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Competition Shocks, rival reactions and return comovement

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Competition shocks, rival reactions, and return comovement

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Abstract

We estimate changes in within-industry stock-return comovement caused by the reaction of rival firms to significant tariff cuts. In theory, rivals react by either increasing or decreasing product differentiation. Increased differentiation lowers cash flow correlation and return comovement, while reduced differentiation increases comovement. Large-sample tests show that tariff cuts in manufacturing industries increase comovement and more so for within-industry 'followers' than 'leaders'. The notion that this comovement-increase reflects efficiency-enhancing rival reactions is also supported by evidence of increased cost-efficiency measures. One channel for this efficiency-increase is M&A activity among industry followers.

GEL classification: G34, G38, L10, L25

Keywords: Return comovement, inframarginal rent, competition shock, rival reaction, product differentiation, scale economies, industry follower

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An important but largely unanswered empirical question in industrial economics is how rival firms tend to react to increased industry competition. We focus on two broad classes of strategic reactions, both of which are designed to protect inframarginal rents, and develop a novel large-sample empirical test with the power to discriminate between the two. In the first of these two mutually exclusive classes of strategic reactions, rivals use research and development (R&D) to increase the firm's product-line differentiation and endogenous entry deterrence (Arrow, 1962; Salop, 1979; Sutton, 1991). Practical examples include adding new features to existing products (a camera to the smart-phone), introducing an entirely new product (Tesla's electric car), and dropping a product that to some extent overlaps with the products of rival firms (Volvo eliminating its production of diesel engines).

The second class of strategic reaction is the opposite to the first: reduce product differentiation in order to lower costs of production, e.g. by taking advantage of scale economies. This may be achieved by either lowering R&D expenses altogether (Schumpeter, 1943) or focusing R&D on developing a more cost-efficient production technology (Spence, 1984). For example, if Ford and GM both 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). This response may also vary within the industry as the R&D expenditures needed to go neck-and-neck with Tesla may require a pre-shock level of inframarginal rents that is available to the industry leaders but not necessarily to their followers or "industry laggards" (Aghion, Bloom, Blundell, Griffith, and Howitt, 2005).

Direct measures of whether rivals react by increasing or lowering product differentiation are, of course, inherently difficult to obtain on a large-sample basis. The fundamental measurement problem is that firms' strategic decisions that involve marginal changes in product characteristics and quality, as well as in operating efficiencies, are largely unobservable to the econometrician. Also, even observable changes in R&D cannot resolve this inference problem. As research shows, R&D are often used for *both* product- and process-based technological improvements, thus affecting *both* product differentiation and cost efficiency (Shaked and Sutton, 1987; Bena, Ortiz-Molina, and

Simintzi, 2018; Bellstam, Bhagat, and Cookson, 2019; Hoberg and Maksimovic, 2019).

Our novel empirical test strategy involves estimating the change in rival firms' bi-firm idiosyncratic stock return comovement (henceforth, return comovement) caused by a large sample of tariff reductions in U.S. manufacturing industries. Our estimated treatment effect is particularly informative as it measures the stock market's evaluation of how rival reactions are expected to change the underlying within-industry cash-flow correlations. As such, it is a readily available summary statistic for *any* form of rival reaction. As we explain in Section I below, our estimated treatment effect is also sufficient to discriminate between the two broad classes of hypotheses for rival reactions—increasing versus lowering product differentiation. The availability of stock return data allows not only an economy-wide analysis of these two fundamentally different rival reactions but also conditioning the peer-firm reaction on observable industry and firm characteristics.

We measure the within-industry return comovement between firms i and j over year t (denoted ρ_{ijt}) after removing not only the influence of common risk factors (Fama and French, 2015) but also the firm's exposure to its own major 3-digit Standard Industrial Classification (SIC) industry portfolio. Our removal of the firm's exposure to the average industry stock return is important as it would otherwise mask the within-industry (firm-level) rival reactions to the industry shocks. In other words, removing the average industry return helps identify idiosyncratic within-industry valuation effects. We employ a difference-in-difference (DID) test approach, which controls for changes in ρ_{ijt} that are unrelated to the tariff shock itself.

The following examples illustrate why we remove the industry average return when estimating the return comovement. While the invention of a more powerful micro-chip technology may be positive for the smart-phone industry as a whole (through increased future consumer demand), the innovation may be negative for some rivals—what's good for Apple may be bad for Samsung. Or, although the European restriction on diesel engines in the wake of the recent "dieselgate" scandal hurts the average car company, it hurts producers of diesel engines (Volkswagen, Peugeot, Citroën, Opel) more as it possibly benefits producers of hybrid and electric car engines (Tesla, Toyota and

Nissan).[1] In both these two examples, removing the average industry return is necessary to identify the shock-induced changes in idiosyncratic within-industry rival firm return comovement.

In our empirical analysis, we are able to double (from 91 to 180) the number of significant tariff-cuts originally identified by Frésard (2010) and Frésard and Valta (2016) for U.S. manufacturing industries (4-digit SIC codes 2000–3999). We also benefit from the tariff data made available on Valta's home page (www.valta.ch). Our larger sample is possible because our study requires fewer firm-level data to be available on Compustat (Standard&Poor). For all firms, we estimate the bi-firm idiosyncratic stock-return comovement ρ_{ijt} annually using one year of daily stock returns from CRSP (the Center for Research in Security Prices). The treatment effect of tariff cuts is then identified using the standard DID estimator for events staggered through time, with time- and firm-pair (ij) fixed effects. In the process, we confirm the parallel trend assumption (Bennet, Stulz, and Wang, 2020), and also address the potential for bias when treated firms subsequently reappear as control firms in the standard DID setup (Cengiz, Dube, Lindner, and Zipperer, 2019; Baker, Larcker, and Wang, 2021).

