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Market power and systematic risk

Fabian Hollstein[1] | **Marcel Prokopczuk**[2,3] | **Christoph Matthias Würsig**[2]

[1]School of Human and Business Sciences, Saarland University, Saarbruecken, Saarland, Germany

[2]School of Economics and Management, Leibniz University Hannover, Hannover, Germany

[3]ICMA Centre, Henley Business School, University of Reading, Reading, UK

Correspondence
Fabian Hollstein, School of Human and Business Sciences, Saarland University, Campus C3 1, 66123 Saarbruecken, Saarland, Germany.
Email: fabian.hollstein@uni-saarland.de

Abstract

We examine the impact of product market competition on firms' systematic risk. Using a measure of total product market similarity, we document a strong negative relationship between market power and market betas. The effect more than triples in the most recent period of low competition. Anticompetitive mergers result in a significant reduction in market betas. Firms facing less competition seem to be partially insulated from systematic discount-rate shocks. Lower equity costs therefore imply that market power is partly self-perpetuating.

KEYWORDS

discount-rate beta, market beta, market power, mergers and acquisitions, product market competition, systematic risk

1 | INTRODUCTION

Competition between firms, or the lack of it, has been one of the most important topics in both the academic literature and the financial press in recent times. A number of studies have linked market power to various macroeconomic trends in the economy: For example, a decline in the labor share (Autor et al., 2020), lower investment and productivity growth (Covarrubias et al., 2020), an increase in the capital share, a decrease in low-skilled wages, a decrease in labor force participation, a decrease in labor flows, and a decrease in migration rates (De Loecker et al., 2020), as well as delayed innovation and a slowdown in aggregate output (Bae et al., 2021). Cairó and Sim (2020) propose a model in which these effects can be generated by a rise in market power in both product and labor markets and show that this increase in market power can cause financial instability.

Even more obvious than the effects on the economy as a whole, market power has strong implications for individual firms. Firms with market power can limit output or refrain from investment. This leads to higher stability of cash flows and lower idiosyncratic volatility (De Loecker et al., 2020; Gaspar and Massa, 2006; Gutiérrez and Philippon, 2019; Hoberg and Phillips, 2010b).

Several previous studies examine the relationship between market power and systematic risk on a theoretical basis.[1] Depending on the assumptions made, the model predictions range from a negative relationship between the two (e.g., O'Brien, 2011; Subrahmanyam & Thomadakis, 1980) to no clear effect (e.g., Alexander and Thistle, 1999; Peyser, 1994; Wong, 1995), or a positive relationship (e.g., Bustamante and Donangelo, 2017). Empirical studies appear to be similarly divided, with some documenting a negative effect (e.g., Binder, 1992; Sullivan, 1978). However, for every study documenting a negative relation, there appears to be an equal number of studies documenting no relation at all (e.g., Abdoh & Varela, 2017; Bernier, 1987; Curley et al., 1982; Moyer and Chatfield, 1983), or indirectly positing a positive one (e.g., Bustamante and Donangelo, 2017). Thus, based on the literature, there could be a negative, positive, or no relationship between market power and firm betas.

In this study, we contribute to the literature by comprehensively reexamining this issue. Importantly, we use the textual analysis-based measure of total product market similarity introduced by Hoberg and Phillips (2010a). This measure has its roots in the innovation and product differentiation literature. As shown by Hotelling (1929), Chamberlin (1933), Sutton (1998), and Hoberg and Phillips (2016), among others, such an innovation-based measure of market power can matter independently and is potentially more empirically relevant than the standard measure based on industry sales concentration.

We use panel regressions with firm and year fixed effects, as well as several other control variables that potentially determine market beta. Our main finding is that market power is significantly negatively related to systematic risk. The results are both statistically and economically significant. Moreover, the same patterns hold for both the industry sales concentration and the product market similarity measures of market power, although the effect of the latter is stronger. For example, the difference between the market beta of a firm with total product market similarity that is two standard deviations below the average (a firm with high market power) and an otherwise similar firm with average total product market similarity is up to −0.24, implying a substantial difference in Capital Asset Pricing Model (CAPM)-based expected returns. In a realistic hypothetical scenario, this main effect is associated with a reduction of about 1.4 percentage points in the cost of equity and 1.0 percentage points in the weighted average cost of capital (WACC).[2] Thus, CAPM-based equity valuations of firms with market power are substantially higher and financing is substantially cheaper than for their peers.[3] In economic terms, therefore, market power has a profoundly self-perpetuating effect: firms with more market power have lower costs of capital. They can be more profitable and continue to grow, making it harder for new competitors to enter the market. Our findings thus support the case for policymakers to tighten antitrust rules and actively promote competition.

To examine any impact of the recent downward trend in competition (e.g., Covarrubias et al., 2020; Grullon et al., 2019), we analyze different subsamples. We find that the effect on market betas of a two-standard-deviation decrease in market power from the mean increases more than 2.5 times when comparing the post-2005 period with the first 16 years of our sample period between 1989 and 2004. Thus, (i) the effect of market power on betas appears to be substantially stronger in the current low-competition market environment. (ii) This result provides a partial explanation for the conflicting results of previous studies: the effect used to be substantially weaker. Although we observe an effect in the earlier sample with total product market similarity, it is more difficult to detect with the traditionally used proxies for market power. These proxies seem to be empirically less relevant with respect to systematic risk.

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[1] In this paper, we use the terms "systematic risk" and "market beta" interchangeably.

[2] To obtain these figures, we assume a market risk premium of 6% per annum and a two-thirds equity ratio: $-0.24 \cdot 6\% = -1.44\%$ and $-1.44 \cdot 2/3 = -0.96\%$.

[3] This conjecture is based on previous research showing that firms rely primarily on the CAPM for capital budgeting (Graham and Harvey, 2001; Graham, 2022; Jacobs and Shivdasani, 2012). For example, a project paying $1 in perpetuity has a value of $17.64 using a discount rate of 5.67% (the WACC resulting from a risk-free rate of 0.5%, a market beta of 1, a 2/3 equity structure, a market risk premium of 6%, and a cost of debt of 4%). If the WACC falls by 0.96 percentage points to 4.71%, the value rises by more than 20% to $21.23. Thus, these seemingly modest effects on the cost of capital have large real effects.

Next, we analyze the effect of anticompetitive mergers on market betas. If market power leads to lower systematic risk, an anticompetitive merger should result in a significant decrease in a firm's market beta estimates. This is exactly what we find. First, we document that the overall product market similarity of the acquiring firms does indeed decrease after an anticompetitive merger. We then show that, controlling for other effects, market betas are indeed significantly depressed after a merger. We show that non-anticompetitive mergers and withdrawn mergers do not produce such an effect. Analyzing the relationship in more detail, we show that the strongest decrease does indeed occur immediately after the merger.

We take several steps to further analyze the relation between market power and beta. First, we follow Campbell and Vuolteenaho (2004) and decompose betas into parts due to cash-flow and discount-rate news. We find that it is mainly the discount-rate beta that is affected by market power. Thus, while they are still exposed to cash-flow shocks, firms that face little competition appear to be partially insulated from aggregate discount-rate shocks. Second, a decomposition into upside and downside betas, as proposed by Ang et al. (2006), helps us to identify the different effects of market power on market betas in bull and bear markets. Third, we analyze the effect of market power on tail risk and document a significant negative relation. Firms with high market power not only have lower systematic risk, but also lower left tail risk.

Taken together, these results point to two main channels through which market power may affect systematic risk: (i) firms with market power appear to be partially insulated against cost-of-capital shocks, and (ii) in some situations, firms may use their market power to respond to adverse idiosyncratic and systematic shocks by raising product prices. Discount-rate shocks hurt financially constrained firms more. Thus, the lower discount-rate betas of firms with market power suggest that they are less affected by financial constraints. This is consistent with Gutiérrez and Philippon (2017, 2018), who show that firms with little competition tend to invest less. Thus, overall our results point to channel (i), while channel (ii) is of course also relevant in the case of market power.

Finally, we conduct several tests to document the robustness of these results. We confirm the negative relationship between market power and realized returns. Furthermore, we obtain qualitatively similar results for a variety of measures (e.g., a text-based Herfindahl–Hirschman Index [HHI] measure, a product market fluidity measure, and an adjusted HHI measure based on Census data) and alternative beta estimators.

We contribute to the literature by comprehensively reexamining whether market power affects firms' systematic risk. Compared to the previous literature, our study offers three main advances. First, we use an empirically more relevant measure of market power rooted in the innovation literature. Second, our sample years cover the recent period of low competition. Our finding of a much stronger relationship based on the total product market similarity measure and in the recent low-competition environment helps to reconcile the results of previous studies: The standard measures of market power are less strongly related to systematic risk, so they fail to detect the weaker effect during their sample periods. Finally, we analyze anticompetitive mergers as a shock to market power. We show that systematic risk decreases substantially and significantly after such a merger.

We also add to the literature on the determinants of market betas. Fama and French (1997), Grundy and Martin (2001), Gomes et al. (2003), Carlson et al. (2004), Cosemans et al. (2015), and Chincarini et al. (2020), among others, relate market betas to several firm-specific variables. By resolving the ambiguity in the results of the previous literature, we document that market betas clearly depend not only on the firm itself, but also on its competitive environment in product markets.

We also contribute to the literature on the interaction between product markets and capital structures. Chevalier (1995a, 1995b) analyzes leveraged buyouts in the supermarket industry and finds that increases in leverage lead to higher prices and less product market competition. Hackbarth and Morellec (2008) use a real-options framework to analyze the behavior of stock returns and market betas before and around mergers. They find that the premerger change in market betas depends on the relationship between the betas of the acquirer and the acquired firms, with a reversal occurring right after the merger announcement. The authors focus mainly on the premerger period and the characteristics of the merging firms. They do not analyze the impact of the competitive environment. In particular, they do not focus on anticompetitive mergers, which we show is crucial for capturing the full postmerger impact on market betas. Hackbarth and Miao (2012) analyze the effect of the competitive environment on the characteristics of mergers. However, they do not examine the impact on market betas. Krüger et al. (2015) argue that firms tend to use a single discount rate for the entire firm. They show that mergers in which the target's market beta exceeds that of the acquirer lead to lower announcement returns.

2 | DATA AND METHODOLOGY

2.1 | Data

The main data used in this study come from the Center for Research in Security Prices (CRSP) and Compustat. We obtain data on returns, prices, and shares outstanding, as well as on several accounting items for all companies in the (merged) data sets. Details on the construction of all variables can be found in Appendices A–D. Our main sample period is 1989–2019, based on the availability of the main measure of market power used in this study. We use the Thomson Reuters EIKON merger data set, obtaining all mergers of firms in the United States. We follow Erel et al. (2012) and exclude deals involving share purchases, buybacks, and self-tenders or recapitalizations. In addition, we require a material change in ownership (the acquiring company can hold no more than 10% of the target, which is the reporting threshold, and must acquire at least 50% of the shares during the transaction). Our tail risk calculations are based on the interpolated Volatility Surface from OptionMetrics. The options data set begins in 1996 and ends in 2019, which limits the analysis of tail risk to this period.

We estimate the value spread using data from Kenneth French's webpage.[4] In addition, we obtain the price–earnings ratio from Robert Shiller's webpage and the term yield spread from Amit Goyal's webpage.[5]

2.2 | Main variables

2.2.1 | Market power

The main measure of market power we use is the total product market similarity (*tsim*) proposed by Hoberg and Phillips (2010a, 2016).[6] This measure is based on a textual analysis of business descriptions in annual 10-K forms. In particular, the authors focus on the firms' product text descriptions and form text-based network industry classifications (TNIC). They generate a matrix containing the pairwise product cosine similarities across all firms in a given year. The bivariate cosine similarity is higher the more two firms tend to use the same words to describe their products.[7] The total similarity measure is then calculated as the sum of all the bivariate cosine similarities of a firm in a given year. Thus, *tsim* measures the intensity of competition a firm faces in its product markets. It is thus an inverse measure of market power. The higher the product market similarity, the more competition a firm faces for its products. On the other hand, low product market similarity indicates low competition and hence high market power.

