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Mergers and Acquisitions Over the Cycle – An Empirical Investigation[*]

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ABSTRACT

Using US firm-level data from 1985-2019, this paper investigates how the characteristics of matches between acquirers and targets of mergers and acquisitions (M&A) vary over the business cycle. We document several findings. (1) Acquirers are on average larger, more profitable, and in a stronger financial position than targets. (2) Targets are more innovative than acquirers, and (3) M&A targets during a recession have worse financial health but higher levels of innovation compared to M&A targets in booms. Our empirical evidence suggests that an economy may benefit from an economy may benefit from adjusting its antitrust stance over the business cycle.

Keywords: mergers, M&A, business cycle, R&D, productivity

JEL codes: E22, E32, G34

1 Introduction

When a firm merges with or acquires another firm, there is a reallocation of not just capital and labor but also knowledge. Some of this knowledge is tangible, in the form of patents, but much of the knowledge transfer is accounted for by intangible capital or goodwill. The importance of mergers and acquisitions (M&A) in reallocating these different factors of production is likely to vary depending on the economic environment faced by the companies involved.

Utilizing individual M&A transactions in the US over the period 1985-2019, we investigate how the characteristics of acquirers and targets of M&A deals vary over the business cycle in this paper. Our key findings are: 1) acquirers are on average larger, more profitable, and in a stronger financial position than targets, 2) targets are on average more innovative than acquirers, 3) M&A targets during a recession have worse financial health but higher levels of innovation compared to M&A targets in booms. This latter result suggests that firms in a strong financial position entering a recession tend to target more innovative firms that are in a more financially perilous position.

We are not the first paper to consider the characteristics of acquirers and targets of M&A deals. Jovanovic and Rousseau (2002) find a pattern of higher productivity firms buying lower productivity firms and propose a "q-theory of mergers" to explain this phenomenon. On the contrary, Rhodes-kropf and Robinson (2008) find evidence of positive assortative matching between acquirers and targets, suggesting that firms may benefit from complementarities in acquiring similar firms. More recently, David (2021) suggests that these results can be reconciled with alternative measures of productivity and a flexible Cobb-Douglas form of production. Our contribution is to investigate how the characteristics of matches between acquirers and targets vary over the business cycle.

Our paper also contributes to the literature on M&A activity and its impact on firms' innovation. Phillips and Zhdanov (2013) studies how M&A activity and competition affect the decision to conduct R&D and to innovate. They show that small firms value the option of selling their innovations to larger firms. Using large and unique patent-merger data from 1984 to 2006, Bena and Li (2014) show that companies with large patent portfolios and low R&D expenses are more likely to be acquirers, while companies with high R&D expenses and slow growth in patent filings are more likely to be targets. Haucap et al. (2019) shows that the average patent filing and R&D of the merged entity and its rivals decline substantially in post-merger periods. More recently, Cunningham et al. (2021) show that in the US pharmaceutical industry, targets' research projects are more likely to be dropped if those projects overlap with acquirers' portfolio, and such phenomenon is more frequent when acquirers possess dominant market positions. Our result highlights the importance of financial health in M&A activity during recessions. This suggests that small innovative firms may be more likely to attempt to compete directly with larger firms in booms when financial conditions allow for a quick expansion, while they may choose to sell their firm in recessions when tighter financial conditions threaten their viability.

More generally, our paper is related to the large literature on M&A activity and how it impacts the real economy. In particular, Lambrecht (2004) analyzes the timing of mergers and shows that mergers motivated by economies of scale are positively correlated with product demand. Andrade and Stafford (2004) find strong evidence of clustering over time and by industry and that M&A activity provides an important role in industry restructuring. Dimopoulos and Sacchetto (2017) studies mergers' impact on the productive efficiency in a dynamic industry-equilibrium model that features entry and exit by heterogeneous firms. They find that the presence of a merger market induces a higher entry rate and a lower exit rate, and it increases the aggregate productivity in the economy. David (2021) develops a search and matching model for M&A and finds that firm selection and resource reallocation between firms can improve aggregate welfare. Our finding suggests that M&A might have quite different aggregate impacts on the real economy in booms versus recessions. A similar point is made by Cabral (2018) who suggests a merger policy that restricts start-up acquisitions could lead in some situations to lower innovation.

Our paper also has important implications for antitrust policies. Existing studies often focus on the impact of antitrust policy on economic growth (e.g., Cavenaile et al., 2021; Fons-Rosen et al., 2022). Even in recent proposed merger guidelines, the US Department of Justice (DOJ) and the Federal Trade Commission (FTC) use the Herfindahl-Hirschman Index ("HHI") to gauge whether certain M&A activity is causing an increase in market concentration. However, the threshold for HHI[1] does not vary over time or with the general economic condition. Our paper points out the need to consider antitrust regulation differently over the cycle. In particular, an economy may benefit from adjusting its antitrust stance over the business cycle.

The remainder of this paper is organized as follows. Section 2 describes and summarizes the data. Section 3 documents the characteristics of M&A activity over the business cycle at the aggregate level. Section 4 uses micro-level data to analyze the characteristics of acquirers and targets over the business cycle. Section 5 summarizes our results and discusses some potential policy implications, while Section 6 concludes.

2 Data and Measurements

2.1 Data

There are two main datasets for our exercise: (i) the Thomson Reuters SDC Platinum database, (ii) the CRSP/Compustat merged database (CCM). For the SDC database, we extract transactions announced between 1985 and 2019. We limit the sample to completed transactions (which is about 81% of the total transactions) and those not classified as hostile or unsolicited takeovers (about 0.5% of all deals). We exclude transactions in which the acquirer owns less than 50% of the target post-merger, or

[1]See Page 7 in the draft merger guidelines https://www.ftc.gov/system/files/ftc_gov/pdf/p859910draftmergerguidelines2023.pdf.

owned over 50% prior to the merger. At this stage, we do not trim firms by industry in order to obtain as many acquirers and targets as possible. The final sample consists of 220,028 transactions.