Given the novelty of our comovement estimates, we begin by documenting general statistical properties and cross-sectional determinants of ρ_{ijt} over the period 1970–2010, which helps validate our empirical approach from an economic perspective. For example, ρ_{ijt} is significantly positively correlated with product-similarity scores developed and analyzed by Hoberg and Phillips (2010, 2016), which is as expected when the return comovement reflects underlying business strategies of firm-pairs. Moreover, as is well known, stock returns reflect changes in firms' underlying cash flows (Collins, Kothari, Shanken, and Sloan, 1994; Kothari and Zimmerman, 1995). We add to this accounting-based evidence by showing that ρ_{ijt} predicts future cash-flow comovement. Last but nor least, we identify several cross-sectional determinants of ρ_{ijt}, such as capital structure, R&D, relative industry position, and geographical location, which confirm that ρ_{ijt} does indeed reflect economic fundamentals of rival firms.

Turning to the treatment effect of competition shocks caused by significant tariff cuts, we

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

report four major results. First and most important, for both the signed and absolute values of the return comovement, the treatment effect is positive and statistically significant on average. In the vernacular of Section I, this suggests that rival peers tend to react by becoming more similar in terms of their operating strategies following the competition shocks. Also important, we find that the treatment effect is concentrated among the relatively less profitable industry 'followers', which are defined relative to industry 'leaders' using a combination of market shares, cash balances, and return-on-assets (ROA). In other words, competition shocks caused by significant tariff cuts have the most significant consequences for the rival peers with relatively low levels of inframarginal rents. While an intuitively reasonable finding, ours is the first study to identify—across a large sample of four-digit SIC manufacturing industries—this within-industry differential rival firm reaction to increased competition.

Third, we show that, following tariff cuts, cash-flow based measures of cost efficiencies (functions of cost-of-goods-sold or COGS, R&D, working capital, and employment) also increase significantly. This is reassuring since it directly supports that rival firms react by implementing cost-reducing operating strategies, which in turn leads to market anticipation of increased within-industry stock return comovement. Fourth, we single out within-industry merger activity (M&As) as one of several mechanisms that possibly drives the estimated increase in firm-level cost-efficiencies following tariff cuts. Consistent with cost-savings driving synergy gains in large-sample studies of M&As (Eckbo, 2014; Dessaint, Eckbo, and Golubov, 2021), we find a statistically significant increase in the probability that industry followers are involved in M&As in the wake of tariff cuts. Moreover, a triple DID analysis shows that this increase in M&A activity itself leads to an increase in future within-industry stock-return comovement, as expected under our cost-efficiency hypothesis describing rival reactions to tariff cuts.

The remainder of the paper is organized as follows. In Section I, we introduce the concept of idiosyncratic return comovement (ρ_{ijt}) and explain our central theoretical predictions. Section II characterizes the empirical properties of ρ_{ijt}. Section III presents the paper's main empirical analysis—the treatment effect of competition shocks—with robustness issues discussed in Section

IV. Section V examines effects of tariff cuts on merger activity, which possibly channels rival reactions to increase cost efficiency. Section VI concludes the paper.

I Predicting comovement changes

In this section, we present two mutually exclusive hypotheses for how ρ_{ijt} may be affected by shocks to industry competition.

I.A Comovement definition

Let ρ_{ijt} denote the bi-firm correlation coefficient of the idiosyncratic stock returns ϵ_i and ϵ_j of firms i and j in year t, which is estimated using a minimum of 90 daily stock returns within the calendar year:

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

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} in the following return generating process for firm i:

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

F is a vector of the 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.

As explained in the introduction, we include the industry index in the model generating expected return so as to remove the average industry-wide valuation effect of industry-specific shocks to competition. Since we estimate Eq. (2) annually on a rolling basis, we control for time-series changes in the factor exposures (β), which may impact return correlations (Hanley and Hoberg, 2019). Our main empirical conclusions are also robust to using a 4-digit SIC rather than a 3-digit industry index in regression Eq. (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); and including the liquidity factor ("low-minus-high" stock-turnover portfolio) developed and tested in Eckbo and Norli (2005) as an additional pricing factor.

I.B Two mutually exclusive hypotheses

The menu of rivals' strategic responses to shocks increasing industry competition is wide-ranging and complex (Shapiro, 2011). Consistent with theory, these strategic responses fall into one of two distinct groups, both of which are designed to protect against an erosion of inframarginal rents. The first involves increasing product differentiation (Hotelling, 1929; Arrow, 1962; Salop, 1979). In the second broad category, the firm reduces investment in product differentiation and instead works to increase cost-efficiencies and scale economies (Schumpeter, 1943; Spence, 1984). Below, we illustrate implications for changes in ρ_{ijt} that allows us to empirically discriminate between these two broad categories of rival firm responses.

First, suppose rivals react to a competition-increasing shock by choosing to become *more differentiated*. 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 and hence lowers ρ_{ijt}. This scenario underlies the upper branch of Figure I, where a positive shock to industry competition leads to rivals becoming more differentiated. Since $-1 \leq \rho_{ijt} \leq 1$, we have that $\rho_{ijt} \to 0$ from either above or below zero: the absolute value of ρ_{ijt} declines. In other words, with greater differentiation, rival i's firm-specific information is now less relevant to the equity-pricing of rival j. In sum, and denoting the absolute value of the change in ρ_{ijt} as $\Delta|\rho_{ij}|$:

Hypothesis 1: *If rivals react to competition shocks by becoming more differentiated (less similar), then $\rho_{ijt} \to 0$ from initial values of ρ_{ijt} that are either above or below 0: $\Delta|\rho_{ij}| < 0$.*

In the second broad scenario, depicted in the lower-left branch of Figure I, rivals instead react by becoming *less differentiated*. While lowering product differentiation (e.g., 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 reduces 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 perhaps taking advantage of scale-economies.[2]

As rival firms become less differentiated, their cash flows become more highly correlated: $\rho_{ijt} \to \pm 1$ from either positive or negative initial values of ρ_{ijt}: $\Delta|\rho_{ij}| > 0$. As a result, new firm-specific cash-flow information pertaining to the equity pricing of one firm becomes more highly relevant for the equity pricing of the other. Moreover, as indicated by the two arrows in the lower right of the figure, there are now two scenarios to consider as the change in ρ_{ij} may be either positive or negative. That is, as the two rivals become more closely aligned in terms of both products and operations, new firm-specific information that benefits one firm may either benefit or hurt the rival peer.

