SYSTEMATIC RISK AND MEASURES OF MONOPOLY POWER

John Schleider
Washington and Lee University

Thesis Committee: Camilo Alvarez (Chair), Joseph Guse, Aliaa Bassiouny

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ABSTRACT: This paper empirically assesses the relationship between systematic risk, measured by CAPM beta, and various measures of monopoly power. I find that the most theoretically sound measure of power, the Lerner index, indicates a negative relationship, but other measures commonly used in the literature imply an inconsistent or positive relationship. The results with the Lerner index confirm most theoretical findings regarding this subject, and, when combined with theory, might suggest the Lerner index is a better measure of monopoly power compared to the Hirshman Herfindahl index, Tobin's Q, and the price-cost margin.

INTRODUCTION

The relationship between a firm's monopoly power and exposure to systematic risk impacts a firm's financing and investment decisions, and is important to understanding key dynamics in industrial organization. A negative relationship would confer additional benefits to monopolies by lowering their costs of capital (Alexander and Thistle 1999). It would also make entry by new firms more difficult because these new entrants have a cost of capital disadvantage. Alternatively, a positive relationship would encourage continual disruption, where competitive firms break monopolies with a cheaper cost of capital. Similarly, any economically significant relationship would change the incentive for monopolies to innovate or expand. A negative relationship between risk and power would encourage monopolists to innovate by lowering the required return of new projects only for them, while a positive relationship would see monopolists avoiding innovation, where it would instead come from smaller companies. Finally, the relationship between systematic risk and monopoly power connects the financial and product market theories of the firm (Alexander and Thistle 1999). Determining the direction and magnitude of this relationship can further our understanding of innovation, market structure, corporate finance, and, by extension, industrial organization. It has implications for firms, regulators, and investors alike.

The direction of the relationship between a firm's risk and monopolism is not yet settled empirically—this area of research remains "murky", and "the relationship between competition and systematic risk is still unsettled" (Abdoh and Varela 2018). The contributions of this thesis are as follows. First, I extend previous studies by employing different measures of monopoly power using a common firm sample to compare the measures, versus previous studies that typically focus on a single measure at a time. Second, I am the first to use the Lerner index, a theoretically stronger measure of power that remains unexplored in this facet of economics. I show empirically that the relationship between systematic risk and monopoly power depends on the measure used. The Lerner index, the most theoretically rigorous measure of monopoly power, associates negatively with risk, while other measures—such as the accounting price-cost margin and concentration metrics—associate positively with risk. The results might suggest that the Lerner index a better measure of monopoly power versus concentration, valuation, and profitability metrics.

LITERATURE REVIEW

Though my paper focuses on empirical analysis, a brief theoretical literature review of the relationship between systematic risk and monopoly power might be helpful. I encountered eight[1] theoretical models finding a clearly negative relationship, and Subrahmanyam and Thomadakis' 1980 paper (which I call S&T for brevity) remains the cornerstone of this facet of research. The motivational model in this thesis takes from the literature and makes simplifications so that we focus on the empirical methodology and findings. However, I found three[2] that suggest an ambiguous, negative, or unclear relationship.

Empirical research is just as varied. Sullivan (1974) examined the relationship between industry concentration (via the Hirshman-Herfindahl index (HHI) and the k-firm concentration ratio) and excess returns (calculated with the CAPM beta), reporting a negative relationship between concentration and returns. Similarly, Alexander and Thistle (1999) find a similar relationship using concentration at the industry level. Hollstein et al (2023) reveal a negative relationship by regressing on product similarities and HHI. Finally, Booth and Zhou (2015) examine concentration measures and profit margins, concluding that monopoly power and risk are negatively related—this paper claimed to use the Lerner index, but the figure used is more accurately termed the EBITDA margin (a type of accounting profit margin) by finance professionals. I encountered no paper that used *marginal* profits like the price-cost margin or the Lerner.

About as many empirical papers report the opposite result. Jose and Stevens (1987) and Bustamante and Donangelo (2017) use concentration measures and find that competition makes firms less risky. Abdoh and Varela (2017) find that concentration reduces idiosyncratic risk and not systematic risk, finding in a later publication that the two are positively related (2018). Stevens (1986) finds that power and risk are positively related using Tobin's Q as a measure of monopolism.

Empirical papers disagree for several reasons. First, authors use different measures of monopoly power. In antitrust and industrial organization, monopoly power is "indicated by a variety of factors—such

[1] Booth (1991); Subrahmanyam and Thomadakis (1980); O'Brien (2011); Lee, Thomas, and Rahman (1990); Sun (1993); Chen, Cheng, and Hite (1985); Binder (1992); Cressy (1995)
[2] Conine (1983); Sun (1993); Wong (1995)

as market concentration, barriers to entry, and the particular conduct of the firm in question. Antitrust enthrones no single quantitative measure” (Elzinga and Mills 2011). Existing literature reflects the diversity of monopolism metrics—concentration, market share, profitability, and more are all represented. Researchers also differ on calculating those metrics. The HHI, the most common in this area of literature, can be calculated differently depending on the dataset and where one draws the line between one industry and another, as HHI is an industry-level statistic. Finally, researchers pursue different strategies that yield different results. Bustamante and Donangelo (2017) and Sullivan (1974), for example, examine the association between power and systematic risk by analyzing monopoly power and common stock returns. Booth and Zhou (2015) focus on dividend yields in their empirical work. Some papers, like Alexander and Thistle (1999), investigate the industry-level relationship, while most other research pursue the firm-level interaction between risk and power, like Stevens (1986) and Sullivan (1974). Finally, the existing papers use different datasets, meaning their findings on measures of power are not perfectly comparable to each other. Thus, there exists a clear need for a paper that analyzes several different measures with the same data, as this paper does.

