Competition shocks, rival reactions, and stock return comovement*

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June 10, 2024

Abstract

To protect inframarginal rents, rivals react to competition shocks by increasing product differentiation or lowering costs by standardizing products and production processes. We test these two mutually exclusive reactions by exploiting changes in rivals' idiosyncratic stock return comovement following significant tariff cuts. While increased product differentiation implies a reduction in return comovement, greater standardization implies the opposite (a comovement increase). Difference-in-differences tests indicate that tariff cuts cause a significant increase in return comovement—in particular among within-industry "followers". Treatment effects on cash flows, product counts, similarity scores, and business-segment counts further support cost-cutting strategies.

GEL classification: G34, L10, L25

Keywords: Return comovement, competition shock, strategic rival reaction, product differentiation, scale economies, industry follower, industry leader

*We have benefitted from the comments and suggestions of Nihat Aktas, Farooq Ahmad, Sergey Chernenko (discussant), Jean-Gabriel Cousin, David Godsell, Davidson Heath (discussant), Gerard Hoberg (discussant), Michel Levasseur, Lars Persson (discussant), Gordon Phillips, and Karin Thorburn, as well as of seminar and conference participants at the University of Lille, American Finance Association, European Finance Association, European Association for Research in Industrial Economics, Finance Organizations and Markets Conference, Midwest Finance Association, Nordic Initiative for Corporate Economics Conference, Norwegian School of Economics, and WHU-Otto Beisheim School.

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I Introduction

This paper presents a novel large-sample analysis of a longstanding empirical question that goes back to the classical contributions of Hotelling (1929), Chamberlin (1933), Schumpeter (1943) and Arrow (1962): How do rival firms strategically react to a significant increase in industry competition that threatens their inframarginal rents—and does this reaction differ fundamentally between industry leaders and followers (laggards)? Will they primarily focus on increasing product differentiation vis-a-vis industry rivals to stave off the increased competition? Or, will they primarily focus on standardizing products and production technologies to realize cost efficiencies? Empirically discriminating between these types of rival reactions is of great importance not only for our understanding of the dynamics of industry structure and organization but also for the design of international trade policy—in this paper represented by a significant lowering of import tariffs.

Since rivals' strategic reactions are for the most part unobservable to the econometrician, a large literature in industrial economics approaches this issue through the observable but indirect lens of *R&D*. However, while innovation may help shield against low-cost foreign competition, the private incentives to undertake *R&D* are complex. Developing new products or, alternatively, new cost-reducing production processes (process innovation) *both* require investment in *R&D*. Hence, observing increased *R&D* is not by itself sufficient to infer whether rivals strategically react by increasing product differentiation or focusing on product and production process standardization, which is a central focus of this paper.[1]

[1] Using *R&D* to go neck-and-neck with competitors may also require a level of inframarginal rents available to within-industry leaders only, while less profitable and possibly credit constrained industry followers or "laggards" may be forced to cut back on *R&D* following a competition increase (Aghion, Bloom, Blundell, Griffith and Howitt, 2005). Also, firms' strategic reactions depend on whether the industry's products are complements or substitutes prior to the competition shock. For wide-ranging discussions of the use and

We present a novel test statistic with power to discriminate between two broad hypotheses describing the predominant rival reaction to competition shocks—greater product differentiation (H1) or greater standardization and cost-cutting (H2). Under market efficiency, stock prices capture expected changes in cash flows caused by exogenous competition shocks, which in turn changes within-industry stock return comovement among rival firms. Hence, we use the treatment effect on return comovement to infer whether the strategic rival-firm reaction is consistent with H1 or H2—two nested but mutually exclusive hypotheses. Furthermore, by grouping rivals into industry "leaders" and "followers" (based on accounting measures of profitability), we also address whether these two categories of peer firms tend to react differently to increased competition, as theory suggests.

Apart from its simplicity, a study of shock-induced changes in return comovement offers several econometric advantages. Perhaps most important, this test statistic is general in that it does not condition on a theoretically pre-specified type of rival reaction. Moreover, it is readily available for any competition shock where the affected firms are publicly traded, which covers most U.S. industries. For consistency of interpretation of the treatment effect, we also link our test results back to observable changes in firm-level cash-flow measures ($R\&D$ investments, operating costs and changes in working capital), changes in products (the number of products and product-similarity scores), and business strategy (the number of business segments and upstream industries supplying inputs).

To identify the treatment effect, we first remove from the distribution of raw return not only the influence of priced risk factors but also that of industry average return. To

impact of $R\&D$, see also Salop (1979), Spence (1984), Shaked and Sutton (1987), Grossman and Helpman (1991), Shapiro (2011), Bloom, Draca and Reenen (2016), Hombert and Matray (2018), Bellstam, Bhagat and Cookson (2020), Bena, Ortiz-Molina and Simintzi (2022), Hoberg and Maksimovic (2022), and Hoberg and Phillips (2024).

see why, consider an industry shock such as the invention of a relatively powerful microchip technology. While this invention may be positive for the smart-phone industry as a whole (through increased future consumer demand), it may affect some rivals negatively—what's good for Apple may be bad for Samsung. Or, consider the European restriction on diesel engines in the wake of the 'dieselgate' scandal in 2017.[2] While this shock may hurt the average car company, and it hurts producers of diesel engines (Volkswagen, Peugeot, Citroën, Opel) the most, while it may even benefit producers of hybrid and electric car engines (Tesla, Toyota and Nissan). In both these two examples, removing the average industry return is necessary to identify the shock-induced changes in what we label the idiosyncratic within-industry return comovement or, in short, the return comovement.

Figure 1 illustrates of the power of a significant industry shock to impact the return comovement ρ_{ijt} of firms i and j in period t (the estimation of ρ_{ijt}, which is explained in the table heading, is further detailed in Section III.A below). Centered on the OPEC-driven four-fold fuel price hike in 1973, the figure plots the average annual values of pairwise airline return comovement based on raw returns only, as well as our ρ_{ijt} statistic, across eleven public national airline companies that survived over the nine years from 1969 through 1977 (ending just prior to the 1978 Airlines Deregulation Act). Notice first that, notwithstanding the significantly negative airline industry shock, there is no detectable impact on the comovement of the airlines' unadjusted (raw) returns. In contrast, the average idiosyncratic return comovement ρ_{ijt} changes from negative (-0.048) prior to 1973 to positive (0.171) after the fuel-price hike. In the vernacular of this paper, this increase is driven by individual rival

[2] "During Volkswagen's Dieselgate Hell Week, An Explosive Sacrificial Lamb Theory Emerges", *Forbes*, March 20, 2017.

airlines' reactions to the fuel hike—causing the operating policies of rival airlines to become more highly correlated, i.e., less differentiated.[3]

Figure 1 here

The industry-wide shocks caused by the tariff cuts that we examine in this paper are, of course, less dramatic than the airline fuel-price effect of the OPEC embargo. Hence, the treatment effects that we report are also expected to be smaller than what is shown in Figure 1. In addition, the treatment effects will also be smaller in magnitude because, unlike in Figure 1, we use a difference-in-differences approach that subtracts the normal (untreated) return comovement using a control sample. It is also worth noting that our tariff cuts occur in a wide cross-section of U.S. manufacturing industries, many of which likely trigger rival reactions that are more complex than the case may be for the relatively homogeneous airline industry. Nevertheless, as our empirical analysis below demonstrates, our difference-in-differences procedure is sufficiently powerful and robust to identify significant changes in return comovement also in our more general setting.

The main competition shocks that we use is the *first* significant—and therefore relatively unanticipated—tariff cut experienced by U.S. manufacturing industries over the period 1975–2005. While domestic producers may lobby for tariff *protection* against import competition (Mayer, 1984; Bohara and Kaempfer, 1991; Trefler, 1993), tariff *cuts* likely represent exogenous events as they cause a lowering of industry protection.[4] As we require less restrictive

[3]The negative comovement prior to 1973 is consistent with federal airline industry regulations (through the Civil Aeronautics Board) restricting entry of new airlines and airline route creation (Slovin, Sushka and Hudson, 1991). This regulation may have contributed to industry competition being akin to zero-sum game between airlines, in which increased market share of one airline reduces the market share of another.

[4]Using an instrumental variable approach to account for latent factors, Lie and Yang (2023) find a negative correlation between tariff size and sales by domestic producers, which suggest that politicians use tariff increases to protect domestic industries facing dwindling sales. On the other hand, there are few if any incentives for industry members to lobby for significant tariff-cuts that threaten profits. It also worth pointing out that our difference-in-differences estimator is quite robust to the potential presence of time-varying latent factors that may be correlated with the variables of interest. Specifically, the parallel trends assumption underlying our estimator only requires that these latent factors do not diverge between the

data for U.S. manufacturing firms than do Frésard (2010) and Frésard and Valta (2016) in their original study of tariff cuts, we are able to double (from 91 to 180) their number of significant tariff cuts. For all firms, we estimate ρ_{ijt} annually using one year of daily stock returns from CRSP. The treatment effect of tariff cuts is then identified using the two-way fixed effect difference-in-differences estimator for events staggered through time, with time- and firm-pair (ij) fixed effects.[5]

Given the novelty of our idiosyncratic return comovement statistic ρ_{ijt}, we begin by documenting its statistical properties and cross-sectional determinants to validate our empirical approach from an economic perspective. For example, we confirm that ρ_{ijt} is higher the higher is the Hoberg and Phillips (2010) product-similarity scores of the two firms (SS_{ijt}). Moreover, consistent with extant evidence from the accounting literature that stock returns reflect changes in firms' cash flows (e.g., Collins, Kothari, Shanken and Sloan, 1994; Kothari and Zimmerman, 1995), we further show that ρ_{ijt} is a significant predictor of subsequent comovement of the rivals' cash-flow return on assets (ρ_{ijt}^{ROA}). Last but not least, we identify several cross-sectional determinants of ρ_{ijt}, such as capital structure, $R\&D$, relative industry position, and geographical location, all of which confirm that ρ_{ijt} does reflect economic fundamentals driving the idiosyncratic return comovement among industry peers.

We perform our main empirical analysis in two steps. First, using the total sample of tariff cuts, we document robust evidence of a positive and statistically significant average increase in the signed and absolute value of ρ_{ijt} following these industry shocks. This finding is con-

treated and the control groups.

[5]We confirm the parallel trend assumption and also that our main results are robust to a potential staggered-event bias (Cengiz, Dube, Lindner and Zipperer, 2019; Goodman-Bacon, 2021; Baker, Larcker and Wang, 2022) as well as to using a single (non-staggered) alternative shock as our quasi-experiment: the case of U.S. Congress granting China permanent status as 'normal trade relations' (NTR) in year 2000 (Pierce and Schott, 2016).

sistent with our hypothesis H2 (increased standardization of the post-shock modus operandi of rival firms) while failing to support H1 (increased product differentiation). Again, while H1 and H2 refers to interesting specific strategies such as "differentiation" and "standardization", the treatment effect is more general and consistent with any rival reaction that causes the return distribution of industry rivals to be more 'similar' (more correlated). We therefore present substantial evidence that corroborates our interpretation of the average treatment effect. This includes treatment effects of tariff cuts on firm-level cash-flow based measures of cost efficiencies (cost-of-goods-sold ($COGS$), working capital and employment), on the number of products and product-similarity scores, and on the number of business segments and upstream industries supplying the rival firms, all of which supports H2.[6]

Last, but not least, we split the rival firms of a given industry into two groups: industry leaders and followers. This categorization, which is meant to capture differences in industry performance and rents, separates leaders and followers using differences in a combination of market shares, cash balances, cash-flow return-on-assets (ROA), and $R\&D$ intensity. We find that the positive treatment effect observed in the overall data is largely concentrated among industry followers—the rivals with relatively low levels of inframarginal rents and $R\&D$ intensity. In our vernacular, it appears that the choice of implementing cost-cutting strategies is concentrated among industry followers, with the result that cash flows and, hence, idiosyncratic stock returns for this subgroup become more highly correlated. While this interpretation is both intuitive and reasonable, to our knowledge, ours is the first study to identify this heterogeneous within-industry rival firm reaction to industry-specific compe-

[6]While interesting although not central to this paper, we also show that the tariff cuts on average cause a significant reduction in $R\&D$.

tition shocks.

Our paper joins prior research that employs stock returns to infer the competitive effect of shocks to industry competition. While our industry shocks unambiguously increase competition, Eckbo (1983) examines the within-industry wealth effect—the change in industry rents—triggered by horizontal mergers that were challenged by U.S. antitrust authorities with harming competition. He concludes that this wealth effect does not fit the prediction of market power theory that motivates the government challenge.[7] In this paper, rather than estimating changes in the level of industry rents, we examine whether the shocks induce rivals to adopt more or less similar operating strategies. Thus, we are looking for persistent (long-run) effects of competitive shocks on the comovement of rival firms' stock returns across broad swaths of the U.S. economy. This empirical approach is important as it helps to identify the economic impact of competition changes largely ignored by the field of industrial economics.

Hoberg and Phillips (2016), in a study that is perhaps most closely related to ours, examine how the shock to military spending following the 9/11 attack in 2001 affected new entries and competition in the military industry. They conclude that this particular industry shock led to "increases in product market similarity as rivals relocated in the product market space to areas of common high demand." (abstract). While our econometric tests differ

[7] In its Merger Guidelines, the U.S. Department of Justice specifies certain industry-concentration thresholds above which the merger will most likely be challenged under Section 7 of the Clayton Act. Eckbo (1985) also rejects the prediction of the industry concentation doctrine underlying these thresholds. His rejection is based on cross-sectional regressions of the industry welth effect on the merger-induced increase in concentration. Fee and Thomas (2004) and Shahrur (2005) further reject the notion that horizontal mergers tend to harm the merging firms' downstream (publicly traded) customers. The overall consensus is that the within-industry wealth effect of horizontal mergers, which is positive on average, is best interpreted as an "in-play" effect in which the merger raises the likelihood of rival firms becoming future targets (Song and Walkling, 2000). See Betton, Eckbo and Thorburn (2008) for a review.

substantially from theirs, this conclusion appears complementary to our own multi-industry difference-in-differences analysis which, in addition, uncovers within-industry heterogeneity in rivals' strategic responses to tariff cuts. We do, however, make extensive use of the Hoberg-Phillips product-similarity scores to corroborate our interpretation of the treatment effect of tariff cuts on return comovement reported here.

II Return Comovement: Empirical Properties

While rival firm reactions to increased industry competition are likely wide-ranging and complex, they have in common that they produce changes in the firm's cash flow distribution and, hence, in the stock price and (most likely) within-industry return comovement. In this section, we define our novel comovement measure and document its basic properties. This evidence is important as it supports our assumption that the return comovement reflects within-industry economic fundamentals, which we subsequently include as control variables when estimating the treatment effects of tariff cuts.

II.A Comovement Definition

Our main test statistic is the within-industry idiosyncratic stock return comovement, labelled ρ_{ijt}. As shown in equations (1) and (2) below, ρ_{ijt} is the bi-firm correlation coefficient of the idiosyncratic stock returns ϵ_i and ϵ_j of firms i and j in calendar year t, estimated using daily stock returns within year t:

$$\rho_{ijt} \equiv \frac{COV(\epsilon_{it}, \epsilon_{jt})}{\sigma_{\epsilon_{it}}\sigma_{\epsilon_{jt}}}. \tag{1}$$

Here, $\sigma_{\epsilon_{it}}$ and $COV(\epsilon_{it}, \epsilon_{jt})$ are the standard deviation and the bi-firm covariance, respectively, of the residuals ϵ_{it} generated by OLS estimation of the following return generating process for firm i:

$$R_{it} = \alpha_i + \beta_{\mathbf{i}}'\mathbf{F_t} + \epsilon_{it}. \tag{2}$$

$\mathbf{F}$ is the vector of five risk factors in Fama and French (2015) (FF) plus one industry index, and $\beta_{\mathbf{i}}$ is the (transposed) vector of factor exposures. The risk and industry factors are as follows: $\mathbf{F} = [R_M - R_f,\ SMB,\ HML,\ RMW,\ CMA,\ I_{SIC3}]$, where $R_M - R_F$ is the excess return on the Center for Research in Security Prices (CRSP) value-weighted market portfolio, and SMB, HML, RMW and CMA are the returns on the FF long-short size, book-to-market, profitability, and investment portfolios. Finally, the industry index I_{SIC3} is the value-weighted portfolio of all CRSP firms, excluding firm i, that are in firm i's 3-digit SIC industry and that survive the data filtering described below.

Throughout the paper, we use the phrase 'return comovement' interchangeably with ρ_{ijt} in equation (1). Again, our hypotheses and empirical analysis focus on the reaction of individual rival firms to increased competition *after* extracting the industry's own return—the industry factor i_{SIC3} in equation (2). Since this industry factor itself reflects the industry's competitive structure and expected performance, the change in ρ_{ijt} identifies return implications at the firm level of rival reactions to increased industry competition.

