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The triggers and clustering properties of merger waves

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Abstract

This paper studies the triggers and the agglomeration of M&A activity within clusters constituted by time, market and industry. Based on almost 500,000 individual transactions, we find that industry factors play a significant role in triggering activity and that M&A agglomerates strongly across related industries. While clustering in time turns out to be insignificant, stock-market effects can be either an attracting or a repelling force, depending on the type of deal examined. This supports the view that merger waves are largely driven by industry shocks.

Keywords: merger wave; clustering; acquisitions; industry shocks; behavioral

JEL codes: L2, G3

1 Introduction

It is well documented that the occurrence of mergers and acquisitions (M&A) is not uniformly distributed, but that M&A tend to cluster in various dimensions - a phenomenon often referred to as merger waves.¹ This article employs data on almost 500,000 M&A in the 1989 to 2009 period to i) study the factors that trigger merger activity and ii) construct measures of temporal, geographic and industrial proximity to estimate the relative importance of these dimensions in the distribution of M&A.

There is a large literature discussing both the emergence of merger waves and the patterns they assume. In spite of the substantial amount of evidence gathered, there is no general consensus on either question. The origin of merger waves has been traced back to various types of shocks occurring at the industry level (supply and demand shocks, technology shocks, regulatory shocks) as well as management and stock market related phenomena, such as overvaluation of stocks, managerial hubris or bandwagon

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¹We use the term 'merger wave' in a liberal sense, encompassing mergers as well as different types of acquisitions.

effects. Investigations of their shape unfailingly find peaks and troughs in time, yielding the eponymous wave pattern, but there is also strong evidence that M&A accumulate in specific industries (Mitchell and Mulherin, 1996; Andrade and Stafford, 2004; Harford, 2005) and locations (Di Giovanni, 2005; Erel et al., 2012). Thus, while the literature recognizes the significance of the dimensions of time, industry and location, there is no consensus with respect to their relative importance in creating and shaping merger waves. Further, it remains unclear whether the shape of M&A over time - the wave - is an artifact of a temporal dimension implicit to the drivers at the industry and geographic level or if, after controlling for industry and geographic factors, a distinct temporal pattern remains.

We first investigate the triggers of acquisition activity, i.e. the determinants of a positive number of transactions occurring in a cluster defined by time, market and industry. Specifically, we estimate models using variables related to industry performance and the development of financial markets, finding that the occurrence of overall M&A activity as well as various subtypes (public deals or private deals, mergers or acquisitions, cross-border or domestic transactions) in specific clusters correlates with both sets of variables. Results show some heterogeneity with respect to the different types of deals in the sample, but indicate that the typical constellation leading to the emergence of transactions is compatible with an increase in competition in the sector and/or high inflation and crises of the financial system.

Next, we examine the degree of clustering in the three dimensions proposed by constructing measures of temporal, market and industrial proximity. The latter two are constructed by market/industry and by time period, such that they vary over time. Thus the first measure, the time trend, captures purely time-specific factors, while the temporal dimension of market or industry shocks is accounted for. Again, there is evidence of heterogeneous effects in various subsamples and the degree of agglomeration or dispersion in markets depends on the type of deal. However, the time dimension of merger waves turns out to be insignificant in all regressions, suggesting that the wave pattern of M&A is owed to the time dimension of underlying industry and geographic effects and that no significant, uniquely time-related dynamic exists. The results on stock-market clustering are very heterogeneous: while most coefficients are significant, their sign depends on the type of deal. Thus, some types of transactions cluster around specific stock markets, while others are dispersed. One common result is that all types of transactions strongly and significantly agglomerate in related industries. This indicates that industry shocks are strong drivers of M&A activity irrespectively of the specific type of deal examined.

In summary, the findings suggest that while M&A are typically triggered through both shocks at the industry level and financial markets, they predominantly propagate into clusters of industrial adjacency. Therefore, merger waves appear to be mostly driven by economic forces necessitating restructurization, consistent with the industry shock hypothesis.

The next section discusses the previous literature on the topic and the contribution of the current study. Section 3 first describes how the sample is created and how the different measures of clustering are obtained, then presents some summary statistics of the data. Section 4 presents the main results: first we look at the triggers of transaction activity in specific clusters, then we examine which dimensions are relevant in the creation of merger waves. Section 5 sums up the findings.

2 Literature & Hypotheses

The existing literature has proposed three dimensions in which merger waves agglomerate: First, and most evidently, M&A cluster in time; evaluating aggregate M&A activity over successive periods yields the characteristic wave pattern. The literature has shown that merger activity over time can be reasonably well depicted by first-order auto-regressive processes (Shughart and Tollison, 1984), Markov-switching processes (Town, 1992), sine waves (Golbe and White, 1993), long-memory processes (Barkoulas et al., 2001) or a survival function (Kastrinaki and Stoneman, 2012). In the analysis we will therefore consider the effect of M&A in temporally adjacent clusters on current M&A.

