Who Gains From Greater Market Power

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Abstract:
Marketing practice seeks to create and exploit market power. However, few studies examine who gains more from market power partially because the direction of causality is often unclear. We mitigate that problem by studying exogenous variation in market power in markets with many competitors. Theoretically, greater market power increases the gains from discriminatory marketing practices. We confirm that claim measuring discrimination as the price difference between identical products except for a costless feature. We find the gains from market power are greater for smaller firms with more rivals, better-perceived value, larger fixed costs and less similarity with rivals. Surprisingly, greater market power does not necessarily benefit firms with higher quality. Also surprisingly, greater market power does not necessarily benefit firms with more heterogeneous customers. Our empirical analysis explicitly controls for the possibility that larger markets attract more rivals.

Keywords: Market-power, Pricing, Discriminatory-Practices

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1. Introduction

Often marketing practices seek to exploit market power. Although, we know greater power allows higher prices, we know less about when and how greater market power actually changes marketing practices. No past empirical analysis isolates how and when variation in market power change discriminatory marketing practices in markets with many competitors while controlling for potential confounds (different firms, products, etc.).

Our analysis mitigates two common problems facing any study of market power. First, we cannot observe whether marketing practices create market power or whether they exploit existing power. So, we study power created by exogenous factors (i.e., seasonality).

Measuring discrimination can be difficult given hidden costs and other omitted variables. For instance, Gerardi and Shapiro (2009) find opposite results from Borenstein and Rose (1994) with the same data. We compare prices of the same product, from the same firm in the same market in the same period with and without a costless feature.

Although proxies (e.g., price dispersions) are interesting, they can differ from discrimination (Pan, Ratchford and Shankar 2004). To measure discrimination, we use the epidemiological case-control (Breslow & Day, 1987) or matching (Rubin, 1973; Dehejia & Wahba, 1999) methods. Rather than comparing two different groups (e.g., treatment and control groups), the case control method matches similar cases in each group. Matching reduces confounding.

We use lodging data with carefully paired hotel rooms in the same period on every feature except a costless one, i.e., sea-view (W) versus no-sea-view $(\bar{W})$. Selling either paired room incurs the same cleaning, physical depreciation and other marginal costs, where $\bar{W}$ resembles a damaged good (Deneckere & McAfee, 1996). Paired rooms at different prices are discriminatory because higher prices reflect higher unit profit margins not different costs.

Willingness-to-pay for views is very heterogeneous (Masiero, Heo, and Pan 2015). Views are only moderately important (Monty & Skidmore 2003; Fleischer 2012). Sea-view rooms do not dominate no-sea-view rooms outside our statistical pairing. Sea-view rooms with one bed at 3-star hotels without beach access have far lower rates than no-sea-view rooms with two beds, with beach-access, at 5-star hotels. This fact makes our pairing process so powerful.

In sum, case-control controls for cost differences and directly measures discrimination. When $d > 0$, we know W and $\bar{W}$ sort buyers by willingness to pay for sea-views.

1. Measuring Market Power

Market power raises the price above the marginal cost (Stigler, 1957). As market power decreases, market prices approach natural prices. Hence, any exogenous demand-driven factor that changes unit profit margins can change a firm's market power. The oldest and widely used measure of market power, called the Lerner index (Lerner, 1934; Kwoka, 1985; Elzinga & Mills 2011), infers market power from prices. Recent studies in both marketing (Sudhir, Chintagunta, Kadiyali 2005) and economics (Koetter, Kolari, and Spierdijk 2012) use the Lerner index (denoted Λ). In fact, The Lerner Index has over 5700 applications since 2000 (Google Scholar 3/27/2016). Equation (1) provides Λ.

$$\Lambda = \frac{p-c}{p} = \frac{1}{n\left|\varepsilon_M\right|}. \tag{1}$$

where:	Λ	=	Lerner Index	p	=	observed price
	ε_M	=	market price elasticity of demand	c	=	marginal cost
	n	=	number of firms in the market.			