MOTIVATIONAL MODEL

Consider monopolist i with constant marginal cost and linear demand (for simplicity, assume marginal cost includes the rents to capital and the firm has no capital stock). The slope of the demand curve, b_i, represents monopoly power, where higher values imply more power. I set the intercept of the linear demand equal to $b_i q_{ie} + c_i$, where q_{ie} is the socially optimal quantity, so that an increase in b_i does not result in a decrease in demand. The firm cannot change the socially optimal quantity.

$$\mathbb{E}\left[D_i\right] = P_i(q_i) = (b_i q_{ie} + c_i) - b_i q_i$$

$$\mathbb{E}\left[\Pi_i(q_i)\right] = q_i\left((b_i q_{ie} + c_i) - b_i q_i - c_i\right)$$

Now we introduce uncertainty. Here, I follow a method employed by Subrahmanyam and Thomadakis (1980), where the authors add risk to demand via an uncertain intercept. In this single-period model, the firm chooses q before it knows the exogenous shock to demand. Unlike S&T, I do not add uncertainty to input costs for simplicity and because the model yields a similar beta-monopolism relationship without it, as shown by Blinder (1992). The rest of the economy's firms share this demand uncertainty—in other words, e represents a systematic risk.

$$\mathbb{E}[e] = 0, \qquad \mathrm{Var}(e) = \sigma^2$$

$$D_i = P_i(q_i) = (b_i q_{ie} + c_i)(1 + e) - b_i q_i$$

$$\Pi_i(q_i) = q_i\big((b_i q_{ie} + c_i)(1 + e) - b_i q_i - c_i\big)$$

$$\mathrm{Var}(\Pi_i) = q_i^2 (b_i q_{ie} + c_i)^2 \sigma^2$$

We assume the monopolist intends to maximize a mean-variance utility function (Markowitz 1952). This makes the monopolist risk-averse—an aggregation of the utility functions of the firm's owners. Though unusual in other parts of economics, a risk-averse firm is common in this area of research. One can justify this by noting investors are clearly risk averse, as financial markets discount risky investments. Also, directors of firms represent the owners and have a fiduciary responsibility to represent owners' interests (Black 2001). Following this, directors will manage the firm with some risk-aversion. A risk-averse firm with mean-variance utility is therefore appropriate. We write the utility function

$$U_i(q_i) = \mathbb{E}\big[\Pi_i(q_i)\big] - \mu_i \mathrm{Var}(\Pi_i)$$

where μ_i is the firm's risk aversion coefficient. Thus, given an $\mathbb{E}\big[D_i(q_i)\big]$, a firm solves the following:

$$\max_{q_i} \mathbb{E}\big[\Pi_i(q_i)\big] - \mu_i \mathrm{Var}(\Pi_i)$$

$$q_i = \frac{b_i q_{ie}}{2\left(\mu_i b_i^2 q_{ie}^2 \sigma^2 + 2\mu_i b_i c_i q_{ie} \sigma^2 + b_i + \mu_i c_i^2 \sigma^2\right)}$$

Given that this is a partial equilibrium, the first order condition categorizes the solution. From it, we have three theorems.

Theorem 1: A change in the variance of the demand shock is inversely related to quantity.

$$\frac{\partial q_i}{\partial \sigma^2} < 0$$

We see this by inspecting the formula for optimal q_i.

Theorem 2: A change in the firm's optimal quantity is inversely related to a change in monopoly power if $b_i q_{ie} - c_i > 0$.

$$b_i q_{ie} - c_i > 0 \Rightarrow \frac{\partial q_i}{\partial b_i} < 0$$

We observe this with the derivative of optimal q_i with respect to b_i. This is intuitive: as b_i approaches zero, the firm has no monopoly power and thus no incentive to produce when there is variance in demand. Specifically, this model predicts that until the demand intercept is twice marginal cost c_i, the firm will increase production with b_i, and afterwards it will decrease production with b_i.

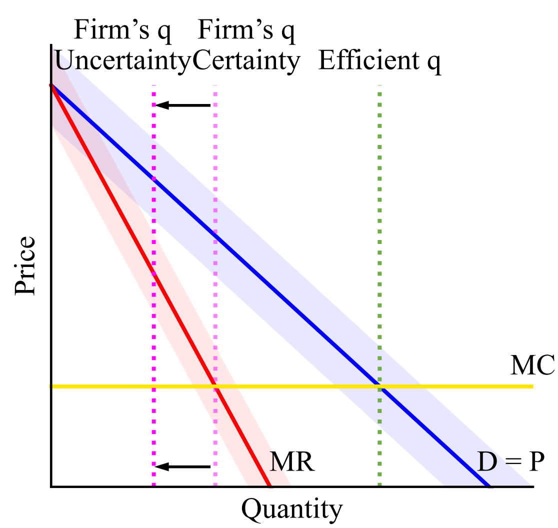
$$\frac{\partial q_i}{\partial b_i} = \frac{-\mu_i q_{ie} \sigma^2 (b_i q_{ie} - c_i)(b_i q_{ie} + c_i)}{2\left(\mu_i b_i^2 q_{ie}^2 \sigma^2 + 2\mu_i b_i c_i q_{ie} \sigma^2 + b_i + \mu_i c_i^2 \sigma^2\right)^2}$$

Theorem 3: A change in monopoly power is positively related to the firm's profit.

$$\frac{\partial \Pi_i}{\partial b_i} > 0$$

I include the derivative in Appendix I. Through inspecting $\frac{\partial \Pi_i}{\partial b_i}$ we observe that its terms are positive.