II.B Cross-Sectional Determinants

We estimate ρ_{ijt} in equation (1) annually—on a rolling basis—using all industrial firms (SIC codes 2000 through 3999) that are available on the daily CRSP database.[8] Since ρ_{ijt} is estimated using daily data within one calendar year, our identification strategy only requires that a significant portion of the full treatment effect of the competition shock is reflected in stock prices over the course of the year. Also, the annual estimation means that we control for time-series changes in the factor exposures (β), which may impact return correlations (also noted by Hanley and Hoberg, 2019). Figure IA.1 and Table IA.1 in our Internet Appendix (IA) detail the empirical frequency distribution of ρ_{ijt}. As shown, the six-factor return-generating process produces a symmetric distribution that centers the distribution of ρ_{ijt} on zero—as expected when the factor model successfully captures all priced risk factors.[9]

The control variables are defined in Table 1 and the associated cross-sectional parameter estimates are shown in Table 2. In Panel A of Table 1, the seven variables with "QUARTILE" in the name are dummy variables indicating that the firm-pair ij are in the same quartile of the sample distribution in year t. These quartile indicators include AGE (public listing age using CRSP), BM (book-to-market ratio),[10] LEV (leverage ratio based on long-term

[8]To be included, a firm must satisfy the following restrictions: Share code 10 or 11 (common stocks) and stock exchange code 1 (NYSE) or 2 (Amex) or 3 (Nasdaq), and with a stock price $\geq$ \$1. In any given calendar year, the firm must have a minimum of 90 available return observations. Missing prices are replaced by the midpoint of the bid-ask spread. With these restrictions, the average annual number of manufacturing firms in our sample is 1,974.

[9]While not tabulated, our main empirical conclusions are qualitatively robust to using a 4-digit SIC rather than a 3-digit industry index in regression equation (2); adding lead- and lag values of the factor portfolios as a check on non-synchronous trading, dynamic market learning, and other market micro-structure effects (Scholes and Williams, 1977; Dimson, 1979); including the liquidity factor ("low-minus-high" stock-turnover portfolio) developed and tested in Eckbo and Norli (2005) as an additional pricing factor; and to replacing the pre-specified factors with (up to ten) principal components extracted from the variance-covariance matrix of the raw returns. We also find a strong upward time-trend in the regression R^2 after year 2000. We control for this increase, which occurs whether we include the market return only or all six factors in equation (2), by including year-dummies in our difference-ind-ifferences tests in Section III.D below.

[10]Book common equity is computed as the Compustat book value of stockholders' equity, plus balance-

debts plus current liabilities), *R&D*, *CASH* (ratio of cash plus short-term investment to total assets) and *INTG* (ratio of intangible assets to total assets).

Table 1 here

In Panel B of Table 1, the four variables are *LEADER* (indicating that i and j are industry leaders using the two alternative definitions explained in Section III.E in the text, *HHI* (indicating that i and j are in a highly concentrated SIC3 industry, with the Herfindahl-Hirschman Index exceeding 1,500), and *LOCATION* (indicating that i and j are headquartered in the same state, as per the Compustat LOC field). *LOCATION* is included because there is evidence that stock returns are affected by firm location (Garcia and Norli, 2012). Intuitively, firms operating in similar geographic regions tend to cluster in terms of technology and labor markets, suggesting a degree of operational similarity that is expected to affect ρ_{ijt}. The variable *I/O-QUARTILE* takes a value of one if firms i and j are in the *top quartile* of the distribution of the absolute value of the difference between the input vectors of i and j (source: Bureau of Economic Analyses USE tables). *I/O-QUARTILE* is included in a separate regression only as it reduces the sample by 90%.[11]

To study the relation between return comovement and our control variables. the following regression is estimated year-by-year over the period 1970–2010, where $\mathbf{x_{ijt}}$ is a vector with the determinants in Table 1:

$$\rho_{ijt} = \alpha_i + \alpha_j + \mathbf{X'_{ijt}}\mu + \epsilon_{ijt}. \tag{3}$$

sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock.

[11]Lee, Shi, Sun and Zhang (2024) use a similar BEA USE tables-based variable, labelled COMPL, to capture production complementarities between firms. The main difference is that the authors rely on a cosine measure of similarity between input/output vectors, while we use the Euclidean distance.

Here, α_i and α_j are, respectively, fixed effects for firms i and j. While the year-by-year cross-sectional regressions do not include firm-pair fixed effects (they would absorb the determinants that are constant by firm pairs), switching the estimation to a panel data setting with both year fixed effects and firm-pair fixed effects produces similar statistical inferences.

Table 2 reports the average annual estimate of the parameter vector μ and corresponding standard errors, which controls for cross-sectional correlation (Fama and MacBeth, 1973). The quartile variables in all receive positive and significant coefficient estimates at the 1% level of confidence. Moreover, ρ_{ijt} also increases significantly in *LEADER*, *HHI* and *LOCATION*, whether or not we include *I/O QUARTILE*. The inclusion of *I/O QUARTILE* further shows that ρ_{ijt} is lower the less similar is the two firms' input-output mixes. As a check on whether the standard errors in Table 2 are overly influenced by the large number of observations (Lin, Lucas and Shmueli, 2013; Harvey, 2017), Column (3) reports the average coefficient estimate based on 1,000 randomly selected sub-samples of 5% of the observations in the original sample. Our inferences are confirmed. The results in Table 2 strongly support that—after extracting the six factors in equation (2)—intra-industry firm-pair return comovement is higher the more similar firm and industry characteristics.

Table 2 here

II.C Return Comovement as Predictor of Cash-Flow Comovement

A large accounting literature demonstrates that stock returns predict future cash flows (e.g., Collins et al., 1994; Kothari and Zimmerman, 1995). Hence, we use the following time series regression to test whether this predictive property also holds for our idiosyncratic comovement measure:

$$\rho_{ij,t+1}^{ROA} = \alpha_{ij} + \beta_t + \gamma\rho_{ijt} + \epsilon_{ij,t+1}, \quad t = 1970, .., 2009 \tag{4}$$

where α_{ij} are firm-pair ij fixed-effects and β_t are year fixed-effects, respectively. Here, ROA is the ratio of quarterly operating income before depreciation to total assets, and $\rho_{ij,t+1}^{ROA}$ is the five-year forward-looking cash-flow comovement (from year $t+1$ through $t+5$) computed using twenty quarterly observations from Compustat.

The results are shown in Table 3. In columns (1) and (2), $\rho_{ij,t+1}^{ROA}$ is computed using ROA itself, while in columns (3) and (4), ROA is replaced by the residuals from a 20-quarter regression of ROA on either the equal-weighted market ROA index (ROA_{Mkt}^{Resi}) or on the market ROA plus an equal-weighted 3-digit SIC industry ROA index (ROA_{SIC3}^{Resi}). In all cases, the estimated γ coefficient is positive and highly statistically significant (at the 1% level). In Panel A, the regressions roll forward annually and all years from 1970 through 2009 are used for the test of statistical significance. Since overlapping rolling windows generate autocorrelation in the residuals, we also test for statistical significance using non-overlapping five-year periods in Panel B. The results in Panel B confirm that current stock-return comovement is a significant predictor of future cash-flow comovement. Table 3 here

II.D Return Comovement and Product Similarity Scores

Since this paper's main hypotheses concern whether rival firms react to a competition shock by either increasing product differentiation or product and process standardization, we are particularly interested in how our return comovement measure ρ_{ijt} correlates with Hoberg and Phillips (2010)'s product-similarity score, SS_{ijt}, which is available for Compustat firms starting in 1989. This correlation is shown by the following time series regression, where standard errors are clustered at the firm-pair ij level:

$$\rho_{ijt} = \alpha_{ij} + \beta_t + \gamma SS_{ijt} + \epsilon_{ijt}, \quad t = 1989, .., 2010. \tag{5}$$

SS_{ijt} is the (cosinus) distance between vectors of specific word binary indicators in firms' SEC filings (two firms' product portfolios are more similar the greater the vector overlap).

Table 4 shows the results, where Panel A employs our total sample firms. Matching SS_{ijt} to ρ_{ijt} for firm ij pairs belonging to manufacturing industries year by year results in a total of 34,925,933 matches. The univariate sample correlation between ρ_{ijt} and SS_{ij} is a statistically significant 0.032 (p-value 0.00). The decrease in the estimate of γ from Column (1) to Column (3) in Table 4 is as expected since the inclusion of firm-pair fixed effects mechanically absorbs the cross-sectional correlation. We report corresponding results for the sub-sample of single-segment firms, identified using the Compustat segment database, in Panel B and reach similar conclusions. Table 4 here

A graphical representation of the relation between ρ_{ijt} and SS_{ij} is displayed in Figure 2. The red line plots the fitted value of the regression function in Column (1) of Panel A in Table 4. The dots represent the average values of the pairs (ρ_{ijt}, SS_{ijt}) after grouping these into 40 bins, forming a binned scatter plot. The figure confirms that the positive slope coefficient estimate when regressing γ on SS_{ijt} is supported by the underlying binned scatter plot, which is built using close to 35 million observations. Figure 2 here

In sum, there is, on average, a significant and positive relation between SS_{ijt} and our measure of idiosyncratic comovement. Note also that, while SS_{ijt} is computed using the current (period t) product-word description, ρ_{ijt} also reflects expected future values of SS_{ijt}. It is precisely the capitalization of potential changes in product similarities that makes it so powerful to use ρ_{ijt} to help decipher rival firm reactions to competition shocks.

III Treatment Effects of Significant Tariff Cuts

III.A Mutually exclusive and nested hypotheses

In this section, we develop simple but mutually exclusive hypotheses for the implications of rival firms' strategic reactions to increased industry competition. While the strategic reactions that we refer to reflect well-know classical theories of industrial economics, our focus is to associate these theories with shocks to within-industry return comovement.

Consider first that rivals choose to react by developing a more differentiated product line. Product differentiation is generally enhanced by adding new features to existing products (e.g., a camera to the smart-phone), by introducing an entirely new product (e.g., Tesla's electric car), and by dropping a product that overlaps with rivals' (e.g., Volvo eliminating its production of diesel engines). These changes, which likely require substantial $R\&D$ investment, lowers cash-flow correlations between rivals. We label this scenario, where a positive shock to industry competition leads rivals to become more differentiated (less correlated in terms of cash-flow distributions), as our hypothesis H1. With greater differentiation, firm i's firm-specific information becomes less relevant for the equity pricing of it's rival j.

Alternatively, under our hypothesis H2, industry peers primarily react by implementing operating strategies that make rival firms less differentiated or more standardized (more highly correlated cash-flow distributions). While lowering product differentiation—such as by copying the product design of rival firms or by dropping existing but outdated products—exposes the firm to more competition from its rivals, it may be an optimal strategy as it also allows the firm to reduce production costs. For example, if Ford and GM add electrical car models in response to Tesla, then their respective product lines become less differentiated—and even more so if they also drop some outdated car models in the process—while at the same time taking advantage of increased scale-economies resulting from greater standardization of production. As rival firms become less differentiated (more standardized), their cash flows and hence idiosyncratic stock returns necessarily become more highly correlated.[12]

We track changes in both the signed- and the absolute value of the return comovement, denoted as $\Delta\rho_{ijt} \equiv \rho_{ijt} - \rho_{ij,t-1}$ and $\Delta|\rho_{ijt}| \equiv |\rho_{ijt}| - |\rho_{ij,t-1}|$, respectively. By tracking both these two values, we control for the fact that a positive or negative comovement change may occur from an initially negative or positive value (since $-1 \leq \rho_{ijt} \leq 1$). The initial value is negative when the products of firm i and j are substitutes ($-1 \leq \rho_{ijt} \leq 0$), and positive when they are complements ($0 \leq \rho_{ijt} \leq 1$).[13]

H1 (**increased differentiation**): If rival reactions primarily increase product differenti-

[12] The car industry also provides an interesting historical precedent in this context: following import tariff reductions and state-side car assembly by foreign brands that began in the 1970s, U.S. domestic car producers responded by making their cars smaller and more aerodynamic—closer to the design of foreign imports. Moreover, following the lead of rival car producers in Japan (Fanuc) and Sweden (Volvo), companies in Detroit created economies of scale by substantially increasing the use of automatization and robots. Yet another strategic response was General Motors's joint venture with Toyota to build cars in California.

[13] An example where ρ_{ijt} increases from an already positive value is when information about a patent violation or a consumer class-action suit affects both firms in the same direction and at a greater intensity after rivals have become more similar. An example where ρ_{ijt} increases (in absolute value) from an already negative value is when the two firms' products are close substitutes at the outset, so that firm-specific information that increases the demand for one firm reduce the demand for the other (what's good for Apple is bad for Samsung), with the effect being stronger after the competition shock.

ation (lowering return comovement), the idiosyncratic return comovement changes as follows:

(i) *Initial complements*: $\Delta\rho_{ijt} < 0$ and $\Delta|\rho_{ijt}| < 0$

(ii) *Initial substitutes*: $\Delta\rho_{ijt} > 0$ while $\Delta|\rho_{ijt}| < 0$.

H2 (**increased standarization**): If rival reactions increase product standardization (increasing return comovement), the idiosyncratic return comovement changes as follows:

(iii) *Initial complements*: $\Delta\rho_{ijt} > 0$ and $\Delta|\rho_{ijt}| > 0$.

(iv) *Initial substitutes*: $\Delta\rho_{ijt} < 0$ while $\Delta|\rho_{ijt}| > 0$.

Finally, in our empirical tests, we partition the rival firms into two groups: industry 'leaders' or 'followers', respectively. As explained in Section III.E below, industry followers are defined relative to leaders using information on sales-based market shares, financial ratios and *R&D*, which is likely to be correlated with a firm's level of inframarginal quasi-rents. The idea is that, since followers likely earn smaller inframarginal rents than do industry leaders, and since implementing a product differentiation strategy may be resource intensive, they are more likely to adopt a cost-reducing (standardizing) strategic response to increased competition:

H3 (**leaders and followers**): *The reaction of a rival firm to a competition increase depends on its level of quasi-rents. The lower the rents, the greater the likelihood that the rival will react by cutting production costs and standardizing products rather than investing in additional R&D to increase product differentiation. Hence, tariff cuts are expected to increase* $|\rho_{ijt}|$ *more for industry followers than for industry leaders.*

Classical industrial economics provides theoretical support for H3 in that, going back to Schumpeter (1943), the incentive to innovate is often modelled as declining in the level of industry competition. However, the issue is complex as a positive shock to competition may also increase the incremental profits from innovating and thus encourage $R\&D$ investments aimed at escaping competition (Arrow, 1962). As in Aghion et al. (2005), this incentive may be particularly strong in sectors where incumbent firms are operating at similar technological levels ('neck-and-neck firms') and where pre-innovation rents are more strongly reduced by an increase in product market competition. Moreover, as proposed by our H3, the marginal impact of a competition increase on the incentives to further differentiate their product lines may well differ across industry leaders and followers.

III.B Sampling of Significant Tariff Cuts

We begin by downloading the information on tariff rates for the 507 4-digit SIC manufacturing industries, 1975–2005, which is made available on the web site of Philip Valta (www.valta.ch). After imposing various data restrictions from both CRSP and Compustat, Frésard and Valta (2016) identify and use in their own analysis a total of 91 of these tariff cuts (covering 74 different 4-digit SIC industries), which they classify as causing a significant tariff reduction. While we use their definition of what constitutes a significant tariff cut, we only require data to also be available on CRSP (not Compustat). This allows us to identify and include in our analysis twice as many significant cuts:

(1) Using the procedure developed in Frésard and Valta (2016)'s definition, but before imposing their CRSP-Compustat data restrictions, we identify 477 tariff cuts as 'sig-

nificant'. A tariff cut is defined as significant if the cut is at least three times larger than the industry's average tariff change (positive or negative) over the sample period.

(2) Within each industry, we restrict the sample to the *first* significant tariff cut only. This restriction, which leaves 324 cuts, concentrates our sample on cuts that were relatively unanticipated by the stock market and therefore improves our ability to identify shocks to equity prices and hence changes in ρ_{ijt}.

(3) We merge the 324 industries with the estimates of ρ_{ijt} described in Section II above, and we require a minimum of five listed rival firms to be available per industry. Requiring at least five rival firms helps improve the precision of the estimated average treatment effect. This results in a final sample of 180 four-digit SIC manufacturing industries with initial significant tariff cuts.