Paul Samuelson (1964) declared that "Today [the Lerner index] may seem simple, but I can testify that no one at Chicago or Harvard could tell me in 1935 exactly why $p = c$ was a good thing, and I was a persistent Diogenes". Friedrich Hayek (Caldwell, 1997) and subsequent economists (Grossman, 1976; Grossman & Stiglitz, 1976; Frydman, 1982) argue that market prices capture vast amounts of information, far more than any firm or buyer has. The Lerner index captures that information without the need to define the market.

An issue when using the Lerner Index is measuring marginal cost c across firms. However, we avoid that problem by comparing the Lerner Index for rooms with and without a costless feature (i.e., the view). Like ubiquitous event studies, periodic (e.g., weather-induced) demand variations are exogenous events that can cause exogenous variation in market power.

When prices (unit profit margins) vary, we again use case control to measure variation in discrimination, but here, across (rather than within) periods. We compute price differences for the same product, firm, market and period.

In sum, any exogenous demand-driven factor increases market power when it allows firms to increase unit profit margins. By observing industries without the capacity to increase supply, price changes could be sufficiently large so that variation in market power potentially changes marketing practices. For example, exogenous demand variation (e.g., weather, holidays, etc.) can cause prices and profits to vary at many coastal tourist destinations.

We do not assume demand variations create market power, we only detect when they do.

2. Empirical Analysis: Data Collection

We use lodging industry data because it exhibits the necessary variability in market power. Specifically, we focus on coastal hotels from seven coastal cities: Miami, Maui (United

States), Sydney (Australia), Rio (Brazil), Cape Town (South Africa), Nice (France), and Barcelona (Spain). National Geographic ranks these seven cities as the top ten beach cities and each experiences significant demand variation across the year.

We select diverse cities to establish robustness. Three of our sample cities, Sydney, Rio, and Cape Town, are in the South Hemisphere, while four are in the North Hemisphere. Rio and Cape Town are in developing countries, while our other cities are in developed countries. Our seven coastal cities include Continental North America (Miami), Polynesia (Maui), South America (Rio), Australasia (Sydney), Europe (Nice and Barcelona), and Africa (Cape Town).

To maximize variation, we identify peak (greater market power) and off-peak periods (less market power) with historical city tourism statistics. For example, the 2001-2013 Historical Visitor Statistics of the Hawaii Tourism Authority (HTA) identifies September and October as Maui's off-peak (i.e., fewer visitors), and December and January as Maui's peak..

We employ the previously discussed pairing procedure to control for cross-market confounds. To measure discrimination, we compare the same room (except for the costless feature) at the same hotel in the same city in the same market in the same period.

We search TripAdvisor for hotels with both room types. As noted, our case-control procedure allows additional controls and statistical power. It eliminates hidden costs by matching these identical products (room size, number of beds, bed size, bathroom type, room amenities, etc.). We obtain pricing data for paired hotel rooms on three days of peak and off-peak: specifically, Miami, Maui, Cape Town (low: September 28-30; high: December 28-30); Sydney (low: August 24-26; high: December 28-30); Rio (low: September 11-13; high: January 1-3); Nice and Barcelona (low: November 23-25; high: August 24-26).

We measure variation in market power by observing demand-driven price variation across periods. Avoiding possible endogeneity, for any focal hotel, we use the price ratio (peak price over off-peak price) for similar nearby hotels to calculate the magnitude of the peak. Consistent with Ghose, Ipeirotis, and Li (2012), we define "similar" as having a quality (star) rating within 0.5. For example, 3-star hotels are similar to nearby hotels with star ratings between 2.5 or 3.5. Using these prices, we construct three different metrics for peak/off-peak price differences. Equations (2), (3) and (4) provide these three metrics for hotel i.

$$E_{1i} = \left(\overline{a}_i' + a_i'\right) / \left(\overline{a}_i + a_i\right) \quad \textbf{(2)}$$

$$E_{2i} = \overline{a}_i' / \overline{a}_i \quad \textbf{(3)}$$

$$E_{3i} = a_i' / a_i \quad \textbf{(4)}$$

$$
\begin{aligned}
where:\quad \overline{a}_i &= \sum\nolimits_{j\neq i}\overline{p}_j \Big/ \sum\nolimits_{j\neq i}1 && \text{average off-peak no-view price for matching hotels nearby hotel } i,\\
a_i &= \sum\nolimits_{j\neq i}p_j \Big/ \sum\nolimits_{j\neq i}1 && \text{average off-peak view price for matching hotels nearby hotel } i,\\
\overline{a}'_i &= \sum\nolimits_{j\neq i}\overline{p}'_j \Big/ \sum\nolimits_{j\neq i}1 && \text{average peak no-view price for matching hotels nearby hotel } i,\\
a'_i &= \sum\nolimits_{j\neq i}p'_j \Big/ \sum\nolimits_{j\neq i}1 && \text{average peak view price for matching hotels nearby hotel } i.
\end{aligned}
$$