Although the SDC database has many characteristics of the firms involved in an M&A, the fact that there are many private firms included in the SDC implies that the reporting standards and data coverage of the firms will be quite different. To ensure better data coverage in multiple dimensions of acquirer and target, we merge firms in these deals into the CCM dataset following David (2021) and rely on the CCM data to perform our subsequent analysis. The merge is not trivial, since these two datasets have different firm identifiers. The most specific identifier provided by SDC is the 6-digit CUSIP for both parties in each transaction. However, this is not sufficient for the match because CCM only records the most recent CUSIP rather than a CUSIP history. Because of this, matching on CUSIP may result in missed pairs and erroneous matches. To perform the match, we utilize the CRSP translator to associate 6-digit CUSIPs from SDC with the CRSP company identifier. We then match this identifier with the CCM database, which already associates the CRSP identifier with the set of Compustat firms. We follow this process for both acquirers and targets. We associate transactions with the Compustat data for the fiscal year preceding the year of the merger announcement.

After merging, we have 226,035 firm-year observations, of which more than 20% are involved with mergers and acquisitions: 40,431 firm-year observations for acquirers and 9,622 for targets. This appears to be a sharp drop compared to the number of transactions observed in the SDC, but it is not surprising for at least two reasons: (i) as documented in David (2021), there are many acquirers that engage in repeat acquisitions, so the number of transactions is not equivalent to the number of actual acquirers and targets; (ii) by focusing on all publicly listed firms for better data quality, all private firms involved in the transactions in the SDC are eliminated.

We then manipulate the merged dataset in the following way. We follow Dimopoulos and Sacchetto (2017) to exclude deals where the target or acquirer is a regulated utility (SIC codes 4900 to 4949), a financial institution (SIC codes 6000 to 6799), or a quasi-public firm (SIC codes greater than 9000). We deflate all nominal variables to constant 2009 dollars using the CPI from the Bureau of Labor Statistics. Our final dataset has 157,322 firm-year observations, with 30,447 for acquirers and 6,972 for targets.

2.2 Measurements

In order to have a better understanding of acquirer and target characteristics over the business cycle, we group the variables of interest into four categories: size, profitability, innovation and financial conditions. We now turn to the description of each measure while leaving the details of their construction in Appendix A.

Size

We rely on four common measures in the literature regarding firm size: (i) **Net sales** (in millions), (ii) **Employment** (in thousands): which represents the number of workers in the company reported to shareholders, (iii) **Net PPE** (in millions), which measures the cost of tangible fixed property used in the production of revenue, less accumulated depreciation; (iv) **Total assets** (in millions), which represents current assets plus net property, plant, and equipment plus other noncurrent assets (including intangible assets, deferred charges, and investments and advances). All four measures are increasing in the size of the firm.

Profitability

We rely on four standard measures of a firm's profitability : (i) **Market value** (in millions), which is calculated as the product of common shares outstanding and the closing price at the end of a fiscal year, (ii) **Return on assets**, which is calculated as the ratio between EBITDA (annual earnings before interest and taxes and depreciation) and total assets. (iii) **EBITDA/sales**, which is the ratio between EBITDA and net sales. (iv) **Net income/sales**, which is a firm's net income over its total sales. Like the size measures, all these four measures are increasing in the firm's profitability.

Innovation

We focus on four measures in this category: (i) **TFP growth rate**. Our firm-level TFP measure is computed using the semi-parametric method initiated by Olley and Pakes (1996), following the replication package in İmrohoroğlu and Tüzel (2014). As suggested by Hall (2011), the growth rate of TFP is a reasonable measure of successful innovation in almost all kinds of economy and at multiple levels of aggregation. (ii) **Price-to-research ratio (PRR)**, which is the ratio between a firm's market value and its expenditure on R&D. This measure provides a comparison of how much money a firm spends on research and development in relation to its market capitalization. (iii) **R&D intensity**, which is the expenditure of R&D over the sales, measuring the percentage of revenue of a firm that is reinvested in R&D. (iv) **Intangible capital** (in millions), which we follow Ewens et al. (2019) to account for both organizational capital and knowledge capital. This is a more accurate measure of intangible capital compared to the one originally provided in CCM, which is not able to fully capture intangible capital on firms' balance sheets due to the anachronism of US GAAP[2]. Except for PRR, which decreases in the firm's innovation level, all other three measures are increasing in the firm's innovation level.

[2] As written in Lev and Gu (2016), *"Revolutionary changes, shifting economies and business enterprises from the industrial to the information age, started to profoundly affect the business models, operations and values of companies in the 1980s, yet, amazingly, did not trigger any change in accounting. Entire industries, which are largely intangible (conceptual industries, as Alan Greenspan called them), including software, biotech, and internet services, came into being during the 1980s and 1990s. And for all other businesses, the main value drivers shifted from property, plant, machinery, and inventories, to patents, brands, information technology, and human resources. The latter set, all missing from companies' balance sheets because accountants treat intangible investments like regular expenses (wages, or interest), thereby distorts both the balance sheet and income statement. The constant rise in the importance of intangibles in companies' performance and value creation, yet suppressed by accounting and reporting practices, renders financial information increasingly irrelevant."*

Financial conditions

We focus on four measures in this category: (i) **Interest coverage ratio**, which is the firm's EBITDA over its interest expenses. This measure is used to measure how well a firm can pay the interest due on outstanding debt. (ii) **Z-score**, which is a measure that takes into account a firm's profitability, leverage, liquidity, solvency, and activity ratios. This is a widely adopted measure to gauge a company's likelihood of bankruptcy. (iii) **WW index**, which, according to Whited and Wu (2006), measures the level of difficulty for firms in accessing external financing. (iv) **KZ index**, which follows Lamont et al. (2001) takes the regression coefficients from Kaplan and Zingales (1997) and applies them to the following five categories: cash flow to total capital, the market-to-book ratio, debt to total capital, dividends to total capital and cash holdings to capital. Except for the interest coverage ratio and Z-score, which are decreasing in the firm's financial constraints, the other two measures are increasing in the firm's financial constraints.