Figure 3 shows the annual distribution of our sample of 180 significant import tariff reductions. Since we use the definition of a significant tariff cut developed by Frésard and Valta (2016)—but with fewer Compustat data restrictions—the figure also shows the annual distribution of their 91 tariff cuts (74 different industries) in order to illustrate the difference in the timing of the respective samples. In the regression analyses below, we use as our regression period 1970–2010, which adds five years on each side of the sample period in Frésard and Valta (2016).

Figure 3 here

III.C Verifying the Parallel-Trend Assumption

We begin our analysis by verifying that the trend lines for the average values of ρ_{ijt} of treated and control firms are parallel before the competition shock and divert afterward

(Angrist and Pischke, 2009). Figure 4 shows that this parallel-trends assumption is satisfied as it plots the eleven event-parameters γ_τ estimated using the following event-study difference-in-differences (DID) regression:

$$\rho_{ijt} = \alpha + \beta_t + \sum_{\tau=-5}^{+5} \gamma_\tau D_{ij}^{\tau} + \epsilon_{ijt}, \quad t = 1975, ..., 2005 \tag{6}$$

where α is a constant term and β_t are year fixed effects. This regression uses all tariff cuts over the sample period to estimate each parameter γ_τ in the eleven-year event window $[\gamma_\tau = -5, ..., \gamma_\tau = 5]$, where year $\tau = 0$ is the year of the tariff cut. Hence, D_{ij}^{τ} is a dummy variable that takes a value of one in year τ if the firm-pair ij is in a treated industry (experiencing a significant tariff cut in event-year 0), and zero otherwise. We follow the standard practices and constraint to zero D_{ij}^{-1}.

The horizontal line in Figure 4 means that the divergence between the comovement of the treatment and control groups remain unchanged through event time and indistinguishable from zero, which is equivalent to parallel developments of the two groups ($\gamma_\tau = 0$). The series of the eleven estimated values of γ_τ therefore provides a graphical representation of the parallel trend assumption. As shown, the 5% confidence interval around the estimated treatment effects ($\hat{\gamma}_\tau$) stops including $\gamma_\tau = 0$ for the first time in event year $\tau = 0$, the event year. Figure 4 is consistent with the parallel-trends assumption underlying our two-way fixed effects DID estimator (explained in Section III.D below). The fact that investors typically receive early indications of a forthcoming tariff cuts—causing the partial anticipation to affect stock prices—helps to explain why the estimated treatment effect $\hat{\gamma}_\tau$ starts to rise above zero just prior to the event year itself.

Figure 4 here

III.D Effects on Return Comovement: All Rivals

We use the parameter γ in the following two-way fixed effects (TWFE) DID regression as baseline specification to identify the average treatment effect of tariff cuts on ρ_{ijt}:

$$(7)\quad \rho_{ijt} = \alpha_{ij} + \beta_t + \mathbf{CONTROLS}'\mu + \gamma(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt}, \quad t = 1970, .., 2010$$

where α_{ij} are firm-pair ij fixed-effects, β_t are year fixed-effects. Firm i is always in a treated industry while firm j is either in a treated industry or not. $TREATED_{ij}$ is an indicator variable equal to one if the firm-pair ij is treated (i.e., the two firms are operating in the same treated industry), $POST_{ijt}$ is an indicator variable equal to one for the post event periods, and **CONTROLS** is a vector of nine control variables. These controls are the statistically significant determinants identified in Table 2: $AGE, BM, LEV, R\&D, CASH, INTG$ (all quartile indicator variables), as well as the $LEADER$, HHI and $LOCATION$ dummies.

As the dependent variable ρ_{ijt} is restricted to the subset of firm pairs ij where firm i is always in the industry experiencing the competition shock while firm j is in either this industry or in another, we isolate the treatment effect on ρ_{ijt} as the difference between ρ_{ijt} when firm j is in the shocked industry and ρ_{ijt} when firm j is not in the shocked industry. It excludes the possibility that changes in ρ_{ijt} for firm pairs unaffected by competition shocks impact our empirical results.

Columns (1) and (2) of Table 5 show the γ-estimates without and with the control variables, respectively.[14] Standard errors are clustered at the firm-pair (ij) level. As shown,

[14] We choose to also report results without controls because inclusion of "bad" controls possibly contaminates DID estimates (Angrist and Pischke, 2009).

the treatment effect γ is positive and statistically significant at the 1% level whether we use the signed values of ρ_{ijt} in Panel A or the absolute value ($|\rho_{ijt}|$) in Panel B. The magnitude of the comovement change is 3.8% of the standard deviation of ρ_{ijt}. The unconditional comovement values shown in the Internet Appendix (Table IA.1 and Figure IA.1), which are generally small, show that this is a substantial treatment effect.[15]

Table 5 here

The γ-estimates in columns (1) and (2) of Table 5 fail to support hypothesis H1 but are consistent with hypothesis H2 from Section III.A above: Rival firms on average react to tariff cuts by becoming less differentiated (more similar) relative to the control firms following industry shocks caused by tariff reductions. In other words, rival reactions to these shocks appear to reduce differences in product offerings (reduced product differentiation) and/or to increase production process standardization, perhaps so as to realize cost-saving economies—increasing the odds of survival.

While our empirical strategy of using large-sample tests for shock-induced effects on idiosyncratic return comovement is unique to the literature, we note that the above conclusion complements that of Hoberg and Phillips (2016), who focus on two industries: the shock to military goods and services industry represented by September 11, 2001, and the post-2000 collapse of the software industry, respectively. For the military industry, they conclude that the shock led to "increases in product market similarity as rivals relocated in the product market space to areas of common high demand" (p. 1426). Increases in product market similarities is also consistent with our hypothesis H2, as is increased standardization of rival

[15] While not tabulated, we also break down the estimate the treatment effect in Column (2) of Table 5 at the level of 3-digit SIC industries. This is done by expanding equation (7) with interaction terms between $TREATED_{ij} \times POST_{ijt}$ and a vector of 3-digit SIC code indicator variables equal to one when firm i belongs to the corresponding industry. This industry-level breakdown shows that a total of 28% of the industries experience a treatment-effect that is positive and significant at the 1% level or better, while only 9% are associated with a significantly negative treatment effect.

firms' production processes.

III.E Effects on Return Comovement: Industry Leaders v. Followers

The estimated increase in within-industry comovement shown in columns (1) and (2) of Table 5 is consistent with a cost-cutting response to the decline in revenue caused by the tariff cut. It is therefore reasonable to also expect that the rivals with the lowest inframarginal rents and highest financial constraints are particularly likely to react by adopting cost-cutting operating strategies. To examine this proposition, we separate industry leaders and followers, and test for differences in the effect of competition shocks on their respective average return comovement.

To rank industry rivals, we use two alternative definitions, where the first focuses on inframarginal rents and the other on $R\&D$ intensity. In the first definition, followers (leaders) are firms that are in one of the three lowest (the highest) quintiles of the yearly frequency distribution of sales-based market share or cash balances or else return on assets (ROA), all within the 3-digit SIC3 industry containing the 4-digit SIC industry experiencing the tariff cut. Our assumption is that this dichotomy achieves a split on the level of pre-shock inframarginal rents earned by leaders and follower, respectively. In the second definition, industry followers are relatively low $R\&D$ firms. i.e., firms in the three lowest quintiles of the industry's $R\&D$ intensity distribution, with industry leaders in the highest quintile. We measure $R\&D$ intensity as the natural logarithm of one plus the firm's $R\&D$ stock, divided by total assets, where we follow Hombert and Matray (2018) and compute $R\&D$ stock using a perpetual inventories formula and a 15% amortization rate.

We use an expanded version of regression equation (7) to separate the average treatment effects γ_1 and γ_2 for the industry followers and leaders, respectively, and where γ_3 is the average treatment effect for the remaining rival firms in between:

$$\begin{aligned}\rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS'}\mu \\ &+\gamma_1(TREATED_{ij} \times POST_{ijt} \times D_{FOLLOWER_i}) + \gamma_2(TREATED_{ij} \times POST_{ijt} \times D_{LEADER_i}) \\ &+\gamma_3(TREATED_{ij} \times POST_{ijt} \times (1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})) + \epsilon_{ijt}.\end{aligned} \tag{8}$$

Here, D_{LEADER_i} and $D_{FOLLOWER_i}$ are dummy variables that take a value of one if firm i is an industry leader or a follower, respectively, in the year prior to the year of the tariff cut, and zero otherwise.

Column (3) in Panel A of Table 5 shows the three γ-coefficient estimates using the industry-rents definition of followers and leaders. Interestingly, the column shows that the treatment effect of the tariff cuts is positive and significant for industry followers only. Specifically, $\hat{\gamma}_1 = 0.004$, which is statistically significant at the 1% level, while the impact on Leaders is negative and weakly significant ($\hat{\gamma}_2 = -0.002$, significant at the 10% level). A Fisher test of difference between $FOLLOWER$ and $LEADER$ coefficients confirm that the difference between $\hat{\gamma}_1$ and $\hat{\gamma}_2$ is statistically significant at the 1% level of confidence. The remaining firms experience a treatment effect that is insignificantly different from zero ($\hat{\gamma}_3 = -0.001$). The inferences from Panel B of Table 5, which uses the absolute rather than the signed value of ρ_{ijt}, are also consistent with our hypothesis H3. Hence, we conclude that the tariff cuts on average increase the return comovement across industry peers, and in particular for industry followers.

Table 6 shows the estimated treatment effects when we instead define industry followers as low-*R&D* firms. The results again show that the treatment effect of tariff cuts causes an increase in the idiosyncratic return comovement of industry followers (statistically significant at the 5% level)—but not of industry leaders. In sum, Table 5 and Table 6 both show that the positive and significant average treatment effect in the total sample of rival firms is largely concentrated among industry followers, suggesting that these firms react by increasing cost efficiency measures. Also, our finding that the significant increase in return comovement occurs among industry followers whether defined using a proxy for quasi-rents or *R&D* intensity is reassuring: The resources of relatively low-rent firms are likely to be constrained when it comes to *R&D* spending. Table 6 here

Finally, again classifying leaders and followers using the rent definition in Table 5, we separate the treatment effects on the covariance term in the numerator of ρ_{ijt} in equation (1) above from effects on the denominator. This allows us to check that it is indeed an increase COV_{ijt} rather than a decline in $\sigma_{it}\sigma_{jt}$ that drives the significant increase in ρ_{ijt} for the group of industry followers.[16] In Panel A of Table 7, the dependent variable is $COV_{ijt}/IQR_{COV_{ij}}$, the signed value of the annual idiosyncratic covariance divided by its inter-quartile range $IQR_{COV_{ij}}$. The inter-quartile range is the difference between the third and first quartile of the distribution of the signed value of the annual idiosyncratic covariance COV_{ijt} computed at the firm-pair ij level. Standardizing COV_{ijt} is necessary since the covariance is otherwise

[16] Campbell, Lettau, Malkiel and Xu (2001), Brandt, Brav, Graham and Kumar (2010), and Nam, Khaksari and Kang (2017) document a positive time trend in average idiosyncratic (unconditional) stock return variances and covariances. Irvine and Pontiff (2009) find evidence consistent with the hypothesis that the increase in idiosyncratic return volatility is in part driven by more intense economy-wide industrial competition. While not tabulated, we have tested for but find no time trend in ρ_{ijt}. Note also that our inclusion of year fixed effects in the DID tests controls for any such time trend should it exist in the data.

unbounded: it permits controlling for the cross-sectional heterogeneity in COV_{ijt}. In Panel B of Table 7, the dependent variable is the cross-product of the two standard deviations, $\sigma_{it}\sigma_{jt}$.

Table 7 here

The results in Panel A show that the treatment effect is positive and significant (at the 10% level) for the numerator of ρ_{ijt}. Moreover, in panels A and B, the treatment effect is positive and significant for *both* the numerator and the denominator of ρ_{ijt} (at the 1% and 5% levels of confidence, respectively) for industry followers. Since the ρ_{ijt} itself is increasing (Table 5), this shows that the treatment effect on the numerator is sufficiently large to overcome the attenuating effect of the simultaneous increase in denominator.

IV Robustness Checks

In this section, we perform numerous robustness checks of the main results in Table 5.

IV.A The 2×2 DID Estimator

First, recall from equation (7) above that we estimate the average treatment effect of multiple tariff cuts that are staggered through time (restricted to the first significant cut in any given industry—arguably the least anticipated shock). Baker, Larcker and Wang (2022) points to a potential bias in a TWFE DID estimator that compares not only treated and untreated groups of firms but also treated groups across time. To address this potential bias, they recommend using stacked regressions in event time. As each tariff-cut in our sample has a control group consisting of several million observations, stacking these panels 180 times creates a prohibitively large dataset. We instead study the distribution of the 2×2 DID estimator $\gamma^{2\times 2}$ that compare, event by event, the treated and untreated groups using the following regression specification (Cunningham, 2021):

$$\rho_{ijt} = \alpha_{ij} + \beta_t + \gamma^{2\times 2}(TREATED_{ij} \times POST_t) + \epsilon_{ijt}. \tag{9}$$

In this regression, $\gamma^{2\times 2}$ is estimated using two groups (one treated and one control) and two periods (one pre-event and one post-event).[17] Figure 5 shows the histogram of the estimated values of $\gamma^{2\times 2}$ across the 134 tariff cuts available for this test. Eliminating the fat tails by winsorizing at 5/95% produces an average coefficient estimate of $\hat{\gamma}^{2\times 2} = 0.0063$ with a standard-error of 0.0021 and a corresponding Student-t statistic of 3. This shows that the average treatment effect is robustly positive and significant also after adjusting for the potential bias described above.

Figure 5 here

IV.B Treatment Effect of a Non-Staggered Competition Shock

The potential for staggered events to bias the estimated treatment effect can also be addressed by apply our general methodology to a single non-staggered competition shock. For this, we turn to the U.S. Congress' decision to grant China normal trade-relations (NTR) status in year 2000 also used by Autor, Dorn and Hanson (2013). This decision by the

[17]Using the $\gamma^{2\times 2}$ estimator, the source of the potential bias affecting the TWFE DID estimator γ is illustrated by the following decomposition (Goodman-Bacon, 2021):

$$\gamma = \sum_{k\neq U} s_{kU}\gamma_{kU}^{2\times 2} + \sum_{k\neq U}\sum_{l>k} s_{kl}\left[\mu_{kl}\gamma_{kl}^{2\times 2,k} + (1-\mu_{kl})\gamma_{kl}^{2\times 2,l}\right].$$

Here, U is the untreated group, $k \in \{E, L\}$ with E the early treated group and L the late treated group, and s and μ are weights that depend on the number of observations in each group and the time-lapse between treatments. The first summation captures comparisons between treated and untreated groups, while the second (double) summation captures comparisons between early and late treated groups. The latter is the potential source of bias, which Baker et al. (2022) show may cause γ to flip sign.

Congress eliminated the possibility of a substantial tariff increase that China faced up to that point. Using data from the U.S. Bureau of Economic Analysis, Pierce and Schott (2016) show that this change in U.S. trade policy lead to a substantial increase in import competition from China. Specifically, they find that industries more exposed to the change experienced greater employment loss, increased imports from China, and higher entry by U.S. importers and foreign-owned Chinese exporters.

We estimate the treatment effect of the China-NTR event using our equations (7) and (8) after making the necessary adjustments to the definitions of the variables $TREATED$ and $POST$. In this single-event application, where the estimation period is now the eleven-year period 1995–2005 (centered on the event-year 2000), we replace $POST_{ijt}$ with the dummy variable $POST_i^{2001}$ that takes a value of one in year 2001 and thereafter. To identify the treatment intensity, we apply the approach of Pierce and Schott (2016) at the firm (not plant) level using Compustat.[18] They construct a so-called $NTRGAP$ variable at the plant level as their measure of the ex ante uncertainty about U.S. trade policy towards Chinese imports. $NTRGAP$ measures the difference between NTR and non-NTR tariff rates so that a higher gap indicates a greater potential increase in tariff rates if the NTR-status is revoked.

As shown in Table 8, this alternative quasi-experiment also produces treatment effects (δ coefficients) that are positive and statistically significant—and again restricted to industry followers. The level of statistical confidence for this single exogenous shock is 5%, except in columns (1) and (2) of Panel A where it is at the 10% level. Overall, these findings further

[18] Pierce and Schott (2016)'s analysis is at the plant level as they use the Longitudinal Business Database of the U.S. Census Bureau's, which is not available for this paper. While Pierce and Schott (2016) also measure NTR Gap for upstream and downstream industries, we limit ourselves to the focal industry NTR Gap. Apparently, the Bureau of Economic Analysis file needed to build these additional variables (http://www.bea.dov/industry/zip/NDN0317.zip) is no longer available.

support our main conclusion that rival firms exposed to a significant increase in import competition tend to adopt cost-reducing (standardizing) business strategies.