Figure 1: The monopolist constricts quantity due to systematic risk via demand uncertainty



Now we consider systematic risk—beta. In this single period model of the firm, we find beta with

$$\beta_i = \frac{\text{Cov}(\Pi_i, \Pi_m)}{\mathbb{E}(\Pi_i)} \times \frac{\mathbb{E}(\Pi_m)}{\text{Var}(\Pi_m)},$$

as in S&T's equation 6 (1980), where Π_m is the sum of profits for all firms in the economy. Recall that the firm shares the demand shock e in different magnitudes with the rest of the economy. Since the economy shares this demand uncertainty, the formula for β_i above provides us with a measure of systematic risk à la CAPM. I differ from S&T by using the firm's profits as both its value and flows—this is because the firm in this model has no capital and its marginal cost includes capital rents. We now examine Π_m, $\mathrm{Var}(\Pi_m)$ and $\mathrm{Cov}(\Pi_i, \Pi_m)$.

$$\Pi_m = \sum_j \Pi_j = q_m(A_m(1+e) - b_m q_m - c_m)$$

$$\mathrm{Var}(\Pi_m) = q_m^2 A_m^2 \sigma^2$$

$$\mathrm{Cov}(\Pi_i, \Pi_m) = q_i(b_i q_{ie} + c_i) q_m A_m \sigma^2$$

We substitute these into the formula for beta.

$$\beta_i = \frac{q_i(b_i q_{ie} + c_i) q_m A_m \sigma^2}{q_i\big((b_i q_{ie} + c_i) - b_i q_i - c_i\big)} \times \frac{\mathbb{E}(\Pi_m)}{q_m^2 A_m^2 \sigma^2}$$

$$\beta_i = \frac{(b_i q_{ie} + c_i)}{(b_i q_{ie} + c_i) - b_i\left(\dfrac{b_i q_{ie}}{2\big(\mu_i b_i^2 q_{ie}^2 \sigma^2 + 2\mu_i b_i c_i q_{ie} \sigma^2 + b_i + \mu_i c_i^2 \sigma^2\big)}\right) - c_i} \times \frac{\mathbb{E}(\Pi_m)}{q_m A_m}$$

$$\beta_i = \frac{2\mathbb{E}(\Pi_m)(b_i q_{ie} + c_i)(\mu_i b_i^2 q_{ie}^2 \sigma^2 + 2\mu_i b_i c_i q_{ie} \sigma^2 + b_i + \mu_i c_i^2 \sigma^2)}{A_m b_i q_{ie} q_m (2\mu b_i^2 \sigma^2 + 4\mu_i b_i c_i q_{ie} \sigma^2 + b_i + 2\mu_i c_i^2 \sigma^2)}$$

Theorem 4: Beta, β_i, is inversely related to monopoly power, b_i, and the relationship is not linear.

$$\frac{\partial \beta_i}{\partial b_i} < 0$$

I include the derivative in Appendix I, where we observe that since all the variables are positive, $\frac{\partial \beta_i}{\partial b_i}$ must be negative. This result mirrors the findings of S&T (1980) and other similar models, like Booth (1981) and Lee et al. (1990). This simple model demonstrates how risk and monopoly power might be related and serves as motivation for the empirical analysis in this paper.

MEASURES OF RISK AND POWER

I examine five common measures of monopoly power and their relationship with systematic risk in this paper: the price-cost margin, the Lerner index, the Hirshman-Herfindahl concentration index, market share, and Tobin's Q ratio. For systematic risk, I use the unlevered CAPM beta.

The unlevered beta represents the riskiness of a firm to all its investors, not just the common stockholders whose risk the CAPM beta regression directly computes. I estimate the equity CAPM beta with the standard single factor model

$$r_{it} - r_{ft} = \alpha_i + \beta_{L,i}\left(r_{mt} - r_{ft}\right), \qquad \beta_{L,i} = \text{Firm } i \text{ equity (levered) beta}$$

using 60-month rolling regressions. To find the unlevered beta, I take the levered beta and apply the formula

$$\beta_{UL,it} = \frac{\beta_{L,it}}{1 + (1 - \tau_t)\left(\frac{\text{Debt}_{it}}{\text{Mkt. Cap}_{it}}\right)},$$

where τ_t is the statutory corporate tax rate during the last year of the rolling beta's window, "Debt" represents the firm's long- and short-term debt as recorded on its balance sheet, and "Mkt. Cap" represents the firm's market capitalization—the number of shares times the company's stock price. I use this unlevered beta as the endogenous measure of systematic risk, as it reflects the systematic risk for the whole of the firm, not just the equity portion. Unlevered beta is the endogenous variable in the main regressions of this thesis.

The Lerner index measures the gap between the price a monopolist charges and marginal cost in economic terms (Elzinga and Mills 2011)—in addition to the explicit costs reported by firms, economic costs include the expected returns to capital. Theoretically, the Lerner is the difference between price and marginal cost divided by price, $\frac{P-c}{P}$. The Lerner is superior to other measures of power because it requires no information about the firm's output market or competitors, and it directly captures the economic profit a monopolist should experience (Shaffer and Spierdijk 2019). Other measures of monopoly power do not capture the economic profit characteristic of a monopoly. Measures of profitability often ignore rents to owners of capital that eat into deceivingly high accounting profit margins. Measures of concentration assume market share is a good proxy for power, but there are competitive market structures that allow for concentration. I further explain the limitations of these measures later in this section. In short, the Lerner index beats other measures of power because it measures attributes of monopolists regardless as to the market structure.