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 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

[2] The car industry 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.

(what's good for Apple is bad for Samsung), with the effect being stronger after the competition shock. Hypothesis H2 summarizes these implications:

Hypothesis 2: *If rivals react to competition shocks by becoming less differentiated (more similar), then $\rho_{ijt} \to +1$ from initial positive values, and $\rho_{ijt} \to -1$ from initial negative values: $\Delta|\rho_{ij}| \geq 0$.*

While our main conclusions come from testing the effect of tariff cuts on ρ_{ijt}, we also provide corroborating evidence on cash-flow effects of our competition shocks. These include changes in cash-flow ratios such as sales to costs of good sold, working capital to property, plant and equipment, employees to total assets, and R&D to total assets. The latter ratio is particularly interesting since R&D has been shown to play an important role in both product- and process-based innovation. (Bellstam, Bhagat, and Cookson, 2019; Bena, Ortiz-Molina, and Simintzi, 2018; Hoberg and Maksimovic, 2019). Evidence of an increase in R&D intensity is consistent with both H1 and H2 since it does not indicate whether the additional R&D effort is used to develop new products or new lower-cost production processes. However, a decrease R&D tends to rule out that rivals' strategic response is one of new product development.

I.C Within-industry leaders and followers

While testing H1 versus H2 requires using all rivals in the same industry, we also partition these rivals into two groups, labelled industry 'leaders' and 'followers', respectively. Industry followers are defined relative to leaders using information on sales-based market shares and financial ratios (details in Section III.B below), which are correlated with a firm's level of quasi-rents. The idea is that, since followers likely earn smaller inframarginal rents, they are also more likely to adopt a cost-reducing strategic response to increased competition:

Hypothesis 3: *The reaction of a rival firms to competition increase depends on its level of quasi-rents. The lower the rents, the greater the incentive to react by cutting production costs 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 (Aghion, Bloom, Blundell, Griffith, and Howitt, 2005). This incentive may be particularly strong in sectors where incumbent firms are operating at similar technological levels ('neck-and-neck sectors') and where pre-innovation rents are more strongly reduced by an increase in product market competition. Moreover, as stated in H3, within industries, the marginal impact of a competition-increase on the incentives to further differentiate their product lines may differ across industry leaders and followers.

II Characteristics of annual comovement

In this section, we report general time-series and cross-sectional characteristics of ρ_{ijt} over the period January 1970 through December 2010. As detailed in Section III below, this sample period is the result of starting with (and subsequently expanding) the tariff cuts in Frésard and Valta (2016), which start in 1975 and end in 2005, and requiring an eleven-year event-window centered on the year of each tariff cut (years -5 through +5). The characteristics that we consider below include statistical properties of the pooled annual and cross-sectional frequency distribution of ρ_{ijt}, time-series persistence, correlation with the product similarity scores of (Hoberg and Phillips, 2010) and with cash-flow-based comovement and, finally, annual cross-sectional determinant of ρ_{ijt} that include both firm- and industry-level characteristics.

II.A Frequency distribution

We estimate ρ_{ijt} annually using all industrial firms (SIC codes 2000 through 3999) that are available on the daily CRSP database that also 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. Missing prices are replaced by the midpoint of the bid-ask spread. In any given calendar year, the firm must have a minimum of 90 available return observations. With these restrictions, the average annual number of firms is 1,974.

Figure II plots the frequency distribution of ρ_{ijt}. As shown, our six-factor model, which includes the 3-digit SIC industry index in addition to the five Fama and French (2015) factors, centers the distribution of ρ_{ijt} on zero—as expected when the factor model successfully captures all priced risk factors. The information reported in Table I further confirms that the frequency distribution is symmetric and centered on zero. Starting with the raw (unadjusted) return correlation in the first row, each subsequent row adds additional factors from the return generating process (Eq. 2). Thus, in the row labelled 1fρ_{ijt} we adjust for the firm's exposure tho the market return only, while the rows labelled 3fρ_{ijt}, 5fρ_{ijt} and 6fρ_{ijt} adjust for the first three factors, the first five factors and all six factors in the vector $\mathbf{F} = [r_m - r_f,\ smb,\ hml,\ rmw,\ cma,\ i_{sic3}]$. Column (6) shows that the average R^2 ranges from 10.5% when the market return is the only included risk factor to 18.9% when using the full six-factor model.[3]

II.B Comovement and product similarity scores

Hoberg and Phillips (2010) introduce a product similarity score (SS) based on product descriptions in SEC filings. SS is the (cosinus) distance between vectors of specific word binary indicators—two firms' product portfolios are more similar the greater the vector overlap. While the SS measure is driven by current product word overlap, ρ_{ijt} measures firm similarity driven by market expectations of future cash flows. In this section, we show that ρ_{ijt} and SS provide highly correlated categorization of bi-firm similarity.

SS is publicly available starting in 1989 for all Compustat firm pairs. Matching SS 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). Moreover, beginning in year 1989, we estimate the following regression with ρ_{ijt} as

[3] We also find a strong upward time-trend in the regression R^2 after year 2000. This increase occurs whether we include the market return only or all six factors in Eq. (2).

dependent variable and SS as the single regressor (with standard errors clustered at the firm-pair ij level):

$$\rho_{ijt} = \alpha_{ij} + \beta_t + \gamma SS_{ijt} + \epsilon_{ijt}, \quad t = 1989, .., 2010. \tag{3}$$

Table II shows the results, where Panel A employs our total sample firms and the sample in Panel B is restricted to single-segment companies. In both panels, the coefficient estimate γ on SS is positive and highly significant and with almost identical coefficient estimates. Also, the estimate of γ decreases from Column (1) to Column (3), which is expected since the inclusion of firm-pair fixed effects mechanically lowers the cross-sectional correlation.