Second, there is a large body of literature that sees M&A activity as being caused by industry shocks. Typically, mergers serve as a means of asset reallocation between efficient and inefficient firms in response to shocks in industries experiencing fundamental changes. Jovanovic and Rousseau (2002) develop a model of mergers based on Tobin's q , where firms decide between internal growth (investment) and external growth (M&A), finding that high- q firms optimally acquire low- q firms and that merger waves are triggered by reallocation of assets across sectors.

In the models proposed by Fauli-Oller (2000) and Qiu and Zhou (2007), firms endogenously decide to merge in response to demand shocks. Due to mergers being strategic complements such that firms' incentives to merge increase when other firms merge, the decision of two firms can trigger a strategic merger wave. Moreover, forward-looking firms might even engage in seemingly unprofitable mergers with the expectation of triggering a wave.

Alternative explanations regard merger waves in industries as a consequence of preemptive considerations. Toxvaerd (2008) considers a setting in which the profitability of deals depend on exogenous market conditions and potential acquirers can either buy a target or wait for a better deal at the risk of being preempted by another firm. As a consequence of this strategic interaction, market conditions allowing a positive payoff from merging induce all potential acquirers to purchase immediately, thereby causing a merger wave. Employing a similar preemption mechanism, Fridolfsson and Stennek (2005) find that firms may engage in a merger race to avoid being left stranded without a suitable merger target and thereby,

again, create a wave.

Another mechanism based on industry dynamics is examined by Neary (2007): in a model of Cournot competition, efficient firms in one country can profitably acquire less efficient firms in another country. In this setting, the abolition of trade barriers between countries can trigger international merger waves, driven by comparative advantages.

These models yield the prediction that merger waves not only cluster in time, but also in industries where exogenous shocks necessitate asset reallocation, as well as in related industries. There exists ample empirical support for this prediction: most studies taking the industry dimension of M&A into account also find significant industry effects. For example, Mitchell and Mulherin (1996) study M&A activity in 51 sectors in the 1980s and find that transactions strongly cluster within industries. Furthermore, restructuring is triggered by both 'broad' shocks (defined as deviations of industry sales and employment growth from the average growth) and 'specific' shocks (identified through deregulation and demand changes in particular industries). Andrade and Stafford (2004) also report that M&A cluster in industries whereas internal investment does not. Using data on industry capacity utilization, they find that mergers can both be used as a vehicles of expansion and contraction. Harford (2005) finds support for industry merger waves, subject to a capital liquidity constraint. Thus, restructuring is driven by economic, regulatory or technological industry shocks that will propagate into a wave given sufficient capital liquidity. Two exceptions to the finding of significant clustering of M&A at the industry level are Resende (1996) and Gärtner and Halbheer (2009), who find no such result for the UK and the US respectively.

Third, behavioral explanations emphasize the role of market imperfections and irrational agents: companies whose stock is overvalued by the market have an incentive to exchange it for real assets (Shleifer and Vishny, 2003) and irrational managers might be prone to engage in too many mergers (Mueller, 1969). These explanations provide a link between the often concurrent phenomena of stock market booms and merger waves and suggest that acquisitions cluster around countries with high stock market performance. In that vein, Rhodes-Kropf and Viswanathan (2004) propose a model in which misvaluation can rationally lead to merger waves. Essentially, this is achieved by decomposing misvaluation into a firm-specific (and privately known) part and a market-wide, unknown component. Merger waves result from the uncertainty induced by large realizations of the market-wide misvaluation component in this setting.

Gorton et al. (2009) propose a model in which defensive merger waves are triggered by managers' desire to have their companies remain independent rather than be acquired. If managers are sufficiently rational, only profitable acquisitions occur. However, if their preference for organizational independence is strong enough, managers will engage in defensive acquisitions. Assuming that larger firms are harder to take over, managers want to expand their firms through unprofitable acquisitions to avoid being (profitably)

acquired themselves. This self-reinforcing dynamic leads to a merger wave.

Again, there is a number of empirical studies finding consistent patterns in the data. Clarke and Ioannidis (1996) examine 20 years of UK merger activity and conclude that stock market prices Granger-cause both the number and the value of deals. Rhodes-Kropf et al. (2005) find support for the theory that stock market misvaluations lead to merger waves by decomposing market-to-book ratios into a firm, a sector and a long run component. They find that merger activity strongly correlates with short-run deviations of valuation from the trend. Erel et al. (2012) test an array of factors that can be attributed to behavioral theories. They find that geographic location, institutional quality, relative currency movements and stock market performances all play an important role in the determination of M&A volumes between country-pairs. Finally, Gugler et al. (2012) exploit differences in the acquisition conduct of listed and unlisted firms - which are respectively affected and unaffected by stock market effects - to distinguish between different merger motives, finding that behavioral theories are consistent with the patterns they observe.

Even though most economists would agree that the industry-based and behavioral theories of merger waves are complementary rather than mutually exclusive, there is no general consensus as to which is the more relevant driver of M&A clustering. Few of the studies cited above start out by considering both types of theories and then formally testing one against the other.² Thus the existing literature has mostly either confirmed or disconfirmed the existence of behavioral and industry forces in the formation of merger waves in varying samples of merger activity, but not formally tested one theory against the other.