To link with the existing literature, we also include the traditional HHI measure in our main analysis.[8] To identify the industries, we use the North American Industry Classification System (NAICS), using historical NAICS codes

[4] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[5] The corresponding URLs are http://www.econ.yale.edu/~shiller/data.htm(Robert Shiller) and http://www.hec.unil.ch/agoyal/(Amit Goyal).

[6] This measure and all other Hoberg–Phillips measures can be obtained from: https://hobergphillips.tuck.dartmouth.edu/.

[7] More specifically, the measure is based on the common usage of nouns. The authors discard all words used by more than 25% of the firms, as well as geographic words.

[8] Appendix E illustrates how the *tsim* and HHI measures differ for the Dow Jones Industrial Average (DJIA)-30 stocks.

from Compustat whenever available. When these are missing, we fill in the remaining NAICS classifiers following Grullon et al. (2019). We explain this in more detail in Appendix B. We use the innovation-based *tsim* as our main measure. Hoberg and Phillips (2010a, 2016) show that the total product market similarity measure is consistent with firms reporting "high competition" in the Management's Discussion and Analysis section of the 10-K filings. The measure also correctly identifies competitors explicitly mentioned by managers in the 10-K files.[9] Finally, as a measure of product market competition, the total product market similarity should be better at capturing demand elasticity, which Subrahmanyam and Thomadakis (1980) identify as the main link between market power and systematic risk.

For robustness tests, we also use the TNIC HHI measure of Hoberg and Phillips (2016), which assigns industries based on the authors' text-based network classifications instead of the NAICS. In addition, we use the product market fluidity measure of Hoberg et al. (2014), which is a dynamic measure of market power. It is also based on product descriptions in firms' 10-K files, and captures the cosine similarity between the words a firm uses to describe its products and the aggregate change in word usage across firms. Finally, to account for potential effects of omitting private firms, we also use the adjusted HHI measure, adjusted using Census data and provided by Hoberg and Phillips (2010b).[10]

2.2.2 | Market beta

Our main variable of interest is market beta as a measure of systematic risk. To obtain beta estimates, we use a past historical window and regress an asset's excess return on a constant and the market excess return:

$$r_{i,\tau} - r_{f,\tau} = \alpha_{i,t} + \beta^M_{i,t}(r_{M,\tau} - r_{f,\tau}) + \epsilon_{i,\tau}, \tag{1}$$

where $\beta^M_{i,t}$ is the estimate of the market beta of asset i at time t. We use data from time $t-k$ to t, observed at discrete intervals τ, where k is the length of the past historical window. $r_{i,\tau}$, $r_{M,\tau}$, and $r_{f,\tau}$ denote the return of the asset i, the return of the market portfolio, and the risk-free rate, respectively, all observed at time τ. We use the CRSP value-weighted index as a proxy for the market return and the 1-month Treasury bill rate from Kenneth French's website to proxy for the risk-free rate. To obtain timely conditional betas from the historical rolling windows, we use an exponential weighting scheme and estimate Equation (1) with weighted least squares (WLS). The weights are $\frac{\exp(-|t-\tau|\phi)}{\sum_{\tau=1}^{t-1}\exp(-|t-\tau|\phi)}$ with $\phi = \frac{\log(2)}{\iota}$. ι characterizes the horizon to which the half-life of the weights converges for large samples. Following Hollstein et al. (2019) and Hollstein (2020), we set ι to two thirds of the number of observations in the estimation window.

For our main analysis, we estimate beta with monthly data, using a window of $k = 60$ months. For robustness, we also consider an unweighted beta as well as the shrinkage estimator of Vasicek (1973). In addition, we use an estimator with $k = 24$ months of daily data. The results for all of these are qualitatively similar (see Section 6).[11]

[9] Furthermore, the authors show that their industry classifications are significantly better at explaining differences in profitability, sales growth, and market risk across industries.

[10] The authors use Census data on private firms in the manufacturing sector. For these firms, they fit a model that regresses the private firm HHI measure on the Compustat HHI measure and two employment measures. They use the fitted coefficients from this regression to estimate the adjusted HHI measure (*fithhi*) for all industries. Due to the availability of the adjusted measure, this analysis is limited to the period 1989 to 2005.

[11] Another alternative would be to use the conditional betas of Ferson and Harvey (1991). With this specification, the betas change in a more timely fashion based on macroeconomic conditioning information. However, they are of limited use for our application because they can only capture the beta sensitivity to the state of the macroeconomy, not to firm-specific events. For example, these betas would not be able to capture the effect of mergers (see Section 4).

2.2.3 | Partial betas and tail risk

To refine our analysis, we separate market betas into cash-flow and discount-rate betas ($\beta_{i,t}^{CF}$ and $\beta_{i,t}^{DR}$), as defined by Campbell and Vuolteenaho (2004). In addition, we also separate the market betas into downside and upside betas ($\beta_{i,t}^{Down}$ and $\beta_{i,t}^{Up}$), as defined by Ang et al. (2006). We estimate the betas as follows:

$$\begin{aligned}
\beta_{i,t}^{CF} &= \frac{\operatorname{cov}(r_{i,t}-r_{f,t},\widehat{N}_{CF,t})}{\operatorname{var}(\widehat{N}_{CF,t}-\widehat{N}_{DR,t})},\\
\beta_{i,t}^{DR} &= \frac{\operatorname{cov}(r_{i,t}-r_{f,t},-\widehat{N}_{DR,t})}{\operatorname{var}(\widehat{N}_{CF,t}-\widehat{N}_{DR,t})},\\
\beta_{i,t}^{Down} &= \frac{\operatorname{cov}(r_{i,t}-r_{f,t},r_{m,t}-r_{f,t}\mid r_{m,t}<r_{f,t})}{\operatorname{var}(r_{m,t}\mid r_{m,t}<r_{f,t})}, \text{ and}\\
\beta_{i,t}^{Up} &= \frac{\operatorname{cov}(r_{i,t}-r_{f,t},r_{m,t}-r_{f,t}\mid r_{m,t}>r_{f,t})}{\operatorname{var}(r_{m,t}-r_{f,t}\mid r_{m,t}>r_{f,t})},
\end{aligned} \tag{2}$$

where $\widehat{N}_{CF,t}$ and $\widehat{N}_{DR,t}$ denote the parts of the market return associated with cash-flow and discount-rate news, as defined in Appendix C. All other variables are as defined above. We also use WLS based on the same weight specification to obtain the partial betas.

For further analysis, we also use various firm-specific risk measures. We estimate tail risk following Bollerslev and Todorov (2011). Dierkes et al. (2023) show that this tail risk measure performs better than others in predicting both tail risks and the associated risk premia. We present a more detailed description of the implementation of the tail risk measure in Appendix D.

2.3 | Summary statistics

In Figure 1, we show the average sales-weighted total product market similarity. We observe an overall decline over time, suggesting that the overall market has become less competitive over time. In particular, the level of aggregate total product market similarity is substantially lower in the years after 2004 than before. For comparison, Figure 1 also includes the time series of average markups of De Loecker et al. (2020) (gray line). We find that while the average total product market similarity decreases over time, the average markups increase substantially over time. The trends in these two variables are entirely consistent: as firm-level competition declines, firms are able to charge higher markups.

Table 1 presents the summary statistics for the main variables used in this study. For our main sample, we have just over 1 million firm–month observations for which all variables are available. The *tsim* has a mean of 3.80 and an average cross-sectional standard deviation of 6.04. Its distribution is characterized by positive skewness and high kurtosis. Thus, a substantial share of the stocks appears to have extreme values of total product market similarity. The natural logarithm of the industry sales concentration measure (*HHI*) has a mean of 6.48. Its standard deviation of 0.75 is much smaller than that of total product market similarity. This is probably because the *HHI* measure is constant within industries.

The average market beta is 1.14.[12] The average cross-sectional standard deviation is 0.78 and the market beta distribution is also positively skewed and has positive excess kurtosis. Among the partial betas, the average level of the

[12] It is not exactly one because we report the equal-weighted average across the stocks. The value-weighted average beta is, by definition, exactly one when considering all stocks in the market.

FIGURE 1 Aggregate total product market similarity time series.

Note: This figure plots the sales-weighted cross-sectional average total product market similarity (solid black line). Each year, we aggregate the monthly observations of total product market similarity by weighting each firm's measure by its share of sales across all sample firms in that year. This gives us an aggregate measure of market power in the product market. In addition, we show the average markups of De Loecker et al. (2020) (solid gray line). We highlight business-cycle contractions as defined by the National Bureau of Economic Research (NBER) in light gray.

TABLE 1 Summary statistics.

	Nobs	*Mean*	*SD*	*Median*	*Min*	*Max*	*Skewness*	*Kurtosis*
tsim	1,011,287	3.80	6.04	1.55	1.00	77.05	4.48	34.67
log(*HHI*)	1,011,287	6.48	0.75	6.36	4.97	9.24	0.67	3.36
β^{M}	1,011,287	1.14	0.78	1.04	−2.45	6.19	0.74	6.61
β^{CF}	1,011,287	0.19	0.26	0.17	−2.36	2.16	0.04	15.84
β^{DR}	1,011,287	0.86	0.64	0.79	−2.34	5.37	0.76	7.10
β^{Up}	1,011,287	0.33	0.46	0.29	−2.57	4.39	0.93	12.83
β^{Down}	1,011,287	0.62	0.64	0.58	−3.50	8.69	1.87	51.00
LT	324,638	0.25	0.20	0.20	0.01	1.84	2.50	15.06
RT	324,638	0.25	0.22	0.19	0.00	1.85	2.26	12.14

Note: This table presents summary statistics of the main variables used in this study. These include total product market similarity (*tsim*), industry sales concentration (*log*(*HHI*)), market beta (β^{M}), partial betas, and tail risk. β^{CF} is the cash-flow beta, β^{DR} is the discount-rate beta, β^{Up} is the upmarket beta, and β^{Down} is the downmarket beta. All betas are computed with weighted least squares (WLS) using monthly data and a 60-month forecasting window. *LT* and *RT* are the left and right tail risk measures. *Nobs* is the total number of available observations. *Mean* is the sample mean, *SD* is the sample standard deviation, *Median* is the sample median, *Min* is the minimum, and *Max* is the maximum. *Skewness* and *Kurtosis* are the third and fourth central moments of the distributions. All numbers presented are time-series averages of the cross-sectional summary statistics.

discount-rate beta is higher than that of the cash-flow beta, consistent with Campbell and Vuolteenaho (2004).[13] The downside beta is on average higher than the upside beta, which is also consistent with Ang et al. (2006). The distributions of all partial betas are also characterized by positive skewness and high excess kurtosis. The left and right tail risks are of similar magnitude on average.

Table 2 also shows the correlations between the main variables used in this study. Consistent with our motivation, the magnitude of the correlation between the negative of total product market similarity and industry sales concentration measures is rather small at 0.24. Because it is an inverse measure of market power, we continue to use the negative of *tsim* in all subsequent analyses. Otherwise, the two measures would have different interpretations, since the industry sales concentration is a direct measure of market power. The small magnitude of the correlation reflects to some extent the constancy within an industry of the industry sales concentration measure.[14] Since competitors for the overall product market similarity measure are identified based on product descriptions, there is also considerable variation in the measures within industries. Furthermore, as Hoberg and Phillips (2016) show, implicit industry assignments based on text analysis of 10-K files yield quite different results from the NAICS classification. They report that only 54% of firms are in the same industry based on their methodology and the NAICS codes. Both measures of market power are largely uncorrelated with all control variables. None of these correlations exceed 0.1 in magnitude.