While not tabulated, we also estimate the annual cross-sectional correlation between ρ_{ijt} and SS by running the first of the three regression specifications in Table II year-by-year. These annual cross-sectional regressions produce γ-estimates that are all significant at the 1% level or better except in year 1999. Moreover, the annual estimate of γ is positive in all years except years 2000 and 2001 when it turns negative. This switch from a positive to a negative correlation is almost certainly driven by the collapse of the internet bubble, which strongly affected stock returns (increasing average ρ_{ijt} significantly) but not the Hoberg-Phillips SS score. We do not pursue this issue further, however, as our inclusion of year fixed effects (β_t) accounts for time trends in ρ_{ijt}.

In sum, there is, on average, a significant and positive relation between SS and our measure of idiosyncratic comovement, further supporting the underlying assumption that our designated industry peers operate in similar product markets.

II.C Return-comovement as predictor of cash-flow comovement

It is well established that stock returns predict future cash-flows. However, the extant literature has not addressed whether stock-return comovement predicts cash-flow comovement, which is necessary for our subsequent empirical inferences back to our two central empirical hypotheses in Section I.B. Table III shows the results of estimating the following predictive regression, from 1970–2010:

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

where α_{ij} are firm-pair ij fixed-effects and β_t are year fixed-effects, respectively. 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 regression results in Table III show that, in all cases, the estimated γ coefficient is positive and highly statistically significant. In Panel A, all years from 1970 through 2010 are used for the test of statistical significance. Since overlapping rolling windows generate auto-correlation 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, as expected.

II.D Annual cross-sectional determinants

The above analysis shows that ρ_{ijt} is increasing in the Hoberg-Phillips product similarity score and a significant predictor of future cash-flow movement. In this section we perform additional cross-sectional multivariate analyses of the determinants of ρ_{ijt} over the sample period 1970–2010. Again, the purpose is to demonstrate the economic relevance of ρ_{ijt} for testing our main hypotheses in Section I.B. In each year t we use the determinants defined in Table IV as explanatory variables $\mathbf{x_{ijt}}$ in the following cross-sectional regression:

$$\rho_{ijt} = \alpha_i + \alpha_j + \mathbf{x'_{ijt}}\mu + \epsilon_{ijt}, \quad t = 1970, .., 2010 \tag{5}$$

where α_i and α_j are, respectively, fixed effects for firms i and j. Eq (5) is estimated each year and the table reports the average annual estimate of the coefficient vector μ and its statistical significance, which controls for cross-sectional correlation as in Fama and MacBeth (1973). While these 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.

In Table IV, the seven variables that include the word "quartile" in the name are dummy-variables indicating that firms i and j 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),[4] *Lev* (leverage ratio based on long-term debts plus current liabilities), *R&D*, *Cash* (ratio of cash plus short-term investment to total assets) and *Intg* (ratio of intangible assets). Moreover, 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%.

The remaining four determinants in Table IV are *SIC3*, *Leader* (indicating that i and j are industry leaders, i.e., among the top three SIC3 firms by sales), *HHI* (indicating that i and j are in a highly concentrated SIC3 industry, with the Herfindahl Index HHI exceeding 1,500), and *Location* (indicating that i and j are headquartered in the same state, as per the Compustat LOC field). We include *Location* 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 coefficient estimates reported in Table V strongly support the key notion underlying this paper's analysis: stock returns two firms with more similar firm and industry characteristics tend to comove more strongly. Virtually all of the quartile variables are positive and significant. Moreover, ρ_{ijt} also increases significantly in *Leader*, *HHI* and *Location*, whether or not we include

[4]Book common equity is computed as the COMPUSTAT book value of stockholders' equity, plus balance-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.

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. To check whether the p-values in in Table V are overly influenced by the extraordinary large number of observations (Lin, Lucas, and Shmueli, 2013; Harvey, 2017), Column (3) of Table V reports the average coefficient estimate based on 1,000 randomly selected sub-samples of 5% of the observations in the original sample. This robustness check confirms our inferences from the coefficient estimates reported in Column (1).[5]

Finally, the fact that the coefficient estimate for SIC3 is significant in the cross-section suggests that our inclusion of the industry index in the time series regression of Eq. (2) does not fully remove the average industry-level effect on stock returns. This residual industry impact on the error terms ϵ_{it} in Eq. (2) is not surprising since each firm is represented by a single SIC code that is updated at discrete points in time.

III Rival reactions to tariff cuts

In this section, we test our hypothesis H1 against H2 by estimating the average treatment effect 180 significant tariff cuts experienced by 4-digit SIC manufacturing industries (SIC codes 2000–3999). Moreover, we test our hypothesis H3 by conditioning the treatment effect on whether the rivals are industry leaders or followers. Finally, we corroborate our inferences based on comovement-effect by also estimate the impact of tariff cuts on cash-flow measures of production-cost efficiencies.

III.A Sampling 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

[5] As a further robustness test, we have also performed a joint test of the significance of the coefficients using Bayesian inference (Bayes factors), which is itself insensitive to the sample size (Jeffreys, 1961). This test also confirms the significance of the model in Table V.

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 may 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 'significant'. 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, restrict the sample to the *first* significant tariff cut. 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) Merge the 324 industries with the estimates of ρ_{ijt} described in Section II above, and require a minimum of five listed rival firms to be available per industry to ensure a precise estimation of the average shock to ρ_{ijt}. Requiring at least five rival firms helps improve the precision of the estimated treatment effect. This results in a final sample of 180 four-digit SIC manufacturing industries with initial significant tariff cuts.