To further address endogeneity, we construct additional non-price metrics including the number of online customer reviewers (a proxy for the number of visitors).

$$E_{4i} = r'_i / r_i \tag{5}$$

$where:\ (r'_i, r_i)$ denotes the number of guest reviews for hotel i, (peak, off-peak).

Finally, we construct a metric for measuring weather-related demand using the temperature data. Coastal cities (e.g., Miami and Maui), with many beachfront and outdoor activities, often attract more visitors when their relative temperature is high. Accordingly, Equation (6) provides the metric for weather-related demand.

$$E_{5i} = \left(t'_i - T'_i\right) - \left(t_i - T_i\right) \tag{6}$$

$where:\ t_i, t'_i$ = temperature of hotel i's location (off-peak, peak),
T_i, T'_i = mean country for hotel i (off-peak, peak).

Our analysis includes 5 metrics for peak demand and other variables that might strengthen or weaken the relationship between discrimination and market power. See Table 1.

Table 1: Variables

Variable	Description
Number of Rivals ($rivals_i$)	The number of rivals in the market, defined as the total number of hotels within 1 kilometer of the focal hotel i.
Quality ($quality_i$)	Defined by the hotel class
Brand ($brand_i$)	Whether the hotel is a chain-branded hotel
Perceived Value ($value_i$)	Percentage of positive consumer reviews.
Non-Business $Nbusiness_i$	$Nbusiness_i$ is the ratio of vacation over business trips.
Information ($info_i$)	Total consumer reviews
Age (age_i)	Year hotel built age
Size ($size_i$)	number of rooms at the hotel... a measure of firm size
Similarity ($similarity_i$)	number of outside attractions (e.g., museums, theaters, shopping centers, third-party restaurants)
Fixed costs ($fixed_i$)	No. of high fixed cost amenities (e.g., pool, fitness center, internet, bar/lounge, business center, restaurant ...)
Covariates	City Effect (Maui, Sydney, Rio, Cape, Nice, and Barcelona).| The variable coefficients are relative to Miami

3. Estimation and Results

We examine how different variables affect the relationship between market power and the prevalence of discrimination. Prevalence should increase as more firms gain from discrimination. First, we estimate the LOGIT model for the binary S_i variable in following equation.

$$\text{Log-Odds of } [S_i = 1 | \mathbf{x}_i^T] = \beta_0 + \mathbf{x}_i^T \boldsymbol{\beta} = \beta_0 + \beta_1 E_{ki} + \beta_2 rivals_i + \beta_3 quality_i + \beta_4 brand_i + \beta_5 value_i$$
$$+ \beta_6 \text{Nbusiness}_i + \beta_7 \text{info}_i + \beta_8 age_i + \beta_9 size_i + \beta_{10} similarity_i + \beta_{11} fixed_i + \beta_{12} \text{maui}_i + \beta_{13} sydney_i$$
$$+ \beta_{14} rio_i + \beta_{15} cape_i + \beta_{16} nice_i + \beta_{17} barcelona_i + \varepsilon_i$$
$$where: \quad k = 1, \ldots, 5 \quad \varepsilon_i = \text{disturbance term (hotel } i\text{)}, \quad \boldsymbol{\beta}, \beta_j = \text{estimated parameters} \, (j = 1, ..., 17)$$

We estimate this equation for each measure of market power $(E_{ki}, k = 1, 2, \ldots 5)$. The prevalence of discrimination (S_i) increases as market power increases regardless of the measure (e.g., for E_1 , β_1=1.559, p<0.05). Firms with more rivals in the immediate area are more likely to gain from greater market power during off-seasons. Despite loyalty programs at chain-brands, chain-brands are more likely to gain from greater market power. See Table 2.