In Table 1 we provide summary statistics for all the measures mentioned above, conditioning on their status. In terms of our **size** measures, it appears that acquirers, compared to targets, on average have higher sales, employ more workers, have a larger net capital stock and have more assets, while the targets appear not to differ much from the population in the CCM along these dimensions. Regarding our **profitability** measures, acquirers on average have higher market capitalization, higher returns on assets, and higher EBITDA/sales and higher net income/sales, compared to the targets. Targets resemble a typical firm in CCM along these measures. For **innovation** measures, acquirers on average have a higher TFP growth rate than a CCM population firm, which has a slightly higher TFP growth rate than targets. Interestingly, our three R&D-related measures deliver the same message: targets are more R&D intensive than acquirers, in the sense that they have a lower PRR, a higher R&D intensity, and more intangible capital. Finally, regarding our **financial condition** measures, they give a consistent message that targets on average have worse financial conditions compared to acquirers: they have a lower interest coverage ratio, are more likely to bankrupt (lower Z-score), and are more financially constrained (higher WW index and KZ index). Across our financial measures, acquirers seem to have superior financial conditions, compared to the population in CCM.

In summary, according to our measures, we find that acquirers, on the one hand, are larger, more profitable, and have better financial conditions than targets. Targets, on the other hand, have a higher level of innovation than acquirers. Although these features hold in a cross-sectional sense, less is known about their time-series behavior, which is crucial for our understanding of mergers and acquisitions over the business cycle. We turn to the time-series dimension in the next section.

3 Mergers and Acquisitions at the Macro Level

3.1 Total number of M&A

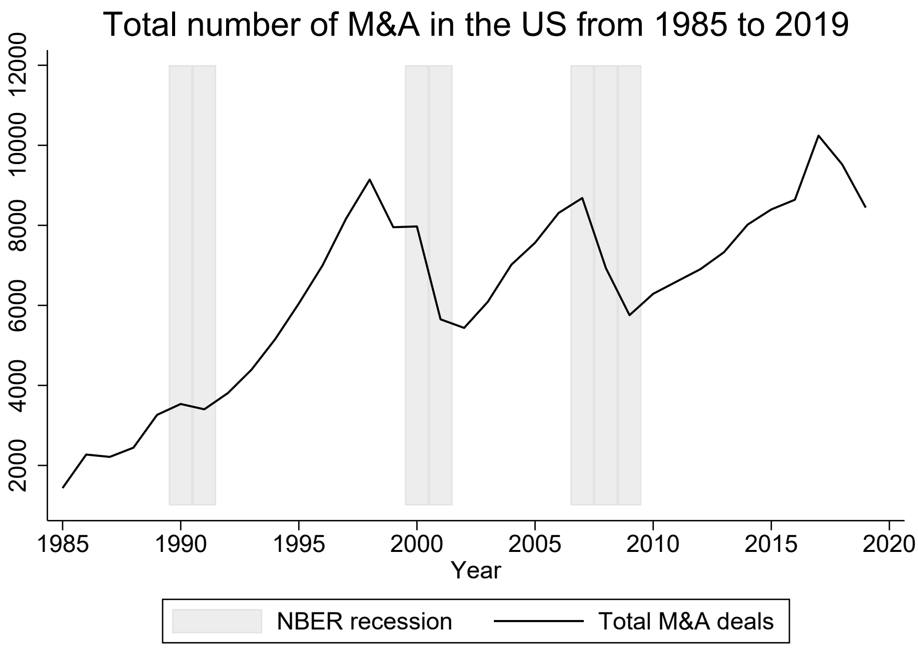
We begin by documenting the total number of mergers and acquisitions that occurred in the US domestic market during the period 1985-2019. Since we are interested in the total number of deals and its time-series feature, we rely on the original SDC dataset to perform our analysis.

Table 1. Summary statistics

		Acquirers			Targets			Population		
Groups	Measures	25th percentile	75th percentile	Median	25th percentile	75th percentile	Median	25th percentile	75th percentile	Median
	Sales ($millions)	108	2,033	489	70.3	924	257	43	1,105	225
	Employment (thousands)	.391	8.3	1.9	.247	4.19	.956	.176	5.5	.97
Size	PPE ($millions)net	12.9	444	79.5	7.96	242	41.6	5.91	285	39.2
	Total assets ($millions)	105	2,035	467	67.6	944	228	48.2	1,117	214
	Market value ($millions)	120	2,383	564	47.6	784	182	45.6	1,130	216
	Return on assets	.0694	.18	.126	.0127	.164	.102	.00464	.163	.1
Profitability	EBITDA/sales	.0511	.189	.109	.0133	.158	.0786	.0158	.174	.0834
	Net income/sales	.00176	.0786	.0361	-.0884	.0537	.0135	-.0623	.0695	.0215
	TFP growth rate	-.0785	.0957	.00743	-.114	.101	-.0043	-.108	.0919	-.00557
	PRR	30.1	1,326	202	15.9	1,436	135	19.8	1,384	139
Innovation	R&D intensity	.0341	1.16	.147	.0388	1.2	.181	.0341	1.22	.15
	Intangible capital ($millions)	.101	.476	.232	.11	.621	.283	.108	.598	.269
	Interest coverage ratio	3.56	36.6	9.25	1.56	34.8	6.01	1.75	36.9	6.88
Financial	Z-score	2.42	6.93	4.01	1.51	5.85	3.25	1.84	6.57	3.59
conditions	WW index	-.374	-.185	-.285	-.318	-.156	-.239	-.339	-.131	-.239
	KZ index	-66.8	17.7	-10.4	-21.8	54.8	-.452	-35	34.4	-2.08

Notes: Summary statistics based on the SDC and CCM merged dataset from 1985-2019. All variables of interest are winsorized at the bottom and top 1% of its distribution in a specific year and within each 3-digit SIC industry. All monetary variables are deflated using the CPI from the Bureau of Labor Statistics, with 2009 as the base year.

Figure 1. Total number of M&A



Note: Total number of the U.S. domestic mergers and acquisitions based on the Thomson Reuters SDC Platinum database from 1985-2019.

