic capabilities, form, and function. *Academy of Management Journal*, 44(6), 1263–1280.
- Rios, L. A. (2021). On the origin of technological acquisition strategy: The interaction between organizational plasticity and environmental munificence. *Strategic Management Journal*, 42(7), 1299–1325.
- Schommer, M., Richter, A., & Karna, A. (2019). Does the diversification–firm performance relationship change over time? A meta-analytical review. *Journal of Management Studies*, 56(1), 270–298.
- Schweizer, L., Wang, L., Koscher, E., & Michaelis, B. (2022). Experiential learning, M&A performance, and post-acquisition integration strategy: A meta-analysis. *Long Range Planning*, 55(6), 102212.
- Seth, A. (1990). Sources of value creation in acquisitions: an empirical investigation. *Strategic Management Journal*, 11(6), 431–446.
- Shepherd, D., & Wiklund, J. (2009). Are we comparing apples with apples or apples with oranges? Appropriateness of knowledge accumulation across growth studies. *Entrepreneurship Theory and Practice*, 33(1), 105–123.
- Sivadasan, J., Balasubramanian, N., Dharwadkar, R., & Ren, C. (2025). How do US firms grow? New evidence from a growth decomposition. *Strategic Management Journal*, 46(1), 49–81.
- Strobl, A., Bauer, F., Shepherd, N. G., Lou, B., Tarba, S. Y., & Dao, M. A. (2025). Dynamic capabilities in acquisitions: When acquirer and target employees face contradictory and complementary human resource signals. *British Journal of Management*, 36(3), 1146–1164.
- Sydow, J., Schreyögg, G., & Koch, J. (2009). Organizational path dependence: Opening the black box. *Academy of Management Review*, 34(4), 689–709.
- Symeonidou, N., Leponen, A., Autio, E., & Bruneel, J. (2022). The origins of capabilities: Resource allocation strategies, capability development, and the performance of new firms. *Journal of Business Venturing*, 37(4), 106208.
- Tidhar, R., Hallen, B. L., & Eisenhardt, K. M. (2025). Measure twice, cut once: Unit profitability, scalability, and the exceptional growth of new firms. *Organization Science*, 36(1), 88–120.

- Trichterborn, A., Zu Knyphausen-Aufseß, D., & Schweizer, L. (2016). How to improve acquisition performance: The role of a dedicated M&A function, M&A learning process, and M&A capability. *Strategic Management Journal*, 37(4), 763–773.
- Vermeulen, F. (2005). *How acquisitions can revitalize companies*. MIT Sloan management review.
- Vermeulen, F., & Barkema, H. (2001). Learning through acquisitions. *Academy of Management Journal*, 44(3), 457–476.
- Vidal, E., & Mitchell, W. (2018). Virtuous or vicious cycles? The role of divestitures as a complementary Penrose effect within resource-based theory. *Strategic Management Journal*, 39(1), 131–154.
- Volberda, H. W., Khanagha, S., Baden-Fuller, C., Mihalache, O. R., & Birkinshaw, J. (2021). Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms. *Long Range Planning*, 54(5), 102110.
- Wager, S., & Athey, S. (2018). Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association*, 113(523), 1228–1242.
- Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3), 326–349.
- Welch, X., Pavičević, S., Keil, T., & Laamanen, T. (2020). The pre-deal phase of mergers and acquisitions: A review and research agenda. *Journal of Management*, 46(6), 843–878.
- Wooldridge, J. M. (1995). Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics*, 68(1), 115–132.
- Wooldridge, J. M. (2013). *Introductory Econometrics: A modern approach* (5th ed.). South-Western.
- Zaheer, A., Castañer, X., & Souder, D. (2013). Synergy sources, target autonomy, and integration in acquisitions. *Journal of Management*, 39(3), 604–632.
- Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, 27(2), 185–203.
- Zhou, Y. M. (2011). Synergy, coordination costs, and diversification choices. *Strategic Management Journal*, 32(6), 624–639.
- Zhou, H., & van der Zwan, P. (2019). *Is there a risk of growing fast? The relationship between organic employment growth and firm exit*. Industrial and Corporate Change.
- Zollo, M., & Singh, H. (2004). Deliberate learning in corporate acquisitions: Post-acquisition strategies and integration capability in US bank mergers. *Strategic Management Journal*, 25(13), 1233–1256.

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