Table 2: LOGIT Coefficients: Prevalence of Price Discrimination (S_i) on Market Power

	E_1 (k=1)		E_2 (k=2)		E_3 (k=3)		E_4 (k=4)		E_5 (k=5)	
Variable	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**
Intercept	-12.374	19.491	-11.267	19.509	-12.822	19.446	-13.747	21.471	-9.130	19.233
E_k	1.559**	0.726	1.499**	0.726	1.532**	0.704	2.055**	0.509	0.161*	0.083
rivals	0.044**	0.019	0.043**	0.019	0.045**	0.019	0.042**	0.021	0.044**	0.018
quality	1.075**	0.487	1.118**	0.486	1.046**	0.489	1.468**	0.527	1.293**	0.496
value	-0.109	1.927	-0.159	1.923	-0.141	1.923	-3.020	2.139	-0.855	1.867
info	-0.0003	0.0004	-0.0003	0.0004	-0.0002	0.0003	-0.0001	0.0004	-0.0002	0.0004
brand	0.897**	0.447	0.890**	0.447	0.890**	0.446	0.690	0.466	0.807*	0.433
fixed	0.144	0.098	0.139	0.098	0.149	0.099	0.022	0.109	0.133	0.104
similarity	-0.014	0.012	-0.013	0.012	-0.014	0.012	-0.011	0.013	-0.011	0.011
nbusiness	0.004	0.006	0.004	0.006	0.003	0.006	0.011	0.008	0.007	0.007
size	-0.001	0.001	-0.001	0.001	-0.001	0.001	-0.001	0.001	-0.001	0.001
Age	0.003	0.010	0.002	0.010	0.003	0.010	0.004	0.011	0.002	0.010
Maui	0.811	0.774	0.841	0.789	0.744	0.757	0.510	0.732	-0.445	0.944
Sydney	0.568	1.010	0.609	1.029	0.483	0.988	-0.512	0.893	0.612	1.012
Rio	0.360	1.049	0.420	1.078	0.242	1.015	-0.076	0.952	-0.135	0.829
Cape	-0.577	1.215	-0.473	1.236	-0.719	1.194	-0.398	1.225	-0.647	1.028
Nice	2.923	1.912	3.116	1.932	2.727	1.896	2.700	1.906	3.192	1.884
Barcelona	-0.274	0.966	-0.141	0.982	-0.424	0.956	-0.492	0.982	-0.257	0.951
AIC		109.81		110.24		109.54		92.54		108.04
SC		169.36		169.79		169.09		152.09		164.28
z-2LogL		73.81		74.24		73.54		56.54		74.04
	** p<.05; * p<.10									

Some of these findings may be surprising. For example, chain-branded hotels are more likely to gain from market power, even though, the former have arguably loyal guests. Hotels with more rivals gain more from market power more hotels with fewer rivals.

Although the prevalence of discrimination increases at higher quality hotels, we will later see that the magnitude is insignificant. Estimating the following equation reveals the factors influencing the magnitude of the gain from discrimination (Δ_{di}).

$$\Delta_{di} = \phi_0 + \mathbf{x}_i^T \mathbf{\Phi} = \phi_0 + \phi_1 E_{ki} + \phi_2 rivals_i + \phi_3 quality_i + \phi_4 brand_i + \phi_5 value_i + \phi_6 \text{Nbusiness}_i + \phi_7 \text{info}_i + \phi_8 age_i$$
$$+ \phi_9 size_i + \phi_{10} similarity_i + \phi_{11} fixed_i + \phi_{12} \text{maui}_i + \phi_{13} sydney_i + \phi_{14} rio_i + \phi_{15} cape_i + \phi_{16} nice_i + \phi_{17} barcelona_i + \eta_i$$
$$where: \quad k = 1,\dots,5 \quad \eta_i = \text{disturbance term (hotel } i\text{)}, \quad \phi_j, \mathbf{\Phi} = \text{estimated parameters} \, (j = 1,\dots,17).$$

Our estimation uses the five different measures of market power $(E_{ki}, k = 1, 2, \dots 5)$. We also test for multicollinearity. The largest variance-inflation factor (VIF) is less than 5, indicating no evidence of significant multicollinearity. We estimate this model using OLS with hetero-scedasticity-consistent standard errors to control for heteroscedasticity.