Table 8 here

IV.C Expanding the Use of Fixed Effects

There are several industry-level time-varying latent factors that could drive our results. Examples are changes in investment opportunities due to tariff cuts, new and cheaper procurement alternatives, new opportunities for out-sourcing production, and impacts of industry-level business cycles. Recall that the fixed effects in our baseline regression (equation 7) already control for potential time-varying latent factors that are common to all firm (ij) pairs. However, to further address latent factors, we expand our regression specification to also include the interaction between industry- and year-fixed effects.

In Table IA.2, we progressively add fixed effects ranging from just year-fixed effects to a combination of firm-pair (i,j) and industry*year fixed effects. The table shows that the point-estimates of the treatment effects based on the baseline-model regressions (Table 5) are highly robust to these additions. This is noteworthy because the combination of firm pair (ij) and industry*year fixed effects will absorb any industry level time varying latent factors, in addition to firm pair (ij) specific time-constant latent factors already absorbed by firm pair (ij) fixed effects.

IV.D Dropping the Control Group

Here, we repeat the regression analysis of Table 5 while dropping the control group of firms for each event altogether. This mechanically eliminates the potential for bias when control groups in staggered events include observations that have been—or later will be—treated. As documented in Table IA.3, the main conclusions from Table 5 remain largely unchanged after restricting the sample to treated firms only: The average treatment effect remains positive and statistically significant at the 5% level when using the signed value of ρ_{ijt} in Panel A, and at the 1% level when using the absolute value of ρ_{ijt} in Panel B. Moreover, for industry followers, the estimated treatment effect using the signed value of ρ_{ijt} in Panel A remains positive and highly significant at the 1% level of confidence. These results confirm that the treatment effect evidenced Table 5 are indeed driven by the treated sample—not the control sample.

IV.E Additional Robustness Checks

First, Table IA.4 shows that restricting treated firms to be present in the sample at least one year before the year of the tariff cut, which reduces the sample size by close to 7.5 million observations, produces results that are consistent with those in Table 5 (at the 5% level of confidence for the average treatment effect and at the 1% level for industry followers and leaders, respectively). Second, Table IA.5 confirms that the coefficient estimate for industry followers remains statistically significant (at the 10% level of confidence) also when standard errors are double-clustered at the 4-digit SIC industry and year levels.

Third, Table IA.6 shows that the statistical significance of the treatment effects reported in Panel A of Table 5 is confirmed when using randomized p-values produced by a random shuffling of the treatment variable. Since random shuffling eliminates any causal treatment effect in the randomized permutations of the data (Cunningham, 2021), this finding strengthens our confidence that the standard errors that we report are not understated due to our large sample size.[19]

Fourth, we explore the correlation between return comovement and recessions, both at the aggregate economy level and at the industry level.[20] Business cycles are indeed sources of common shocks, potentially affecting return comovements. First, using our Compustat-CRSP sample of manufacturing firms, Figure IA.2 shows aggregate economic downturns indicated by NBER recession periods (the bars) along with the average idiosyncratic comovement (the solid line) over the 1970–2010 period. The average idiosyncratic comovement tends to peak during these aggregate recession periods, especially during 1980-1982, 2001 and 2008-2009.

To identify 3-digit SIC industry-level recession periods, we start by computing 36 months rolling-window industry-level compound returns. A given 3-digit SIC industry month is defined to be in recession if the corresponding compound return is negative. Recession years are years containing at least one such month of recession. To build this industry-level recession indicator, we use CRSP monthly stock returns and all ordinary shares (share codes 10 and 11) for firms listed on the NYSE, AMEX and Nasdaq (exchange codes 1, 2 and 3), and the 3-digit SIC industry returns are value-weighted.

In Table IA.7, we use the industry-level recession indicator variable as an additional explanatory variable for ρ_{ijt}. Importantly, this analysis is performed within industry—i and

[19]Specifically, after estimating regression equation (7) above on the original data, we re-estimate the treatment-effect parameter γ—the sensitivity of ρ_{ijt} to $TREATED_{ij} \times POST_{ijt}$—one hundred times. Each re-estimation uses randomly shuffled data for $TREATED_{ij} \times POST_{ijt}$. The randomization p-value (two-sided test) is then the number of times the absolute value of the randomized estimate of γ exceeds the absolute value of the γ-estimate when using the original data, divided by 100 (the number of randomized samples).

[20]We thank a referee for suggesting this additional analysis.

j now always belong to the same industry. Finally, to check whether our results are driven by recessions and not tariff cuts, we include both the industry recession indicator variable and the tariff cut indicator variable in the regression specifications. Columns (1)–(4) of Table IA.7 indicate (at the 10% confidence level) a positive relation between within-industry comovement and industry-level downturns. This positive correlation disappears, however, once industry fixed effects are included in the regression specification (columns 5 through 8). Also, across all specifications in Table IA.7, the tariff-cut treatment effect remains positive and highly significant, thus confirming our baseline results reported in Table 5.[21]

V Economically Corroborating Treatment Effects

V.A Effect of tariff cuts on similarity scores

Recall the significantly positive association between ρ_{ijt} and SS_{ijt} shown in Table 4 and Figure 2 above. Hence, we check whether the positive treatment effect of the tariff cuts on ρ_{ijt} is corroborated by a tariff-induced increase in SS_{ijt} as well. Our hypothesis H2 predicts this to be the case if rival firms react by offering more similar products. The results of this test are shown in Table 9. As SS_{ijt} is available starting in 1988, the available sample is 5,959,039 observations—about one-third of the sample size for the comovement regressions in Table 5 above (which starts in 1970).

The difference-in-differences test results in Table 9 support the hypothesis that the product similarity among industry rivals increase in the wake of tariff reductions (relative to

[21] Table IA.7 differs from Table 5 in that it examines the interaction between two shocks: the tariff cut and the business cycle downturn. Our baseline model specification is more powerful as it compares firm-pairs across treated and untreated industries while Table IA.7 focuses exclusively on within-industry comovement.

the control firms). This is true without the inclusion of control variables (column 1), with control variables (column 2), and for both industry followers and industry leaders (column 3). In columns (1) and (2), the results are significant at the 10% level, while in Column (3) the confidence level is 1% or better. Also interesting, the estimate of γ_1 for industry followers in column 3 is 0.004, which is twice that of the estimated γ_1 for industry leaders—a statistically significant difference at the 5% level of confidence (shown by test in the second to the last row of the table). Consistent with H2, these results corroborate that competitive pressures to standardize following significant tariff cuts indeed trickles down to the product level among rivals.

Table 9 here

V.B Effect of Tariff Cuts on Cash Flows

Second, we test for the presence of cash-flow treatment effects of the tariff cuts. Table 10 shows the results of estimating the following regression specification, with year t running from event-window year -5 through year +5:

$$(10)\quad Y_{it} = \alpha + \mathbf{CONTROLS'}\mu + \beta_1 TREATED_i + \beta_2 POST_t + \gamma(TREATED_i \times POST_t) + \epsilon_{it}$$

As dependent variable, Y_{it}, we use one of the following three alternative measures of changes in cost efficiencies, listed in the same order as columns (1)–(3) in the table: (1) sales divided by the cost of goods sold and administrative expenses ($COGSX$), (2) $R\&D$ divided by total assets (TA), and (3) working Capital (WC) divided by property, plants and equipment (PPE). For each tariff cut, we use an eleven-year estimation period centered on the year of the tariff cut (year -5, year +5, where year 0 is the year of the cut), and the sample of firms represents the Compustat-CRSP universe of manufacturing firms (4-digit SIC codes 2000 to 3999). Standard-errors are clustered at the firm i level, and the row labelled Romano-Wolf p-val refers to p-values obtained using the Romano and Wolf (2005) test for multiple hypotheses with 1,000 bootstrap replicates.

The estimated treatment effects ($\hat{\gamma}$) in Table 10 are all statistically significant at the 1% level. Moreover, coefficient signs are generally consistent with the notion underlying our hypothesis H2 that rivals tend to react to tariff cuts by implementing cost-cutting strategies. First, the positive coefficient-estimate in Column (1), where the dependent variable is $SALES/COGSX$, suggests that the net effect of cost-cutting is to increase the spread between revenues and sales (the price-cost margin). Also, the negative coefficient on WC/PPE in Column (3) suggests that the rival cost-cutting strategies also involve a reduction in the need for costly working capital (perhaps by lowering inventories).

Table 10 here

The negative coefficient-sign in Column (2) is interesting as it shows that the shock-induced competition increase *lowers* the rate of *R&D* spending. This type of cost-cutting is also consistent with our hypothesis H2 as it suggests that lowering *R&D* may be a direct and effective cost-saving strategy—and probably more so for industry followers who may find it too costly to catch up by process innovation. Moreover, it fails to support our alternative hypothesis H1 as it is difficult to square a decrease in *R&D* intensity with developing increased product differentiation.[22]

[22] This evidence is also interesting given Hombert and Matray (2018)'s finding that ex-ante *R&D*-intensive firms tend to be more resilient in terms of avoiding post-shock declines in sales growth and profitability caused by the 2000 China-NTR competition shock discussed in Section IV.B above (which we confirmed also led to an increase in return comovement). While not pursued further in this paper, one interpretation of our evidence of significant increases in shock-induced return comovement is that a resilience caused by high ex ante (pre-shock) *R&D* intensity may manifest itself through a lower demand for *R&D* expenditures when time comes to react to significant competition increases.

V.C Effects on Product-Word Counts, Business Segments, and Suppliers

We use the regression specification in equation (10) above to also estimate tariff-cut treatment effects on three firm-level dependent variables that help to further link tariff cuts to real changes in operating strategies and product standardization. The variables are (1) changes rival firms' product-word count, (2) the number of business segments, and (3) the number of upstream industries supplying inputs into the production process. The results of using each of these three dependent variables are shown in Table 11.[23]

Table 11 here

Starting with the product-word count as the dependent variable (Y_{it}), it represents the number of words in the product description section of the firm's annual 10K SEC filing. This data has been generously supplied to us by Gerard Hoberg and Gordon Phillips and covers universe of firms underlying Hoberg and Phillips (2010) (this data has, to our knowledge, not been applied elsewhere). Our idea here is that a tariff-cut treatment effect that lowers the product-word count—a reduction in the product description section of the 10K—is consistent with a reduction in the firm's portfolio of products and increased product standardization.

Columns (1) and (2) Table 11 show a highly significant negative treatment effect on the product-word count (standard errors are clustered at the firm i level). The coefficient estimate in Column (1) means that, on average across the full sample, the number of words in the product description section declined by 553. Moreover, Column (2) shows that this decline in the word count is restricted to the within-industry followers who experience an average word-count decline of 621. This evidence is interesting as it supports our interpre-

[23]The estimation center on the eleven-year event windows (-5,+5) where year 0 is the year of the tariff cut.

tation of the significant increase in the return comovement among industry followers in our main Table 5 above as indicating a move towards product standardization.

In columns (3) and (4) of Table 11, we use the number of business segments reported by the firm at the 3-digit SIC code level (obtained from Compustat, 1983–2010)). The idea is that a firm's number of reported business segments is likely to be positively correlated with its number of products. The negative and statistically significant treatment effect for industry followers in Column (4) is again consistent with the notion that these industry rivals react to the increased competition by narrowing production, in this case by concentrating the number of business segments .

Finally, the last column of Table 11 shows a negative and significant treatment effect on the number of upstream industries that supply inputs to the downstream manufacturing companies experiencing tariff cuts. The number of upstream industries is from the Bureau of Economic Analyses USE tables, 1970-2010. Again, the negative and significant treatment effect is consistent with downstream companies simplifying their production processes by cutting back on the number of upstream suppliers.[24]

In sum, together with Table 5, the evidence in Table 11 helps to support our hypothesis H2 that rival firms—in particular industry followers—tend to react to tariff cuts by simplifying (standardizing) their product lines and production processes.

[24]The last column of Table 11 reportx results for all rivals only as this treatment effect turns out not to be specific to industry followers.

VI Conclusion

When industries experience competition-increasing shocks, do individual rival firms react by increasing product differentiation? Or, will they instead primarily focus on standardizing products and production processes to realize cost efficiencies? How do these opposing strategic reactions depend on the firms' competitive position as industry leader or follower (laggard)? Since rival reactions are for the most part unobservable to the econometrician, these fundamental empirical questions have remained largely unanswered in the field of industrial economics.

The main contributions of this paper are twofold: (1) to develop necessary implications of competition-increasing shocks for within-industry stock return comovement between rival firms, and (2) to present large-sample tests of those implications using the treatment effect across industries experiencing significant tariff cuts. Our core test statistic—the idiosyncratic return comovement among rival firms—is both new to the literature on industrial economics and available for all listed firms. Importantly, it expunges not only the influence of priced risk factors on stock returns, but also the average industry return itself, which is necessary to unmask true firm-level rival reactions to competition shocks.

In principle, we argue that rival reactions belong to one of two mutually exclusive categories. In the first category (H1), rivals primarily react to competition shocks by increasing their within-industry product differentiation. The resulting decrease in the within-industry cash-flow correlation implies decreased within-industry stock return comovement. In the second category (H2), rivals primarily focus their reaction by implementing strategies that lower production costs—including simplifying product lines and capturing additional scale economies. This category therefore predicts increased within-industry return comovement. As a corollary (H3), we argue that rivals' strategic reactions will depend on firm-level quasi-rents, which we identify empirically by classifying firms as belonging to groups of either industry leaders or followers.

Our empirical analysis exploits 180 significant tariff cuts in 180 different manufacturing industries that took place over the period 1975–2005. Using a DID regression approach, we report three sets of empirical results that are all new to the literature. Most important, we show that the tariff cuts on average cause a significant increase in within-industry idiosyncratic return comovement. This finding rejects H1 but is consistent with H2. That is, rivals predominantly react to the competition shocks by implementing operating strategies that, as our evidence shows, produce an increase in intra-industry cash-flow correlations and, therefore, in idiosyncratic return correlations.

Consistent with H3, we further show that the shock-induced increase in idiosyncratic return correlation for the most part occurs among the subset of rival firms that we classify as industry followers. These are the more marginally profitable and relatively cash-flow constrained rival firms. As expected by classical theories in industrial economics, they appear more likely than industry leaders to respond by cutting costs rather than making expensive investments in product differentiation. To our knowledge, this is the first large-scale empirical evidence suggesting that industry followers in particular react to increased competition by implementing operating strategies that make these industry peers more similar in terms of idiosyncratic return comovement.

In addition to performing a barrage of robustness checks, we corroborate the important conclusions by also estimating treatment effects on several additional firm-level dimensions.

These include changes in cash-flow measures of cost-efficiencies; in a direct measure of product portfolio size using 10K SEC filing product description section; in the number of business segments in which treated firms are active; and in the number for upstream industries that supply inputs.

The methodological innovation of this paper—using idiosyncratic return comovement to decipher the nature of corporate rivalry—has several additional applications that we leave for future research. For example, it would be interesting to explore in more detail how rival reactions involving specific technological innovations affect the comovement. Another example is to expand on prior work using stock returns to identify potential anticompetitive effects of horizontal merger. Yet another and timely application is to shed light on how the recent pandemic may have changed intra-industry corporate rivalry, particularly in industries that are relatively vulnerable to social distancing.[25]

[25]As generating the (50+ million) pairwise idiosyncratic return correlations underlying this paper requires substantial computer time, the comovement data are available from the authors upon request.

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Table 1: **Definition of Control Variables in Regressions with ρ_{ijt} as Dependent Variable**

The idiosyncratic stock return comovement between firms i and j in year t, ρ_{ijt}, is estimated using equations (1) and (2) in the text.