Additionally, it is not clear which sets of variables are to be employed when looking for industry and behavioral effects. Typically, authors looking for industry explanations use different measures of industry shocks (deregulation, demand shocks, technological shocks, changes in trade barriers, excess capacity etc.), firm level performance (Tobin's q , sales, employment, turnover) and investment behavior (capital expenditures, FDI flows), while proponents of behavioral approaches employ measures of misvaluation, stock market performance and arbitrage possibilities, for instance the dispersion of market-to-book ratios, increases in share value in specific stock markets, exchange rate fluctuations and geographic locations, as well as macro factors and measures of market optimism. While the use of multiple indicators is desirable in principle, it may also be a reason why the comprehensive literature on merger waves has not been able to reach a consensus as to their cause.

Another source of heterogeneous findings are the different datasets used. The level of analysis varies between studies, with some using individual transactions (typically a few hundred up to some tens of thousands³) as the unit of observation and others focusing on aggregate M&A in specific industries.

²Harford (2005) and Gugler et al. (2012) are, to a degree, exceptions.

³A notable exception is the study by Erel et al., which uses almost 200,000 individual transactions.

Studies that are mostly interested in the shape of merger activity over time often employ time series data aggregated at the country level. Similarly, the area of analysis varies, with many studies focusing on the US and the UK, few considering European countries and the case of cross-border mergers and virtually none taking the rest of the world into account.⁴

This article aims at contributing to the literature in three ways. First, we directly test the relative importance of the two explanatory approaches for the triggering and clustering of merger waves. After controlling for the nonrandom occurrence of M&A and its time dimension, we measure the extent of residual clustering that is due to industry and behavioral forces.

Second, we employ very intuitive and general measures of clustering. Specifically, we use the degree of propagation of M&A into related industrial sectors to measure industry clustering and the spillover of M&A in markets experiencing strong changes in market valuation into other markets to measure behavioral clustering.

Third, since these measures are quite parsimonious in terms of data requirements, we are able to use a very comprehensive sample compiled from almost 500,000 individual transactions occurring all over the world in a period of 21 years. Therefore the findings of this study are not restricted to a specific country, industry or time period.

3 Data and methods

3.1 Sample and measurement

The data on acquisitions are obtained from the Thomson Reuters 'Worldwide Mergers & Acquisitions' database, containing all corporate acquisitions worldwide with a minimum deal value of 1 million in CPI-adjusted 2005 USD.⁵ We retain transactions that are either acquisitions of assets, acquisitions of partial or majority interest or mergers, amounting to almost 95% of the data.⁶ Deals in which the acquirer sought to buy less than 50% of the target company are removed (~11% of observations). After dropping transactions for which the acquirer's industry classification is unavailable (<.5% of observations); for which the acquirer's headquarter location is reported as 'undisclosed' (~7% of observations); and those occurring before 1989 (~6% of observations), we obtain a sample of 484,189 M&A that took place in the 21 year period from 1989 to 2009.

⁴Di Giovanni (2005) is an exception; his sample includes almost all nations.

⁵Data on deal values are available for around 45% of observations. In an effort to keep the real threshold for inclusion in the sample constant, we obtain country and year specific CPI data from the World Bank (<http://data.worldbank.org>) and drop observations with a deal value lower than 1 million in CPI-adjusted 2005 USD.

⁶The transactions dropped are mostly buybacks, plus a few exchange offers and recapitalizations.

The acquiring firms in these deals originate from 121 different nations. Most are headquartered in the US (38.6%), followed by the UK (11.1%), Canada (5.4%), Germany (4.7%), France (4%) and Australia (3.5%).⁷

We then define clusters, the size of which is given by the total number of transactions, $\text{acq}_{t,i,m}$, in a specific month t (the time dimension), 4-digit SIC sector i (industry dimension)⁸ and market m (market dimension). This results in 285,586 clusters, containing 1.6 deals on average. Since only clusters with a positive amount of transactions are observed (and since those transactions represent, more or less, the population of relevant deals), we fill the missing empty clusters with zeroes to create a panel of industry/market groups over months, consisting of a total of 2,529,739 clusters, 11.3% of which experience M&A activity.

First, we are interested in the determinants of a cluster being 'active' and thus run a probit regression of an indicator variable on X , a vector of potential trigger factors,

$$I_{[\text{acq}_{t,i,m} > 0]} = \alpha + \beta X + \varepsilon_{t,i,m}. \quad (1)$$

Next, we define measures of time clustering, τ_t , industry clustering, $\iota_{t,i}$, and market-level clustering, $\mu_{t,m}$, where τ_t is defined as the sum of all acquisitions (in all industries and countries) in the current month, plus half of those in the previous and following months. $\iota_{t,i}$ is the sum of acquisitions in all countries and all industries in month t , weighted by the degree of relatedness with industry i , γ_i , and inverse geographical distance to market m , δ_m . Finally, $\mu_{t,m}$ is the sum of acquisitions in all industries and all markets in month t , weighted by a measure of stock-market performance in market m , ν_m and, again, geographical distance to m . Formally, we have

$$\begin{aligned} \tau_t &= \sum_{i,m} \text{acq}_{t,i,m} + \frac{1}{2} \times \sum_{t \in \{t-1, t+1\}} \sum_{i,m} \text{acq}_{t,i,m}, \\ \iota_{t,i} &= \sum_{i,m} \text{acq}_{t,i,m} \times \gamma_i \times \delta_m, \\ \mu_{t,m} &= \sum_{i,m} \text{acq}_{t,i,m} \times \nu_m \times \delta_m, \end{aligned}$$

where \sum_i (\sum_m) indicates summation over all industries (markets) and γ_i , ν_m and δ_m are weights.