Figure III shows the annual distribution of our sample of 180 significant import tariff reductions (the first significant cut in 180 different 4-digit SIC manufacturing industries). 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 show 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).

III.B Effects on return comovement

We use the parameter γ in the following DID regression as baseline specification to identify the average treatment effect of tariff cuts on ρ_{ijt}:

$$\rho_{ijt} = \alpha_{ij} + \beta_t + \gamma(Treated_{ij} \times Post_{ijt}) + \mathbf{Controls}'\mu + \epsilon_{ijt}, \quad t = 1970, .., 2010 \tag{6}$$

where 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 (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 V: Age, Book-to-Market, Leverage, R&D, Cash, Intangibles (all quantile indicator variables), as well as the Leader, HHI and Location dummies. 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. This approach isolates 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 VI show the γ-estimates with and without the control variables (**Controls**), respectively. Standard errors are clustered at the firm-pair (ij) level. We choose to also report results without controls because inclusion of "bad" controls possibly contaminates DID estimates (Angrist and Pischke, 2009). As shown, the treatment effect γ is positive and statistically significant 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 4.5% of the standard deviation of ρ_{ijt}, which is a large effect when considering how small the unconditional comovement values shown in the frequency distribution in Figure II above are. Moreover, of the tariff cuts, 28% of the industries experience a treatment-effect that is positive and significant at the 1% level of better, while only 9% are associated with a significantly negative treatment effect. While not tabulated, these industry-level treatment effects are obtained by expanding Eq. (6) 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.

Using the conceptual framework in Section I above, these γ-estimates fail to support hypothesis H1 but are consistent with hypothesis H2—that rival firms on average becoming less differentiated (more similar) relative to the control firms following industry shocks caused by tariff reductions. That is, rival reactions to these shocks may be to reduce differences in product offerings (reduced product differentiation) so as to realize cost-saving economies of scale—increasing the odds of survival.

While our large-sample tests for shock-induced effects on idiosyncratic return comovement is unique, it is interesting to note that our main conclusion to some extent complements that of Hoberg and Phillips (2016). They study of large exogenous shocks to military goods and services industry represented by September 11, 2001, and the post-2000 collapse of the software industry, respectively, and conclude that these shocks 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 what drives our hypothesis H2.

III.C Industry leaders versus followers

In Column (3) of Table VI, we separate industry leaders and followers, and test for differences in the effect of competition shocks on their respective average return comovement. 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 ratio 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 also achieves a split on the level of pre-shock inframarginal rents earned by leaders and follower, respectively.

The results in Column (3) allows us to infer whether the shock-induced increase in average within-industry return comovement holds for the "laggards" only. Recall that the estimated increase in within-industry comovement shown in columns (1) and (2) 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 are particularly likely to react by adopting cost-cutting operating strategies.

We use the following expanded version of regression Eq. (6) to separate the treatment effects γ_1 and γ_2 for the industry followers and leaders, respectively, and where γ_3 is the treatment effect for the remaining rival firms in between:

$$\begin{aligned}\rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{Controls}'\mu \\ &+\gamma_1(Treated_{ij} \times Post_{ijt} \times D_{Follower_i}) + \gamma_2(Treated_{ij} \times Post_{ijt} \times D_{Leader_i}) \\ &+\gamma_3(Treated_{ij} \times Post_{ijt} \times (1 - D_{Follower_i}) \times (1 - D_{Leader_i})) + \epsilon_{ijt} \qquad (7)\end{aligned}$$

where 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. The estimates of the three γ-coefficients in Column (3) are important as they show that the treatment effect of the tariff cuts is positive and significant for industry followers only. That is, $\hat{\gamma}_1 = 0.004$, 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 laggards and leaders confirm that the difference between $\hat{\gamma}_1$ and $\hat{\gamma}_2$ is statistically significant. The remaining firms experience a treatment effect that is insignificantly different from zero ($\hat{\gamma}_3 = -0.000$).

In sum, Table VI shows that the positive and significant average treatment effect is largely concentrated among industry rivals that are least profitable and with smallest market shares. The significant increase in the return comovement among this group of firms suggests that they react to the increased competition caused by tariff cuts by increasing cost efficiency measures. We next provide some direct evidence on cash-flow measures that corroborates this inference from Table VI.

III.D Effects on cost-efficiency measures

In this section, we test for the presence of cash-flow treatment effects of the tariff cuts. Panel A of Table VII shows the results of estimating the following two regression specifications, with year t running from event-window year -5 through year +5:

$$y_{it} = \alpha + \mathbf{Controls}'\mu + \beta_1 Treated_i + \beta_2 Post_t + \gamma(Treated_i \times Post_t) + \epsilon_{it} \quad (8)$$

$$\begin{aligned} y_{it} = \; & \alpha + \mathbf{Controls}'\mu + \beta_1 Treated_i + \beta_2 Post_t \\ & + \gamma_1(Treated_i \times Post_t \times D_{Follower_i}) + \gamma_2(Treated_i \times Post_t \times D_{Leader_i}) \\ & + \gamma_3(Treated_i \times Post_t \times (1 - D_{Follower_i}) \times (1 - D_{Leader_i})) + \epsilon_{it}. \end{aligned} \quad (9)$$

As dependent variable, y_{it}, we use one of the following four alternative measures of changes in cost efficiencies, listed in the same order as columns (1)–(4) in the table: (1) sales divided by the cost of goods sold and administrative expenses (COGSX), (2) R&D divided by total assets (TA), (3) working Capital (WC) divided by property, plants and equipment (PPE), and (4) the number of employees (Emp) divided by TA. 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.

All four estimated treatment effects ($\hat{\gamma}$) in Table VII are statistically significant at the 1% level. Moreover, the sign of the coefficient estimates are all consistent with the general 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). We return to this ratio in Panel B as it differs between industry leaders and followers.