Variable name	**Dummy variable definition**	**Percent of sample**
A. Firm level controls for firm-pairs i and j		
$SIC3$	i and j are in same SIC3 industry	3.12%
$AGEQUARTILE$	i and j are in same quartile of CRSP listing-age distribution	30.36%
$BMQUARTILE$	i and j are in same quartile of the book to market distribution	22.44%
$LEVQUARTILE$	i and j are in same quartile of the leverage distribution	23.10%
$R\&DQUARTILE$	i and j are in same quartile of the $R\&D$ distribution	32.92 %
$CASHQUARTILE$	i and j are in same quartile of the cash ratio distribution	22.88%
$INTGQUARTILE$	i and j are in same quartile of the ratio of intangible-asset distribution	33.17%
B. Industry and location controls for firm-pairs i and j		
$LEADER$	i and j are industry leaders (among the top three SIC3 firms by sales)	2.47 %
HHI	i and j are in a highly concentrated SIC3 industry (HHI exceeds 1,500)	26.05%
$I/OQUARTILE$	i and j are in top quartile of the I/O distance distribution (I/O distance is the absolute value of the difference between the input vectors of i and j, from the Bureau of Economic Analyses USE tables)	46.82%
$LOCATION$	i and j are headquartered in the same state (Compustat field LOC)	5.60%

Table 2: **Coefficient Estimates for Control Variables Determining Return Comovement**

The table reports average coefficients obtained from the following year-by-year cross-sectional regressions:

$$\rho_{ijt} = \alpha_i + \alpha_j + \mathbf{X}'_{\mathbf{ijt}}\mu + \epsilon_{ijt}, \quad t = 1970, .., 2010$$

where α_i and α_j are, respectively, firm-i and firm-j fixed effects. The idiosyncratic stock return comovement between firms i and j in year t, ρ_{ijt}, is estimated using equations (1) and (2) in the text. Reported coefficients are the average of the forty-one estimates obtained running the yearly cross-section regressions from 1970 to 2010 and standard errors are obtained using the standard deviation of the yearly estimates as in Fama and MacBeth (1973). The vector $\mathbf{x}_{\mathbf{ijt}}$ contains the determinants defined in Table 1. In Column (1), $I/OQUARTILE$ is excluded because its inclusion shrinks the sample size drastically. Using the specification in Column (1), Column (3) reports the average coefficients obtained based on 1,000 randomly selected sub-samples of 5% of the observations in the original sample. The sample (N observations) includes all U.S. manufacturing firms (4-digit SIC code 2000 to 3999) present in the Compustat-CRSP universe. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

	Cross-sectional average coefficient estimates		
	Total sample		Random sub-samples
Regressors	1	2	3
$SIC3$	0.00319***	0.00253***	0.00323***
	(0.00048)	(0.00059)	(0.00055)
$I/OQUARTILE$		−0.00060***	
		(0.00005)	
$AGEQUARTILE$	0.00064***	0.00045***	0.00066***
	(0.0007)	(0.00009)	(0.00012)
$BMQUARTILE$	0.00109***	0.00123***	0.00115***
	(0.00011)	(0.00013)	(0.00014)
$LEVQUARTILE$	0.00043***	0.00055***	0.00035***
	(0.00005)	(0.00009)	(0.00013)
$R\&DQUARTILE$	0.00091***	0.00067***	0.00100***
	(0.00008)	(0.00010)	(0.00012)
$CASHQUARTILE$	0.00045***	0.00037***	0.00036***
	0.00007)	(0.00008)	(0.00009)
$INTGQUARTILE$	0.00038***	0.00053***	0.00049***
	(0.00006)	(0.00012)	(0.00010)
$LOCATION$	0.00122***	0.00212***	0.00121***
	(0.00011)	(0.00021)	(0.00019)
$LEADER$	0.00277***	0.00265***	0.0031***5
	(0.00040)	(0.00046)	(0.00043)
HHI	0.00071***	0.00094***	0.00088***
	(0.00013)	(0.00019)	(0.00021)
Firm i & j FE	Yes	Yes	Yes
Average R^2	0.92		
Average N	1,781,439		

Table 3: Stock-Return Comovement (ρ_{ijt}) as Predictor of Cash-Flow Comovement ($\rho^{ROA}_{ij,t+1}$)

The table shows the coefficient estimates of γ for the following regression:

$$\rho^{ROA}_{ij,t+1} = \alpha_{ij} + \beta_t + \gamma \rho_{ijt} + \epsilon_{ij,t+1}, \quad t = 1970, .., 2009$$

where α_{ij} are firm pair ij fixed-effects and β_t are year fixed-effects, respectively. The idiosyncratic stock return comovement between firms i and j in year t, ρ_{ijt}, is estimated using equations (1) and (2) in the text. ROA is the ratio of quarterly operating income before depreciation to total assets, and $\rho^{ROA}_{ij,t+1}$ is the five-year forward-looking cash-flow comovement in year $t+1$ computed using twenty quarterly observations (from Computat). In columns (1) and (2) , $\rho^{ROA}_{ij,t+1}$ is computed using ROA itself, while in columns (3) and (4), ROA is replaced by the residuals from a 20-quarter regression of ROA on either the equal-weighted market ROA index (ROA^{Resi}_{Mkt}) or on the market ROA plus an equal-weighted 3-digit SIC industry ROA index (ROA^{Resi}_{SIC3}). Starting in 1970, the regressions in Panel A roll forward annually while, in Panel B, the regressions use non-overlapping five-year windows. The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999). The sample period is 1970–2010. Standard-errors, which are reported in parentheses, are clustered at the firm pair ij level. F is the Fisher test statistic for the joint significance of the regression coefficients and N, the number of observations. *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

	Cash-flow comovement (dependent variable)			
	$\rho^{ROA}_{ij,t+1}$	$\rho^{ROA}_{ij,t+1}$	$\rho^{ROA^{Resi}_{Mkt}}_{ij,t+1}$	$\rho^{ROA^{Resi}_{SIC3}}_{ij,t+1}$
Coefficient	1	2	3	4
Panel A: all years				
Predictor ρ_{ijt} : γ	0.0539***	0.0047***	0.0046***	0.0033***
	(0.0029)	(0.0015)	(0.0014)	(0.0013)
Year FE	Yes	Yes	Yes	Yes
Firm pair ij FE	No	Yes	Yes	Yes
R^2	0.005	0.546	0.552	0.526
F	31.83	795.3	466.8	75.29
N	12,296,713	12,296,713	12,296,713	12,259,274
Panel B: Non-overlapping five-year windows only				
Predictor ρ_{ijt} : γ	0.0751***	0.0385***	0.0376***	0.0182***
	(0.0052)	(0.0102)	(0.0097)	(0.0088)
Year FE	Yes	Yes	Yes	Yes
Firm pair ij FE	No	Yes	Yes	Yes
R^2	0.005	0.731	0.735	0.725
F	92.09	192.5	248.6	18.56
N	2,552,847	2,552,847	2,552,847	2,543,728

Table 4: Return Comovement and Hoberg-Phillips Product Similarity Scores

The table shows the coefficient estimates of the coefficient γ in the following regression:

$$\rho_{ijt} = \alpha_{ij} + \beta_t + \gamma SS_{ijt} + \epsilon_{ijt}, \quad t = 1989, .., 2010$$

where α_{ij} is firm-pair ij fixed-effects, β_t is year fixed-effects and SS_{ijt} is the Hoberg-Phillips product-similarity score, which are available from the 1989–2010 subperiod of our total sample period. The idiosyncratic stock return comovement between firms i and j in year t is estimated using equations (1) and (2) in the text. In Panel A, the sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999) and in Panel B, the sample of firms is restricted to single-segment manufacturing firms, identified using the Compustat Segment database. Standard-errors, which are reported in parentheses, are clustered at the firm pair ij level. F is the Fisher test statistic for the joint significance of the regression coefficients and N, the number of observations. *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

	Regression specification		
Regressor	1	2	3
Panel A: All firms			
SS_{ijt}: γ	0.0708***	0.0696***	0.0121***
	(0.0004)	(0.0004)	(0.0011)
Year FE	No	Yes	Yes
Firm pair ij FE	No	No	Yes
R^2	0.001	0.001	0.225
F	31,377	1,879	415.3
N	34,925,933	34,925,933	34,925,933
Panel B: Single-segment firms only			
SS_{ijt}: γ	0.0704***	0.0685***	0.0120***
	(0.0005)	(0.0005)	(0.0016)
Year FE	No	Yes	Yes
Firm pair ij FE	No	No	Yes
R^2	0.001	0.002	0.291
F	19,510	1,032	117.0
N	16,617,675	16,617,675	16,617,675

Table 5: Effect of Tariff Cuts on Return Comovement: Followers v. Leaders Classified by Rents

The table shows coefficient estimates of the average treatment effect of tariff cuts using the following two panel regressions, estimated over the period 1970–2010:

$$
\begin{aligned}
(1)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS}'\mu + \gamma(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt} \\
(2)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS}'\mu + \gamma_1(TREATED_{ij} \times POST_{ijt} \times D_{FOLLOWER_i}) \\
&\quad +\gamma_2(TREATED_{ij} \times POST_{ijt} \times D_{LEADER_i}) \\
&\quad +\gamma_3(TREATED_{ij} \times POST_{ijt} \times (1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})) + \epsilon_{ijt}
\end{aligned}
$$

Regression (1) uses all firms while regression (2) splits all firms into industry followers and leaders, identified using a combination of market shares, cash balances, and return-on-assets. The idiosyncratic stock return comovement between firms i and j in year t, ρ_{ijt}, is estimated using equations (1) and (2) in the text. Firm i is always in a treated industry while firm j is either in a treated industry or not. D_{LEADER_i} and $D_{FOLLOWER_i}$ are dummy variables that take a value of one if firm i is an industry leader or a follower, respectively, in the year prior to the year of the competition shock, and zero otherwise. Their complement is covered by the dummy variable $(1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})$. In Panel A the dependent variable is the signed value of the annual comovement ρ_{ijt}, while Panel B uses the absolute value of $(|\rho_{ijt}|)$. α_{ij} are firm-pair ij fixed-effects, β_t are year fixed-effects. $TREATED_{ij}$ is an indicator variable equal to one if the firm pair ij is treated (their 4-digit SIC industry receives a significant tariff cut), while $POST_{ijt}$ is an indicator variable equal to one for the post-treated periods. **CONTROLS** is a vector of control variables identified in Table 2 as significant determinants of ρ_{ijt} ($BM, LEV, R\&D, CASH, INTGQUARTILE$ as well as the $LEADER$, HHI and $LOCATION$ dummy variables). The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999). Size effects, computed as the coefficient scaled by the standard error of ρ_{ijt}, are reported between square brackets. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the Fisher statistic obtained for a test of equality of coefficients and N is the number of observations. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**Panel A: Signed ρ_{ijt} value**			**Panel B: Absolute ρ_{ijt} value**		
Treatment coefficient	All firms		Followers v. Leaders	All firms		Followers v. Leaders
	1	2	3	1	2	3
$ALLFIRMS$: γ	0.0026***	0.0026***		0.0062***	0.0062***	
	(0.0012)	(0.0012)		(0.0008)	(0.0008)	
	[0.0386]	[0.0384]		[0.13]	[0.13]	
$FOLLOWER$: γ_1			0.0033***			0.0033***
			(0.0009)			(0.0006)
$LEADER$: γ_2			−0.0014*			0.0011**
			(0.0007)			(0.0008)
$INBETWEEN$: γ_3			−0.0011			0.0056***
			(0.0018)			(0.0013)
$CONTROLS$	No	Yes	Yes	No	Yes	Yes
R^2	0.223	0.223	0.223	0.221	0.221	0.221
F	38.89	33.79	32.75	521.79	428.94	412.36
$\gamma_1 = \gamma_2$			13.66		5.94	
N	14,549,529	14,549,529	14,549,529	14,549,529	14,549,529	14,549,529

Table 6: **Effect of Tariff Cuts on Return Comovement: Followers v. Leaders Classified by** $R\&D$

This table replicates the regression specified in Table 5 after separating firms into industry followers and leaders using $R\&D$ intensity, which is defined as the natural logarithm of one plus $R\&D$ stock divided by total assets. $R\&D$ stock is computed using perpetual inventories formula, with a 15% amortization rate. D_{LEADER_i} and $D_{FOLLOWER_i}$ are dummy variables that take a value of one if firm i is an industry leader (the firm belongs to the highest quintile of the $R\&D$ intensity distribution) or a follower (the firm belongs to the three lowest quintiles of the $R\&D$ industry distribution), respectively, in the year prior to the year of the competition shock, and zero otherwise. Their complement is covered by the dummy variable $(1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})$. The dependent variable is the signed value of the annual comovement ρ_{ijt}. Size effects, computed as the coefficient scaled by the standard error of ρ_{ijt}, are reported between square brackets. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the Fisher statistic obtained for a test of equality of coefficients and N is the number of observations. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**Signed ρ_{ijt} value**		
Treatment	All firms		Followers v. Leaders
coefficient	1	2	3
$ALLFIRMS$: γ	0.0026***	0.0026***	
	(0.0012)	(0.0012)	
	[0.0386]	[0.0384]	
$FOLLOWER$: γ_1			0.0026**
			(0.0013)
$LEADER$: γ_2			0.0022
			(0.0016)
$INBETWEEN$: γ_3			0.0029**
			(0.0013)
$CONTROLS$	No	Yes	Yes
R^2	0.223	0.223	0.223
F	38.89	33.79	32.51
$\gamma_1 = \gamma_2$			0.0706
N	14,549,529	14,549,529	14,549,529

Table 7: **Effects of Tariff Cuts on the Numerator v. Denominator of ρ_{ijt}**

This table replicates the regression specified in Table 5 after replacing the dependent variable ρ_{ijt} by either of its two components (numerator or denominator). In Panel A, the dependent variable is $COV_{ijt}/IQR_{COV_{ij}}$, the signed value of the annual idiosyncratic covariance COV_{ijt} divided by its inter-quartile range $IQR_{COV_{ij}}$. The inter-quartile range is the difference between the third and first quartile of the distribution of the signed value of the annual idiosyncratic covariance COV_{ijt} computed at the firm pair ij level. In Panel B, the dependent variable is the cross-product of the standard deviations of firm i's and firm j's idiosyncratic returns, respectively: $\sigma_{it} \times \sigma_{jt}$. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the Fisher statistic obtained for a test of equality of coefficients and N is the number of observations. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**A: Component of ρ_{ijt}: $COV_{ijt}/IQR_{COV_{ij}}$**			**B: Component of ρ_{ijt}: $\sigma_{it} \times \sigma_{jt}$**		
Treatment	All firms		Followers v. Leaders	All firms		Followers v. Leaders
coefficient	1	2	3	1	2	3
$ALLFIRMS$: γ	0.0365*	0.0363*		0.2441	0.2574	
	(0.0197)	(0.0197)		(0.1569)	(0.1572)	
$FOLLOWER$: γ_1			0.0511***			0.5467**
			(0.0191)			(0.2175)
$LEADER$: γ_2			−0.0276*			−0.0499
			(0.0158)			(0.1855)
$INBETWEEN$: γ_3			−0.0200			0.6125**
			(0.0275)			(0.2647)
$CONTROLS$	No	Yes	Yes	No	Yes	Yes
R^2	0.623	0.623	0.623	0.893	0.894	0.894
F	25.64	22.41	21.65	1.663	1.352	1.350
$\gamma_1 = \gamma_2$			0.01			0.10
N	14,078,321	14,078,321	14,078,321	14,078,256	14,078,256	14,078,256

Table 8: **Effect on Return Comovement of Granting China Normal Trade Relations (NTR)**

As the year of the NTR is 2000, we estimate the following regressions over the period 1995–2005:

$$
\begin{aligned}
(1)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS}'\mu + \gamma(TREATED_{ij} \times POST_t^{2001}) + \epsilon_{ijt} \\
(2)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS}'\mu + \gamma_1(TREATED_{ij} \times POST_t^{2001} \times D_{FOLLOWER_i}) \\
&\quad + \gamma_2(TREATED_{ij} \times POST_t^{2001} \times D_{LEADER_i}) \\
&\quad + \gamma_3(TREATED_{ij} \times POST_t^{2001} \times (1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})) + \epsilon_{ijt}
\end{aligned}
$$

The dependent variable is the signed value of the annual comovement ρ_{ijt}; α_{ij} are firm-pair ij fixed-effects; and β_t are year fixed-effects. In Panel A, the treatment intensity ($TREATED_{ij}$) is measured as $NTRGAP^{1999}$, which refers to the $NTRGAP$ variable of Pierce and Schott (2016). It is the difference between the NTR-tariff rates (in percentage points) and non-NTR-tariff rates for Chinese imports in firm i's industry in 1999 (variable s1999 in the file gaps_by_naics6_20150722_fam50.dta from Pierce and Schott's replication package, available at https://www.openicpsr.org/openicpsr/project/112965/version/V1/view). In Panel B, the treatment intensity is measured using $HIGHNTRGAP_j^{1999}$, which is a dummy variable equal to one if $NTRGAP^{1999}$ is above the industry median $NTRGAP$ in 1999. The sample includes only firm pairs ij where firm i $HighNTRGAP_i$ is equal to one. Industries are families of four-digit SIC and six-digit NAICS codes that group related SIC and NAICS categories together over time created by the authors. $POST_t^{2001}$ is a dummy variable equal to one from year 2001. All other variables are as in the main text. **CONTROLS** is a vector of control variables identified as significant determinants of ρ_{ijt} ($BM, LEV, R\&D, CASH, INTGQUARTILE$ as well as the $LEADER$, HHI and $LOCATION$ dummy variables, see Table 2). The sample includes all Compustat manufacturing firms (4-digit SIC codes 2,000 to 3,999) for which the required information is available. Standard errors are clustered at the Pierce and Schott (2016) industry families level. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the Fisher test statistic obtained for a test of equality of coefficients and N is the number of observations. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Treatment intensity measure:	**Panel A: Continuous variable** $NTRGAP_j^{1999}$			**Panel B: Dummy variable** $HIGHNTRGAP_j^{1999}$		
Treatment coefficient	All firms		Followers v. Leaders	All firms		Followers v. Leaders
	1	2	3	1	2	3
$ALLFIRMS$: γ	0.1555*	0.1624*		0.0005**	0.0005**	
	(0.0826)	(0.0826)		(0.0002)	(0.0002)	
$FOLLOWER$: γ_1			0.1639**			0.0005**
			(0.0672)			(0.0002)
$LEADER$: γ_2			0.1111			0.0004
			(0.0843)			(0.0004)
IN: γ_3			0.0225			0.0001
			(0.0999)			(0.0003)
R^2	0.236	0.236	0.236	0.236	0.236	0.236
F	3.55	7.74	7.55	4.98	6.97	6.35
$\gamma_1 = \gamma_2$			0.24			0.00
$CONTROLS$	No	Yes	Yes	No	Yes	Yes
N	18,533,051	18,533,051	18,533,051	18,533,051	18,533,051	18,533,051