⁷When firms with large international presences acquire another firm via a subsidiary, the headquarter location of the subsidiary is listed as the acquirer's nation. We retain this classification.

⁸The assignment to industry codes is deal-specific, not firm-specific. This is important in the case of diversified companies, doing a large number of acquisitions. For example, Nestlé does the bulk of its acquisitions in SIC 2066 (Chocolate and Cocoa Products), some in the related SICs 2064 (Candy and other Confectionery Products) and 2086 (Bottled and Canned Soft Drinks and Carbonated Waters), but also has deals in more distant industries like 2899 (Chemicals and Chemical Preparations) and 8741 (Management Services).

The weights are defined as follows: γ_i is 1 for acquisitions within the same 4-digit SIC code, $\gamma_i \in (\frac{2}{3}, 1)$ for acquisitions within the same 3-digit SIC code, $\gamma_i \in (\frac{1}{3}, \frac{2}{3})$ if the 2-digit industry is the same, $\gamma_i \in (0, \frac{1}{3})$ if the first digit of the industry code is equal and $\gamma_i = 0$ if the industries are unrelated. The specific value of γ_i within the stated intervals depends on the difference in SIC codes within the categories of 3, 2 or 1 digit being equal. For example, the industry classifications for truck trailers (3715) and truck & bus bodies (3713) share the same 3-digit code. Therefore γ_i lies in the $(\frac{2}{3}, 1)$ interval. The absolute difference of the two codes ($3715 - 3713 = 2$) then determines that $\gamma_i = .93$.⁹ γ_i captures the idea that M&A in related industries are more likely to affect M&A in i than those in unrelated industries.

The stock-market performance weight, ν_m , is defined as the squared, yearly, cross-sectional deviation of a countries' stock market development relative to all other markets. ν_m thus captures if the financial markets in a country developed differently than the rest of the world and assigns a high weight to countries whose stock markets either strongly over- or underperformed in a given year.

The geographic weight, δ_m , is the normalized inverse of the great-circle distance between two markets. Since roughly 1/3 of observations are from the US, we assign US firms to their home state in the construction of $\mu_{t,m}$ to obtain some spatial variation within the US.¹⁰ The resulting measures of distance (τ_t , $\iota_{t,i}$ and $\mu_{t,m}$) are then standardized to to a mean of zero and a variance of one to make their regression coefficients more comparable.

In the clustering estimations we include fixed effects for months (242 variables), industries (908 variables) and countries (121 countries + 52 US states = 173 variables). We are interested in a regression of the form

$$\text{acq}_{t,i,m} = \alpha_0 + \alpha_1\tau_{t-1} + \alpha_2\iota_{t-1,i} + \alpha_3\mu_{t-1,m} + \beta X + \lambda + \varepsilon_{t,i,m}, \quad (2)$$

where X contains the different fixed-effects variables, λ is the inverse Mills' ratio obtained from (1) and the α_i ($i = 1, 2, 3$) measure the relevance of clustering in the respective dimensions. The clustering measures enter the estimation equation in lags in order to mitigate endogeneity concerns.

Since around 7/8 of the sample consists of clusters without acquisitions (i.e. where $\text{acq}_{t,i,m} = 0$), there is clearly a selection process involved. Ignoring this would induce censoring bias, in the sense that the findings would only apply to months, countries and industries where M&A are observed. Di Giovanni (2005) and Wong (2008) are confronted with the same problem in dealing with the non-random occurrence of M&A and propose estimation in two stages. We follow their approach.

In the first stage, the selection equation, we estimate equation (1) using variables that are likely to cause M&A in a specific cluster. With a view to testing the competing hypotheses, we employ a set of

⁹Results are not strongly affected by the choice of industry weights.

¹⁰To be clear, M&A between different US states are still coded as 'domestic' transactions, i.e. the US still counts as one country.

instruments indicative of industry shocks (changes in profitability, productivity, sales, income, employment and market capitalization in the 4-digit SIC industry, all calculated using Worldscope data) and financial market characteristics (domestic credit to private sector (% of GDP), credit to government and state owned enterprises to GDP (%), liquid liabilities in millions USD (2000 constant), consumer price index, an indicator variable for banking crises and GDP per capita. All variables are obtained from the Global Financial Development Database, with the choice of variables being determined by data availability). In the second stage, equation (2) is estimated including the inverse Mills ratio and correcting standard errors for the inclusion of an estimated regressor (see Di Giovanni (2005) for further details).