3 | MARKET POWER AND MARKET BETAS

In this section, we estimate the effect of market power on beta in a panel regression. For this analysis, we use year and firm fixed effects and double-cluster the standard errors at the (NAICS) industry and year levels.

[13] Note that the cash-flow and discount-rate betas add up to the beta with respect to the unexpected market return, as shown by Campbell and Vuolteenaho (2004). Because we use the standard definition of beta with the “raw” market return, and not the one with respect to the unexpected market return, the sum of the cash-flow and discount-rate betas does not exactly equal the market beta.

[14] For example, the correlation of the ordinary industry sales concentration measure with that based on Hoberg and Phillips (2016), that is, the TNIC HHI measure, is also quite low at 0.13. Thus, the different definition of a firm’s competitive environment is a major driver of this low correlation.

TABLE 2 Correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) −*tsim*	1.00															
(2) *log*(*HHI*)	0.24	1.00														
(3) *log*(*Age*)	0.10	−0.05	1.00													
(4) *log*(*AT*)	−0.06	−0.01	0.41	1.00												
(5) *Default spread*	0.01	0.03	0.04	0.09	1.00											
(6) *Dividend*	0.08	−0.02	0.44	0.46	−0.01	1.00										
(7) *Financial leverage*	−0.04	0.02	−0.01	0.04	0.04	−0.02	1.00									
(8) *log*(*Firm size*)	−0.08	−0.05	0.36	0.88	0.05	0.42	−0.09	1.00								
(9) *Illiquidity*	0.02	0.03	−0.01	−0.11	−0.01	−0.02	0.03	−0.14	1.00							
(10) *Investment rate*	0.00	−0.01	−0.00	0.00	0.00	0.00	0.01	0.00	−0.00	1.00						
(11) *iVol*	−0.09	−0.02	−0.37	−0.52	−0.00	−0.48	0.05	−0.48	0.04	0.00	1.00					
(12) *log*(*Mkt*/*Book*)	−0.10	−0.07	−0.07	−0.01	−0.10	−0.04	−0.17	0.28	−0.07	−0.00	0.08	1.00				
(13) *Momentum*	0.02	0.01	0.03	0.00	−0.08	0.01	−0.02	0.15	0.00	−0.00	−0.00	0.03	1.00			
(14) *Operating leverage*	−0.00	−0.00	0.00	0.01	−0.01	0.00	−0.00	0.01	−0.01	−0.00	0.00	0.00	0.00	1.00		
(15) *q*	−0.05	−0.03	−0.02	−0.02	−0.01	−0.02	−0.01	0.02	−0.01	0.00	0.04	0.07	0.03	0.00	1.00	
(16) *ROE*	0.03	0.01	0.03	0.03	−0.00	0.03	−0.01	0.03	0.00	0.00	−0.06	−0.14	0.01	−0.00	−0.00	1.00

Note: This table shows the pairwise correlations of total product market similarity (*tsim*) and industry sales concentration (*log*(*HHI*)) measures with all the control variables used in this study. Detailed definitions of the control variables can be found in Appendix A.

The following regression describes our main setup:

$$\beta^M_{i,t} = \gamma_1(-tsim_{i,t}) + \gamma_2(-tsim_{i,t})^2 + \theta_1 log(HHI_{i,t}) + \theta_2 log(HHI_{i,t})^2 + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t}, \quad (3)$$

where $tsim_{i,t}$ is the total product market similarity of firm i at time t. $HHI_{i,t}$ denotes the Herfindahl–Hirschman Index of sales concentration in the NAICS industry of firm i at time t. Dalton and Penn (1976) investigate the relationship between profitability and concentration and suggest that there is a concentration threshold. Furthermore, Table 1 shows that our main measure of market power, *tsim*, is positively skewed. Therefore, to account for potential nonlinearities, we include the orthogonal second-order polynomial of both market power variables in the regression. $C_{i,t}$ is a vector containing all control variables, which are described in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_y is a set of dummy variables capturing year fixed effects and α_i is a set of dummy variables capturing firm fixed effects. $\epsilon_{i,t}$ is the regression residual for firm i in month t. We use monthly data to run this and all other regressions in the paper.

Note that in order to analyze the robustness of the results and to investigate the possible causes of the different results obtained by the previous literature, we include both our main measure *tsim* and the traditional HHI industry sales concentration measure. We examine both measures first in separate regressions and then in a comprehensive regression.

We begin the analysis with panel regressions of market betas on total product market similarity. We present the results in Table 3. In a single regression of market betas on the negative total product market similarity (column (i)), we obtain a highly significant negative coefficient of −0.060. The coefficient on the orthogonal square of total product market similarity is −0.034. Thus, (i) firms with higher market power tend to have lower market betas. (ii) The effect is nonlinear and stronger for firms with low total product market similarity and hence high market power.[15] Econom-

[15] This result does not depend on the inclusion of firm and year fixed effects. In any case (including only one or neither), the main coefficient on *tsim* is negative and highly statistically significant with *t*-statistics below −2.5. The orthogonal square of *tsim* yields a negative coefficient with *t*-statistics below −2. The coefficient estimate for the linear effect is somewhat larger without the firm fixed effects (−0.09). Thus, these fixed effects likely capture part of the market power of firms when it is a very persistent characteristic (e.g., when the firm operates in a natural monopoly).

TABLE 3 Market power and market beta.

	(i)	(ii)	(iii)	(iv)	(v)
−tsim	−0.060***		−0.044***		−0.041***
	(−4.641)		(−4.720)		(−4.765)
$(-tsim)^2$	−0.034**		−0.021*		−0.020*
	(−2.527)		(−1.900)		(−1.875)
log(HHI)		−0.047**		−0.044**	−0.041**
		(−2.293)		(−2.555)	(−2.508)
$log(HHI)^2$		0.008		0.006	0.005
		(0.677)		(0.591)	(0.546)
log(Age)			−0.092**	−0.093***	−0.094***
			(−2.738)	(−2.758)	(−2.875)
log(AT)			0.186***	0.194***	0.184***
			(4.910)	(5.053)	(4.925)
Default spread			0.003	0.003	0.003
			(0.597)	(0.591)	(0.558)
Dividend			−0.092***	−0.094***	−0.092***
			(−4.378)	(−4.438)	(−4.339)
Financial leverage			0.009	0.009	0.009
			(1.460)	(1.445)	(1.455)
log(Firm size)			0.032	0.030	0.031
			(0.919)	(0.856)	(0.887)
Illiquidity			−0.020***	−0.020***	−0.020***
			(−6.750)	(−7.088)	(−6.687)
Investment rate			0.001	0.001	0.001
			(0.406)	(0.325)	(0.376)
iVol			0.336***	0.338***	0.336***
			(9.557)	(9.563)	(9.587)
log(Mkt/Book)			0.013	0.014	0.013
			(1.037)	(1.109)	(1.018)
Momentum			−0.027*	−0.027*	−0.027*
			(−1.968)	(−1.959)	(−1.950)
Operating leverage			0.005**	0.005**	0.005**
			(2.742)	(2.566)	(2.583)
q			−0.003	−0.004	−0.004
			(−0.910)	(−1.048)	(−0.960)
ROE			0.002	0.001	0.001
			(0.485)	(0.476)	(0.456)
R^2	55.44	55.36	60.26	60.25	60.32

(Continues)

TABLE 3 (Continued)

	(i)	(ii)	(iii)	(iv)	(v)
Nobs	1,011,287	1,011,287	1,011,287	1,011,287	1,011,287
FE	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of a regression of firms' market betas on measures of market power as well as several control variables. Conditional market betas are computed via weighted least squares (WLS) based on the last 60 months of monthly returns. As measures of market power, we use the negative of total product market similarity (*tsim*) and the natural logarithm of the Herfindahl–Hirschman Index (HHI) measure of industry sales concentration. We include the measures as well as their orthogonal squares. The regression equation is:

$$\beta^M_{i,t} = \gamma_1(-tsim_{i,t}) + \gamma_2(-tsim_{i,t})^2 + \theta_1 log(HHI_{i,t}) + \theta_2 log(HHI_{i,t})^2 + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where $C_{i,t}$ is a vector of control variables, detailed definitions of which can be found in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_y and α_i are dummy variables that account for year and firm fixed effects (*FE*), respectively. Standard errors are double-clustered at the industry and year levels. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). *Nobs* is the total number of observations. The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

ically, the effect is large. A firm with total product market similarity two standard deviations below the average has a market beta that is 0.24 lower than that of an otherwise similar firm with average total product market similarity.[16]

A single regression using the HHI measure of industry sales concentration (column (ii) of Table 3) yields qualitatively similar results. As industry sales concentration increases, the market betas of firms in the industry decrease significantly. However, the analysis also provides an indication as to why the results of the previous literature may vary across studies: Based on the HHI, the relationship is both statistically and economically weaker than based on the total product market similarity measure. A two-standard-deviation increase in the HHI measure from its mean implies only a 0.08 decrease in market betas. This finding underscores the notion that using the innovation-based measure of market power is important to uncover the relationship with systematic risk. Nevertheless, in our main empirical setup and based on a large sample spanning almost 30 years, we are also able to uncover a significant relationship based on the HHI measure of industry sales concentration.

When controlling for other potential determinants of market betas, the results are qualitatively similar (columns (iii) to (v) of Table 3). The effect of total product market similarity on market betas is positive, statistically significant, and economically large. Moreover, the significant negative coefficient on its orthogonal square indicates that the effect is larger for firms with low total product market similarity. For the industry sales concentration measure, the regression coefficient is also significantly negative. Finally, both the total product market similarity measure and the industry sales concentration measure yield statistically significant coefficients when including both in a joint regression. This result underscores that market power has a negative impact on a firm's market beta. Furthermore, it confirms that the two measures do not contain exactly the same information.

The effects of the control variables on market betas are consistent with those documented in the literature. Age has a significant negative impact, consistent with Chincarini et al. (2020). In addition, the firm's total assets have a positive impact on market betas. Dividend payout and stock illiquidity seem to reduce a firm's beta. Idiosyncratic volatility, on the other hand, seems to have a positive impact on market betas. Operating leverage has a positive effect on market betas, as in Cosemans et al. (2015). Momentum has a weak negative effect on betas, consistent with the results of Grundy and Martin (2001).

[16] We obtain this number directly from the estimated model. It cannot be calculated directly from the parameter estimates because we use orthogonal rather than raw squares in the regression model. A two-standard-deviation increase in the total product market similarity from the mean, on the other hand, increases the market beta by only 0.17, which is much smaller in magnitude.

To shed further light on the different results documented in the previous literature, we analyze subsample periods. That is, we split the sample roughly in half into a pre-2005 period and a post-2005 period. The timing of the sample split roughly coincides with the shift in aggregate product market similarity to a lower level in the years starting around 2005, which can be seen in Figure 1. Covarrubias et al. (2020) argue that from the early 2000s there is increasing evidence of "inefficient concentration," with less competition and higher barriers to entry. Grullon et al. (2019) similarly argue that since the turn of the century, concentration has increased in many US industries, leading to higher markups. Thus, in the overall less competitive environment of our second subsample period, the effect of market power on beta is likely to be stronger.

Indeed, the results presented in Table 4 show just that. In the first half of our sample period until the end of 2004, the effect of market power on systematic risk is significantly weaker than in the more recent sample period starting in 2005. We observe a significant positive effect for our main measure, the total product market similarity, in the first half of the sample period. However, the effect is both economically and statistically weaker than for the full sample period (see Table 3). More importantly, there is no significant effect for the measure of industry sales concentration in the first part of the sample period. This analysis is thus informative as to why the previous literature presents mixed results: (i) the effect of market power on betas was not that large, and (ii) industry sales concentration appears not to pick up the full effect. This is likely why most previous studies fail to document a significant effect based on industry sales concentration or other similar proxies for market power. For an innovation-based measure, the total product market similarity, we show that there is a significant effect even in the early years.