Table 9: Effect of Tariff Cuts on Hoberg-Phillips Similarity Scores

This table replicates the regression specified in Table 5 after replacing the dependent variable ρ_{ijt} with the Hoberg-Phillips similarity score SS. The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999) for which Hoberg & Phillips similarity scores are available. Size effects, computed as the coefficient scaled by the standard error of ρ_{ijt}, are reported between square brackets. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the Fisher statistic obtained for a test of equality of coefficients and N is the number of observations. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**Similarity score** S_{ijt}		
Treatment	All firms		Followers v. Leaders
coefficient	1	2	3
$ALLFIRMS$: γ	0.0043*	0.0043*	
	(0.0022)	(0.0022)	
	[0.1443]	[0.1432]	
$FOLLOWER$: γ_1			0.0044***
			(0.0008)
$LEADER$: γ_2			0.0022***
			(0.0005)
$INBETWEEN$: γ_3			0.0038***
			(0.0012)
$CONTROLS$	No	Yes	Yes
R^2	0.879	0.879	0.879
F	102.11	84.99	80.94
$\gamma_1 = \gamma_2$			5.83
N	5,959,039	5,959,039	5,959,039

Table 10: **Effects of Tariff Cuts on Cost-Efficiency Cash-Flow Measures**

The table shows coefficient estimates of tariff-cut treatment effects using the following regression, with year t running from event-window year -5 through year +5:

$$Y_{it} \quad = \quad \alpha + \mathbf{CONTROLS}'\mu + \beta_1 TREATED_i + \beta_2 POST_t + \gamma(TREATED_i \times POST_t) + \epsilon_{it}$$

$TREATED_i$ is an indicator variable equal to one if firm i is treated (its 4-digit SIC industry receives a significant tariff cut), while $POST_t$ is an indicator variable equal to one for the post-treated periods. **CONTROLS** is a vector of control variables identified in Table 2 as significant determinants of ρ_{ijt} ($BM, LEV, R\&D, CASH, INTGQUARTILE$ as well as the $LEADER$, HHI and $LOCATION$ dummy variables). The dependent variable Y_{it} takes one of three forms: sales divided by the costs of goods sold and administrative expenses ($SALES/COGSX$), $R\&D$ divided by total assets ($R\&D/AT$), and working capital divided by property, plants and equipment (WC/PPE). Estimates are obtained on eleven-year event windows (-5,+5) centered on the year of the tariff reduction (year 0). The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999). Standard errors are clustered at the firm i level. R^2 is for R-squared, F is the Fisher test statistic for the joint significance of the regression coefficients and N, the number of observations. Romano-Wolf p-val refers to p-values obtained using the Romano and Wolf (2005) test for multiple hypotheses with 1,000 bootstrap replicates. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**Cost-efficiency cash-flow measure**		
Treatment coefficient	SALES/COGSX 1	R&D/AT 2	WC/PPE 3
γ	0.0223^{***}	-0.0256^{***}	-0.8932^{***}
	(0.0060)	(0.0021)	(0.2197)
$CONTROLS$	Yes	Yes	Yes
R^2	0.108	0.327	0.189
F	113.92	473.96	181.67
Romano-Wolf p-val	0.0020	0.0010	0.0020
N	44,844	48,063	42,657

Table 11: **Effect of Tariff Cuts on the Number of Product-Words, Business Segments, and Upstream Industries**

This table replicates the regression specified in Table 10 after replacing the dependent variable Y_{it} by either Word count, the number of words in the product description section of SEC 10K filing, the Segment count, the number of 3-digit SIC industry segments reported in the Compustat Segment database, or the Upstream industry count, the number of connected upstream industries. Word count information is obtained thanks to a dataset provided by G. Hoberg and covers the period 1989-2010. Segment count information covers the period 1883-2010, the initial 1978-1982 period being unreliable. The number of connected upstream industries is collected in the Bureau of Economic Analyses USE tables and is available for the whole 1970-2010 period. R^2 is for R-squared, F is the Fisher test statistic for the joint significance of the regression coefficients. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the Fisher statistic obtained for a test of equality of coefficients and N, the number of observations. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

	Dependent variable (Y_{it})				
	Product word count [1989-2010]		**Business segment count** [1983-2010]		**Upstream industry count** [1970-2010]
Treatment coefficient	1	2	3	4	5
ALLFIRMS: γ	-552.78^{***}		$-0.0.0393$		-0.2631^{***}
	(178.76)		(0.1213)		(0.0804)
FOLLOWER: γ_1		-621.11^{***}		-0.2348^{***}	
		(192.34)		(0.0911)	
LEADER: γ_2		357.27		0.1664^{*}	
		(227.71)		(0.0939)	
INBETWEEN: γ_3		-261.05		-0.1600^{*}	
		(174.84)		(0.0896)	
CONTROLS	Yes	Yes	Yes	Yes	Yes
R^2	0.121	0.121	0.091	0.092	0.026
F	130.01	107.16	69.90	55.02	29.73
N	23,621	23,621	30,197	30,197	43,513
$\gamma_1 = \gamma_2$		0.00		0.00	

Figure 1: Effect of the 1973 Oil-Embargo on the Stock Return Comovement among U.S. Airlines

This figure helps to illustrate the potential magnitude of the change in the annual within-industry idiosyncratic bi-firm return comovement caused by a significant shock to industry profitability: in this case the impact of the 1973 OPEC oil-embargo on US publicly traded airlines. Throughout the paper, the within-industry idiosyncratic bi-firm return comovement is denoted ρ_{ijt} for firms i and j, where

$$\rho_{ijt} \equiv \frac{COV(\epsilon_{it}, \epsilon_{jt})}{\sigma_{\epsilon_{it}} \sigma_{\epsilon_{jt}}},$$

and where σ_ϵ is the standard deviation and the error term ϵ_{it} from the following six-factor model generating daily stock returns:

$$R_{it} = \alpha_i + \beta_{\mathbf{i}} \mathbf{F_t} + \epsilon_{it}.$$

The daily return factors are $\mathbf{F} = [R_M - R_F,\ SMB,\ HML,\ RMW,\ CMA,\ I_{SIC3}]$, where $R_M - R_F$ is the excess return on the value-weighted market portfolio, SMB, HML, RMW and CMA are the returns on the Fama and French (2015) long-short size, book-to-market, profitability and investment portfolios, and the value-weighted 3-digit SIC industry index I_{SIC3}. Each ρ_{ijt} is estimated using a minimum of 90 daily returns within calendar year t. The industry index is formed using public firms in SIC industry 451 and excluding firm i. Firms i and j are among eleven publicly traded national U.S. domiciled airlines that survived for the entire nine-year period (American, Braniff, Continental, Delta, Eastern, National, Northeast, Northwest, Pan American, TWA, and United). The dotted line is the correlation coefficient computed using the airlines' raw returns, unadjusted for the factor-vector $\mathbf{F_t}$.

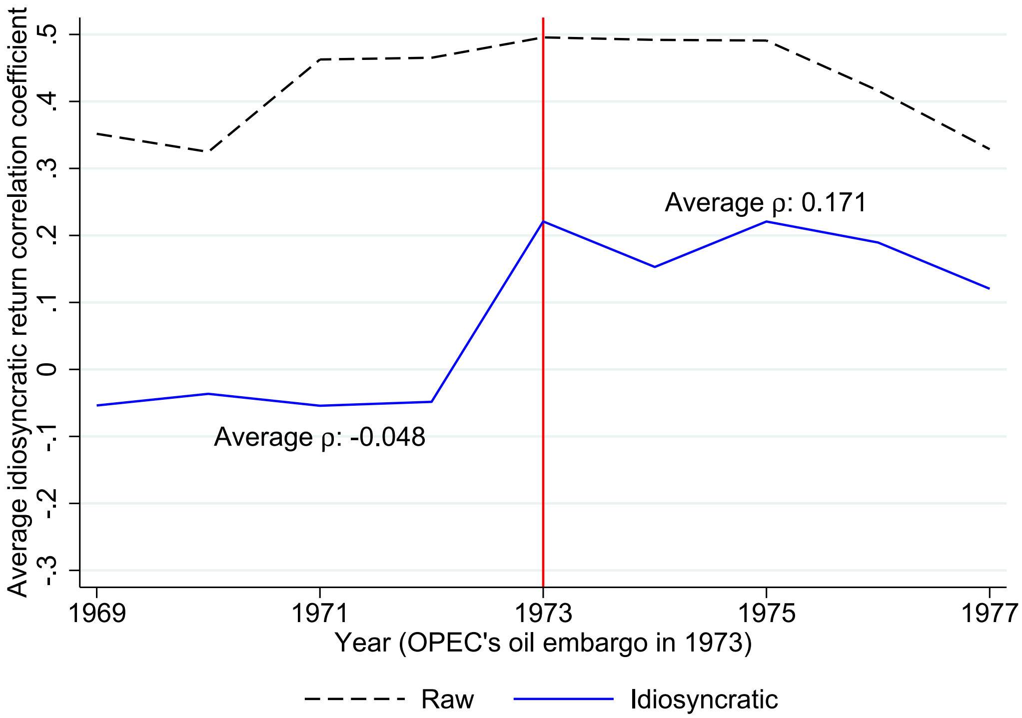


Figure 2: **Idiosyncratic Return Comovement v. Hoberg & Phillips (2010) Similarity Scores**

The figure displays a binned scatter plot between idiosyncratic return comovement and Hoberg & Phillips (2010) product-similarity scores, after winsorization at 1 and 99 percents. Hoberg-Phillips product-similarity score are available for the 1989–2010 subperiod of our sample period. The idiosyncratic stock return comovement between firms i and j in year t, ρ_{ijt}, is estimated using equations (1) and (2) in the text. Each variable is grouped in 40 bins and corresponding arithmetic averages are reported in the scatter plot as blue dots. The red line reports the fitted values of a linear regression estimated on the underlying data (34,925,933 observations).

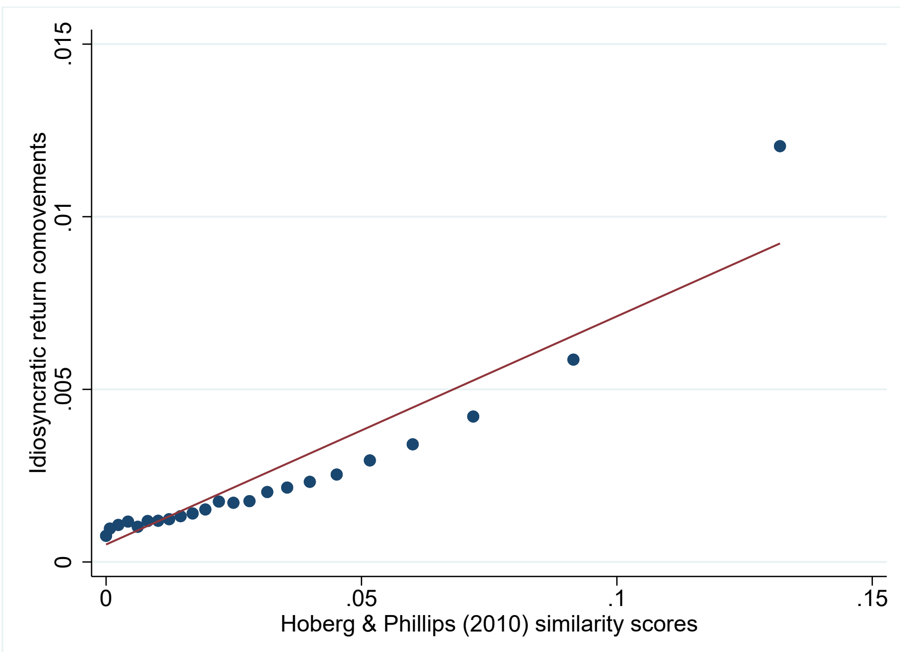


Figure 3: **Significant Import-Tariff Cuts in 4-digit SIC Manufacturing Industries, 1975–2005**

As in Frésard and Valta (2016), a significant tariff cut is at least three times the industry's average tariff change (positive or negative) over their pre-event sample period. After imposing a number of Compustat data restrictions, their total sample is 91 significant cuts, 1975–2005. As we do not require those Compustat data restrictions, we initially identify 477 significant tariff cuts, of which 324 represent the *first* significant cut experienced by any given 4-digit SIC manufacturing industry. Merging these 324 industries with our estimates of the idiosyncratic return comovement between firms i and j in year t (ρ_{ijt}, estimated using equations (1) and (2) in the text), and requiring a minimum of five listed rival firms to be available per treated 4-digit SIC industry, result in our final sample of 180 initial significant tariff cuts.

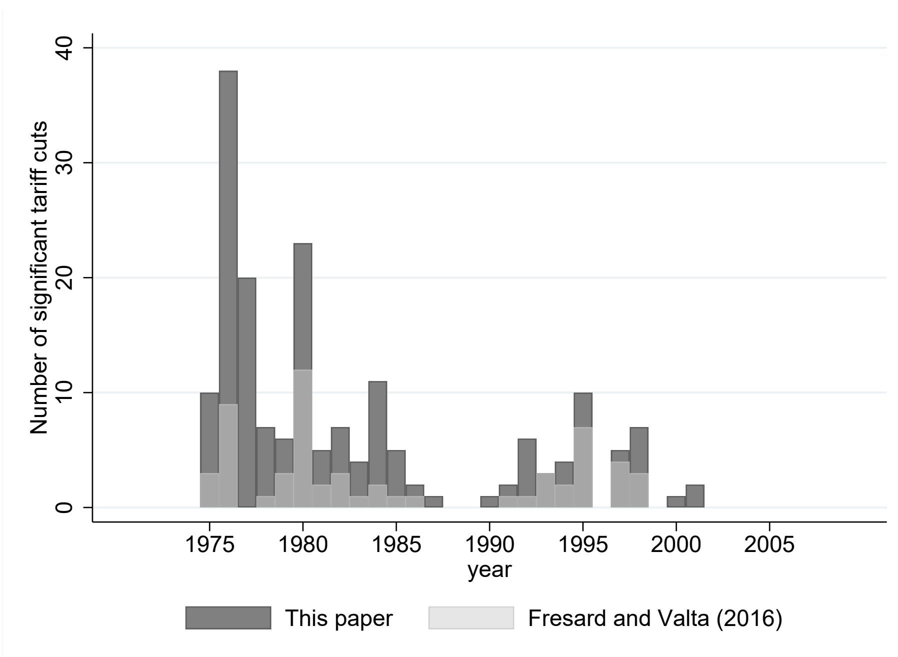


Figure 4: **Annual Comovement in Event Time in Tests of the Parallel Assumption**

The figure displays estimates of γ coefficients in the following regression:

$$\rho_{ijt} = \alpha + \beta_t + \sum_{\tau=-5}^{+5} \gamma_\tau D_{ij}^{\tau} + \epsilon_{ijt}.$$

ρ_{ijt} is the idiosyncratic stock return comovement between firms i and j in year t, which is estimated using equations (1) and (2) in the text. Firm i is always in a treated industry (experiencing a significant tariff cut in event-year 0) while firm j is either in a treated industry or not. Moreover, α is a constant term, β_t are year fixed effects, and D_{ij}^{τ} is a dummy variable that takes a value of one in event year τ if the firm-pair ij is in a treated industry and zero otherwise. Hence, the variables D_{ij}^{τ} capture the differences between the comovement of the treatment and control groups before and after the event. We follow the convention of setting D_{ij}^{-1} to zero so that D_{ij}^{τ} coefficients are differences with respect to the year prior to the event. The series of the estimated values of γ_τ provides a graphical test of the parallel trend assumption behind our difference-in-difference test approach. "95% C.I." denotes the 5% confidence interval. The sample comprises 180 significant tariff cuts in 4-digit SIC manufacturing industries, for tariff cuts over the period 1975–2005 provided in the web-site of Philip Valta (www.valta.ch).