Second, the negative coefficient sign in Column (2) shows that the increased competition lowers the rate of R&D spending. This is also interesting as, while supporting hypothesis H2, it fails to support the alternative hypothesis H1 that rivals react to increased competition by increasing R&D spending to develop increased product differentiation. Third, the negative coefficient on WC/PPE suggest that the rival cost-cutting strategies also involve a reduction in the need for costly working capital (perhaps by lowering inventories). Finally, the positive coefficient sign in Column (4) is also consistent with increased scale economies, which may require additional employees.

In Panel B of Table VII, we separate industry leaders from followers. Again, coefficient γ_1 is the treatment effect for industry followers while γ_2 is for industry leaders. The row labelled $\gamma_1 = \gamma_2$ reports the p-value of a Fisher test of equality of these two coefficients, which is rejected at the 1% level of significant. Notice first that, with the exception of Column (1), the sign of the coefficient estimates in the three remaining columns is identical for the two groups of firms.

The results in Panel B are new and interesting. The coefficients in Column (1) show that $Sales/COGS$ declines for industry followers while it increases for industry leaders. This suggests that, while industry leaders react to tariff cuts by implementing strategies that increase the price-cost margin, industry followers are unable to do so and suffer a margin decline. Also interesting, the coefficients on $R\&D/AT$ in Column (2) are negative and significant for *both* industry followers and leaders, indicating that neither of the two types of firms react by increasing R&D spending to meet the increased foreign competition. Furthermore, Column (3) shows a significant decline in the working capital of industry leaders only, while employment increases for both leaders and followers.

In sum, the results in Table VII provide considerable support for our inference that the significantly positive treatment effect of tariff cuts on rival firm return comovement tends to be driven by cost-cutting reaction strategies. While we have not attempted to identify the precise channel for such cost-cutting strategies—these strategies often involve private information that is inherently unobservable to the econometrician—in Section V below we turn to one example of a channel: increased within-industry M&A activity following tariff cuts. However, we first provide additional robustness checks of the treatment effect documented above.

IV Robustness issues

IV.A Satisfying the parallel assumption

An important identifying assumption behind the DID estimator in Eq. (6) is 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). In Figure IV, we follow Bennet, Stulz, and Wang (2020) and show that this parallel-trends assumption is satisfied using the estimates of δ_τ from the following regression:

$$\rho_{ijt} = \alpha + \beta_t + \sum_{\tau=-5}^{+5} \gamma_\tau D_{ij}^\tau + \epsilon_{ijt}, \tag{10}$$

where α is a constant term and D_{ij}^τ is a dummy variable that takes a value of one in year τ (relative to event year 0) if the firm-pair ij is in a treated industry (experiencing a significant tariff cut in event-year 0), and zero otherwise.

The horizontal line Figure IV means that the divergence between the comovement of the treatment and control groups remain unchanged through event time, which is equivalent to parallel developments of the two groups ($\gamma_\tau = 0$). The series of the estimated values of γ_τ in event time therefore provides a graphical representation of the parallel trend assumption test behind our DID test approach. As shown, the 1% confidence interval around the estimated treatment effects, $\hat{\gamma}_\tau$, stops including $\gamma_t = 0$ for the first time late in event year -1, which confirms the parallel assumption. We also note that, if investors receive information leading to partial anticipation of the tariff cut, the estimated treatment effect $\hat{\gamma}_\tau$ will start to rise above zero some time before the event year itself.

IV.B Ruling out a staggered-event bias

In Eq. (6) above, we estimate the average treatment effect of multiple tariff cuts that are staggered through time. Baker, Larcker, and Wang (2021) points to a potential bias as the DID estimator compares not only treated and untreated groups of firms but also treated groups across time. To illustrate, assume two identical but staggered events. From the notation in Cunninghan (2021), the Goodman-Bacon decomposition (Goodman-Bacon, 2021) shows that the DID estimator (γ^{DD}) is a weighted average of the following 2×2 DID estimators ($\gamma^{2\times2}$):[6]

$$\hat{\gamma}^{DD} = \sum_{k \neq U} s_{kU} \hat{\gamma}_{kU}^{2\times2} + \sum_{k \neq U} \sum_{l > k} s_{kl} \left[\mu_{kl} \hat{\gamma}_{kl}^{2\times2,k}] + (1 - \mu_{kl} \hat{\gamma}_{kl}^{2\times2,l}) \right] \tag{11}$$

where 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 a potential source of bias, which Baker, Larcker, and Wang (2021) show may cause $\hat{\gamma}^{DD}$ to flip sign.

Baker, Larcker, and Wang (2021) suggest a stacked regression in event time approach to solve the potential bias. Applying their approach to our large sample of staggered tariff cuts is not feasible as it would literally require hundreds of gigabytes of random-access memory. We instead follow Cunninghan (2021) and study the distribution of 2×2 DID estimators that compare, event by event, the treated and untreated groups using the following regression specification:

$$\rho_{ijt} = \alpha_{ij} + \beta_t + \gamma(Treated_{ij} \times Post_t) + \epsilon_{ijt}. \tag{12}$$

Figure V shows the histogram of the estimated values of the treatment effect γ across the 134 tariff cuts available for this test. Eliminating the fat tails by winzorizing at 5/95% produces an

[6] For each event, $\gamma^{2\times2}$ is estimated using two groups (one treated and one control) and two periods (one pre-event and one post-event).

average coefficient estimate of $\hat{\gamma} = 0.0063$ with a standard-error of 0.0021 and a Student-t statistic of 2.93. This shows that the treatment effect is robustly positive and significant also after roughly adjusting for the potential bias described above.

Table VIII provides a further perspective on the role played by the control group for our main inference about the treatment effect of the tariff cuts. In this table, we repeat the regression analysis of Table VI while dropping the control group of firms for each event. This further reduces the potential for bias caused by the control groups. As shown, both magnitudes and the statistical inferences remain the same: The treatment effect (γ) remains positive and highly significant and concentrated among the relatively low-rent industry followers.