The picture changes significantly for the second part of the sample period. The impact of total product market similarity on market beta is much stronger, both economically and statistically. The impact of a two-standard-deviation decrease from the mean increases more than 2.5 times for the more recent period. Interestingly, for the period since 2005, we cannot reject that the effect is linear. The coefficient on the orthogonal square of total product market similarity is not statistically significant. Finally, the relationship between market power and market betas in the most recent sample period is also clear for the industry sales concentration measure.

4 | MERGERS AND ACQUISITIONS

To further explore the relationship between market power and systematic risk, we next examine mergers and acquisitions. The main idea of this analysis is that if a firm's systematic risk is related to its market power, then an event that increases a firm's market power should have an immediate negative effect on its market beta. Mergers and acquisitions (within an industry) represent such an event. A large literature shows both theoretically and empirically how horizontal mergers can be used to increase the market power of incumbent firms (e.g., Farrell and Shapiro, 1990; Fathollahi et al., 2022; Perry and Porter, 1985; Stigler, 1950, 1964). Thus, we expect to observe a permanent decrease in a firm's market beta after such a merger.

In particular, we focus on anticompetitive mergers. We use three different definitions: (1) We follow Eckbo (1983) and define anticompetitive mergers as those between firms in the same four-digit SIC industry.[17] (2) Alternatively, since Hoberg and Phillips (2016) show that traditional industry classifications may not be the best way to identify a firm's competitors, we also consider their TNIC3 classification. We define anticompetitive mergers as those between pairs of firms for which the TNIC3 similarity measure is above the threshold defined by the authors. (3) A drawback of these two definitions is that they only capture mergers between public firms. For private firms, data on industry classifications are not available in Compustat. Since some earlier literature shows that the inclusion of private firms in the analysis is important (Ali et al., 2008), we consider an alternative purpose-based specification of anticompetitive mergers as our main definition. In particular, we define mergers as anticompetitive if, according to the

[17] SIC codes are not available for all firms in Compustat. In cases where one or both SIC codes are missing, we consider the target and acquiring firms to be in the same industry if they have the same NAICS codes.

TABLE 4 Market power and market beta — Subsample analysis.

	(i)	(ii)	(iii)	(iv)	(v)
Before 2005					
−tsim	−0.037***		−0.022*		−0.021*
	(−3.144)		(−1.961)		(−1.885)
$(-tsim)^2$	−0.019*		−0.011		−0.010
	(−2.120)		(−1.451)		(−1.389)
log(HHI)		−0.023		−0.020	−0.019
		(−1.262)		(−1.246)	(−1.204)
$log(HHI)^2$		0.006		0.003	0.003
		(0.660)		(0.534)	(0.513)
R^2	64.53	64.50	66.35	66.35	66.36
Nobs	576,784	576,784	576,784	576,784	576,784
Controls	No	No	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
From 2005					
−tsim	−0.118***		−0.091***		−0.085***
	(−4.385)		(−4.585)		(−4.693)
$(-tsim)^2$	−0.036		−0.020		−0.021
	(−1.381)		(−1.070)		(−1.119)
log(HHI)		−0.120***		−0.086***	−0.078***
		(−3.257)		(−3.245)	(−3.149)
$log(HHI)^2$		0.085		0.070	0.061
		(1.634)		(1.561)	(1.480)
R^2	58.00	57.95	64.76	64.71	64.86
Nobs	434,503	434,503	434,503	434,503	434,503
Controls	No	No	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of a regression of firms' market betas on measures of market power. In contrast to the main analysis, we split the sample into two subsamples, one before and one after 2005. Conditional market betas are computed via weighted least squares (WLS) based on the last 60 months of monthly returns. As measures of market power, we use the negative of total product market similarity (*tsim*) and the natural logarithm of the Herfindahl–Hirschman Index (HHI) measure of industry sales concentration. We include the measures as well as their orthogonal squares. The regression equation is:

$$\beta^M_{i,t} = \gamma_1(-tsim_{i,t}) + \gamma_2(-tsim_{i,t})^2 + \theta_1 \log(HHI_{i,t}) + \theta_2 \log(HHI_{i,t})^2 + \eta C_{i,t} + \alpha_y + \alpha_i + \varepsilon_{i,t},$$

where $C_{i,t}$ is a vector of control variables (*Controls*), detailed definitions of which can be found in Appendix A. All explanatory variables are standardized for the full sample to have a mean of zero and a standard deviation of one. α_y and α_i are dummy variables that account for year and firm fixed effects (*FE*), respectively. Standard errors are double-clustered at the industry and year levels. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). *Nobs* is the total number of observations. The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

database, the purpose includes one of the following expressions: “Acquire competitors technology/strategic assets”, “Strengthen existing operations/expand presence in primary market”, “Strengthen operations”, “Create synergies”, and “Concentrate on core businesses/assets”.

The industry-based definitions are, of course, somewhat more rigorous, but due to the limited number of identified mergers, their tests are less powerful. In fact, as reported in Table 5, the first two definitions help us identify 2,047 and 2,314 anticompetitive mergers, respectively, while the purpose-based definition yields 11,540 anticompetitive mergers. For a benchmark analysis, we also consider mergers that are not classified as anticompetitive by any of the three definitions presented above. Finally, we follow Seru (2014) and consider a placebo analysis with anticompetitive mergers that were withdrawn.[18] For these two analyses, we should find that mergers have no effect on systematic risk. Our sample includes 31,706 mergers considered as non-anticompetitive and 284 anticompetitive mergers that were withdrawn.

To determine the effect of these anticompetitive mergers on competition, we first regress the firms’ total product market similarity on a binary variable that takes the value one if an anticompetitive merger (based on our main, purpose-based definition) has been completed in the last 1 or 2 years. We present the results in Table 6. All regressions include fixed effects. We find that in a single regression, an anticompetitive merger in the previous year increases market power and reduces total product market similarity by 0.28 (column (i)). An anticompetitive merger in the two preceding years reduces total product market similarity by 0.31 (column (iii)). The effect is statistically significant in both cases. When the control variables used in this study are included, these results change only slightly and become even statistically stronger. Thus, a broadly defined anticompetitive merger does indeed reduce competition.

Having validated our conjecture about the effect of these mergers, we next turn to analyzing how anticompetitive mergers affect market betas. We run the following regression:

$$\beta_{i,t}^{M} = \gamma_1 M_{i,t}^{D} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t}, \tag{4}$$

where $M_{i,t}^{D}$ is a dummy that is one from the month in which the merger is performed and for the next 24 or 36 months after the merger, and zero at all other times. We limit the period during which the postmerger dummy is one because the strongest effects of the merger are likely to occur during a limited period of time, while the competitive environment may subsequently change due to other forces that dilute the immediate effect of the merger event. On the other hand, we need to consider some time after the merger, because we use rolling-window betas that need time to adjust to the new reality.[19] All other variables are defined as before.

We present the results in Table 5. Indeed, we find that the market beta declines significantly after an anticompetitive merger. The coefficient on the merger dummy in our main specification is −0.048 for a 24-month postmerger horizon and −0.043 for a 36-month postmerger window. The results for horizontal mergers based on TNIC3 and SIC industry definitions are economically stronger, yielding merger dummy coefficients between −0.048 and −0.072, but statistically somewhat weaker. This is exactly what we would expect based on a somewhat more rigorous definition, but with a smaller sample. Nevertheless, these results underscore the negative impact of anticompetitive mergers on systematic risk. When a firm engages in an anticompetitive merger to increase its market power, the beta decreases by at least 0.04 on average.

Our benchmark analysis based on a large sample of non-anticompetitive mergers yields results that are consistent. The average effect is close to zero and clearly not statistically significant. For the small sample of placebo firms, we obtain a small positive effect on market betas. Thus, the effect of market power on systematic risk is potentially causal.[20]

[18] Since these mergers have no effective date, we define the postmerger dummies for them based on the announcement date.

[19] In Section 6, we show that the results are robust to considering both shorter and longer time horizons. In particular, Figure 2 shows that the single largest drop in market betas occurs precisely in the month of the merger.

[20] A possible alternative story is that acquirers select targets based on their market betas. To test for such an effect, we repeat the previous analysis, adding the difference between the acquirer and target market betas as an additional control variable. The results of this untabulated analysis are qualitatively similar

TABLE 5 Merger analysis.

	Anticompetitive (Purpose)		Anticompetitive (TNIC3)		Anticompetitive (SIC)		Not anticompetitive		Placebo	
	24 Months	36 Months	24 Months	36 Months	24 Months	36 Months	24 Months	36 Months	24 Months	36 Months
M^D	−0.048***	−0.043***	−0.048*	−0.060**	−0.066*	−0.072**	−0.007	−0.006	0.015	0.011
	(−3.768)	(−3.060)	(−1.862)	(−2.154)	(−2.015)	(−2.458)	(−0.820)	(−0.529)	(0.159)	(0.103)
log(Age)	−0.093**	−0.093**	−0.091**	−0.091**	−0.091**	−0.091**	−0.091**	−0.091**	−0.091**	−0.091**
	(−2.652)	(−2.655)	(−2.603)	(−2.610)	(−2.601)	(−2.604)	(−2.598)	(−2.600)	(−2.593)	(−2.593)
log(AT)	0.200***	0.201***	0.197***	0.198***	0.196***	0.197***	0.196***	0.196***	0.196***	0.196***
	(5.171)	(5.186)	(5.077)	(5.101)	(5.062)	(5.077)	(5.051)	(5.050)	(5.050)	(5.049)
Default spread	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.647)	(0.643)	(0.640)	(0.639)	(0.638)	(0.637)	(0.636)	(0.637)	(0.636)	(0.636)
Dividend	−0.095***	−0.095***	−0.095***	−0.095***	−0.094***	−0.095***	−0.094***	−0.094***	−0.094***	−0.094***
	(−4.521)	(−4.509)	(−4.492)	(−4.503)	(−4.492)	(−4.496)	(−4.491)	(−4.489)	(−4.483)	(−4.484)
Financial leverage	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
	(1.444)	(1.444)	(1.447)	(1.446)	(1.449)	(1.448)	(1.447)	(1.447)	(1.448)	(1.448)
log(Firm size)	0.034	0.033	0.032	0.032	0.032	0.032	0.032	0.032	0.031	0.031
	(0.949)	(0.939)	(0.906)	(0.911)	(0.904)	(0.904)	(0.923)	(0.921)	(0.888)	(0.888)
Illiquidity	−0.020***	−0.020***	−0.020***	−0.020***	−0.020***	−0.020***	−0.020***	−0.020***	−0.020***	−0.020***
	(−7.027)	(−7.086)	(−7.128)	(−7.125)	(−7.091)	(−7.123)	(−7.113)	(−7.093)	(−7.061)	(−7.160)
Investment rate	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.346)	(0.344)	(0.361)	(0.359)	(0.350)	(0.348)	(0.356)	(0.359)	(0.357)	(0.357)

(Continues)

TABLE 5 (Continued)