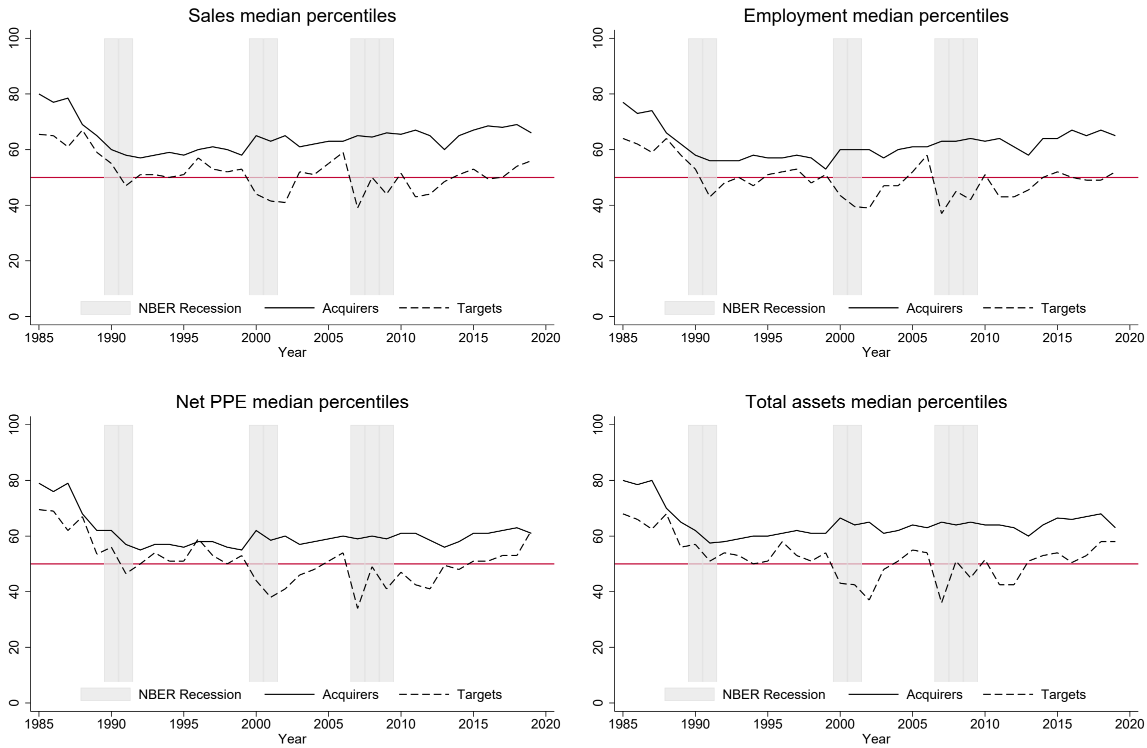
Based on Figure 1, it is evident that the total number of M&A is clearly procyclical. During economic booms, the number of deals increases quite rapidly. In an economic downturn, the number of deals also crashes. With this big picture in mind, we now turn to the acquirers and targets over the cycle and see whether they differ from each other and the population during booms and recessions.

3.2 Acquirers and targets over the cycle

To have a better understanding of how acquirers and targets behave over the cycle, we again resort to the four groups of measures in Section 2.2. For each measure in a given year, we rank all firms in CCM conditioning on their M&A status, and we then look at where a median acquirer and a median target stand, compared to a median firm in CCM.

In Figure 2, we see that acquirers always stay above the population throughout our sample along different size measures, whereas targets seem to fluctuate around the population median over the years, with the exception of the first three years in our sample[3]. In terms of booms and recessions, we do not observe much fluctuation for the acquirers, but targets tend to have a smaller size during recessions, as can be seen from the dip of the dashed line during recessions across our measures.

Figure 2. Size measures for acquirers and targets over the cycle



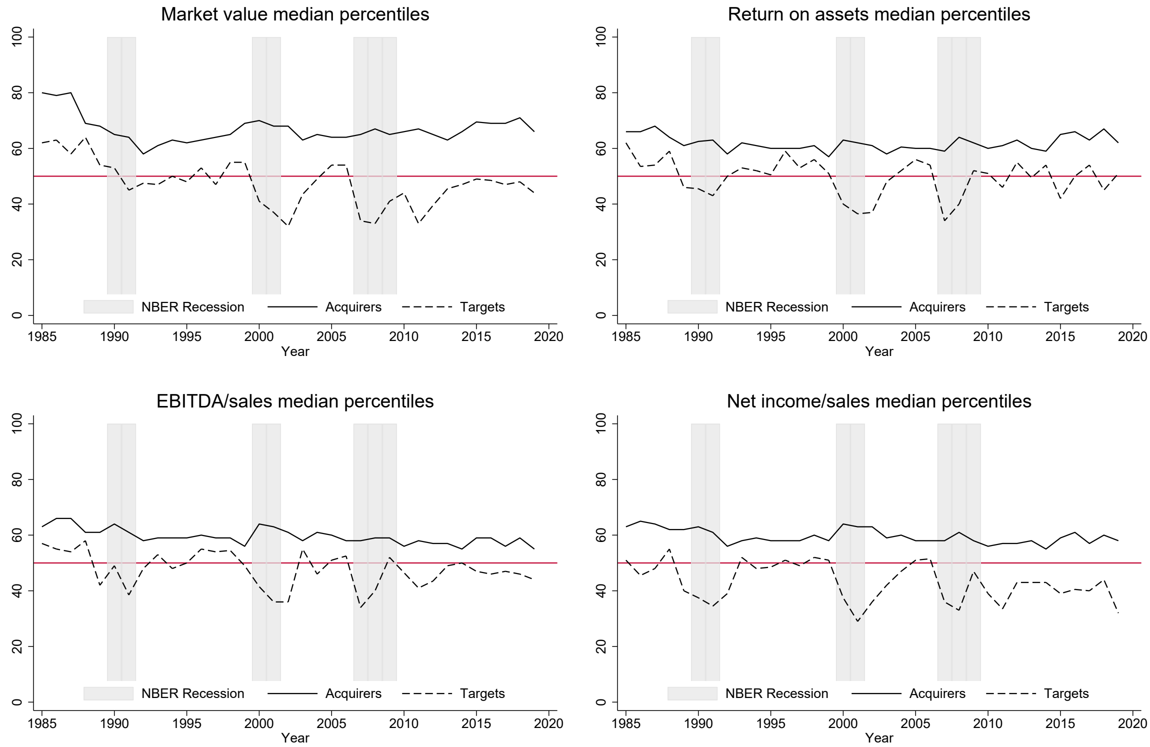
Note: The red horizontal line in each plot represents a median firm in the CCM population. Each point along the plots represents the median ranking of firm conditioning on being an acquirer or target in a given year. The plots are based on the SDC and CCM merged dataset for the period of 1985-2019.