To approximate the Lerner index, I regress accounting profits (earnings before interest and tax, "EBIT") minus the required return to the firm's invested capital on revenue—the coefficient on revenue is the Lerner estimation. The endogenous variable in this regression represents a firm's economic profit. I calculate the required return percentage with a cost of capital formula that multiplies a risk premium of 7% by the firm's unlevered beta and adds the risk-free rate, measured by the 1-year treasury bond rate. I multiply this required return percentage by invested capital to get a dollar amount to subtract from EBIT. By using the unlevered beta in the required return estimation, we capture the required return to both debt and equity sources of capital.[3]

$$\text{Theoretical Lerner Index: } \frac{P_i - c_i}{P_i} > 0 \Rightarrow \text{Monopoly Power}$$

$$\left(EBIT_i - RR_{IC,i}\right) \approx \Pi_i = P_i q_i - c_i q_i - \text{Fixed Costs}_i$$

$$\Pi_i = P_i q_i - c_i q_i - FC_i$$

$$\Pi_i = (P_i - c_i) q_i - FC_i$$

$$\Pi_i = \left(\frac{P_i - c_i}{P_i}\right) P_i q_i - FC_i$$

Estimation for Lerner:

$$\left(EBIT_{it} - RR_{IC,it}\right) = c_{0,i} + m_{1,i}(\text{Revenue}_{it}), \qquad m_{1,i} = \text{Lerner}_i$$

$$RR_{IC} = \left(7\% \times \beta_{UL} + r_f\right) \times IC_i$$

$$IC_i = \text{Balance Sheet Debt}_i + \text{Balance Sheet Equity}_i$$

[3] My empirical strategy examining systematic risk and monopoly power involves regressing the unlevered CAPM beta on measures of power, like the Lerner. Though one might think it is a mistake to include the unlevered beta in both an endogenous and exogenous term, there is no other way to consider the Lerner index—it should account for all costs, including the unseen rent the firm pays (or aims to pay) to the firm's investors. Omitting the required return to investors merely reports an enhanced accounting profit margin.

Firms often report revenue and accounting profit, but converting EBIT into economic profit requires assumptions about the firm's cost of capital, invested capital, and risk, as seen above. Some researchers and practitioners simply avoid that problem and use accounting profits directly with the price-cost margin, with the aim of approximating the Lerner, like Domowitz, Hubbard, and Petersen (1986). One can think of the price-cost margin (PCM) as a "marginal operating profit margin." I regress EBIT (profit before interest on debt and taxes but after all other expenses) on revenue—the coefficient on revenue represents the profit margin on each *additional* dollar of revenue, the PCM. This accounting measure of marginal profit is flawed, as it does not measure the required return to the owners of capital, but it requires only profits and revenue to calculate, two statistics that firms frequently report in their statements. This makes the price-cost margin a simplified measure of monopoly rents commonly found in the literature.

$$EBIT_{it} = c_0 + m_{1,i}(\text{Revenue}_{it}) + \varepsilon_t, \qquad m_{1,i} = \text{PCM}_i$$

The way I calculate the Lerner and PCM assumes a linear cost function, which might be oversimplistic but allows for quick computation for thousands of firms in a dataset with limited financial and economic data. It also allows for a true *marginal* profit measurement since the intercept term absorbs any fixed costs. Such calculations are not rare in the literature: Weiss (1974), Liebowitz (1982), and Feinberg (1980) suggest similar bivariate Lerner index and PCM calculations.

Market share and the Hirshman-Herfindahl index (HHI) remain controversial mainstays of industrial organization empirical research. These metrics are easy to compute, provided one ignores the industry-definition problem. However, their clear connection to monopoly power might be lacking: market share and the HHI suggest monopolism in Stackelberg competition and limit pricing scenarios where price is near marginal cost and no firm is a monopoly. I include these metrics because researchers employ them frequently. We calculate market share for a firm by dividing its revenue by the sum of its industry's revenue.

$$MS_{it} = \frac{\text{Revenue}_{it}}{\sum_{j=1}^{n} \text{Revenue}_{jt}}, \qquad MS_{it} = \text{Market Share of firm } i \text{ at time } t$$

The Hirshman-Herfindahl index is an *industry-level* measure of concentration—firms within the same industry will have the same HHI. To calculate it, one averages an industry's firm's market shares, weighting the terms by market share.

$$HHI_{kt} = \sum_{j=1}^{n} MS_{jt}^2, \qquad HHI_{kt} = \text{Hirshman–Herfindahl Index of industry } k \text{ at time } t$$

I compute both the HHI and market share both for 4-digit NAICS industries (which I call HHI_4 and MS_4) and S&P GICS 8-digit subindustries (which I call HHI_{GICS} and MS_{GICS}) after filtering only for firms that have positive revenue values.

Finally, Tobin's Q is the ratio between the market and replacement values of the firm: a firm with a market value higher than the replacement value ($Q > 1$) implies "the whole is greater than the sum of the parts," which might be attributable to monopoly power. The owners of capital in such a scenario believe the firm is worth more than its capital. I use total assets as a proxy for the denominator of Q. Under most circumstances, the value of assets that a firm reports relates directly to the price it paid to procure them. This does not reflect the current cost to replace the assets, only the historical cost adjusted for depreciation. Curtis et. Al. (2015) find this element of US accounting rules does impact financial ratios. However, computing the true replacement value of thousands of firms' assets over time is not practical.

$$\mathrm{Q}_{it} = \frac{EV_{it}}{\text{Assets}_{it}} = \frac{\text{Debt}_{it} + \text{Market Capitalization}_{it} - \text{Cash}_{it}}{\text{Assets}_{it}}$$