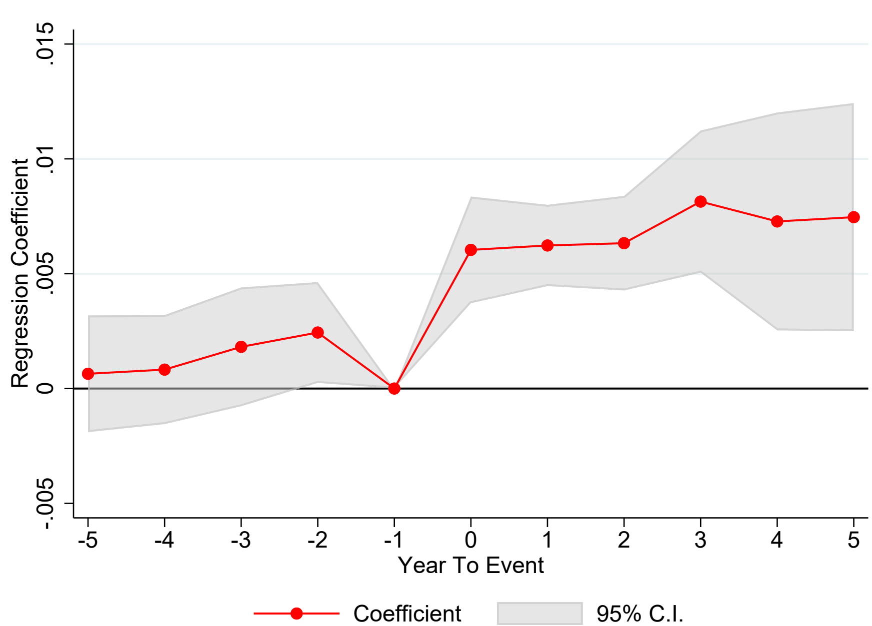
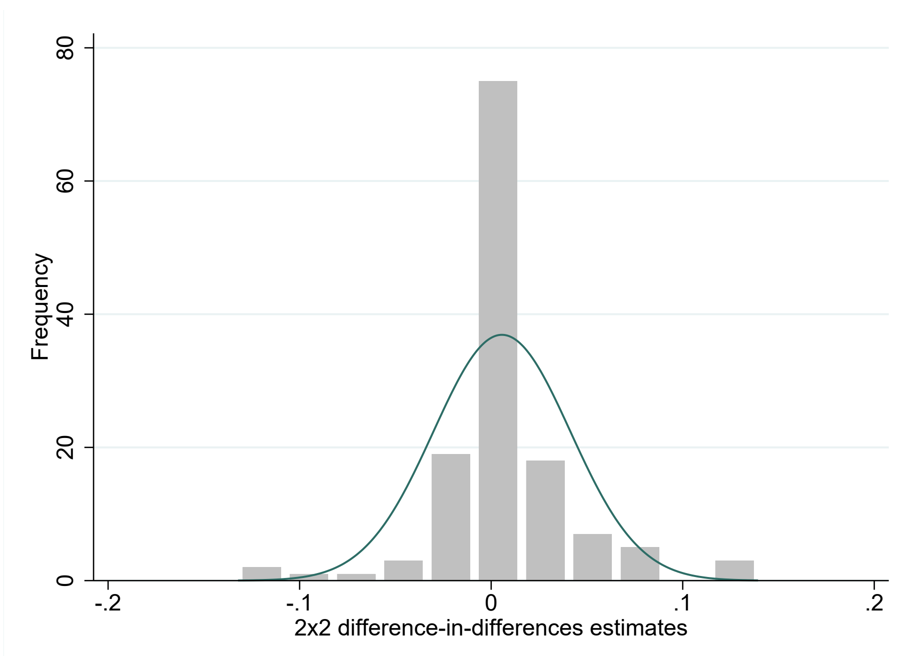


Figure 5: Frequency Distribution of the Two-Way DID Estimator

For each of 134 significant tariff cut, the two-way (2×2) DID estimator $\gamma^{2\times2}$ involves comparing two groups (one treated and one control) and two periods (one pre-event and one post-event), using the following regression specification:

$$\rho_{ijt} = \alpha_{ij} + \beta_t + \gamma^{2\times2}(TREATED_{ij} \times POST_t) + \epsilon_{ijt}$$

where α_{ij} and β_t are firm-pair and year fixed-effects, respectively, $TREATED_{ij}$ equals one if the firm pair ij is in a 4-digit SIC industry that receives a tariff cut (and zero otherwise), and $POST_t$ equals one for the post-treated periods (and zero otherwise). The estimation is performed on an eleven-year event period centered on the year of the tariff cut. The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999). Estimates are winsorized at 5% and 95%, respectively.



Internet Appendix

Competition shocks, rival reactions, and stock return comovement

June, 2024

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(*Journal of Financial and Quantitative Analysis*)

Contents

Summary

In this internet appendix, we start by reporting descriptive statistics on return comovement. Figure IA.1 displays the distribution of the annual bi-firm idiosyncratic return correlations, as defined in equation (1) in the main text. As shown, the distribution is centered around zero and well-behaved. This confirms that the return generating process used to obtain idiosyncratic returns (the Fama and French (2015) five risk factors, complemented with the 3-digit SIC industry index) captures the priced risk factors.

Table IA.1 tabulates the corresponding distribution moments (mean, median, standard deviation, skewness, kurtosis), successively adding factors to the return generating process. The importance of extracting the Fama and French (2015) five risk factors and the 3-digit SIC industry index from the raw returns to obtain idiosyncratic returns is again clearly apparent. In Table IA.1 Column (6), we also report the average R2 of the return generating process firm-year regressions. Our six factors model explain close to 18% of the daily return variance over the 1970-2010 period for our sample of Compustat-CRSP manufacturing firms.

Next, we report five different robustness tests of the significance of the treatment effect of the tariff cuts reported in Table 5 in the main text. The first test progressively saturates the baseline regression model with fixed effects, capturing time-varying industry-level latent factors (Table IA.2). The second test computes the treatment effect using treated firms only (Table IA.3), while the third test restricts the sample to firm ij pairs to the ones existing at least one year before the treatment (Table IA.4). The fourth test reports 4-digit SIC industry and year double clustered standard errors (Table IA.5).

In the fifth test (Table IA.6), we compute significance levels using a randomized treatment

procedure (Cunningham, 2021). This randomized treatment procedure involves obtaining p-values from random permutations of the data under the null hypothesis of no treatment effect and computing the number of times we observe (by chance) a test statistic that rejects this null. More precisely, we proceed as follows:

1. Estimate the regression on the original dataset and store the estimated test statistic of the coefficient of interest (the coefficient of $TREATED_{ij} \times POST_{ijt}$ in the present case—see equation 7 in the text).

2. Shuffle (randomly mix) the variable of interest to generate a randomized sample.

3. Estimate the regression on the randomized sample and store the randomized test statistic of the coefficient of interest.

4. Repeat steps 2 and 3 above one hundred times (a restriction reflecting the size of our dataset).

5. Compute the number of times the randomized test statistic exceeds the critical value in a two-tails test.

6. Divide the number in step 5 by one hundred (the number of randomized samples) to obtain the randomized p-value.

In the seventh and final test, we explore the relations between return comovement and business cycles. Figure IA.2 focuses on aggregate economic downturns, identified using the NBER recession indicator. The figure reports the evolution of the average idiosyncratic comovement from 1970 to 2010 (the red curve) for our Compustat-CRSP sample of manufacturing firms with corresponding NBER recession periods (the grey bars). Average idiosyncratic comovement peaks during aggregate recessions, especially during the 1980-1982, 2001 and 2008-2009 episodes. Note, however, that whether aggregate recessions drive increase in comovement or vice-versa is unclear as the 2000 comovement peaks clearly predates the 2001 recession.

To identify 3-digit SIC industry level recession periods, we start by computing 36 months rolling-window industry-level compound returns. A given 3-digit SIC industry month is defined to be in recession if the corresponding compound return is negative. Recession years are years containing at least one such month of recession. Stock returns are collected in the CRSP Monthly database and all ordinary shares (share codes 10 and 11) listed on the NYSE, AMEX and Nasdaq (exchange codes 1, 2 and 3) are included in the sample. 3-digit SIC industry returns are value-weighted.

Armed with this industry-level recession indicator variable, we study the effect of industry-level recessions on within industry comovement (ρ_{ijt}). Importantly, as indicated by the header of Table IA.7, this analysis is performed at the firm-pair level (the ij subscript, where i and j always belong to the same industry). Finally, to check whether our results are driven by recessions and not tariff cuts, we include both the industry recession indicator variable and the tariff cut indicator variable in our regression specifications.

The results in Table IA.7 indicate, at the 10% confidence level (see columns 1 through 4), the presence of a positive relation between within-industry comovement and industry-level downturns. As expected, this positive correlation disappears once industry fixed effects are included in the regression specification (columns 5 through 8). We note also that, across all specifications, the tariff-cut treatment effect remains positive and highly significant, confirming our baseline results reported in Table 5 in the main text.[26]

Table IA 1: Annual return comovement: descriptive statistics

The table reports characteristics of the distribution of annual idiosyncratic within-industry return correlation coefficients ρ_{ijt} between firms i and j, estimated using a minimum of 90 daily returns observations within each calendar year, as follows:

$$\rho_{ijt} \equiv \frac{COV(\epsilon_{it}, \epsilon_{jt})}{\sigma_{\epsilon_{it}} \sigma_{\epsilon_{jt}}}$$

where σ indicates standard deviation, and ϵ is the residual from the following daily return-generating factor model:

$$r_{it} = \alpha_i + \beta_{\mathbf{i}} \mathbf{F_t} + \epsilon_{it}$$

The daily return factors are $\mathbf{F} = [R_M - R_F,\ SMB,\ HML,\ RMW,\ CMA,\ I_{SIC3}]$, where $R_M - R_F$ is the excess return on the value-weighted market portfolio, SMB, HML, RMW and CMA are the returns on the Fama and French (2015) long-short size, book-to-market, profitability and investment portfolios, and the industry index I_{SIC3} is the value-weighted portfolio of all CRSP firms, excluding firm i, that are in firm i's 3-digit SIC (standard Industrial Classification) industry. Column (6) shows the average R^2 of the return generating factor model. The first row shows the descriptive statistics for the raw-return correlation coefficient $(COV(r_{it}, r_{jt})/\sigma_{r_{it}} \sigma_{r_{jt}})$ unadjusted for any risk factor exposures. Rows 2–5 successively add more risk factors: 1f ρ_{ijt} adjusts for the market portfolio only; 3f ρ_{ijt} adjusts for the first three risk factors; 5f ρ_{ijt} the first five risk factors; and 6fρ_{ijt} adjusts for all six factors. The sample period is 1970–2010 and encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999).

Factor adjustment	Mean (1)	Median (2)	Stdev (3)	Skewness (4)	Kurtosis (5)	R^2 (6)
Raw ρ_{ijt}	-0.0108	-0.0107	0.0610	-0.0694	4.4188	
1f ρ_{ijt}	0.0146	0.0132	0.0726	0.2103	4.0516	0.1055
3f ρ_{ijt}	0.0021	0.0013	0.0694	0.1414	3.8167	0.1474
5f ρ_{ijt}	0.0020	0.0013	0.0694	0.1191	3.6854	0.1731
6f ρ_{ijt}	0.0017	0.0011	0.0687	0.0791	3.5063	0.1896

[26] Table IA.7 differs from the paper's main analysis (Table 5) in that it examines the interaction between two shocks: the tariff cut and the business cycle downturn. Our baseline model specification is more powerful as it compares firm-pairs across treated and untreated industries while Table IA.7 focuses exclusively on within-industry comovement.

Table IA 2: **Effect of tariff cuts on return comovement: adding fixed-effects structures**

The table shows coefficient estimates of the average treatment effect of tariff cuts using the following six panel regressions, estimated over the period 1970–2010:

$$
\begin{aligned}
(1)\quad \rho_{ijt} &= \alpha + \beta_t + \mathbf{CONTROLS}'\mu + \delta(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt} \\
(2)\quad \rho_{ijt} &= \alpha_i + \beta_t + \mathbf{CONTROLS}'\mu + \delta(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt} \\
(3)\quad \rho_{ijt} &= \alpha + \beta_t + \gamma_{SIC3} + \mathbf{CONTROLS}'\mu + \delta(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt} \\
(4)\quad \rho_{ijt} &= \alpha + \gamma_{SIC3\times Year} + \mathbf{CONTROLS}'\mu + \delta(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt} \\
(5)\quad \rho_{ijt} &= \alpha_i + \gamma_{SIC3\times Year} + \mathbf{CONTROLS}'\mu + \delta(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt} \\
(6)\quad \rho_{ijt} &= \alpha_{ij} + \gamma_{SIC3\times Year} + \mathbf{CONTROLS}'\mu + \delta(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt}
\end{aligned}
$$

Equation (1) includes only year fixed-effects. Equation (2) adds firm i fixed-effects. Equation (3) drops firm i fixed-effects but add industry (3-digit SIC code level) fixed-effects. Equation (4) includes industry fixed-effects interacted with year fixed-effects. Equation (5) adds firm i fixed-effects. Equation (6) replaces firm i fixed-effects by firm ij fixed-effects. Columns (1) to (6) report corresponding results, with the fixed-effects structure describes in the bottom part of the table. Like in Table 5 in the paper, the idiosyncratic stock return comovement between firms i and j in year t, ρ_{ijt}, is estimated using equations (1) and (2) in the text. Firm i is always in a treated industry while firm j is either in a treated industry or not. The dependent variable is the signed value of the annual comovement ρ_{ijt}. $Treated_{ij}$ is an indicator variable equal to one if the firm pair ij is treated (their 4-digit SIC industry receives a significant tariff cut), while $Post_{ijt}$ is an indicator variable equal to one for the post-treated periods. **CONTROLS** is a vector of control variables identified in Table 2 as significant determinants of ρ_{ijt} ($BM, LEV, R\&D, CASH, INTG\ QUARTILE$ as well as the $LEADER$, HHI and $LOCATION$ dummy variables). The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999). FEs stands for fixed-effects. F is the Fisher test statistic for the joint significance of the regression coefficients. N is the number of observations. Standard errors, clustered at the level encompassing the fixed-effects structure, are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**Signed ρ_{ijt} value**					
coefficient	(1)	(2)	(3)	(4)	(5)	(6)
$AILFIMRS$: δ	0.006***	0.005***	0.006***	0.006***	0.006***	0.003**
	(0.0004)	(0.0009)	(0.0021)	(0.0021)	(0.0008)	(0.0015)
$CONTROLS$	Yes	Yes	Yes	No	Yes	Yes
Year FEs	Yes	Yes	Yes	No	No	No
Firm FEs	No	Yes	No	No	Yes	No
Firm pair FEs	No	No	No	No	No	Yes
SIC3 FEs	No	No	Yes	No	No	No
SIC3 × Year FEs	No	No	No	Yes	Yes	Yes
R^2	0.00	0.00	0.00	0.00	0.00	0.18
F	116.12	14.79	134.01	31.56	62.49	9.68
N	14,549,529	14,549,529	14,549,529	14,549,529	14,549,526	13,870,729

Table IA 3: Estimating the effect of tariff cuts with treated firms only

The table shows coefficient estimates of the average treatment effect of tariff cuts using the following two regressions, with year t running from 1970–2010:

$$
\begin{aligned}
(1)\ \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS'}\mu + \gamma POST_{ijt} + \epsilon_{ijt} \\
(2)\ \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS'}\mu \\
&\quad + \gamma_1 (POST_{ijt} \times D_{FOLLOWER_i}) + \gamma_2 (POST_{ijt} \times D_{LEADER_i}) \\
&\quad + \gamma_3 (POST_{ijt} \times (1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})) + \epsilon_{ijt}
\end{aligned}
$$