In Figure 3, we see that acquirers always stay above the population throughout our sample in terms of: market value, return on assets, EBITDA/sales, and net income/sales. On the other hand, targets seem to fluctuate around the population median over the years along all measures. In terms of booms and recessions, acquirers seem to have a very mild increase during recessions along these four measures, while targets are clearly dipping in their ranking during recessions. This suggests acquirers are generally more profitable than targets, and targets' profitability deteriorates substantially

[3]According to David (2021), this could be due to the fact that SDC Platinum started to cover all domestic deals after 1992. However, before 1992, it only included all transactions involving at least 5% of the ownership of a company where the transaction was valued at $1 million or more.

during recessions.

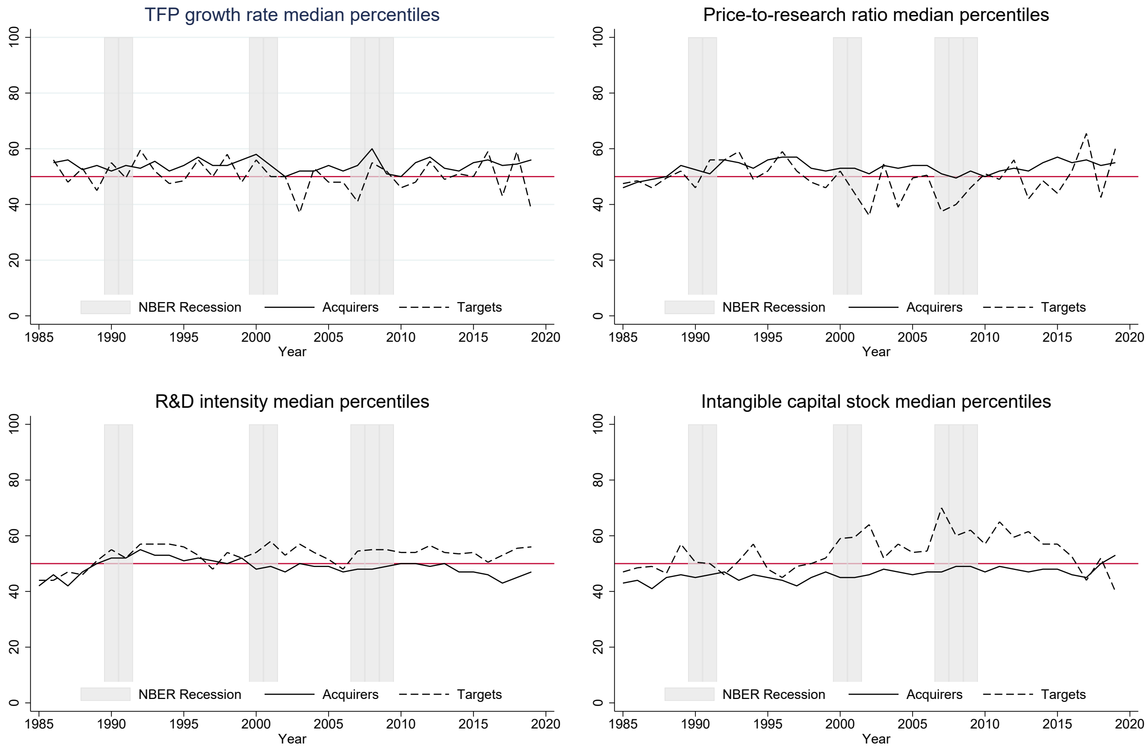
Figure 3. Profitability measures for acquirers and targets over the cycle



Note: The red horizontal line in each plot represents a median firm in the CCM population. Each point along the plots represents the median ranking of firm conditioning on being an acquirer or target in a given year. The plots are based on the SDC and CCM merged dataset for the period of 1985-2019.

In Figure 4, we see that acquirers have a slightly higher TFP growth rate than the population median, whereas targets are not obviously different from the population. In terms of the R&D-related measures, we find no obvious difference between acquirers and the population median, but some interesting pattern among the targets: the price-to-research ratio seems to go down mildly during the downturn, whereas the R&D intensity seems to spike up in recessions, with a more pronounced pattern for the intangible capital. In terms of booms and recessions, we do not observe clear patterns for acquirers, but for targets, except the dipping of PRR during recessions, the other three measures seem to be spiking during recessions.

Figure 4. Innovation measures for acquirers and targets over the cycle



Note: The red horizontal line in each plot represents a median firm in the CCM population. Each point along the plots represents the median ranking of firm conditioning on being an acquirer or target in a given year. The plots are based on the SDC and CCM merged dataset for the period of 1985-2019.

In Figure 5, all four measures are fairly consistent across the board: acquirers consistently have better financial conditions compared to the targets and the population. Targets appear to have a higher chance of bankruptcy and are more financially constrained, especially during economic downturns.

Figure 5. Financial condition measures for acquirers and targets over the cycle

Note: The red horizontal line in each plot represents a median firm in the CCM population. Each point along the plots represents the median ranking of firm conditioning on being an acquirer or target in a given year. The plots are based on the SDC and CCM merged dataset for the period of 1985-2019.

In summary, we find: (i) the total number of deals of M&A is highly procyclical. (ii) Acquirers are larger and more profitable in general, whereas targets are smaller and less profitable, especially in recessions. (ii) Acquirers tend to have great financial conditions throughout our sample, whereas targets are more financially vulnerable in general, but much worse during economic downturns. (iv) Interestingly, targets seem to be more R&D intensive and are more innovative during recessions.

4 Mergers and Acquisitions at the Micro Level

While the above analysis provides an interesting overview, it does not take advantage of the granular information we have at the firm level. In this section, we turn to regression analysis and investigate the characteristics at the firm level that are crucial for a firm's M&A decision over the cycle. Given that our size and profitability measures are very often treated as controls, here we mainly focus on our innovation and financial condition measures.