	Anticompetitive (Purpose)		Anticompetitive (TNIC3)		Anticompetitive (SIC)		Not anticompetitive		Placebo	
	24 Months	36 Months	24 Months	36 Months	24 Months	36 Months	24 Months	36 Months	24 Months	36 Months
iVol	0.338***	0.338***	0.338***	0.338***	0.338***	0.338***	0.338***	0.338***	0.338***	0.338***
	(9.537)	(9.537)	(9.530)	(9.531)	(9.532)	(9.534)	(9.536)	(9.535)	(9.528)	(9.527)
log(Mkt/Book)	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014
	(1.133)	(1.132)	(1.133)	(1.132)	(1.135)	(1.136)	(1.136)	(1.135)	(1.136)	(1.136)
Momentum	−0.028*	−0.028*	−0.028*	−0.028*	−0.028*	−0.028*	−0.028*	−0.028*	−0.028*	−0.028*
	(−1.994)	(−1.987)	(−1.984)	(−1.985)	(−1.985)	(−1.985)	(−1.993)	(−1.991)	(−1.978)	(−1.978)
Operating leverage	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005**	0.005**	0.005**	0.005***
	(2.760)	(2.774)	(2.772)	(2.767)	(2.778)	(2.786)	(2.717)	(2.724)	(2.738)	(2.768)
q	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004
	(−0.999)	(−1.001)	(−1.005)	(−1.005)	(−1.004)	(−1.005)	(−1.005)	(−1.006)	(−1.005)	(−1.004)
ROE	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.487)	(0.497)	(0.483)	(0.478)	(0.507)	(0.508)	(0.506)	(0.505)	(0.509)	(0.509)
R^2	60.57	60.57	60.56	60.56	60.56	60.56	60.55	60.55	60.55	60.55
Nobs	11,540	11,540	2,314	2,314	2,047	2,047	31,706	31,706	284	284
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the results of a regression of the monthly market betas on a dummy (M^D) as in Equation (4). The merger dummy is one for a given period after the merger. We consider different merger samples: The first is purpose-based, where mergers have one of these purposes: “Acquire competitors technology/strategic assets”, “Strengthen existing operations/expand presence in primary market”, “Strengthen operations”, “Create synergies”, and “Concentrate on core businesses/assets”. The second and third are based on horizontal mergers only, with the second defined by the TNIC3 classification of Hoberg and Phillips (2016) and the third by four-digit SIC codes. We also consider mergers that are not classified as anticompetitive by either of these definitions. Finally, we consider a placebo analysis with anticompetitive mergers that were withdrawn. We consider postmerger horizons of 24 and 36 months. Detailed definitions of the control variables can be found in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. All panel regressions include dummies that account for firm and year fixed effects (*FE*). Standard errors are double-clustered at the industry and year levels. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). *Nobs* is the number of merger observations. The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 6 Mergers and product market similarity.

	Merger in the previous year		Merger in the previous 2 years	
	(i)	(ii)	(iii)	(iv)
M^D	−0.282*	−0.262**	−0.306*	−0.277**
	(−1.899)	(−2.630)	(−1.848)	(−2.746)
log(Age)		−0.545*		−0.539
		(−1.711)		(−1.692)
log(AT)		0.955***		0.976***
		(2.757)		(2.787)
Default spread		−0.104***		−0.102***
		(−2.946)		(−2.948)
Dividend		−0.172		−0.173
		(−1.171)		(−1.176)
Financial leverage		−0.063		−0.063
		(−0.754)		(−0.758)
log(Firm size)		−0.297		−0.296
		(−1.132)		(−1.130)
Illiquidity		−0.004		−0.003
		(−0.368)		(−0.357)
Investment rate		−0.020		−0.020
		(−0.959)		(−0.973)
iVol		0.062		0.062
		(1.132)		(1.122)
log(Mkt/Book)		0.158*		0.158*
		(2.031)		(2.023)
Momentum		−0.031		−0.031
		(−1.203)		(−1.185)
Operating leverage		−0.007		−0.007
		(−0.445)		(−0.447)
q		−0.056*		−0.056*
		(−1.803)		(−1.800)
ROE		0.004		0.005
		(0.269)		(0.284)
R^2	74.70	74.90	74.71	74.90
Nobs	11,540	11,540	11,540	11,540
FE	Yes	Yes	Yes	Yes

Note: This table presents the results of a regression of total product market similarity on a merger dummy variable (M^D) as well as several control variables. The merger dummy is one in the one or two calendar year(s) after the merger was completed. We only consider completed mergers and acquisitions. In particular, we focus on anticompetitive mergers (using the purpose-based definition). Detailed definitions of the control variables can be found in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. All panel regressions include dummies to account for firm fixed effects (*FE*). Standard errors are double-clustered at the industry and year levels. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). *Nobs* is the number of merger observations. The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Finally, to further analyze the evolution of market betas around the merger, we also run a regression with monthly dummy variables, considering both the pre- and postmerger periods. We present the results in Figure 2. We find that the largest decline does indeed occur in the month of the merger. The market betas are significantly lower than before. Thus, this additional analysis underscores that market power has a negative impact on market betas. An anticompetitive merger clearly seems to be the driving force behind the decrease in beta. We also observe a slight decrease in beta prior to the merger. This is likely due to the announcements that often precede the actual merger.[21] On average, the merger announcement occurs 2 months before the merger is completed. In addition, the anticipation of a merger is likely to play a role. There are likely rumors or investors extrapolate from merger activity in the same industry, which tends to cluster (Cai et al., 2011).

Having documented the relationship between market power and systematic risk, we can turn back to assess the theoretical models of this relationship. Overall, important properties of models consistent with our results seem to be the assumption of Cobb–Douglas production functions for capital and labor, isoelastic demand, and, importantly, flexible output (O'Brien, 2011). On the other hand, static demand-shock Cournot competition models with fixed output yield no relationship between beta and market power (Alexander and Thistle, 1999; Wong, 1995). The threat-of-entry channel included in the recent model of, among others, Bustamante and Donangelo (2017) also seems to be of less importance. Subrahmanyam and Thomadakis (1980), another model whose main prediction is consistent with our results, also assumes fixed output, but implicitly requires a negative relationship between operating costs and stock returns. Peyser (1994) argues that without this assumption, the relationship between systematic risk and market power is more complex.

5 | PARTIAL BETAS AND TAIL RISK

In this section, we further analyze the impact of market power on different parts of market betas. The primary goal is to learn more about the exact economic channel through which market power affects market betas.

5.1 | Cash-flow and discount-rate betas

We first examine the effect of market power on cash-flow and discount-rate betas separately. That is, we examine whether market power primarily insulates firms from cash-flow or discount-rate shocks. This is important to understand the economic channel through which market power operates. If market power mainly affects cash-flow betas, this would imply that firms with market power are better able to withstand aggregate cash-flow shocks (systematic changes in future investment opportunities). On the other hand, if market power mainly affects discount-rate betas, this would imply that firms with market power are better able to withstand systematic discount-rate shocks (situations where current wealth and future investment opportunities are adversely affected). Campbell and Vuolteenaho (2004) argue that cash-flow news are likely to be unconditionally more severe and have a higher price of risk.

Both cash-flow and discount-rate channels are conceivable. On the one hand, firms with market power may be better able to adjust their prices following a cash-flow shock and thus be more insulated from it. On the other hand, discount-rate shocks are likely to hurt financially constrained firms that need to invest. An increase in the discount rate raises the cost of financing. Thus, firms that can postpone investment are less exposed to these shocks. As shown by Gutiérrez and Philippon (2017, 2018), firms with market power do not have strong incentives to innovate and tend to invest less. Thus, market power may also primarily insulate firms from discount-rate shocks.

to those reported above. We do not use this control variable in our main specification because the target market beta is only available for a subset of the mergers in our sample.

[21] All results in this section are qualitatively similar when we define the merger dummies based on the merger announcement dates rather than effective dates.

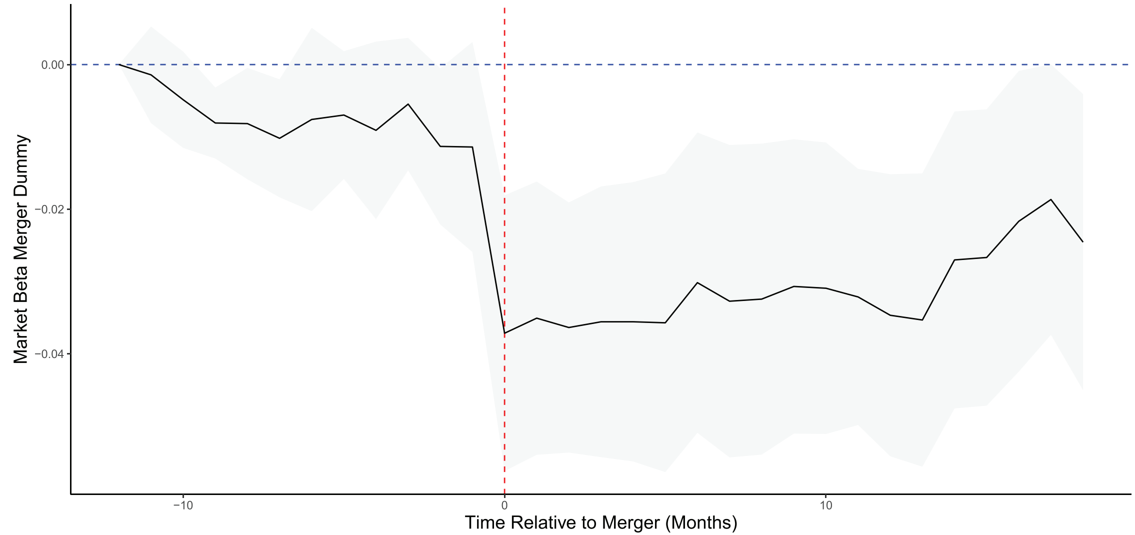

FIGURE 2 Merger dummies over time.
[Color figure can be viewed at wileyonlinelibrary.com]

Note: This figure shows the coefficients γ_{-11} to γ_{18} of the following regression: $\beta^M_{i,t} = \phi_0 M^0_{i,j} + \sum_{j=-11}^{-1} \gamma_j M^D_{i,j} + \gamma_0 M^D_{i,0} + \sum_{j=1}^{18} \gamma_j M^D_{i,j} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t}$, where $\beta^M_{i,t}$ is the market beta of firm i at time t, $M^0_{i,j}$ is a dummy variable that is equal to one at all times more than 12 months before and more than 18 months after a merger. $M^D_{i,j}$ is a set of monthly dummy variables equal to one in a given month j from 11 months before to 18 months after a merger of firm i, and zero otherwise. $M^D_{i,0}$ is one for the month of the merger. The dummy coefficients directly capture the average difference. We plot the coefficients for each dummy variable along with the corresponding 90% confidence interval in the shaded gray area. Standard errors are double-clustered at the industry and year levels. The red vertical line indicates the month of the merger. The horizontal zero reference line is shown in blue.

TABLE 7 Market power and partial betas.