Note that since $\iota_{t,i,m}$ and $\mu_{t,i,m}$ are measured on a monthly basis, they vary over the time dimension. This seems reasonable since i) the 'baseline' merger activity of an industry or market is already captured by the inclusion of fixed-effects and ii) industry or market-related phenomena that might lead to industry restructuring typically have a limited temporal extent. The explicit measure of time, τ_t , thus captures whether there is additional temporal clustering if the time dimension of industrial and geographic effects is controlled for.

To account for the fact that different types of transactions may respond to different triggers and/or cluster in different dimensions, we run the estimation approach sketched above in i) the full sample, comprising all types of M&A transactions and ii) in six subsamples, distinguishing different types of transactions. First, we discern deals where the acquirers are publicly listed firm from deals where the acquirers are privately held. We classify acquirers to be public (private) firms if they are either publicly listed (privately held) or the subsidiary of a publicly listed (privately held) company. In the sample, 58% of deals are initiated by public acquirers and 38% by private ones.¹¹ While many differences in the corporate governance structures of public and private firms can plausibly be assumed to exist, we believe that the most fundamental point is that the latter are detached from the evolution of stock markets. Thus, while publicly listed firms will be exposed to the whole spectrum of phenomena related to financial markets, privately held firms will only correlate with stock markets to the degree to which the markets' evolution reflects underlying economic forces.

Secondly, we construct a sample of mergers and a sample of acquisitions, accounting for 19% and 81% of the sample respectively.¹² Here the main difference lies in the motive of the transaction: while acquisitions are primarily a vehicle for restructurization and asset transfer that can be used either for expansion or for consolidation, mergers are typically proposed to exploit specific complementarities between two firms. Thus, since the two are strategic responses to different scenarios, it appears plausible that they might

¹¹For the remaining 4% the ownership status of the acquirer could not be determined. These observations are not used in the construction of the public/private subsamples.

¹²Deals are classified as either mergers or acquisitions in the dataset. We retain that classification.

differ with respect to their triggers and clustering properties.

Finally, we distinguish cross-border and domestic deals by checking whether the acquirer and target firm are headquartered in different nations, finding that 29% of deals in the sample are cross-border and 71% are domestic in nature. The differences between these two categories may be less striking than those of the other distinctions, but are nonetheless important: while cross-border deals can be used as tools for entry into new markets, be driven by the differential stock market and/or exchange rate performances between countries or be the consequence of a comparative advantage firms in one country enjoy over firms in another, the motivation for domestic transactions is more likely to be restructuring, complementarities or market power considerations. Again, this might give rise to different triggers and clustering properties.

3.2 Summary statistics

Table 1 summarizes the amount of transactions per cluster for the whole sample and for the six subsamples described above.

Table 1: Transaction activity by type of deal

	All	Public	Private	Merger	Acquisition	Cross-border	Domestic
Mean	1.594091	.9246777	.6136575	.3332726	1.260818	.4645116	1.129579
SD	2.594055	1.141523	2.193262	.7873276	2.213795	.8383895	2.22852
Min	1	0	0	0	0	0	0
Max	119	44	100	38	102	28	96

Notes: This table reports the mean, standard deviation, minimum and maximum of transactions per cluster for the whole sample (column 1) and for the three pairs of subsamples (columns 2-7). Only the 285,586 clusters with at least one transaction (of any type) are reported.

Figure 1 illustrates the clustering dimensions defined above. The top panel color-codes the quartiles of total transaction volumes by country from 1985 to 2009¹³, normalized by GDP. The highest transaction volumes are observed in Canada and the US, Western Europe, Australia, New Zealand, Malaysia, the Phillipines and South Africa. The third quartile comprises large parts of Asia and South America, as well as some Central European and East African nations. The second quartile consists of mostly African and eastern European countries and the lowest transaction volumes are observed in West African nations and the countries of the Greater Middle East.