IV.C On the economic size of the treatment effect

Recall from Figure II and Table I that the unconditional return comovement is centered around zero, with a mean (median) value of 0.0017 (0.0011) and a standard deviation of 0.0687. Values centered on zero are expected when the factor model does not omit significant priced risk factors, and it means that one cannot in general expect numerically large changes in ρ_{ijt} in response to competition shocks. This is also borne out by Table VIII, where the treatment effect, while highly significant, is relatively small after eliminating the control-firm benchmark altogether.

Of course, even if the numerical size of the treatment effect ($\Delta\rho_{ijt}$, estimated by the parameter γ) is relatively small, our three key test results strongly support hypothesis H2 while, at the same time, rejecting H1. As a reminder, these three key test results are: (1) the positive sign of the treatment effect; (2) that this effect is primarily concentrated among the relatively low-rent industry followers; and (3) that the treated firms also experience reductions in R&D and increases in cash-flow-based cost-efficiency measures. While the literature exploiting tariff cuts does not quantify how much these cuts by themselves increase industry competition, the treatment effects reported here are both economically relevant and new to the literature on industrial organization.

However, to further illustrate that $\Delta\rho_{ijt}$ will be larger when responding to a more dramatic industry shock than our tariff cuts *per se*, we turn to the effect on ρ_{ijt} among airline companies of the OPEC-driven fuel price hike in 1973. This embargo caused the oil price to increase fourfold from \$3 to \$12 per barrel. Much like a tariff cut, the exogenous embargo-shock lowers the airline industry's price-cost margin—albeit this time through a cost-increase rather than a revenue-decline. Moreover, in this illustration, we measure $\Delta\rho_{ijt}$ for the airline industry alone and not as a DID relative to a control group.

Figure VI, which is centered on 1973, plots the annual average ρ_{ijt} across eleven publicly listed national U.S. airlines that survived over the nine years from 1969 through 1977 (the figure ends just prior to the 1978 Airlines Deregulation Act). The industry index i_{SIC3} is the return on a value-weighted airline industry index formed using the public firms in SIC industry 451 and excluding firm i.[7] Also, as in our robustness Table VIII above, we do not include control firms in this illustration. Again, without the DID estimation, the value of $\Delta\rho_{ijt}$ shown in Figure VI represents the total change in ρ_{ijt} and not just the change above and beyond that of the comovement of the control-firms, hence showing more directly the size of the treatment impact.

Notice first that when we use the airlines' raw returns (unadjusted for risk and industry factors), there is no detectable impact of the 1973 embargo on the average pairwise return correlation, which is positive throughout the entire period. However, this changes when we instead use our idiosyncratic return comovement estimate. Interestingly, the comovement is negative with average value of ρ_{ijt} (-0.048) prior to 1973, which 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). That is, the 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. Moreover, as shown in Figure VI, the treatment effect of the 1973 oil embargo is large: the average ρ_{ijt} turns positive and increases to 0.171. Again, since we have removed the industry index return i_{SIC3}, this increase is driven by the individual airlines' reactions to the fuel shock—resulting in the operating policies of rival airlines becoming

[7] The industry index contains 28 public airlines in 1973. The eleven national airlines are American, Braniff, Continental, Delta, Eastern, National, Northeast, Northwest, Pan American, TWA, and United. With $N = 11$ firms, the number of pairwise correlations in this industry average is $55=\frac{N(N-1)}{2}=11*10/2$.

more highly correlated.

The industry-wide shocks caused by tariff cuts are less dramatic than the oil-price effect of the OPEC's embargo. On the other hand, the tariff cuts studied here likely produce more complex rival reactions than what may have been be feasible in the relatively homogeneous airline industry.

V Tariff cuts and M&A activity

While the above empirical analysis documents treatment effects of tariff cuts on return comovement that are consistent with product standardization to lower production costs, it does not directly reveal underlying reaction-mechanisms. One possible mechanism is cost-cutting expansion through M&As. Asset complementarities, scale economies, and product similarities are all factors that have been shown to play an important role in the pairing of bidder and target firms, both generally and in response to economic industry shocks (Mitchell and Mulherin, 1996; Harford, 2005; Srinivasan, 2020). There is also evidence that some acquirers consolidate their product offerings by discontinuing and streamlining existing product lines (Maksimovic and Phillips, 2001; Hsu, Li, Liu, and Wu, 2021). It is therefore natural to examine whether significant tariff cuts increase the propensity for rival firms to become involved in M&A transactions. This analysis tests for the presence of a causal relation running from increased foreign competition to strategic rival reactions through M& activity.

We begin the analysis by studying whether tariff cuts increase the likelihood of treated firms to become targets using the following two panel regressions, with year t running from 1981–2007:

$$ln(1 + Int_{it}^{M\&A[t,t+\tau]}) = \alpha_i + \beta_t + \mathbf{Controls}'\mu + \gamma(Treated_i \times Post_t) + \epsilon_{it} \quad (13)$$

$$\begin{aligned} ln(1 + Int_{it}^{M\&A[t,t+\tau]}) &= \alpha_i + \beta_t + \mathbf{Controls}'\mu \\ &+\gamma_1(Treated_i \times Post_t \times D_{Follower_i}) + \gamma_2(Treated_i \times Post_t \times D_{Leader_i}) \\ &+\gamma_3(Treated_i \times Post_t \times (1 - D_{Follower_i}) \times (1 - D_{Leader_i})) + \epsilon_{it} \quad (14) \end{aligned}$$

where α_i and β_t are firm- and year fixed-effects, and **Controls** is the vector of control variables from above.

The dependent variable, $Int_{it}^{M\&A[t,\tau]}$, is the number of M&As targeting firms in firm i's 3-digit SIC industry in the period $[t, t+\tau]$ scaled by the number of firms in that industry. M&A transactions are from SDC Refinitiv and include all completed acquisitions of partial interests, acquisitions of assets, acquisitions and mergers by private and public U.S. acquirers of U.S. listed targets (a total of 2,274 transactions). We include partial acquisitions and asset sales because, for some industry rivals, it may be cost-efficient to sell a division or certain assets. For the same reason, we do not follow the broader merger literature and impose a minimum transaction value.