	β^{CF}	β^{DR}	β^{Up}	β^{Down}
−tsim	−0.002	−0.036***	−0.012*	−0.018*
	(−0.380)	(−5.305)	(−1.912)	(−1.949)
(-tsim)^2	−0.006*	−0.016**	−0.005	0.011
	(−1.741)	(−2.169)	(−0.949)	(1.071)
log(HHI)	−0.001	−0.030**	−0.012	−0.004
	(−0.339)	(−2.364)	(−1.684)	(−0.588)
log(HHI)^2	0.001	0.006	−0.001	−0.002
	(0.341)	(0.654)	(−0.437)	(−0.723)
log(Age)	−0.030***	−0.084***	0.000	−0.083***
	(−2.874)	(−3.219)	(0.024)	(−3.999)
log(AT)	−0.006	0.123***	0.056*	0.128**
	(−0.351)	(4.130)	(1.728)	(2.713)
Default spread	−0.001	0.009	0.005	0.018
	(−0.229)	(0.875)	(0.315)	(0.887)
Dividend	−0.022***	−0.064***	−0.033***	−0.044***
	(−2.840)	(−3.954)	(−2.908)	(−3.080)
Financial leverage	0.005*	0.004	0.010	0.000
	(1.723)	(1.119)	(1.526)	(−0.122)
log(Firm size)	0.060***	0.053*	−0.006	−0.007
	(2.865)	(1.836)	(−0.196)	(−0.151)
Illiquidity	−0.002***	−0.018***	−0.004***	0.009
	(−3.610)	(−8.692)	(−4.363)	(1.511)
Investment rate	0.000	0.001	0.003	−0.002
	(−0.049)	(0.246)	(0.699)	(−1.199)
iVol	0.043**	0.262***	0.095***	0.205***
	(2.619)	(9.695)	(4.182)	(5.247)
log(Mkt/Book)	−0.004	0.015	0.003	0.022*
	(−0.789)	(1.293)	(0.262)	(1.788)
Momentum	−0.010	−0.027*	−0.005	−0.016
	(−1.164)	(−1.820)	(−0.553)	(−1.171)
Operating leverage	0.001	0.003**	0.001	0.003
	(0.974)	(2.285)	(0.579)	(1.629)
q	−0.002**	−0.002	−0.002	−0.004
	(−2.292)	(−0.623)	(−0.873)	(−1.547)
ROE	−0.002	0.003*	−0.002	0.001
	(−0.594)	(1.707)	(−0.750)	(0.249)
R^2	45.96	57.05	46.98	45.23

(Continues)

TABLE 7 (Continued)

	β^{CF}	β^{DR}	β^{Up}	β^{Down}
Nobs	1,011,287	1,011,287	1,011,287	1,011,287
FE	Yes	Yes	Yes	Yes

Note: This table presents the results of a regression of firms' partial market betas on measures of market power as well as several control variables. Conditional market betas are computed via weighted least squares (WLS) based on the last 60 months of monthly returns. As measures of market power, we use the negative of total product market similarity (*tsim*) and the natural logarithm of the Herfindahl–Hirschman Index (HHI) measure of industry sales concentration. We include the measures as well as their orthogonal squares. The regression equation is:

$$\beta^X_{i,t} = \gamma_1(-tsim_{i,t}) + \gamma_2(-tsim_{i,t})^2 + \theta_1 log(HHI_{i,t}) + \theta_2 log(HHI_{i,t})^2 + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where $\beta^X_{i,t}$ is either the cash-flow (*CF*), discount-rate (*DR*), upside (*Up*), or downside (*Down*) beta. $C_{i,t}$ is a vector of control variables, detailed definitions of which can be found in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_y and α_i are dummy variables that account for year and firm fixed effects (*FE*), respectively. Standard errors are double-clustered at the industry and year levels. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). *Nobs* is the total number of observations. The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The corresponding results are shown in Table 7. We find that market power has almost no effect on cash-flow betas. Thus, market power does not seem to protect firms from the effects of aggregate cash-flow news. On the other hand, the results show that market power has a strong negative impact on discount-rate betas. The coefficient on total product market similarity is significantly negative. That of industry sales concentration is also significantly negative, although the effect is again weaker. Thus, the presence of some degree of market power does seem to insulate firms from aggregate discount-rate shocks in particular. This result is somewhat at odds with the general equilibrium model of Corhay et al. (2020), in which both cash-flow and discount-rate effects appear to be at play.

5.2 | Upside and downside betas

Next, we decompose the market betas into upside and downside betas. This analysis allows us to examine whether market power has an asymmetric effect in bull and bear markets. Lower downside betas insulate firms' stock prices to some extent from downward moves in bad market conditions. Ang et al. (2006) and Lettau et al. (2014) argue that investors are likely to care more about these than about upside betas. Thus, if the effect of market power on downside betas were even larger than that on upside betas, this would likely reduce firms' cost of capital even more than if both were lower by similar amounts.

The results for this analysis are also shown in Table 7. We find no reliable evidence that downside and upside betas are heterogeneously affected by market power. Total product market similarity has a positive effect on both upside and downside betas. The effect is both economically and statistically weaker than for the total market beta, likely due to the additional noise one inevitably faces when estimating partial betas. For industry sales concentration, we find no significant effect after controlling for total product market similarity.

5.3 | Tail risk

In a further analysis, we test the impact of market power on option-implied tail risk. Gaspar and Massa (2006) and Abdoh and Varela (2017) both examine the impact of market power on idiosyncratic realized volatility, but they do not

TABLE 8 Tail risk.

	LT	*RT*
−tsim	−0.009*	−0.008
	(−2.015)	(−1.707)
(-tsim)^2	−0.002	−0.004
	(−0.784)	(−1.487)
log(HHI)	−0.005	−0.005
	(−1.357)	(−1.046)
log(HHI)^2	0.002**	0.002*
	(2.234)	(1.883)
log(Age)	−0.034***	−0.038***
	(−3.263)	(−3.202)
log(AT)	0.041*	0.051**
	(1.779)	(2.131)
Default spread	−0.008	−0.006
	(−0.660)	(−0.572)
Dividend	0.000	0.000
	(−0.063)	(−0.046)
Financial leverage	0.016***	0.014***
	(4.004)	(4.125)
log(Firm size)	−0.150***	−0.185***
	(−5.777)	(−6.951)
Illiquidity	0.003	0.006
	(1.142)	(1.424)
Investment rate	0.000	0.000
	(−0.320)	(−0.957)
iVol	0.051***	0.052***
	(6.438)	(6.079)
log(Mkt/Book)	0.021***	0.024***
	(4.376)	(4.914)
Momentum	−0.026***	−0.027***
	(−4.010)	(−4.217)
Operating leverage	−0.002	−0.002
	(−1.413)	(−1.281)
q	0.004	0.003
	(1.515)	(0.919)
ROE	−0.002***	−0.002**
	(−2.952)	(−2.683)
R^2	63.47	67.88
Nobs	324,638	324,638

(Continues)

TABLE 8 (Continued)

	LT	*RT*
FE	Yes	Yes

Note: This table presents the results of a regression of firms' tail risk on measures of market power. We compute option-implied conditional left and right tail risk (*LT* and *RT*) using the approach of Bollerslev and Todorov (2011). As measures of market power, we use the negative of total product market similarity (*tsim*) and the natural logarithm of the Herfindahl–Hirschman Index (HHI) measure of industry sales concentration. We include the measures as well as their orthogonal squares. The regression equation is:

$$TR_{i,t} = \gamma_1(-tsim_{i,t}) + \gamma_2(-tsim_{i,t})^2 + \theta_1 log(HHI_{i,t}) + \theta_2 log(HHI_{i,t})^2 + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where $TR_{i,t}$ is either $LT_{i,t}$ or $RT_{i,t}$. $C_{i,t}$ is a vector of control variables, detailed definitions of which can be found in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_y and α_i are dummy variables that account for year and firm fixed effects (*FE*), respectively. Standard errors are double-clustered at the industry and year levels. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). *Nobs* is the total number of observations. The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

incorporate forward-looking information through option markets. By looking at tail risk, we aim to investigate whether firms with market power are more insulated from the risks associated with extreme events.[22]

Table 8 shows the results. We find that left tail risk increases significantly with an increase in total product market similarity. A two-standard-deviation decrease in total product market similarity decreases the left tail risk by 0.0277. For the right tail risk, only the orthogonal square of the total product market similarity (and that of the HHI) has a significant effect. Thus, firms with market power seem to be somewhat insulated from severe negative tail risk. When hit by an (idiosyncratic) negative event, it seems that the market expects firms with market power to be better able to withstand it. One possible channel is that their ability to withhold investment and/or raise product prices after a severe negative event seems to allow them to cushion the blow to some extent.

6 | ROBUSTNESS

6.1 | Market power and realized returns

In the main part of the paper, we discuss the effect of market power on the cost of capital. This is motivated by the overwhelming evidence in the literature that Chief Financial Officers (CFOs) of US firms use the CAPM for capital budgeting (e.g., Graham and Harvey, 2001; Graham, 2022; Jacobs and Shivdasani, 2012). Confirming these studies, Dessaint et al. (2021) document that the use of the CAPM in capital budgeting has negative real effects. Firms acquiring low-beta firms appear to overpay and have negative abnormal returns after the announcement. Thus, although market betas are at most weakly related to realized returns in the cross section (e.g., Fama and French, 1992), they have immediate real effects for firms.

Nevertheless, it is also interesting to examine whether market power is related to realized returns. To test this, we use Fama and MacBeth (1973) regressions of monthly stock excess returns on market power and several control variables:

$$r_{i,t} - r_{f,t} = \alpha + \gamma_1(-tsim_{i,t}) + \gamma_2(-tsim_{i,t})^2 + \theta_1 log(HHI_{i,t}) + \theta_2 log(HHI_{i,t})^2 + \eta C_{i,t} + \epsilon_{i,t}, \tag{5}$$

[22] The correlation between idiosyncratic volatility and tail risk is only about 0.5.

TABLE 9 Market power and returns.

	(i)	(ii)	(iii)	(iv)	(v)
Const	0.734**	0.725**	0.735**	0.736**	0.738**
	(2.556)	(2.529)	(2.550)	(2.561)	(2.589)
−tsim	−0.098*	−0.094*			−0.059
	(1.733)	(1.714)			(1.143)
(-tsim)^2		−0.070			−0.060
		(−1.476)			(−1.276)
log(HHI)			−0.124***	−0.137***	−0.127***
			(−3.086)	(−3.247)	(−3.421)
log(HHI)^2				0.095*	0.084*
				(1.917)	(1.826)
log(Age)	−0.029	−0.025	−0.050*	−0.055*	−0.042
	(−0.999)	(−0.857)	(−1.717)	(−1.874)	(−1.475)
log(AT)	0.709***	0.713***	0.743***	0.762***	0.755***
	(3.759)	(3.793)	(4.025)	(4.199)	(4.133)
Dividend	−0.019	−0.005	−0.031	−0.034	−0.022
	(−0.235)	(−0.063)	(−0.374)	(−0.419)	(−0.274)
Financial leverage	−0.535***	−0.534***	−0.521***	−0.524***	−0.543***
	(−4.589)	(−4.586)	(−4.414)	(−4.444)	(−4.657)
log(Firm size)	−1.098***	−1.116***	−1.118***	−1.136***	−1.150***
	(−5.511)	(−5.638)	(−5.619)	(−5.773)	(−5.883)
Illiquidity	0.074	0.074	0.082	0.084	0.086
	(0.555)	(0.555)	(0.617)	(0.627)	(0.646)
Investment rate	−0.044	−0.043	−0.028	−0.043	−0.030
	(−0.186)	(−0.181)	(−0.122)	(−0.184)	(−0.130)
iVol	−0.195*	−0.199*	−0.195*	−0.198*	−0.199*
	(−1.884)	(−1.929)	(−1.846)	(−1.876)	(−1.927)
log(Mkt/Book)	0.127**	0.130**	0.133**	0.136**	0.136**
	(2.365)	(2.424)	(2.446)	(2.517)	(2.533)
Momentum	0.142*	0.144*	0.143*	0.143*	0.144*
	(1.692)	(1.726)	(1.695)	(1.701)	(1.741)
Operating leverage	0.094	0.102	0.066	0.075	0.098
	(1.081)	(1.171)	(0.783)	(0.857)	(1.098)
q	−0.136	−0.145	−0.109	−0.132	−0.158
	(−0.801)	(−0.839)	(−0.653)	(−0.743)	(−0.866)
ROE	0.286***	0.284***	0.285***	0.285***	0.287***
	(2.705)	(2.710)	(2.690)	(2.694)	(2.719)

(Continues)

TABLE 9 (Continued)

	(i)	(ii)	(iii)	(iv)	(v)
R^2	4.13	4.19	4.01	4.08	4.33

Note: This table presents the results of Fama and MacBeth (1973) regressions of firms' monthly excess returns on measures of market power as well as several control variables. Monthly excess returns are calculated as the next month's total return ($r_{i,t}$) minus the risk-free rate ($r_{f,t}$). As measures of market power, we use the negative of total product market similarity (*tsim*) and the natural logarithm of the Herfindahl–Hirschman Index (HHI) measure of industry sales concentration. We include the measures as well as their orthogonal squares. The regression equation is:

$$r_{i,t} - r_{f,t} = \alpha + \gamma_1(-tsim_{i,t}) + \gamma_2(-tsim_{i,t})^2 + \theta_1 log(HHI_{i,t}) + \theta_2 log(HHI_{i,t})^2 + \eta C_{i,t} + \epsilon_{i,t},$$

where α is the intercept and $C_{i,t}$ is a vector of control variables, detailed definitions of which can be found in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

where α is the intercept. All other variables are defined as in the main analysis.