We utilize a simple linear probability model for our regression analysis. We estimate regressions in which we correlate the status of being an acquirer or target with different sets of firm characteristics as follows

$$d_{it} = \alpha + \beta \times \mathcal{I}_{it} + \gamma \times \mathcal{I}_{it} \times \text{Recession} + \delta \times \mathcal{C}_{it} + \lambda_{st} + \epsilon_{it} \tag{1}$$

where d_{it} represents either a dummy variable for being an acquirer or a dummy variable for being a target of firm i in year t. $\mathcal{I}_{it}$ is an indicator variable for the characteristic of a particular firm that we are interested in, e.g., TFP growth, R&D intensity, and financial conditions. Thus, β measures the difference in the probability of becoming an acquirer or target according to a particular measure. When interacting with the recession dummy, the coefficient γ measures the impact of these features during the recession. $\mathcal{C}_{it}$ refers to a set of indicator variables based on firm-level characteristics and their interaction with the recession dummy as our controls. Note that the results are by no means causal but are interested in documenting the level difference between firms. λ_{st} refers to industry$\times$ year fixed effects, which capture unobserved shocks at a detailed industry level, such as demand shocks. ϵ_{it} is the error term.

Innovation level and M&A status

We begin by looking at targets. Table 2 presents the estimates of our benchmark specifications to study the link between the target status and the firm's innovation measures and the impact of recessions on it. Although the measures do not agree with each other in general, as can be seen in the odd columns in the table, their message during recessions is clear and consistent: firms that have higher levels of innovation are more likely to become targets during recessions. We perform the same exercise for acquirers and report the results in Table 4. Although some of our measures indicate that a higher level of innovation is associated with a lower chance of becoming an acquirer, none of them are statistically significant when interacting with the recession dummy. Without making any causal claims, it is evident that a higher level of innovation is associated with a higher chance of becoming a target during economic downturns.

Financial conditions and M&A status

Table 3 presents the estimates of our benchmark specifications to study the link between the target status and the measures of the firm's financial condition and the impact of recessions on it. Our measures deliver a different message in non-recession times, low interest rate coverage ratio, and high WW index are negatively associated with the probability of being a target, while low z-score and high KZ index are positively associated with the chance of being a target. Interestingly, when interacting our measures with the recession dummy, we find consistent and significant results across four measures: those firms that possess poor financial conditions are more likely to become targets during recessions. The result is robust when we control for other characteristics at the firm level. We also performed a similar exercise for acquirers. It is natural to ask whether being in good financial condition increases the chance of being an acquirer. So compared to targets, we now take the opposite indicator variables (e.g. firms with low-interest coverage ratio vs. firms with high-interest coverage ratio) as our independent variables. The results are reported in Table 5. Our measures deliver quite different messages. While some of them suggest that a better financial condition does not imply a higher chance of becoming an acquirer, others suggest that a better financial condition could even reduce the chance of becoming a buyer during the recession. This seems to suggest that firms are more cautious about becoming a buyer during recessions, even for those with good financial health. Put simply, a bad financial condition significantly increases the chance of a firm becoming a target during the recession, but a good financial condition does not imply that a firm will likely become an acquirer during economic downturns.

Table 2. Innovation and probability of being a target

Measures	(1) $d_{it}^{\text{Target}} = 1$	(2) $d_{it}^{\text{Target}} = 1$	(3) $d_{it}^{\text{Target}} = 1$	(4) $d_{it}^{\text{Target}} = 1$	(5) $d_{it}^{\text{Target}} = 1$	(6) $d_{it}^{\text{Target}} = 1$	(7) $d_{it}^{\text{Target}} = 1$	(8) $d_{it}^{\text{Target}} = 1$
High TFP growth rate	-0.0115***	-0.0137***						
	(0.0015)	(0.0016)						
High TFP growth rate×Recession	0.0107***	0.0092**						
	(0.0033)	(0.0035)						
Low PRR			0.0141***	0.0157***				
			(0.0019)	(0.0019)				
Low PRR×Recession			0.0160***	0.0145***				
			(0.0045)	(0.0044)				
High R&D intensity					-0.0109***	-0.0122***		
					(0.0023)	(0.0023)		
High R&D intensity×Recession					0.0099*	0.0100*		
					(0.0053)	(0.0054)		
High intangible capital							0.0046**	0.0078***
							(0.0018)	(0.0018)
High intangible capital×Recession							0.0122***	0.0123***
							(0.0042)	(0.0042)
Observations	156,050	156,050	156,050	156,050	156,050	156,050	156,050	156,050
R-squared	0.0772	0.0926	0.0779	0.0935	0.0773	0.0927	0.0773	0.0929
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variables are a dummy variable that takes the value equal to 1 if the firm is a target in a particular year. The 'High' and 'Low' stand for the top and bottom quintiles of the distribution of each measure. The control variables are indicator variables for the firm's size and age along with their interaction with recession. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Financial conditions and probability of being a target

Measures	(1) $d_{it}^{\text{Target}}=1$	(2) $d_{it}^{\text{Target}}=1$	(3) $d_{it}^{\text{Target}}=1$	(4) $d_{it}^{\text{Target}}=1$	(5) $d_{it}^{\text{Target}}=1$	(6) $d_{it}^{\text{Target}}=1$	(7) $d_{it}^{\text{Target}}=1$	(8) $d_{it}^{\text{Target}}=1$
Low interest coverage ratio	-0.0017	-0.0056***						
	(0.0016)	(0.0016)						
Low interest coverage ratio×Recession	0.0129***	0.0133***						
	(0.0039)	(0.0041)						
Low Z-score			0.0103***	0.0101***				
			(0.0017)	(0.0017)				
Low Z-score ×Recession			0.0211***	0.0193***				
			(0.0042)	(0.0043)				
High WW index					-0.0143***	-0.0265***		
					(0.0015)	(0.0018)		
High WW index×Recession					0.0094**	0.0113***		
					(0.0037)	(0.0042)		
High KZ index							0.0047***	-0.0085***
							(0.0017)	(0.0017)
High KZ index×Recession							0.0094**	0.0138***
							(0.0039)	(0.0039)
Observations	156,050	156,050	156,050	156,050	156,050	156,050	156,050	156,050
R-squared	0.0776	0.0930	0.0779	0.0932	0.0794	0.0935	0.0776	0.0927
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variables are a dummy variable that takes the value equal to 1 if the firm is a target in a particular year. The 'High' and 'Low' stand for the top and bottom quintiles of the distribution of each measure. The control variables are indicator variables for the firm's size and age along with their interaction with recession. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Innovation and probability of being an acquirer