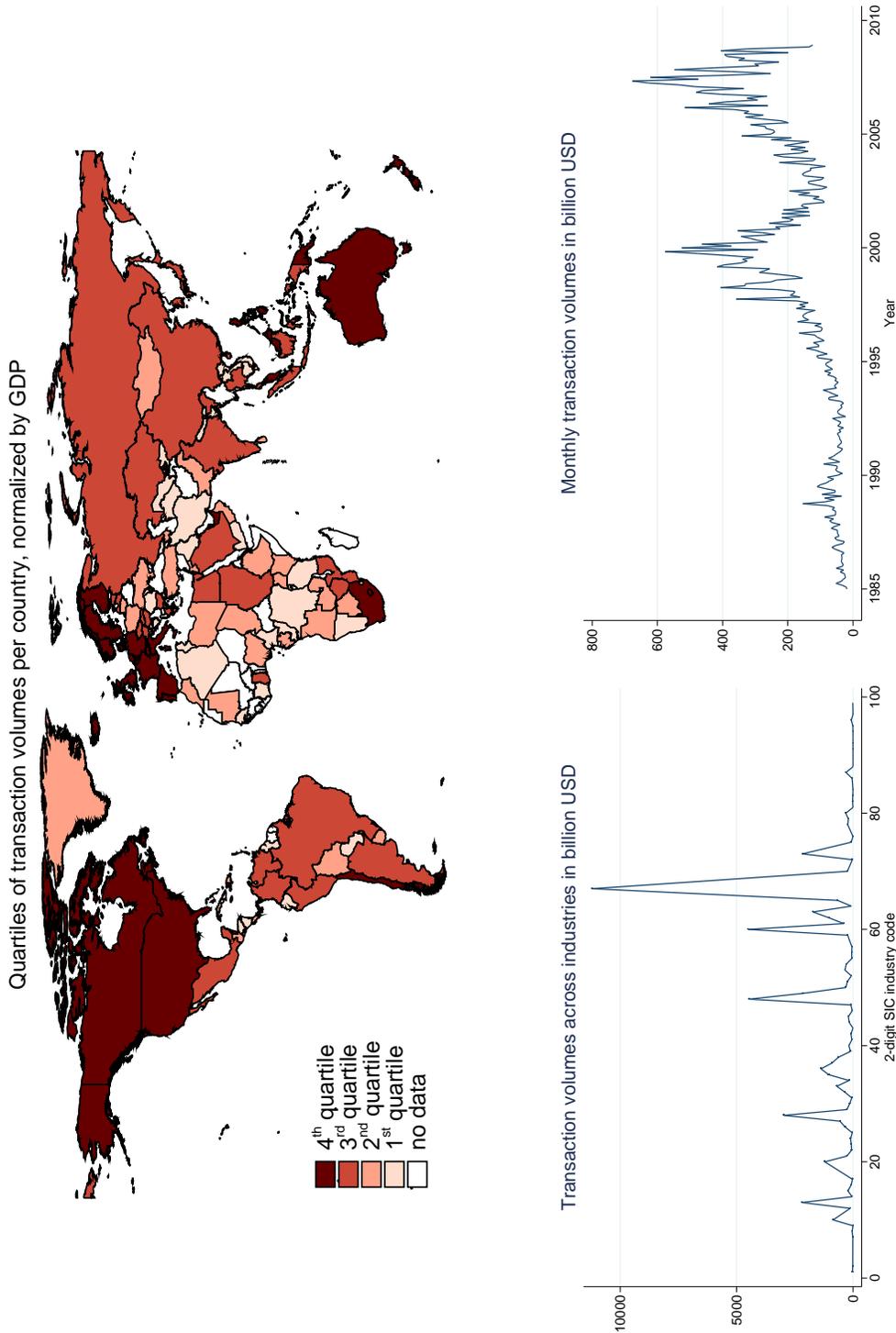
The lower-left panel of figure 1 shows the distribution of transaction values across 2-digit SIC industries.

¹³The 1985-1989 period is included in the figure, but not in the estimation sample because data on industry and financial market performance are unavailable.

The most notable peak occurs around industry 67 (investment offices and investors), two similarly-sized spikes are observed for industries 48 (communications) and 60 (banks). Further high activity sectors are 13 (oil and gas extraction), 28 (chemicals and allied products), 49 (electric, gas and sanitary services), 63 (insurance carriers) and 73 (business services).

Finally, graphing transaction volumes per month in the lower-right panel yields the familiar shape of the two most recent merger waves: the 1990s merger wave, building up to its peak in 1999/2000 and then ending abruptly with the bursting of the dot-com bubble and the most recent wave, starting to gain momentum in 2004 and ending in late 2008 in the wake of the financial crisis.

Figure 1: Spatial, industrial and temporal clustering of acquisitions



4 Results

4.1 Triggers of acquisition activity

In a first step we investigate the specific industry triggers that lead to M&A activity in a cluster. Since M&A can serve either as a vehicle of firm growth or as a consolidation strategy, it is natural to ask which force dominates in the aggregate. To this end we regress the indicator of M&A activity, $I_{[\text{acq}_{t,i,m} > 0]}$, on two sets of variables, one reflecting the performance of firms in the focal industry, the other the state of financial markets in the focal country.

To measure industry performance, we calculate average, yearly changes in profitability (return on assets), productivity (output per employee), sales, net income, market capitalization and employment on the industry level from more than 50,000 listed firms contained in the Thomson Reuters Worldscope database.¹⁴ Since all of these variables are positively related with the economic well-being of firms in the industry, their coefficients will indicate whether M&A - in the aggregate - tend to be triggered by expansionary or contractionary industry shocks.

To capture the development and performance of national financial markets, we gather data on the extent of credits to private firms and credits to publicly owned firms (both as a percentage of GDP), the ratio of liquid liabilities to GDP, the consumer price index with base year 2005, a dummy variable indicating whether the country was experiencing a banking crisis and GDP per capita (all variables obtained from the Global Financial Development Database). The indicators on credits and liabilities capture how easily firms can borrow money to finance transactions, the CPI reflects the influence of inflation, the banking crisis dummy indicates shocks to the financial economy, while GDP per capita measures the countries' overall development. Table 2 reports the results.