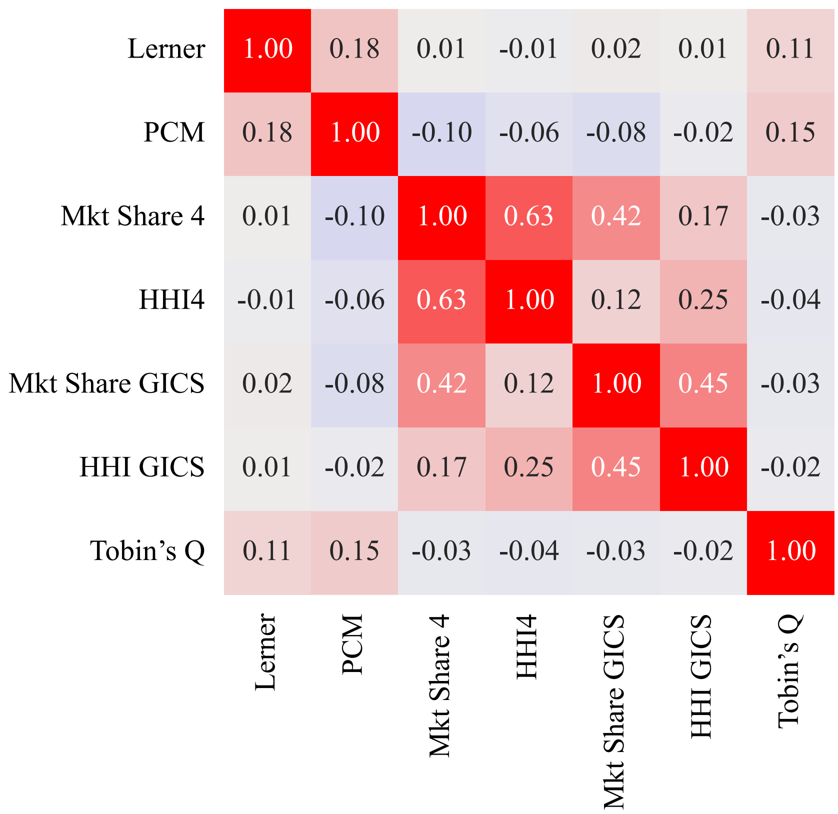
Table 1 reports descriptive statistics for these measures of monopoly power. We see with the correlogram in Figure 2 that the measures of power seem to fall into two groups. The Lerner index, PCM, and Tobin's Q all weakly correlate with each other, while the HHIs and market shares strongly correlate. Since a firm's market share is a component of its industry's HHI, the latter is not surprising, though the weak correlation between NAICS and GICS concentration measures indicates those metrics' weakness. The weak positive correlation between the other measures of power indicates some agreement despite their different methodologies.

Table 1: Descriptive statistics of CAPM beta and measures of monopoly power

Statistic	β	β_{UL}	Lerner	PCM	MS_4	HHI_4	MS_{GICS}	HHI_{GICS}	Tobin's Q
Mean	1.163	0.957	0.051	0.180	0.102	0.218	0.055	0.150	1.668
Std. Dev	0.574	0.441	0.171	0.154	0.191	0.195	0.106	0.113	2.046
Min*	-0.489	-0.082	-0.624	-0.133	0.000	0.012	0.000	0.028	-0.029
Median	1.116	0.939	0.037	0.148	0.021	0.155	0.016	0.115	1.199
Max*	20.050	2.243	0.947	0.842	1.000	1.000	1.000	1.000	225.261

*The filtering process explicitly removed the extreme top and bottom 10% of observations for the Lerner index, price-cost margin, and unlevered CAPM beta. See the Data Filtration section.

Figure 2: Correlation among measures of monopoly power



DATA AND FILTRATION

I obtained firm-level quarterly data on revenues, profits, assets, debt, and other financial data from S&P Compustat via the Wharton Research Data Service for all publicly traded, non-financial US firms (as defined by WRDS) from 1976 to 2022. I obtained monthly stock and total returns data from the same source over the same period. I use a simple bivariate rolling regression to calculate the CAPM beta for each quarter, using a 60-month (5-year) window. I use a month's de-annualized 1-year US Treasury Bill yield as the risk-free rate (obtained from FRED, code DGS1), and the S&P 500 monthly total return, including dividends, as the market portfolio (obtained from WRDS). I compute the Lerner index and the price-cost margin with 20-quarter (5-year) rolling regressions. I associate each rolling regression (both the CAPM beta and the relevant monopoly statistics) with the quarter of the last observation of that rolling regression.

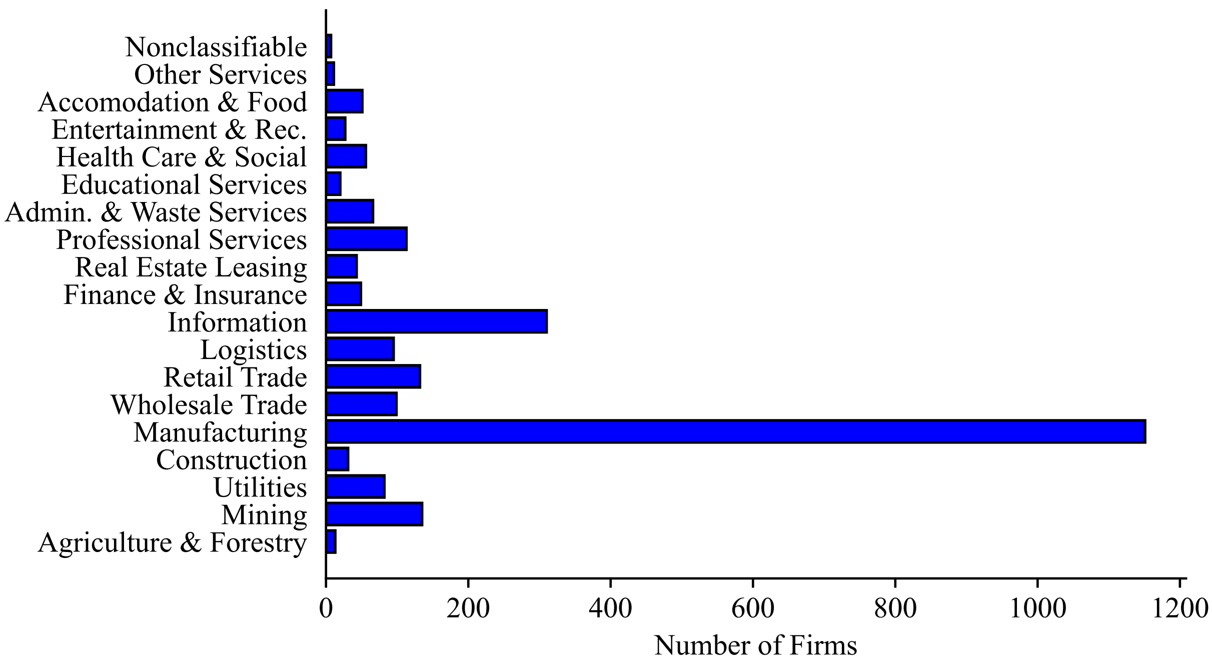
I include only firms that were public for at least five consecutive years (to compute all the rolling statistics), have a revenue greater than \$0 in each of those years, have a CAPM beta that is not exactly zero or undefined, and have a market capitalization greater than \$0. These filters remove firms for which monopoly statistics cannot reasonably be calculated and leave 11,879 firms with 419,238 firm-quarter observations. I then filter out all firm-quarter observations with a market capitalization less than \$25 million, assets less than or equal to zero, or an EBIT margin, unlevered CAPM beta, Lerner index, and price-cost margin above the 90th or below the 10th percentiles of a quarter. Should a firm-quarter observation not meet these standards, that firm-quarter observation is dropped, but that firm can be allowed back into the dataset if it meets the filter's requirements in some other quarter. I also remove firm-quarter observations associated with dates before 2012. This second set of filters removes unreasonable outliers, firms with bad data, and small firms which one cannot reasonably expect to be monopolistic—for example, many firms removed in this step have percentage profit margins in the thousands (or negative thousands), and firms with CAPM betas well above 100 or below –10. Table 2 reports the effect of each filter on the dataset after the first step—the restrictions ultimately shrink the dataset with 419,238 firm-quarter observations to 2,491 firms and 45,349 firm-quarter observations.