Measures	(1) $d_{it}^{\text{Acquirer}} = 1$	(2) $d_{it}^{\text{Acquirer}} = 1$	(3) $d_{it}^{\text{Acquirer}} = 1$	(4) $d_{it}^{\text{Acquirer}} = 1$	(5) $d_{it}^{\text{Acquirer}} = 1$	(6) $d_{it}^{\text{Acquirer}} = 1$	(7) $d_{it}^{\text{Acquirer}} = 1$	(8) $d_{it}^{\text{Acquirer}} = 1$
High TFP growth rate	-0.0586***	-0.0339***						
	(0.0038)	(0.0037)						
High TFP growth rate×Recession	0.0006	0.0050						
	(0.0061)	(0.0066)						
Low PRR			-0.0889***	-0.0817***				
			(0.0048)	(0.0046)				
Low PRR×Recession			0.0052	0.0084				
			(0.0073)	(0.0073)				
High R&D intensity					-0.0226***	-0.0018		
					(0.0068)	(0.0066)		
High R&D intensity×Recession					-0.0128	-0.0127		
					(0.0097)	(0.0098)		
High intangible capital							-0.0898***	-0.0757***
							(0.0045)	(0.0044)
High intangible capital×Recession							-0.0114*	-0.0098
							(0.0069)	(0.0070)
Observations	156,050	156,050	156,050	156,050	156,050	156,050	156,050	156,050
R-squared	0.0772	0.0926	0.0779	0.0935	0.0773	0.0927	0.0773	0.0929
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variables are a dummy variable that takes the value equal to 1 if the firm is an acquirer in a particular year. The 'High' and 'Low' stand for the top and bottom quintiles of the distribution of each measure. The control variables are indicator variables for the firm's size and age along with their interaction with recession. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Financial conditions and probability of being an acquirer

Measures	(1) $d_{it}^{\text{Acquirer}} = 1$	(2) $d_{it}^{\text{Acquirer}} = 1$	(3) $d_{it}^{\text{Acquirer}} = 1$	(4) $d_{it}^{\text{Acquirer}} = 1$	(5) $d_{it}^{\text{Acquirer}} = 1$	(6) $d_{it}^{\text{Acquirer}} = 1$	(7) $d_{it}^{\text{Acquirer}} = 1$	(8) $d_{it}^{\text{Acquirer}} = 1$
High interest coverage ratio	-0.0195***	-0.0169***						
	(0.0040)	(0.0040)						
High interest coverage ratio×Recession	0.0069	0.0064						
	(0.0068)	(0.0068)						
High z-score			0.0081***	0.0108***				
			(0.0042)	(0.0042)				
High z-score×Recession			0.0285***	0.0258***				
			(0.0072)	(0.0072)				
Low WW index					0.1160***	0.1023***		
					(0.0068)	(0.0064)		
Low WW index×Recession					0.0050	0.0082		
					(0.0072)	(0.0084)		
Low KZ index							0.1007***	0.0835***
							(0.0057)	(0.0051)
Low KZ index×Recession							0.0209***	0.0240***
							(0.0072)	(0.0077)
Observations	156,050	156,050	156,050	156,050	156,050	156,050	156,050	156,050
R-squared	0.0772	0.0926	0.0779	0.0935	0.0773	0.0927	0.0773	0.0929
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variables are a dummy variable that takes the value equal to 1 if the firm is an acquirer in a particular year. The 'High' and 'Low' stand for the top and bottom quintiles of the distribution of each measure. The control variables are indicator variables for the firm's size and age along with their interaction with recession. All standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

5 Discussion

5.1 Link to theory

Our results suggest that targets of M&A in recessions have higher levels of R&D activity compared to targets of M&A in economic booms. These results complement the framework established in Phillips and Zhdanov (2013) which models the impact of M&A activity on the incentives for R&D expenditure. Their theory and empirical evidence suggest that large firms innovate through acquiring smaller, more R&D intensive firms. In turn, they suggested that smaller firms value the option value of being bought out and that the possibility that a firm may be acquired amplifies the potential gains from innovation.

In the context of our result, the option value suggested by Phillips and Zhdanov (2013) can be recast as an insurance option. Small, innovative firms have two options: allow an acquisition from a bigger firm and exit the market, or attempt to compete directly with the bigger firms. Direct competition between small and large firms would likely require small firms to undergo significant capital investment to take their innovations to market. This is more likely to be feasible when financial conditions are good, such as in times of economic booms. However, during recessions, when financial conditions worsen, smaller firms may struggle to survive. In the latter case, smaller firms may prefer to be acquired by a larger, more financially healthy firm. From the perspective of an entrepreneur, this insurance effect is likely to incentivize the process of idea creation through R&D.

This paper shows how in recessions, it is innovative firms that are less financially healthy that are more likely to be targets of M&A. This is an important caveat to the point raised by Cunningham et al. (2021) who show that much M&A activity in the pharmaceutical industry is anti-competitive as firms are bought out in order to shut down rival products. We suggest this mechanism is less likely to hold in recessions as financially vulnerable firms are less likely to pose a competitive risk to incumbent firms.

5.2 Policy Implications

On 19 July 2023, the US Department of Justice (DOJ) and the Federal Trade Commission (FTC) released a draft update of their merger guidelines[4]. This document acknowledges the importance of small innovative firms in ensuring market competitiveness. Their Guideline 4 states that "Mergers Should Not Eliminate a Potential Entrant in a Concentrated Market".

Our results suggest that the economy may benefit from changing antitrust regulations to more explicitly account for the business cycle. In particular, our findings suggest that in economic downturns it may be beneficial to allow acquisitions as this may provide an important insurance role for small innovative firms that may not have the financial strength to survive a recession. While the DOJ and FTC draft merger guidelines do not explicitly take into account the economic cycle, they do discuss whether the weak financial position of one of the merging parties will prevent a lessening of competition. However, the conditions required to meet this defense are relatively stringent. Our paper suggests that, in addition to broadening the definition of a failing firm, there may be a benefit in explicitly taking into account macroeconomic conditions. A similar point is made by Cabral (2018) who suggests a merger policy that restricts start-up acquisitions could lead in some situations to lower innovation.

Further work is needed before being able to proscribe a particular policy change. Small innovative firms are likely to adjust both their R&D investment and their financing decisions in response to any policy change. Policy changes may result in distorted incentives as noted in Dijk et al. (2023). The find firms may have an incentive to adjust

[4] The DOJ and FTC published their draft update of the merger guidelines online at https://www.ftc.gov/system/files/ftc_gov/pdf/p859910draftmergerguidelines2023.pdf.

their research portfolio to make them a more attractive acquisition rather than a long-term rival to incumbents. Along similar lines, a more lenient antitrust policy may result in greater moral hazard and incentivize firms to take more financial risk.