The findings on the industry-level variables are rather homogenous across the different samples: the occurrence of all kinds of deals is negatively related to changes in industry profitability, industry income and, most importantly and significantly, market capitalization. Changes in industry productivity, industry sales and industry employment carry positive and mostly significant coefficients. It is noteworthy, that all transactions are more likely to manifest in industries with declining market capitalization. This holds even for deals among private firms, suggesting that decreasing market valuations are indicative of a

¹⁴Since the industry averages are calculated from accounting data they vary on the yearly level, whereas the sizes of the clusters are calculated monthly. While this reduces the efficiency with which the available information is employed, it does not pose econometric problems, particularly with a view to the large sample size. Furthermore, calculating sample sizes on the yearly level does not qualitatively change any findings reported in table 2. We retain the monthly specification for consistency with the results reported in table 3. The regressions in tables 2 and 3 contain fewer observations than discussed in section 3, because industry averages are unavailable for ~4% of observations.

Table 2: Industry and financial market characteristics as triggers of M&A

	All	Public	Private	Merger	Acquisition	Cross-border	Domestic
Δ Profitability	-0.01*** (0.00)						
Δ Productivity	0.01*** (0.00)	0.01*** (0.00)	0.00 (0.00)	0.00 (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.00*** (0.00)
Δ Sales	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Δ Income	-0.00** (0.00)	-0.00*** (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00*** (0.00)	-0.00** (0.00)	-0.00* (0.00)
Δ Market Cap.	-0.04*** (0.00)	-0.04*** (0.00)	-0.03*** (0.00)	-0.03*** (0.00)	-0.04*** (0.00)	-0.04*** (0.00)	-0.03*** (0.00)
Δ Employment	0.01*** (0.00)	0.00*** (0.00)	0.01*** (0.00)	0.00 (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.00*** (0.00)
Credit private	0.02*** (0.00)	0.06*** (0.00)	-0.01*** (0.00)	0.05*** (0.00)	0.02*** (0.00)	0.05*** (0.00)	0.02*** (0.00)
Credit public	-0.02*** (0.00)	-0.03*** (0.00)	0.00 (0.00)	-0.01*** (0.00)	-0.02*** (0.00)	0.02*** (0.00)	-0.04*** (0.00)
Liabilities	0.01*** (0.00)	0.03*** (0.00)	-0.03*** (0.00)	0.01*** (0.00)	0.00 (0.00)	-0.16*** (0.00)	0.09*** (0.00)
CPI 2005	10.59*** (0.18)	6.80*** (0.20)	14.73*** (0.24)	13.89*** (0.28)	8.79*** (0.19)	14.21*** (0.25)	8.04*** (0.19)
Bank crisis	0.04*** (0.00)	-0.00*** (0.00)	0.07*** (0.00)	0.01*** (0.00)	0.04*** (0.00)	0.03*** (0.00)	0.03*** (0.00)
Per capita GDP	0.00** (0.00)	-0.02*** (0.00)	0.04*** (0.00)	-0.04*** (0.00)	0.02*** (0.00)	0.07*** (0.00)	-0.04*** (0.00)
Observations	2318769	2343978	2355430	2366495	2330108	2359503	2337174

Notes: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

deterioration of industry prospects, affecting both listed and unlisted companies.

The variables pertaining to financial markets show more mixed results. Credits to private firms make M&A more likely, except for deals among private firms where the opposite is true. Credit to public firms make most deals less likely, while making cross-border deals more likely to occur. The level of liabilities and per capita GDP have very mixed impacts across deal types. Banking crises generally increase the probability of M&A occurring except for the case of public deals (with a tiny coefficient). Only the CPI has an unanimously positive effect on all types of deals.

Overall, based on the statistical and economical significance of the estimates, decreases in industry market capitalization, increases in the CPI and the occurrence of banking crises seem to be the most important drivers of M&A activity.

4.2 Dimensions of clustering

Table 3 reports the results when using a two-step procedure to estimate acquisition clustering. The first-stage regressions (equation 1) from table 2 are used to predict the probability of selection. In the second stage, we estimate equation (2) including the inverse Mills ratio and adjusting standard errors for the inclusion of a constructed variable.

Table 3: Clustering of different types M&A, second-stage regressions

	All	Public	Private	Merger	Acquisition	Cross-border	Domestic
Time ($\tau_{t,i,m}$)	0.21 (0.41)	-0.07 (0.11)	0.40 (0.56)	-0.30 (0.61)	0.12 (0.29)	-0.66 (0.41)	0.23 (0.39)
Market ($\mu_{t,i,m}$)	0.03 (0.03)	-0.03** (0.02)	0.02 (0.07)	0.07*** (0.02)	0.00 (0.03)	-0.06*** (0.02)	0.08** (0.03)
Industry ($t_{t,i,m}$)	0.28*** (0.01)	0.16*** (0.01)	0.19*** (0.02)	0.11*** (0.01)	0.22*** (0.01)	0.12*** (0.00)	0.22*** (0.01)
Constant	2.27*** (0.25)	1.19*** (0.17)	3.66*** (0.45)	0.37* (0.20)	2.38*** (0.26)	1.20*** (0.18)	1.67*** (0.30)
ρ	0.073	0.227	-0.105	0.396	0.010	0.072	0.166
Observations	2318769	2343978	2355430	2366495	2330108	2359503	2337174

Notes: All regressions include month (266 variables), industry (911 variables) and country (216 variables) fixed-effects. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The inverse Mills ratios and the correlation of error terms between first and second stage regressions (the ρ s) are significant in all samples but the acquisition subsample. This indicates that the use of a

two-step estimation procedure is appropriate.