The Lerner Index, the most data-demanding of the monopoly power measures that I use, has the fewest valid observations. When we apply the filter, we remove all the observations without a Lerner Index, making it the most restrictive filter. This also occurs with the unlevered beta and the price-cost margin. With several thousand firms and nearly 50,000 observations, we have a healthy and diverse dataset on which to perform analysis. Figure 3 reports the industry distribution of firms according to their two-digit NAICS code.

Table 2: Filter effects on dataset after basic filtering

Filter	Remaining Observations	Remaining Firms
Dataset after Basic Filtering	419,238	11,879
Assets > $0	416,014	11,862
Market Cap > $25 Million	341,665	10,264
Year >= 2012	159,891	6,547
EBIT Margin < 90th or > 10th Percentiles	329,963	10,758
Unlevered Beta < 90th or > 10th Percentiles	186,953	7,091
Lerner < 90th or > 10th Percentiles	78,584	3,732
Price-Cost Margin < 90th or > 10th Percentiles	278,299	9,623
Valid Current Ratio	366,795	10,776
Combined Filters	45,349	2,491

Figure 3: Distribution of filtered dataset by NAICS 2-digit industry



EMPIRICAL STRATEGY

Model 1

In my first model, I regress unlevered CAPM beta against measures of monopoly power (the variables of interest) with controls for firm size (measured by market capitalization), the logarithm of the firm's stock price, and the firm's current ratio (current assets to current liabilities), the firm's 2-digit NAICS industry (a dummy), and the year of the observation (also a dummy). I control for market capitalization and the firm's stock price because a security's size and liquidity are negatively associated with systematic risk (Fama and French 1992). I include the current ratio because a firm's liquidity position is related to default risk, which by extension is related to systematic risk. The model is a simple heteroskedastic regression where each observation is a firm-quarter.

$$\beta_{UL,it} = a_0 + b_1(\text{Monopoly Metric}_{it}) + b_2(\text{Mkt. Cap}_{it}) + b_3(\ln(\text{Stock Price})_{it}) + b_4(\text{Current Ratio}_{it}) + \Gamma_{I,Y}$$

Model 2

My second model adds an interaction term between revenue and the measure of monopoly power but removes the share price control. The revenue interaction allows for better investigation into the relationship between size and monopolism. These regressions are also heteroskedastic.

$$\beta_{UL,it} = a_0 + b_1(\text{Monopoly Metric}_{it}) + b_2(\text{Mkt. Cap}_{it}) + b_3(\text{Revenue}_{it}) + b_4(\text{Current Ratio}_{it}) + b_5(\text{Revenue}_{it} \times \text{Monopoly Metric}_{it}) + \Gamma_{I,Y}$$

Robustness Checks

I check for robustness by performing the Model 1 regressions on the data after separating out NAICS manufacturing firms, since they are the most overrepresented in the data. I also consider the dataset with less-restrictive filters: 5th to 95th percentiles for β_{UL}, Lerner, PCM, and EBIT margin, and over \$10 million for market capitalization with all other filters remaining the same. This less-restrictive selection leaves 2,963 firms, 58,636 firm-quarter observations, and indicates comparable results. I also perform the regressions from Model 1 again for firms that have quarterly revenue above \$7.8 billion, since the results from Model 2 suggest that measures of power could behave differently for these large firms.

RESULTS

We see in both specifications that the Lerner index has a negative relationship with systematic risk. The PCM, NAICS market share, and NAICS HHI have a positive association with systematic risk. Tobin's Q has no relationship with systematic risk. The GICS HHI has a negative association with risk, but GICS market share has a negative association in Model 1 and a positive in Model 2.