We present the results in Table 9. Consistent with Hou and Robinson (2006), we find that there is a significant negative relationship between market power and average firm excess returns. Interestingly, this relationship is more pronounced for the industry sales concentration measure that Hou and Robinson (2006) also use in their study. However, it is also evident for the innovation-based measure of total product market similarity.

6.2 | Alternative measures of market power

We test the robustness of our main results along several dimensions. First, we consider alternative measures of market power. We use the alternative measure of industry sales concentration of Hoberg and Phillips (2010b) (*fithhi*), which corrects for the underrepresentation of private firms in the traditional Compustat-based measure. In addition, we consider the negative of product market fluidity (*prodmktfluid*) and the industry sales concentration measure based on the Hoberg and Phillips (2016) classification (*tnic3hhi*).

We present the results for all market power measures in combination with different beta estimators in Table 10. As in Equation (3), all regressions include fixed effects and the full set of control variables. We find that the negative relationship between market power and market betas persists across different measures of market power.

6.3 | Alternative beta estimators

We also consider several alternative beta estimation methods without weighting (*unweighted*), with shrinkage (*shrunk*), and with both weighting and shrinkage (*weighted* & *shrunk*). The results are also shown in Table 10. Regardless of the method used to estimate the betas, the negative relationship between market power and market betas persists.

We also repeat the analysis using market betas based on daily rather than monthly data. We use the same estimation window of $k = 60$ months and a shorter window of $k = 24$ months as suggested by Hollstein et al. (2019). The results, presented in Table 11, are qualitatively similar.

6.4 | Mergers

Finally, we test the robustness of the merger analysis. First, we consider changing the time $M^D_{i,t}$ is equal to one, with specifications ranging from 3 and 60 months. As shown in Table 12, this leads to similar conclusions. We also vary the way the betas are estimated. We use all the methods considered so far (without weighting, with shrinkage, with

TABLE 10 Market power and market beta — Robustness.

	unweighted	*weighted*	*shrunk*	*weighted & shrunk*
log(HHI)	−0.044**	−0.044**	−0.043**	−0.043**
	(−2.519)	(−2.555)	(−2.532)	(−2.568)
log(HHI)^2	0.005	0.006	0.005	0.006
	(0.513)	(0.591)	(0.522)	(0.596)
R^2	60.99	60.25	60.94	60.26
log(fithhi)	−0.058***	−0.058***	−0.057***	−0.056***
	(−4.810)	(−4.810)	(−4.833)	(−4.694)
log(fithhi)^2	0.017	0.017	0.017	0.018
	(1.361)	(1.361)	(1.373)	(1.456)
R^2	67.77	67.77	67.77	66.50
−prodmktfluid	−0.051***	−0.051***	−0.050***	−0.050***
	(−3.352)	(−3.325)	(−3.367)	(−3.335)
(*−prodmktfluid*)^2	−0.023***	−0.023***	−0.022***	−0.023***
	(−3.338)	(−3.375)	(−3.313)	(−3.358)
R^2	61.04	60.31	60.99	60.31
tnic3hhi	−0.027***	−0.027***	−0.026***	−0.026***
	(−3.647)	(−3.853)	(−3.670)	(−3.869)
tnic3hhi^2	0.009	0.010*	0.009	0.010*
	(1.598)	(1.834)	(1.615)	(1.846)
R^2	60.95	60.22	60.91	60.22
−tsim	−0.043***	−0.044***	−0.042***	−0.043***
	(−4.749)	(−4.720)	(−4.807)	(−4.746)
(*-tsim*)^2	−0.021**	−0.021*	−0.021**	−0.020*
	(−2.058)	(−1.900)	(−2.084)	(−1.915)
R^2	60.99	60.26	60.95	60.26

Note: This table presents the results of regressions of firms' market betas on measures of market power as well as several control variables. Conditional market betas are computed using ordinary least squares (OLS), weighted least squares (WLS), OLS with shrinkage, or WLS with shrinkage, based on the last 60 months of monthly returns. As measures of market power, we use the natural logarithm of the Herfindahl–Hirschman Index (HHI) measure of industry sales concentration, the fitted HHI (*log*(*fithhi*)), the negative of product market fluidity (*prodmktfluid*), the text-based network industry classifications (TNIC) HHI measures (*tnic3hhi*), and the negative of total product market similarity (*tsim*). We include the measures ($MP_{i,t}$) as well as their orthogonal squares. The regression equation is:

$$\beta^M_{i,t} = \gamma_1 MP_{i,t} + \gamma_2 MP^2_{i,t} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where $C_{i,t}$ is a vector of control variables, detailed definitions of which can be found in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_y and α_i are dummy variables that account for year and firm fixed effects (*FE*), respectively. Standard errors are double-clustered at the industry and year levels. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 11 Market power and market beta—Daily betas.

	(i)	(ii)	(iii)	(iv)	(v)
60 Months					
−tsim	−0.042***		−0.028**		−0.027**
	(−3.065)		(−2.639)		(−2.645)
$(-tsim)^2$	−0.022		−0.012		−0.011
	(−1.392)		(−0.866)		(−0.850)
log(HHI)		−0.030**		−0.024**	−0.023**
		(−2.110)		(−2.135)	(−2.068)
$log(HHI)^2$		−0.001		−0.002	−0.003
		(−0.504)		(−1.119)	(−1.412)
R^2	70.99	70.88	74.22	74.19	74.26
Nobs	1,011,267	1,011,267	1,011,267	1,011,267	1,011,267
Controls	No	No	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
24 Months					
−tsim	−0.039***		−0.024**		−0.023**
	(−2.949)		(−2.518)		(−2.522)
$(-tsim)^2$	−0.022		−0.010		−0.009
	(−1.420)		(−0.781)		(−0.763)
log(HHI)		−0.030*		−0.023*	−0.021*
		(−1.982)		(−2.004)	(−1.918)
$log(HHI)^2$		−0.003		−0.004	−0.004
		(−0.909)		(−1.359)	(−1.402)
R^2	59.38	59.31	63.29	63.28	63.32
Nobs	1,011,267	1,011,267	1,011,267	1,011,267	1,011,267
Controls	No	No	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of a regression of firms' market betas on measures of market power as well as several control variables. Conditional market betas are computed via weighted least squares (WLS) based on the last 60 and 24 months of daily data. As measures of market power, we use the negative of total product market similarity (*tsim*) and the natural logarithm of the Herfindahl–Hirschman Index (HHI) measure of industry sales concentration. We include the measures as well as their orthogonal squares. The regression equation is:

$$\beta^M_{i,t} = \gamma_1(-tsim_{i,t}) + \gamma_2(-tsim_{i,t})^2 + \theta_1 log(HHI_{i,t}) + \theta_2 log(HHI_{i,t})^2 + \alpha_y + \alpha_i + \eta C_{i,t} + \epsilon_{i,t},$$

where $C_{i,t}$ is a vector of control variables, detailed definitions of which can be found in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_y and α_i are dummy variables that account for year and firm fixed effects (*FE*), respectively. Standard errors are double-clustered at the industry and year levels. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). *Nobs* is the total number of observations. The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 12 Merger analysis—Robustness.

	Different horizons				Monthly betas			Daily betas	
	3 Months	6 Months	12 Months	60 Months	unweighted	shrunk	weigh & shr	60 Months	24 Months
M^D	−0.035***	−0.038***	−0.043***	−0.035*	−0.047***	−0.045***	−0.046***	−0.034***	−0.032***
	(−3.238)	(−3.138)	(−3.363)	(−2.037)	(−3.738)	(−3.716)	(−3.754)	(−3.419)	(−2.844)
log(Age)	−0.091**	−0.091**	−0.092**	−0.093**	−0.092**	−0.090**	−0.090**	−0.068**	−0.082**
	(−2.602)	(−2.610)	(−2.626)	(−2.650)	(−2.701)	(−2.672)	(−2.635)	(−2.295)	(−2.632)
log(AT)	0.196***	0.196***	0.197***	0.201***	0.202***	0.196***	0.194***	0.183***	0.116***
	(5.060)	(5.071)	(5.109)	(5.190)	(5.934)	(5.947)	(5.184)	(6.421)	(3.291)
Default spread	0.003	0.003	0.003	0.003	0.002	0.002	0.003	0.002	−0.001
	(0.625)	(0.622)	(0.618)	(0.645)	(0.296)	(0.329)	(0.662)	(0.704)	(−0.178)
Dividend	−0.095***	−0.095***	−0.095***	−0.095***	−0.099***	−0.046***	−0.091***	−0.077***	−0.084***
	(−4.496)	(−4.500)	(−4.514)	(−4.498)	(−4.784)	(−4.754)	(−4.496)	(−4.995)	(−5.279)
Financial leverage	0.009	0.009	0.009	0.009	0.005	0.004	0.009	0.006*	0.007
	(1.449)	(1.449)	(1.448)	(1.444)	(0.917)	(0.891)	(1.422)	(1.969)	(1.442)
log(Firm size)	0.032	0.033	0.033	0.032	0.014	0.014	0.033	0.151***	0.261***
	−0.909	−0.923	−0.940	−0.917	(0.448)	(0.451)	(0.952)	(5.551)	(6.750)
Illiquidity	−0.020***	−0.020***	−0.020***	−0.020***	−0.020***	−0.019***	−0.020***	−0.003	−0.007***
	(−6.979)	(−6.963)	(−6.978)	(−7.078)	(−6.875)	(−6.728)	(−6.924)	(−1.501)	(−4.490)
Investment rate	0.001	0.001	0.001	0.001	0.000	0.000	0.001	−0.001	−0.001
	(0.360)	(0.359)	(0.357)	(0.348)	(0.129)	(0.128)	(0.345)	(−0.822)	(−0.543)
iVol	0.338***	0.338***	0.338***	0.338***	0.321***	0.311***	0.327***	0.112***	0.127***
	(9.533)	(9.534)	(9.536)	(9.532)	(8.662)	(8.613)	(9.495)	(7.424)	(8.554)
log(Mkt/Book)	0.014	0.014	0.014	0.014	0.011	0.010	0.013	0.020***	0.037***
	(1.134)	(1.133)	(1.135)	(1.137)	(1.175)	(1.135)	(1.107)	(4.567)	(5.398)
Momentum	−0.028*	−0.028*	−0.028*	−0.028*	−0.024**	−0.023**	−0.027*	−0.037***	−0.054***
	(−1.979)	(−1.983)	(−1.991)	(−1.978)	(−2.194)	(−2.176)	(−1.984)	(−5.671)	(−5.532)
Operating leverage	0.005**	0.005**	0.005**	0.005**	0.004**	0.004**	0.004**	0.001	0.002**
	(2.735)	(2.661)	(2.638)	(2.754)	(2.443)	(2.403)	(2.717)	(0.704)	(2.229)
q	−0.004	−0.004	−0.004	−0.004	−0.005	−0.005	−0.004	−0.004*	−0.003
	(−1.005)	(−1.003)	(−1.001)	(−1.004)	(−1.404)	(−1.399)	(−0.993)	(−1.762)	(−1.516)
ROE	0.002	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.002
	(0.504)	(0.496)	(0.490)	(0.508)	(0.343)	(0.307)	(0.454)	(0.232)	(1.312)
R^2	60.56	60.56	60.57	60.57	61.30	61.25	60.57	74.40	63.60
Nobs	11,540	11,540	11,540	11,540	11,540	11,540	11,540	11,478	11,478
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the results of a regression of the monthly market betas on a dummy (M^D) as in Equation (4). The merger dummy is one for a given period after the merger. The merger sample is purpose-based, where mergers have one of these purposes: "Acquire competitors technology/strategic assets", "Strengthen existing operations/expand presence in primary market", "Strengthen operations", "Create synergies", and "Concentrate on core businesses/assets". We consider postmerger horizons between 3 and 60 months. In addition, we consider alternative beta estimators, for which we present the results for a 24-month postmerger horizon. These estimators use the last 60 months of monthly returns and ordinary least squares (OLS) (*unweighted*), OLS with shrinkage (*shrunk*), or weighted least squares (WLS) with shrinkage (*weigh & shr*), or the past 60 or 24 months of daily returns and WLS. Detailed definitions of the control variables can be found in Appendix A. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. All panel regressions include dummies that account for firm and year fixed effects (*FE*). Standard errors are double-clustered at the industry and year levels. R^2 is the adjusted coefficient of determination of the regressions (in percentage points). *Nobs* is the number of merger observations. The *t*-statistics are reported in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

weighting and shrinkage, and betas based on daily return data). The results, shown in Table 12, are qualitatively similar in each case.