6 Conclusion

This paper provides macro- and micro-level evidence on the characteristics of M&A deals and how they vary throughout the business cycle. We make several important findings. First, we find that acquirers are on average larger, more profitable, and in a stronger financial position than the targets. Second, we find that targets are on average more innovative than acquirers. This is consistent with the evidence provided by Phillips and Zhdanov (2013) suggesting that firm acquisitions are an important source of large firm innovation. Third, we find that M&A targets during a recession have worse financial health but higher levels of innovation compared to M&A targets in booms. This result suggests that M&A activity provides an insurance mechanism for smaller more innovative firms that may be used more often during recession periods.

Our paper also has important policy implications regarding the role of antitrust regulation over the business cycle. In particular, the empirical evidence we provide suggests that an economy may benefit from adjusting its antitrust stance over the business cycle. Our findings suggest M&A activity during recessions provides a degree of insurance for innovative firms that may be financially vulnerable. While this mechanism suggests a more lenient antitrust stance during recessions may be beneficial for firm innovation and thus aggregate productivity, further work needs to be done to consider the overall welfare impact of such a policy change.

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A Supplementary material

A.1 Definition of measurements

Most measures are fairly straightforward to calculate based on the definitions of variables in the Compustat database. Here, we provide the details of the following four measures: intangible capital, Z-score, WW index, and KZ index.

Intangible capital

The intangible capital in our analysis is taken from the github repository[5] of Ewens et al. (2019). According to Ewens et al. (2019), the intangible capital stock is the sum of knowledge capital stock (G_{it}) and organizational capital stock (S_{it}), which are estimated using the perpetual inventory methods as follows

$$
\begin{aligned}
G_{it} &= (1 - \delta_G) G_{i,t-1} + \gamma_G R\&D_{it} \\
S_{it} &= (1 - \delta_S) S_{i,t-1} + \gamma_S SG\&A_{it}
\end{aligned}
$$

where R&D is the firm's expenditure on R&D, and SG&A is the cost associated with Selling, General, and Administrative, netting out of R&D expense and Research and Development in Process. Parameters are obtained through structural estimation.

Z-score

The Altman z-score is calculated based on the following five financial ratios:

$$
\begin{aligned}
z \equiv & 1.2 \times \frac{\text{Working capital}}{\text{Total assets}} + 1.4 \times \frac{\text{Retained earnngs}}{\text{Total assets}} + 3.3 \times \frac{\text{EBIT}}{\text{Total assets}} \\
& + 0.6 \times \frac{\text{Market value}}{\text{Total liability}} + \frac{\text{Sales}}{\text{Total assets}}
\end{aligned}
$$

[5] https://github.com/michaelewens/Intangible-capital-stocks

where working capital is computed as Item 4 - Item 5, retained earnings is Item 36, EBIT is calculated as Item 172-Item 15- Item 16, market value/total liability is (Item 25$\times$Item 24)/Item 181. Item numbers refer to Compustat annual data items as in the following: 4 (current assets, total), 5 (current liabilities, total), 15 (interest expense), 16 (income taxes, total), 24 (price close), 25 (common shares outstanding), 172 (net income), 181 (total liabilities). The formula takes into account profitability, leverage, liquidity, solvency, and activity ratios. When a z-score is close to 0, it suggests that a company might be likely to bankrupt, while a higher z-score suggests that a company is in a more solid financial condition.

WW index

The WW index is based on the work of Whited and Wu (2006):

$$
\begin{aligned}
WW \equiv & -0.091 \times \frac{\text{Cash flow}}{\text{Total assets}} - 0.062 \times \text{DIVPOS} + 0.021 \times \frac{\text{Long-term debt}}{\text{Total assets}} \\
& - 0.044 \times \text{Log(Total assets)} + 0.102 \times \text{ISG} - 0.035 \times \text{SG}
\end{aligned}
$$

where Cash flow/total assets is computed as (Item 18 + Item 14)/Item 6. DIVPOS is an indicator that takes the value one if the firm pays cash dividends. Long-term debt is Item 9. ISG is the firm's three-digit SIC industry sales growth, and SG is the firm's sales growth. The item number definitions are as follows: 6 (assets, total), 9 (long-term debt, total), 14 (depreciation and amortization), and 18 (income before extraordinary items). A higher WW index is associated with firms more likely to be financially constrained and face higher external financing costs.

KZ index

The KZ index is based on the work of Lamont et al. (2001), who use the regression coefficients from Kaplan and Zingales (1997) to compute:

$$
\begin{aligned}
KZ \equiv & -1.00909 \times \frac{\text{Cash flow}}{\text{Net PPE}} + 0.2826389 \times \text{Tobin's Q} + 3.139193 \times \frac{\text{Debt}}{\text{Total capital}} \\
& - 39.3678 \times \frac{\text{Dividends}}{\text{Net PPE}} - 1.314759 \times \frac{\text{Cash}}{\text{Net PPE}}
\end{aligned}
$$

where Cash flow/Net PPE is computed as (Item 18 + Item 14)/Item 8, Tobin's Q as (Item 6 + CRSP December Market Equity - Item 60 - Item 74)/Item 6, Debt/Total Capital as (Item 9 + Item 34)/(Item 9 + Item 34 + Item 216), Dividends/K as (Item 21 + Item 19)/Item 8, and Cash/K as (Item 1/Item 8). The item number definitions are as follows: 1 (cash and short-term investments), 6 (liabilities and stockholders' equity–total), 8 (net property, plant and equipment), 9 (long-term debt–total), 14 (depreciation and amortization), 18 (income before extraordinary items), 19 (dividends–preferred), 21 (dividends–common), 34 (debt in current liabilities), 60 (common equity–total), 74 (deferred taxes), and 216 (stockholders' equity–total). Data item 8 is lagged. Similarly to the WW index, the KZ index is a relative measurement of reliance on external financing. Companies with higher KZ-Index scores are more likely to experience difficulties when financial conditions tighten, as they may have difficulty financing their ongoing projects.