Table 3: Results from Model 1

Model 1	Lerner	PCM	MS_4	HHI_4	MS_{GICS}	HHI_{GICS}	Tobin's Q
b_1 Coefficient	-0.240	0.052	0.063	0.078	-0.042	-0.049	-0.002
	(0.012)	(0.013)	(0.012)	(0.012)	(0.021)	(0.019)	(0.001)
Z-Score	-20.568	3.843	5.308	6.623	-2.049	-2.628	-1.459
$\Delta\beta_{UL}$ for $1\sigma\Delta$ in monopoly metric	-0.041	0.008	0.012	0.015	-0.004	-0.006	-0.003
(Corresponding change in cost of capital assuming ERP = 7%)	-0.287%	0.055%	0.084%	0.106%	-0.031%	-0.039%	-0.021%

Observations: 45,349 firm-quarters; Firms: 2,491

These results appear contradictory until we consider the theoretical rigor of the different measures of power. The Lerner index is best founded in theory, and clearly shows a strongly significant negative relationship here. Coefficients on the HHI and market share might be positive if firms that are large in their industry but not a monopoly are more common than firms that are large in their industry *and* monopolies. Firms that dominate an industry without monopoly power might be limit pricing or might absorb all the industry's exposure to shocks without monopoly power to insulate itself or competitors with which to share those shocks. Most importantly, however, is that the directions of HHI and market share change based on industry definitions (NAICS vs GICS) and the model used. This furthers the theoretical belief that HHI and concentration metrics are not good measures of power. Coefficients on the PCM might reflect the classic risk-reward tradeoff: a firm with higher risk must provide a higher reward for its owners, thus risk and this marginal profit margin are positively related. If that is the case, the price-cost margin is not a great measure of monopoly power. The theoretically-sound Lerner demonstrates that when we consider marginal economic profit, power and risk are inversely related. In short, the monopolism metric used impacts the results we find in both regressions.

The second model with revenue interactions also presents interesting results. The interaction terms are all statistically significant, but the coefficient on PCM×Revenue is negative, unlike the coefficient on PCM by itself. For firms with quarterly revenue larger than $7.76 billion, the PCM has a negative overall relationship with systematic risk. This implies the PCM shares results with the Lerner for firms that are large enough and further supports a negative relationship between risk and power.

Table 4: Results from Model 2

Model 2	Lerner	PCM	MS_4	HHI_4	MS_{GICS}	HHI_{GICS}	Tobin's Q
b_1 Coefficient	-0.219	0.042	0.105	0.050	0.079	-0.077	0.000
	(0.012)	(0.014)	(0.012)	(0.012)	(0.022)	(0.019)	(0.001)
Z-Score	-17.940	3.040	8.655	4.119	3.587	-3.986	0.144
b_3 Revenue	-4.21E-06	-3.95E-06	-5.92E-06	-5.50E-06	-6.61E-06	-6.53E-06	-5.51E-06
	(3.14E-07)	(3.46E-07)	(4.11E-07)	(4.00E-07)	(4.63E-07)	(5.18E-07)	(3.53E-07)
Z-Score	-13.411	-11.428	-14.398	-13.769	-14.278	-12.601	-15.604
b_5 Interaction	-3.89E-06	-5.41E-06	3.66E-06	4.58E-06	5.60E-06	8.81E-06	1.91E-06
	(1.69E-06)	(1.98E-06)	(9.86E-07)	(1.13E-06)	(1.14E-06)	(1.79E-06)	(3.18E-07)
Z-Score	-2.308	-2.730	3.710	4.034	4.899	4.933	6.009
Quarterly Revenue	Mean: \$2,673; Median: \$475; Std. Dev: \$8,451 million per quarter						

Observations: 45,349 firm-quarters; Firms: 2,491

The findings from 1 and 2 demonstrate consistency across the datasets examined—the Lerner remained negative, the PCM positive, Tobin's Q insignificant, and the concentration measures inconsistent (see Appendix II). The dataset with less restrictive filters provided near-equivalent results to those of the original dataset in Table 3. Clearly, however, there is a difference between manufacturing and non-manufacturing firms. The results for non-manufacturing firms most strongly support the theory that power and risk are negatively related, while manufacturing firms only support that when examining the Lerner index. The S&T model suggests capital intensity as a likely culprit. However, this requires further research that I do not explore here.

When examining only firms with quarterly revenues greater than \$7.76 billion, we do indeed observe a negative coefficient on the price cost margin like the Lerner index (see Appendix II). However, the Lerner no longer takes the lead for the most statistical significance—all four concentration metrics are highly significant and indicate a positive relationship between risk and power. This either further discredits concentration metrics due to their inconsistency across samples, or it indicates a divergence between the world's largest firms and all others.

CONCLUSION

This paper examined the relationship between systematic risk, measured by the unlevered CAPM beta, and monopoly power. While following previous literature and considering traditional measures of monopolism like the Hirshman-Herfindahl index and market share, I also used the Lerner index and the price-cost margin, two measures of truly *marginal* profit that previous literature on the subject has not considered adequately. I found that the relationship between power and risk depends on the measure of power used, but the Lerner index, the most theoretically rigorous of the measures of power here, has a consistent negative relationship with risk. When examining interactions between market power and risk, I found that the price-cost margin might share this negative association with risk for large firms. I also found that concentration measures of monopoly power like market share and the Hirshman Herfindahl index do not remain consistent across models, datasets, and industry definitions. Combined with existing theory, the results suggest monopoly power has had a negative relationship with risk for the past decade and also implies weaknesses with the HHI and market share indicators of power.

These results are important for business managers, regulators, and investors. The negative coefficients on the Lerner suggest industry incumbents and monopolists do not share the risks that new entrants carry, which should interest managers and antitrust officials greatly if risk acts as a barrier to entry. Similarly, it enlightens the discussion on the relationship between monopoly power and innovation by suggesting monopolies can be more innovative due to their lower risk (and by extension lower costs of capital). This study examined firms from 2012 to 2022, which saw innovation by large, monopolistic technology companies—the relationship between risk and power might explain why that was the case. Given a negative relationship, regulators might wish to avoid punishing monopolists, as the greater innovation they provide could offset the costs to the consumer. Future research should investigate whether monopolists do innovate more given their lower cost of capital.