In the sample containing all transactions (column 1) we obtain coefficients suggesting that while there is no significant clustering across stock markets, the agglomeration in the industry dimension is significant and large. Also, after accounting for market and industry clustering, as well as for month, market and industry fixed effects, we do not find significant clustering in the time dimension. This means that the time structure of M&A is accounted for by time-industry interactions (and fixed effects) and that there appears to be no residual, distinct time dimension in M&A activity.

The findings in the subsamples are quite heterogeneous: while transactions between publicly listed firms concentrate in industry and disperse across markets, only the industry dimension seems to be relevant for private deals, suggesting that deals among private firms are predominantly driven by changes in their respective industries and largely unaffected by other influences. Mergers cluster across both markets and industry. In the merger subsample, the effects of markets and industries are most comparable, even though the industry coefficient is still 50% larger. Acquisitions, on the other hand, agglomerate only by industry and do so to a higher degree than most other deal types.

Since market-clustering is based on the stock market of acquirer's nation, the negative market clustering coefficient in the cross-border sample and the positive coefficient in the domestic deal sample are consistent with the interpretation that abnormal stock market performance in a market triggers internal restructurization. Due to the inclusion of fixed effects, the fact that domestic deals positively cluster in national markets is not a pure size effect but indicates that in some countries the reallocation of assets occurs more through M&A than in others.

The main finding of the clustering regressions is that M&A activity spills over into adjacent industry clusters in all regressions. Furthermore, the regression coefficients indicate that this is the strongest clustering force in the main sample as well as in most subsamples. While the coefficient of the measure of market proximity is significant in most regression, its sign varies across samples. The coefficient of time-clustering remains insignificant in all samples.

5 Conclusion

This article contributes to the literature studying the causes and properties of merger waves. Using a comprehensive dataset on M&A, we first analyze the factors that lead to the occurrence to transactions. An investigation of the specific industry dynamics leading to activity shows that M&A are typically triggered by falling profits and market capitalization and rising sales - a scenario compatible with increasing competition in the industry. It therefore appears, that M&A are predominantly employed as a strategy to

cope with rising competitive pressure. The state of financial markets seems to matter as well, with rising price indices and banking crises triggering transactions.

In a next step, we estimate the degree, to which the agglomeration of M&A activity can be ascribed to agglomeration in the respective dimensions of time, market and industry. Defining clusters by month, stock-market and 4-digit SIC industry classification, we calculate how much M&A activity in these clusters affects neighboring clusters. Using a two-stage procedure to account for the nonrandom nature of M&A we find that the coefficient of market clustering, while mostly significant, frequently changes sign in different subsamples. For example, while domestic transactions and mergers agglomerate in or around specific markets, cross-border deals and deals between publicly traded firms are dispersed across markets. Clustering by industry, on the other hand, is positive and highly significant in the main sample as well as in all subsamples considered and always associated with a larger, standardized coefficient. Thus, industry factors appear to be the main channel through which merger waves propagate in the world economy.

Interestingly, and in spite of the characteristic shape of merger waves over time, the time dimension of clustering turns out to be insignificant in all samples. Since the measures of geographic and industry clustering are not constant over time, i.e. have a time dimension themselves, this finding suggests that the shape that merger waves assume over time can be completely explained by interactions with underlying industry and geography related phenomena and that merger waves do not possess a distinct time dimension.

We have also reviewed the ongoing debate between proponents of industry-based and behavioral explanations of merger waves. Previous studies have found rich support for both positions, which could be due to the diversity of triggers and drivers employed in search of empirical evidence. In an effort to minimize the ambiguity induced by different proxies, we propose to identify industry effects by clustering across related industries and behavioral forces by agglomeration across stock-markets. Since behavioral explanations comprise mostly elements of (mis)valuation, market optimism and certain types of bandwagon effects among managers, stock-market factors are in principle appropriate to capture them; however, other channels, like the financial and economic integration between countries, might be relevant as well. With this caveat, we find a preponderance of industry effects over behavioral ones in the transmission of merger waves. Industry variables do a better job at predicting the clustering of M&A. Furthermore, whereas time clustering is entirely insignificant and geographic proximity acts as either an attracting or a repelling force depending on the type of transaction examined, industrial relatedness induces strong and significant agglomeration in all samples.

Still, the view that industry shocks and behavioral theories both have a role to play in the explanation of merger waves is not invalidated by these results, but can be qualified in the following manner: while

industry-related effects unambiguously affect all transactions, the impact of behavioral factors crucially depends on the type of transaction examined. This affirms the approach taken by large parts of the literature to explicitly differentiate between cross-border and domestic transactions and suggests that similar care should be taken in distinguishing deals between public firms from those among privately held firms, as well as mergers from acquisitions.

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