7 | CONCLUSION

In this study, we show that market power has a significant negative relationship with market betas. We aim to resolve the debate in the literature about this relationship by using the innovation-based market power measure of Hoberg and Phillips (2010a). Using subsamples, we show that the effect is substantially stronger in the most recent period. An analysis of anticompetitive mergers underscores that the effect of market power on betas is potentially causal. Finally, we document that market power primarily affects the discount-rate channel, suggesting that firms facing little competition are partially insulated from aggregate discount-rate shocks.

These results suggest that the firms that are already the most powerful reap additional benefits in the capital markets from a lower cost of equity capital. Thus, to some extent, market power appears to be self-perpetuating. By documenting yet another effect that reinforces incumbents with market power, our findings lend support to the growing call for policymakers to actively enhance competition.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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APPENDIX A: CONTROL VARIABLES

We use several variables to control for market beta determinants documented in the prior literature (Cosemans et al., 2015; Chincarini et al., 2020; Kogan & Papanikolaou, 2013). Item numbers cited below refer to the legacy CST item number cited in the Compustat/CRSP (the Center for Research in Security Prices) merged database. For all accounting measures, we use information starting 4 months after the fiscal year end (Hou et al., 2021).

- **Age** is the number of years (plus 1) since a firm first appeared in the CRSP database.
- **Total assets (AT)** is total assets (item 6).
- **Default spread** is the difference between the yields on Baa- and Aaa-rated corporate bonds. We obtain the underlying series from Amit Goyal's website.
- **Dividend** is a dummy variable that equals one if the company paid a dividend in the last financial year (item 26 or 201).
- **Financial leverage** is the ratio of the book value of assets (item 6) to the market value of equity, calculated as the product of the closing price (item 24) and the number of shares outstanding (item 25).

- **Firm size** is the market capitalization of a stock, calculated as the product of the stock price at the end of a month times the corresponding number of shares outstanding.
- **Illiquidity** is constructed by dividing the absolute stock return by the dollar volume (excluding zero-volume days). We then take the average over the previous year (Amihud, 2002).
- **Investment rate** is measured as the ratio of capital expenditures (item 128) to the lagged book value of capital (item 7).
- **Idiosyncratic volatility (iVol)** is defined as the standard deviation of the residuals of a regression of excess stock returns on the Fama and French (1993) factors using monthly returns over the past 60 months.
- **Market-to-book Ratio (Mkt/Book)** is market equity divided by book equity. Market equity is calculated by multiplying the year-end share price (item 199) by the number of shares outstanding (item 25). Book equity is stockholders' equity plus balance sheet deferred taxes and investment tax credit (item 35) minus the book value of preferred stock. Stockholders' equity is calculated in the following order: (i) item 216, (ii) item 60 + item 130 or (iii) item 6 − item 181. The book value of preferred stock is calculated in this order: (i) item 56, (ii) item 10, or (iii) item 130.
- **Momentum** is the cumulative stock return during the months $t-12$ to $t-1$.
- **Operating leverage** is calculated as a 3-year moving average of the ratio of the percentage change in operating income before depreciation (item 13) to the percentage change in sales (item 12).
- **Tobin's *q* (*q*)** is the ratio of common equity (CRSP December market capitalization) plus the book value of debt (item 9) plus the book value of preferred stock (item 56) minus inventories (item 3) and minus deferred taxes (item 74) divided by the book value of capital (item 7).
- **Return on equity (ROE)** is earnings divided by the book equity of the previous year. Earnings are calculated as income before extraordinary items available to common stockholders (item 237) plus deferred taxes from the income statement (item 50) plus investment tax credit (item 51).

APPENDIX B: HERFINDAHL–HIRSCHMAN INDEX (HHI)

To identify industries, we use the three-digit North American Industry Classification System (NAICS) classification. We follow Grullon et al. (2019) to fill in the missing NAICS values using the following process: First, we use Compustat historical NAICS whenever available (NAICSH). Second, we use CRSP historical values (from the msenames table). Third, we use NAICS from the Compustat names table. Finally, if none is available, we fill in the remaining NAICS values by converting the SIC codes to NAICS using the conversion tables from the US Census Bureau.

Using the NAICS classifications, we can calculate the HHI for each industry and infer the degree of concentration in sales. The HHI is calculated as follows:

$$HHI_{j,t} = \sum_{i,k=j} \left(\frac{Sales_{i,k,t}}{\sum_{i,k=j} Sales_{i,k,t}} \right)^2,$$

where $Sales_{i,k,t}$ are the sales (item 117) of firm i, which is in industry k in fiscal year t. This results in one value for $HHI_{j,t}$ for each industry at each point in time.

APPENDIX C: CASH-FLOW AND DISCOUNT-RATE NEWS

In this section, we show how to calculate the cash-flow and discount-rate news according to Campbell and Vuolteenaho (2004). First, we obtain the excess log market return, the term yield spread, and the price–earnings ratio. Second, we compute the small-stock value spread, using data from Kenneth French's website. We use the six size–book-to-market portfolios. The value spread is calculated as the difference between the log(BE/ME) value of the small–high book-to-market portfolio and the log(BE/ME) value of the small–low book-to-market portfolio. We add the cumulative log return of the small–low book-to-market portfolio and subtract the cumulative log return of the small–high book-to-market portfolio.

We estimate the vector autoregressive (VAR) model $z_{t+1} = a + \Gamma z_t + u_{t+1}$. Γ is an $m \times m$ matrix, with the coefficient estimates from a VAR-type regression for each of the input coefficients. z_t is the state vector containing the excess log market return, the term yield spread, the price–earnings ratio, and the small-stock value spread. u_{t+1} represents the residuals from these regressions. The VAR shocks are mapped by λ, where $\lambda = \rho\Gamma(I - \rho\Gamma)^{-1}$. The ρ is set to $0.95^{1/12}$. The cash-flow and discount-rate news can then be calculated as:

$$N_{CF,t+1} = (e1' + e1'\lambda)u_{t+1}$$

$$N_{DR,t+1} = e1'\lambda u_{t+1}\,.$$

For more information, we refer to Campbell and Vuolteenaho (2004).

APPENDIX D: TAIL RISK

Bollerslev and Todorov (2011) construct a measure of tail risk perceived by investors that is based on close-to-maturity deep out-of-the-money options. They construct the model-free risk-neutral right tail (*RT*) and left tail (*LT*) measures as follows:

$$\begin{aligned} RT_t(k) &\approx \frac{e^{r_{f,(t,T]}} C_t(K)}{(T-t)F_{t,T}}, \\ LT_t(k) &\approx \frac{e^{r_{f,(t,T]}} P_t(K)}{(T-t)F_{t,T}}, \end{aligned} \tag{D.1}$$

where $r_{f,(t,T]}$ is the risk-free interest rate between t and the options expiration date T. $C_t(K)$ and $P_t(K)$ are the current call and put prices with strike price K and maturity T. $F_{t,T}$ is the current option-implied forward price. The log moneyness is $k = \log(K/F_{t,T})$. For the estimation, Bollerslev and Todorov (2011) interpolate the option price to the desired moneyness levels, 1.1 for *RT* and 0.9 for *LT*, using Black and Scholes (1973) implied volatilities. Because the term structure of individual stock options can be sparse, we use a set of standardized options from OptionMetrics with 30 days to maturity.

APPENDIX E: MARKET POWER MEASURES: EXAMPLES

Table A1 presents summary information about the *HHI* and *tsim* measures for the Dow Jones Industrial Average (DJIA)-30 companies. Under the *HHI* measure, the three DJIA-30 companies with the highest market power are Home Depot Inc., Nike Inc., and Walgreens Boots Alliance Inc. Under the *tsim* measure, different companies make it to the list of top three by market power: Caterpillar Inc., 3M Co., and Procter & Gamble Co. Interestingly, all of these have recently been subject to antitrust lawsuits in the US or blocked merger attempts.[23]

[23] An antitrust lawsuit against Caterpillar was dismissed on January 22, 2016. 3M was involved in a lawsuit brought forward by LePage's Inc. in 2003. On December 8, 2020, the FTC sued to block the acquisition by Procter & Gamble of Billie Inc. In the 2010s, the company has also received further antitrust fines in Europe. For Home Depot, Nike, and Walgreens, we did not find antitrust action in the top hits searching for "<company> antitrust lawsuit". Nike was fined by the European Commission in 2019, though.

TABLE A1 Market power measures: Examples.

Ticker	Name	Average *HHI* decile	Last *HHI* decile	Average *tsim* decile	Last *tsim* decile
AAPL	Apple Inc.	4	5	6	4
AMGN	Amgen Inc.	2	2	9	9
AXP	American Express Co	4	3	8	7
BA	Boeing Co.	7	8	5	5
CAT	Caterpillar Inc.	5	5	2	2
CRM	Salesforce.Com Inc.	9	9	8	8
CSCO	Cisco Systems Inc.	4	5	8	7
CVX	Chevron Corp	7	8	6	5
DIS	Walt Disney Co.	8	9	5	5
DOW	Dow Inc.	2	2	3	4
GS	Goldman Sachs Group Inc.	8	6	7	9
HD	Home Depot Inc.	10	10	3	3
HON	Honeywell International Inc.	7	8	3	3
IBM	International Business Machines Corp	7	9	3	3
INTC	Intel Corp	4	5	7	4
JNJ	Johnson & Johnson	2	2	3	4
JPM	JPMorgan Chase & Co	8	3	10	9
KO	Coca-Cola Co	7	8	4	4
MCD	McDonald's Corp	8	8	4	4
MMM	3M Co	7	8	2	1
MRK	Merck & Co Inc.	2	2	6	9
MSFT	Microsoft Corp	7	9	8	7
NKE	Nike Inc.	10	10	5	5
PG	Procter & Gamble Co	2	2	2	1
TRV	Travelers Companies Inc.	4	5	9	8
UNH	UnitedHealth Group Inc.	4	5	7	6
V	Visa Inc.	4	3	5	6
VZ	Verizon Communications Inc.	6	7	8	8
WBA	Walgreens Boots Alliance Inc.	10	10	4	4
WMT	Walmart Inc.	9	10	6	3

Note: This table presents the average *HHI* decile, the last *HHI* decile, the average *tsim* decile, and the last *tsim* decile the companies currently in the Dow Jones Industrial Average (DJIA)-30 index are in during our sample period.