Simultaneously, however, this paper does not entirely negate the research of recent decades that found a positive relationship between concentration and beta. The contrasting results this paper finds when comparing measures of power does not clear up the "murky" relationship. Future research should reassess several risk and monopolism measures to confirm a relationship between risk and power. For example, more refined and localized HHI and Market Share measures might better reflect monopoly power, instead of the national level as used here. Similarly, this area of study needs additional investigation into different measures of risk, instead of the diversified investor's risk that this paper uses—for example, though legally obligated to act in equity investors' best interests, managers of firms are far from fully diversified, due to their employment and stock options, and thus might make decisions based on idiosyncratic risk factors not reflected in unlevered beta. Future research should also examine individual industries more deeply: the "information" and "manufacturing" sectors might provide useful insights given their importance in the US economy and the apparent divergence between manufacturing and non-manufacturing firms seen here. Finally, this facet of research needs additional studies to assess the causality relationship between risk and power. However, the new measures used here contribute greatly to this area of economics by comparing previously unexplored measures of power alongside traditional metrics, and researchers should expand their use of these theoretically stronger measures going forward.

Appendix I: Derivatives with respect to b_i

Theorem 3: Profit and monopoly power are positively related.

$$\frac{\partial \Pi_i}{\partial b_i} = \frac{b_i q_{ie}^2 \left(4b_i^3 c_i \mu_i^2 q_{ie}^3 \sigma^4 + 3b_i^3 \mu_i q_{ie}^2 \sigma^2 + 12b^2 c_i^2 \mu_i^2 q_{ie}^2 \sigma^4 + 6b_i^2 c_i \mu_i q_{ie} s^2 + b_i^2 + 12b_i c_i^3 \mu_i^2 q_{ie} \sigma^4 + 3b_i c_i^2 \mu_i \sigma^2 + 4c_i^4 \mu_i^2 \sigma^4\right)}{4\left(b_i^2 \mu_i q_{ie}^2 s^2 \ + \ 2b_i c_i \mu_i q_{ie} \sigma^2 + b_i + c_i^2 \mu_i s^2\right)^3}$$

Because $b_i, q_{ie}, c_i, \mu_i, \sigma > 0$, we see that $\frac{\partial \Pi_i}{\partial b_i} > 0$.

Theorem 4: Beta and monopoly power are negatively related.

$$\frac{\partial \beta_i}{\partial b_i} = \frac{-2\Pi_m \left(2b_i^4 c_i \mu_i^2 q_{ie}^4 \sigma^4 + b_i^4 \mu_i q_{ie}^3 \sigma^2 + 8b_i^3 c_i^2 \mu_i^2 q_{ie}^3 \sigma^4 + 4b_i^3 c_i \mu_i q_{ie}^2 \sigma^2 + 12b_i^2 c_i^3 \mu_i^2 q_{ie}^2 \sigma^4 + 5b_i^2 c_i^2 \mu_i q_{ie} \sigma^2 + b_i^2 c_i + 8b_i c_i^4 \mu_i^2 q_{ie} \sigma^4 + 2b_i c_i^3 \mu_i \sigma^2 + 2c_i^5 \mu_i^2 \sigma^4\right)}{A_m b_i^2 q_{ie} q_m \left(2b_i^2 \mu_i q_{ie}^2 \sigma^2 + 4b_i c_i \mu_i q_{ie} \sigma^2 + b_i + 2c_i^2 \mu_i \sigma^2\right)^2}$$

Because $b_i, q_{ie}, c_i, \mu_i, \sigma > 0$, we see that $\frac{\partial \Pi_i}{\partial b_i} < 0$ due to the -2 coefficient.

Appendix II: Robustness Checks

Table 5: Model 1 regressions with firms that have quarterly revenue >$7.762 billion

Mod. 1 Rev > $8B	Lerner	PCM	MS_4	HHI_4	MS_{GICS}	HHI_{GICS}	Tobin's Q
b_1 Coefficient	-0.307	-0.268	0.379	0.454	0.391	0.590	0.010
	(0.038)	(0.053)	(0.035)	(0.044)	(0.038)	(0.058)	(0.007)
Z-Score	-8.088	-5.091	10.690	10.281	10.202	10.176	1.392
$\Delta\beta_{UL}$ for $1\sigma\,\Delta$ in monopoly metric	-0.052	-0.041	0.073	0.088	0.042	0.067	0.020
(Corresponding change in cost of capital assuming ERP = 7%)	-0.367%	-0.288%	0.508%	0.619%	0.291%	0.468%	0.140%

Observations: 3,191 firm-quarters; Firms: 162

Table 6: Model 1 robustness checks with different filters

Model 1	Lerner	PCM	MS_4	HHI_4	MS_{GICS}	HHI_{GICS}	Tobin's Q
b_1 Weaker Filters	-0.143	0.076	0.058	0.075	-0.103	-0.061	-0.001
58,636 obs.	(0.007)	(0.010)	(0.012)	(0.012)	(0.021)	(0.018)	(0.001)
Z-Score	-20.535	7.593	4.731	6.282	-4.961	-9.306	-2.104
b_1 Manufacturing	-0.188	0.051	0.242	0.228	0.061	0.024	-0.008
21,595 obs.	(0.017)	(0.021)	(0.022)	(0.018)	(0.031)	(0.028)	(0.002)
Z-Score	-11.119	2.455	11.211	12.430	1.939	0.860	-4.407
b_1 excl. Manuf.	-0.290	0.064	-0.028	-0.039	-0.158	-0.131	0.002
23,754 obs.	(0.016)	(0.018)	(0.014)	(0.015)	(0.028)	(0.025)	(0.001)
Z-Score	-18.116	3.585	-2.026	-2.588	-5.667	-5.244	1.706

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