Regression (1) uses all treated firms while regression (2) splits all treated firms into industry followers and leaders, identified using a combination of market shares, cash balances, and return-on-assets. The idiosyncratic stock return comovement between firms i and j in year t, ρ_{ijt}, is estimated using Eqs. (1) and (2) in the text. Firm i is always in a treated industry while firm j is either in a treated industry or not. D_{LEADER_i} and $D_{FOLLOWER_i}$ are dummy variables that take a value of one if firm i is an industry leader or a follower, respectively, in the year prior to the year of the competition shock, and zero otherwise. Their complement is covered by the dummy $(1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})$. In Panel A the dependent variable is the signed value of the annual comovement ρ_{ijt}, while Panel B uses the absolute value of $(|\rho_{ijt}|)$. α_{ij} are firm-pair ij fixed-effects, β_t are year fixed-effects. $Post_{ijt}$ is an indicator variable equal to one for the post-treated periods. **CONTROLS** is a vector of control variables identified in Table 2 as significant determinants of ρ_{ijt} ($BM, LEV, R\&D, CASH, INTG\ QUARTILE$ as well as the $LEADER$, HHI and $LOCATION$ dummy variables). The sample of firms encompasses all treated Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999). Size effects, computed as the coefficient scaled by the standard error of ρ_{ijt}, are reported between square brackets. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the Fisher statistic obtained for a test of equality of coefficients and N is the number of observations. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**A: Signed ρ_{ijt} value**			**B: Absolute ρ_{ijt} value**		
Treatment coefficient	All firms (1)	All firms (2)	Followers v. Leaders (3)	All firms (1)	All firms (2)	Followers v. Leaders (3)
$ALLFIRMS$: γ	0.0032**	0.0033**		0.0034***	0.0033***	
	(0.0013)	(0.0013)		(0.0009)	(0.0009)	
	[0.039]	[0.040]		[0.0590]	[0.0581]	
$FOLLOWER$: γ_1			0.0033***			0.0008
			(0.0013)			0.0007
$LEADER$: γ_2			−0.0014*			0.0005
			(0.0008)			0.0005
$INBETWEEN$: γ_3			−0.0016			0.0024*
			(0.0019)			(0.0013)
$CONTROLS$	No	Yes	Yes	No	Yes	Yes
R^2	0.413	0.413	0.413	0.467	0.468	0.468
F	3.443	3.316	3.404	11.38	9.55	9.06
$\gamma_1 = \gamma_2$			0.00			0.72
N	189,592	189,592	189,592	189,592	189,592	189,592

Table IA 4: Effect of tariff cuts on return comovement restricting the sample to firm ij pairs existing at least one year before the treatment

The table shows coefficient estimates of the average treatment effect of tariff cuts using the following two panel regressions, estimated over the period 1970–2010:

$$
\begin{aligned}
(1)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS'}\mu + \gamma(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt} \\
(2)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS'}\mu \\
&\quad + \gamma_1(TREATED_{ij} \times PSOT_{ijt} \times D_{FOLLOWER_i}) + \gamma_2(TREATED_{ij} \times POST_{ijt} \times D_{LEADER_i}) \\
&\quad + \gamma_3(TREATED_{ij} \times POST_{ijt} \times (1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})) + \epsilon_{ijt}
\end{aligned}
$$

Regression (1) uses all firms while regression (2) splits all firms into industry followers and leaders, identified using a combination of market shares, cash balances, and return-on-assets. Firm i is always in a treated industry while firm j is either in a treated industry or not. D_{LEADER_i} and $D_{FOLLOWER_i}$ are dummy variables that take a value of one if firm i is an industry leader or a follower, respectively, in the year prior to the year of the competition shock, and zero otherwise. Their complement is covered by the dummy $(1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})$. The dependent variable is the signed value of the annual comovement ρ_{ijt}. α_{ij} are firm-pair ij fixed-effects, β_t are year fixed-effects. $TREATED_{ij}$ is an indicator variable equal to one if the firm pair ij is treated (their 4-digit SIC industry receives a significant tariff cut), while $POST_{ijt}$ is an indicator variable equal to one for the post-treated periods. **CONTROLS** is a vector of control variables identified in Table 2 as significant determinants of ρ_{ijt} ($BM, LEV, R\&D, CASH, INTG$ $QUARTILE$ as well as the $LEADER$, HHI and $LOCATION$ dummy variables). The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999). The sample is restricted to firm ij pairs that exist at least one year before the treatment year. Size effects, computed as the coefficient scaled by the standard error of ρ_{ijt}, are reported between square brackets. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the Fisher statistic obtained for a test of equality of coefficients and N is the number of observations. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**Signed return comovement** ρ_{ijt}		
Treatment coefficient	All firms		Followers v. Leaders
	(1)	(2)	(3)
$ALLFIRMS$: γ	0.0026**	0.0026**	
	(0.0011)	(0.0011)	
	[0.0380]	[0.0378]	
$FOLLOWER$: γ_1			0.0056***
			(0.0012)
$LEADER$: γ_2			−0.0045***
			(0.0014)
$INBETWEEN$: γ_3			−0.0026
			(0.0027)
$CONTROLS$	No	Yes	Yes
R^2	0.171	0.171	0.171
F	23.27	20.28	19.89
$\gamma_1 = \gamma_2$			0.00
N	7,108,553	7,108,553	7,108,553

Table IA 5: Effect of tariff cuts on return comovement with 4-digit SIC industry and year double clustered standard errors

The table shows coefficient estimates of the average treatment effect of tariff cuts using the following two panel regressions, estimated over the period 1970–2010:

$$
\begin{aligned}
(1)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS}'\mu + \gamma(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt} \\
(2)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{CONTROLS}'\mu \\
&\quad + \gamma_1(TREATED_{ij} \times POST_{ijt} \times D_{FOLLOWER_i}) + \gamma_2(TREATED_{ij} \times POST_{ijt} \times D_{LEADER_i}) \\
&\quad + \gamma_3(TREATED_{ij} \times POST_{ijt} \times (1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})) + \epsilon_{ijt}
\end{aligned}
$$

Regression (1) uses all firms while regression (2) splits all firms into industry followers and leaders, identified using a combination of market shares, cash balances, and return-on-assets. Firm i is always in a treated industry while firm j is either in a treated industry or not. D_{LEADER_i} and $D_{FOLLOWER_i}$ are dummy variables that take a value of one if firm i is an industry leader or a follower, respectively, in the year prior to the year of the competition shock, and zero otherwise. Their complement is covered by the dummy $(1 - D_{FOLLOWER_i}) \times (1 - D_{LEADER_i})$. The dependent variable is the signed value of the annual comovement ρ_{ijt}. α_{ij} are firm-pair ij fixed-effects, β_t are year fixed-effects. $TREATED_{ij}$ is an indicator variable equal to one if the firm pair ij is treated (their 4-digit SIC industry receives a significant tariff cut), while $POST_{ijt}$ is an indicator variable equal to one for the post-treated periods. **CONTROLS** is a vector of control variables identified in Table 2 as significant determinants of ρ_{ijt} ($BM, LEV, R\&D, CASH, INTG\ QUARTILE$ as well as the $LEADER$, HHI and $LOCATION$ dummy variables). The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999). Size effects, computed as the coefficient scaled by the standard error of ρ_{ijt}, are reported between square brackets. Standard errors are double clustered at the 4-digit SIC industry and year levels. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the Fisher statistic obtained for a test of equality of coefficients and N is the number of observations. Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**Signed return comovement** ρ_{ijt}		
Treatment	All firms		Followers v. Leaders
coefficient	(1)	(2)	(3)
$ALLFIRMS$: γ	0.0026*	0.0026*	
	(0.0015)	(0.0015)	
	[0.0386]	[0.0384]	
$FOLLOWER$: γ_1			0.0033**
			(0.0013)
$LEADER$: γ_2			−0.0014*
			(0.0008)
$INBETWEEN$: γ_3			−0.0011
			(0.0023)
$CONTROLS$	No	Yes	Yes
R^2	0.182	0.182	0.182
F	3.113	9.413	8.408
$\gamma_1 = \gamma_2$			0.00
N	13,870,729	13,870,729	13,870,729

Table IA 6: **Significance levels with randomized treatment**

The table shows coefficient estimates of the average treatment effect of tariff cuts using the following panel data regression, estimated over the period 1970–2010:

$$\rho_{ijt} = \alpha_{ij} + \beta_t + \mathbf{CONTROLS'}\mu + \gamma(TREATED_{ij} \times POST_{ijt}) + \epsilon_{ijt}, \quad t = 1970, .., 2010$$

The dependent variable is the signed value of the annual comovement ρ_{ijt}. α_{ij} are firm-pair ij fixed-effects, β_t are year fixed-effects. $TREATED_{ij}$ is an indicator variable equal to one if the firm pair ij is treated (their 4-digit SIC industry receives a significant tariff cut), while $POST_{ijt}$ is an indicator variable equal to one for the post-treated periods. **CONTROLS** is a vector of control variables identified in Table 2 as significant determinants of ρ_{ijt} ($BM, LEV, R\&D, CASH, INTG\ QUARTILE$ as well as the $LEADER$, HHI and $LOCATION$ dummy variables). The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999). F is the Fisher test statistic for the joint significance of the regression coefficients. The p-values reported in parentheses are obtained using the following procedure, repeated 100 times: re-estimate γ after randomly shuffling the interaction variable $TREATED_{ij} \times POST_{ijt}$. The p-value, reported between parentheses, is then the number of times the absolute value of the estimated γ based on the randomized sample exceeds in absolute value the γ coefficient obtained on the original sample, divided by 100 (the number of randomized samples). Standard errors are in parentheses, and *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**Signed return comovement** ρ_{ijt}		
Treatment coefficient	All firms		Followers v. Leaders
	(1)	(2)	(3)
$ALLFIRMS$: γ	0.003**	0.003**	
	(0.02)	(0.02)	
$FOLLOWER$: γ_1			0.004***
			(0.00)
$LEADER$: γ_2			−0.002**
			(0.05)
$INBETWEEN$: γ_3			−0.000
			(0.53)
$CONTROLS$	No	Yes	Yes
R^2	0.223	0.223	0.223
F	7.012	18.090	7.841
N	14,549,529	14,549,529	14,549,529

Table IA 7: Within-industry comovement and industry-level recessions

The table shows coefficient estimates of the following eigth regressions:

$$
\begin{array}{lrcl}
(1) & \rho_{ijt} & = & \alpha + \beta_t + \gamma TREATED_{ijt} + \epsilon_{ijt} \\
(2) & \rho_{ijt} & = & \alpha + \beta_t + \delta RECESS_{ijt} + \epsilon_{ijt} \\
(3) & \rho_{ijt} & = & \alpha + \beta_t + \gamma TREATED_{ijt} + \delta RECESS_{ijt} + \epsilon_{ijt} \\
(4) & \rho_{ijt} & = & \alpha + \beta_t + \gamma TREATED_{ijt} + \delta RECESS_{ijt} + \mu(TREATED_{ijt} \times RECESS_{ijt}) + \epsilon_{ijt} \\
(5) & \rho_{ijt} & = & \alpha_{SIC3} + \beta_t + \gamma TREATED_{ijt} + \epsilon_{ijt} \\
(6) & \rho_{ijt} & = & \alpha_{SIC3} + \beta_t + \delta RECESS_{ijt} + \epsilon_{ijt} \\
(7) & \rho_{ijt} & = & \alpha_{SIC3} + \beta_t + \gamma TREATED_{ijt} + \delta RECESS_{ijt} + \epsilon_{ijt} \\
(8) & \rho_{ijt} & = & \alpha_{SIC3} + \beta_t + \gamma TREATED_{ijt} + \delta RECESS_{ijt} + \mu(TREATED_{ijt} \times Recess_{ijt}) + \epsilon_{ijt}
\end{array}
$$

where $TREATED_{ijt}$ is equal to one if the firm pair ij belongs to an industry subject to a tariff cut in year t, $RECESS_{ijt}$ is equal to one if the firm pair ij belongs to an industry in recession in year t, α_{SIC3} are industry fixed-effects and β_t are year fixed-effects. The dependent variable is the signed value of the annual comovement ρ_{ijt}. A given 3-digit SIC industry month is in recession if the rolling last 36 months (starting at the current month) compounded return is negative. Recession years ($RECESS_{ijt}$) is equal to one years containing at least one such month of recession. The sample period is 1970–2010. The sample of firms encompasses all Compustat-CRSP universe manufacturing firms (4-digit SIC codes 2000 to 3999) listed on the NYSE, AMEX and Nasdaq. The sample of firm pair comovements ρ_{ijt} is limited to within 3-digit SIC industry firm pairs ij. Standard errors are clustered at 3-digit SIC industry level and reported between parentheses under coefficient estimates. R^2 is for R-squared, F is the Fisher test statistic for the joint significance of the regression coefficients. N is the number of observations. *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Dependent variable:	**Signed ρ_{ijt} value**							
Treament coefficients	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$TREATED_{ijt}$: γ	0.0046***		0.0046***	0.0045***	0.0053***		0.0053***	0.0052***
	(0.0013)		(0.0013)	(0.0014)	(0.0012)		(0.0013)	(0.0013)
$RECESS_{ijt}$: δ		0.0031*	0.0031*	0.0029*		0.0010	0.0008	0.0005
		(0.0017)	(0.0017)	(0.0016)		(0.0011)	(0.0011)	(0.0011)
$TREATED_{ijt} \times RECESS_{ijt}$: μ				0.0003				0.0007
				(0.0008)				(0.0009)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC fixed-effects	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01
F	13.02	3.21	15.20	12.28	18.60	0.81	36.28	25.54
N	491,142	491,142	491,142	491,142	491,142	491,142	491,142	491,142

Figure IA 1: **Frequency distribution of annual idiosyncratic return comovement**

The figure plots frequency distribution of the annual bi-firm idiosyncratic return correlation coefficients ρ_{ijt}, where

$$\rho_{ijt} \equiv \frac{COV(\epsilon_{it}, \epsilon_{jt})}{\sigma_{\epsilon_{it}} \sigma_{\epsilon_{jt}}}$$

σ indicates standard deviation, and the error term ϵ_{it} is from the following six-factor model generating daily stock returns:

$$r_{it} = \alpha_i + \beta_{\mathbf{i}} \mathbf{F_t} + \epsilon_{it}$$

The daily return factors are $\mathbf{F} = [R_M - R_F,\ SMB,\ HML,\ RMW,\ CMA,\ I_{SIC3}]$, where $R_M - R_F$ is the excess return on the value-weighted market portfolio, SMB, HML, RMW and CMA are the returns on the Fama and French (2015) long-short size, book-to-market, profitability and investment portfolios, and the industry index I_{SIC3} is the value-weighted portfolio of all CRSP firms, excluding firm i, that are in firm i's 3-digit SIC (standard Industrial Classification) manufacturing industry (SIC 2000–3999). Each ρ_{ijt} is estimated using a minimum of 90 daily returns within a each calendar year t. Total sample period is 1970–2010.

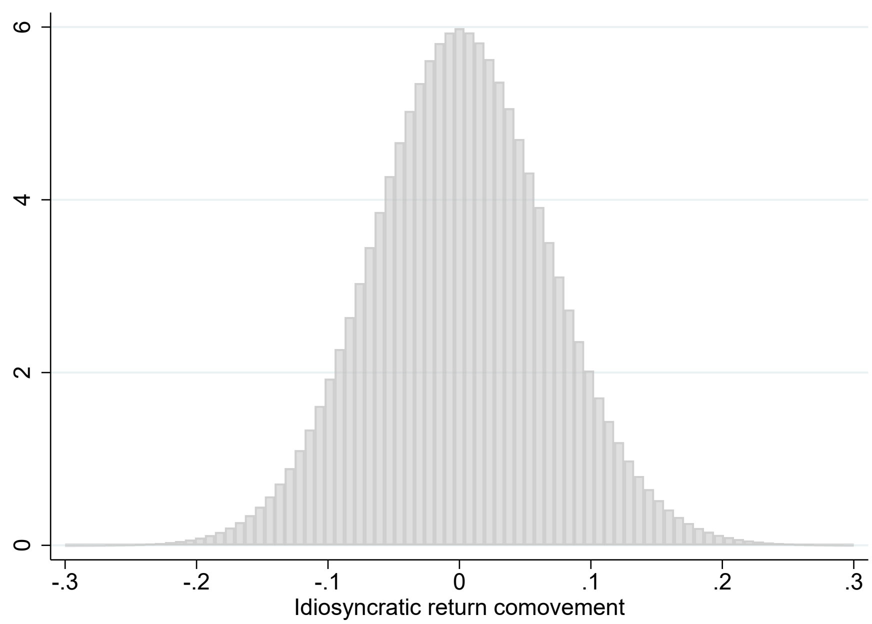

Figure IA 2: Average comovement and NBER recessions

The figure displays the evolution through time of yearly average idiosyncratic comovements ρ_t (red curve) and NBER recessions (shaded areas) for the 1970–2010 period. ρ_t is the equally weighted arithmetic average of idiosyncratic stock return comovement between firms i and j in year t, ρ_{ijt} (14,549,929 observation), estimated using Eqs. (1) and (2) in the text.