Table 2 reflects the likelihood a random firm gains from market power through discrimination. In contrast, Table 3 reflects the magnitude (Δ_{di}) of that gain. When few firms gain from market power, prevalence might be low but average magnitude might still be large. When all firms have small gains, prevalence might be high but magnitude might be small.

Table 3: Estimated Coefficients: Magnitude of Price Discrimination (Δ_{di}) on Market Power

	E_1 (k=1)		E_2 (k=2)		E_3 (k=3)		E_4 (k=4)		E_5 (k=5)	
Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	219.848	250.193	229.441	251.183	214.372	249.569	138.793	233.352	175.922	258.817
E_k	36.286**	11.655	34.507**	11.413	36.564**	11.347	37.746**	6.045	1.793*	0.995
Rivals	1.105**	0.271	1.103**	0.272	1.110**	0.271	0.652**	0.213	1.046**	0.284
Quality	8.787	6.430	9.518*	6.382	8.077	6.448	14.661**	5.320	11.721*	6.460
Value	66.817**	26.290	66.390**	26.409	66.529**	26.042	8.846	18.684	53.246**	25.225
Info	0.004	0.006	0.004	0.006	0.004	0.006	0.007	0.005	0.003	0.006
Brand	8.324	6.101	8.372	6.122	8.153	6.072	5.933	6.092	7.123	6.435
fixed	2.946**	1.171	2.877**	1.165	3.033**	1.176	-0.417	1.135	3.191**	1.226
similarity	-0.317*	0.170	-0.310*	0.172	-0.324**	0.169	-0.091	0.142	-0.257	0.183
nbusiness	-0.027	0.032	-0.024	0.031	-0.029	0.032	0.020	0.022	0.006	0.028
size	-0.050**	0.019	-0.049**	0.019	-0.050**	0.019	-0.040**	0.018	-0.046**	0.017
Age	-0.184	0.130	-0.188	0.131	-0.179	0.130	-0.116	0.123	-0.135	0.137
Maui	3.810	10.722	3.909	10.816	2.722	10.585	-11.201	10.723	-33.812	18.161
Sydney	6.693	15.027	6.815	15.357	5.573	14.588	-18.885	12.941	8.503	16.660
Rio	-10.051	13.995	-9.631	14.128	-11.573	13.711	-21.727	12.372	-21.553	12.214
Cape	-17.372	16.578	-16.432	16.646	-19.286	16.439	-19.584	13.559	-22.482	15.191
Nice	-19.425	16.180	-17.267	16.251	-22.243	16.233	-19.682	12.790	0.885	18.387
Barcelona	-1.771	15.310	0.016	15.540	-4.534	15.034	-19.244	12.053	-17.235	12.789
R square		0.39		0.39		0.40		0.49		0.35
Adjusted R-square		0.34		0.33		0.34		0.44		0.29
	** p<.05; * p<.10									

The magnitude of discrimination (Δ_{di}) increases as market power increases regardless of the measure (e.g., for E_{1i}, ϕ_1=36.286, p<0.05). Variables that strengthen that relationship are:

- Rivals (ϕ_2 = 1.105). Firms with more rivals gain more from greater market power.
- Value (ϕ_5 = 66.817). Firms with more positive reviews gain more.
- Fixed-costs (ϕ_{11} =2.946). Firms with greater fixed-cost amenities gain more.
- Similarity ($\phi_{10} = -0.317$). Firms that are less similar from rivals gain more.
- Size ($\phi_9 = -0.050$). Smaller firms gain more from greater market power.

Table 4 shows the additional market power at the peak significantly enhances the benefits from peak discrimination regardless of the measure of market power. Moreover, the benefits from discrimination are greater for firms with more rivals, firms having higher quality, firms with larger fixed costs, firms with fewer business customers, and smaller firms.

Table 4: Estimated Coefficients: Peak Price Discrimination (d_i') on Market Power

	E_1 (k=1)		E_2 (k=2)		E_3 (k=3)		E_4 (k=4)		E_5 (k=5)	
Variable	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**
Intercept	163.020	341.037	174.081	341.279	158.501	341.30	178.828	349.223	194.199	356.797
E_k	40.302**	16.414	41.135**	16.393	37.995**	15.863	37.229**	7.710	2.764**	1.198
Rivals	0.871**	0.333	0.860**	0.332	0.882**	0.334	0.522*	0.291	0.903**	0.348
Quality	35.480**	10.003	36.135**	9.989	34.911**	9.994	40.909**	8.971	38.008**	9.879
Value	41.082	33.484	41.087	33.482	40.338	33.321	-8.595	30.216	35.195	33.274
info	0.010	0.008	0.010	0.008	0.011	0.009	0.013	0.008	0.009	0.008
Brand	8.939	10.376	9.053	10.386	8.702	10.366	6.776	10.181	7.949	10.586
fixed	4.572**	1.841	4.460**	1.819	4.693**	1.855	1.531	1.968	5.089**	1.880
similarity	-0.300	0.217	-0.289	0.217	-0.309	0.217	-0.105	0.195	-0.269	0.229
nbusiness	0.105**	0.054	0.107**	0.054	0.104**	0.054	0.149**	0.056	0.135**	0.061
size	-0.081**	0.027	-0.081**	0.027	-0.081**	0.027	-0.071**	0.026	-0.077**	0.026
age	-0.183	0.177	-0.191	0.177	-0.176	0.177	-0.162	0.180	-0.184	0.182
Maui	13.868	15.255	16.101	15.806	10.883	14.802	-3.573	14.866	-7.282	22.084
Sydney	4.499	20.847	7.172	21.398	1.160	20.378	-24.336	20.658	26.326	22.482
Rio	2.736	20.417	5.773	21.066	-1.060	19.786	-12.672	17.441	1.903	17.646
Cape	-40.185*	21.537	-36.324*	22.178	-44.546**	20.987	-47.378**	18.524	-31.266*	18.513
Nice	-4.170	22.019	0.074	22.474	-8.503	21.922	-17.897	20.705	3.396	24.925
Barcelona	-22.216	19.512	-17.518	19.978	-27.178	19.213	-37.834**	17.001	-20.990	22.361
R square		0.40		0.40		0.40		0.46		0.37
Adjusted R-square		0.34		0.34		0.34		0.41		0.31
	** p<.05; * p<.10									

Similarly, as fixed costs increase, the prevalence of discrimination does not significantly increase, however the magnitude does. Some firms with larger fixed costs discriminate much more than all other firms. Perhaps a few firms, with very large fixed costs, are more dependent on peaks to recover those costs than those with smaller fixed costs.

Space limitations prevent the presentation of every findings but a summary follows.

4. Summary, Conclusions and Implications

Unlike past empirical studies, that study how market structures affect discriminatory practices, we study how market power affects discriminatory marketing practices controlling for structure. We also study which factors help firms exploit market power. We use case-control to minimize omitted variables and use exogenous variation in market power to avoid reverse causation (i.e., firms creating market power). We directly measure discrimination by comparing prices of the same product, same firm, same period, same market, and same time, where the product only differs on a costless feature (from the firm's perspective). Hence, different prices must reflect discrimination because higher prices reflect higher unit profit margins from consumers who will pay more for the feature.

Like past research, we find discrimination monotonically increases with market power. However, our data reveal several new implications about who gains from market power. Some factors always increase the profits from discriminatory marketing practices, while others only increase profits when the firm has sufficient market power.

Greater market power provides greater gains for:

- Firms with more rivals
- Firms offering better-perceived value
- Firms with higher-fixed costs
- Firms that are less similar to their rivals
- Smaller firms
- National branded firms

Surprisingly, greater market power does not necessarily benefit firms with higher quality. Although higher quality does increase the prevalence of discriminatory marketing practices, it seems independent of the market power of the firm.

Surprisingly, having fewer business customers increases both peak and off-peak discrimination. Perhaps, discrimination between business and non-business customers is not as important as discrimination among non-business customers.

Our findings suggest that market power, quality and customer mix (i.e., business vs. non-business) are orthogonal concepts. Moreover, when demand increases while industry capacity remains fixed, market power increases. However, the benefits do not distribute equally across firms. Firms with more rivals, firms with better ratings, firms less similar to their rivals and smaller firms all gain more from greater market power than their counterparts do.

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