The 2,274 M&A transactions restrict the type of transaction to those labelled by SDC as acquisition of major interest, acquisition of partial interest, acquisition of assets, acquisition, or merger. Moreover, we require both the acquirer and target firms to be U.S. domiciled, and the target to be a public listed firm operating in a manufacturing industry. Restricting the target to be listed allows us to use Compustat to measure the 3-digit SIC industry size. As in the above analysis, in any given year t, the firms used in this panel estimation are from the Compustat-CRSP universe of manufacturing firms (4-digit SIC codes 2000 to 3999) with more than five firms. The period of analysis starts in 1981 (the start of the SDC Refinitiv database) and ends in 2007 (prior to the financial crisis, which itself dramatically affected M&A activity).

Panel A of Table IX, which pools all M&As in the treated industry, shows that the estimated treatment effect (γ) is positive and significant over the event period [0,+1], where year zero is the year of the tariff cut. This gives some support to the notion that rival firms in part react to tariff cuts by restructuring their operations through M&A sales. Also, it makes sense that this treatment effect is stronger over the [0,+1] period than in the event year itself (it takes time to develop an M&A transaction) and that the effect abates over the longer windows (0,+2] and [0,+3]. Even more important, Panel B of Table IX shows that the increase in the propensity to become a target is restricted to industry followers. In columns (1) and (2), the estimated treatment effects for followers are $\hat{\gamma}_1 = 0.001$ and $\hat{\gamma}_2 = 0.002$, respectively, which are both significant at the 5% level. In contrast, for industry leaders, however, the treatment effect is negative for all windows and statistically significant at the 5% level in the event year.

In sum, it is only the low-rent rival firms who react to tariff cuts by increasing the propensity to engage in M&A transactions. To our knowledge, the evidence in Table IX is the first to show that a competition increase causes industry leaders and followers to react differently when it comes to the propensity to engage in M&A transactions. Srinivasan (2020), who also studies merger activity in response to tariff cuts (sampled from SDC and the Unites States International Trade Commission's (USTIC) web-site, 1998–2014), also finds that tariff cuts are followed (in the next year) by an increase in the merger-likelihood. While the sampling and estimation methodology in Srinivasan (2020) differ substantially from ours, our results further shows that the within-industry increase in M&A activity occurs among industry followers only. Again, this finding makes intuitive sense as industry followers are more likely than industry leaders to require cost-savings—including via M&A transactions—to survive the competition increase going forward.

In Table X, using a triple DID treatment effect estimation, we also investigate whether the M&A activity caused by tariff cuts itself affects future return comovement in the 3-digit SIC industry where the M&A activity takes place. In this industry-level analysis, we include private as well as public targets, which substantially increases the number of M&A transactions (from 2,274 transactions in Table IX to 64,597 in Table X). The panel regression specification is as follows:

$$\begin{aligned} y_{ij,t+\tau} &= \alpha_{ij} + \beta_t + \mathbf{Controls}'\mu + \gamma_1(Treated_{ij} \times Post_{ijt}) + \gamma_2 M\&A_{it} \\ &\quad + \gamma_3(M\&A_{it} \times Treated_{ij}) + \gamma_4(M\&A_{it} \times Post_{ijt}) + \gamma_5(Treated_{ij} \times Post_{ijt} \times M\&A_{it}) \\ &\quad + \epsilon_{it}, \quad t = 1981, .., 2007 \end{aligned} \tag{15}$$

Here, the dependent variable $y_{ij,t+\tau}$ is either $\rho_{ij,t+1}$ (the one-year-ahead return comovement) or $\overline{\rho_{ij,t+3}}$ (the three-years-ahead annual average comovement). As before, α_{ij} and β_t are firm-pair and period fixed effects, respectively, and **Controls** is our vector of controls. Moreover, $Treated_{ij}$ 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. $M\&A_{it}$ is defined as the frequency of M&A transactions in year t computed as the ratio of the number of M&A transactions in the 3-digit SIC industry of firm i divided by the number of listed firms in the industry. In all four columns of Table X, the triple DID coefficient estimate of γ_5 is positive and highly significant. In other words, current M&A activity following a competition increase caused by tariff cuts increases future return comovement.

Finally, as is well known, merger transactions occur in waves at the industry level (Harford, 2005; Eckbo, 2014). While our M&A activity variable covers partial acquisitions as well, we have verified that it also exhibits serial correlation. Moreover, separate investigations show that M&A activity and ρ_{ijt} are contemporaneously correlated. Therefore, future M&A activity is a potential endogenous omitted variable in Eq. (15). While not tabulated, we have tested whether the main conclusion from Table X is affected by this potential source of omitted-variable bias. This test, which involves adding future M&A activity in Eq (15) as an additional right-hand side variable, shows that it is not.

In sum, the evidence in tables IX and X show that (1) at the firm level, industry followers react to tariff cuts by increasing M&A activity, and (2) at the industry level, increased M&A activity caused by tariff cuts increases future return comovement. Coupled with our evidence in Table III of a positive correlation between return comovement and cash-flow comovement, and the extant evidence that acquirers often restructure their product offering to achieve efficiency gains, this further suggest a causal relation running from competition shocks to rival reactions—in particular by industry followers—aimed at lowering production costs through greater product standardization.

VI Conclusions

When an industry experiences a positive competition shock—in this paper from significant tariff cuts—do individual rival firms react by increasing or by decreasing their product differentiation? Moreover, how does this reaction depend on the firms' position as industry leaders or followers (laggards)? We provide new, large-scale tests of these core questions. To do so, we estimate shock-induced changes in the idiosyncratic, within-industry stock return comovement between pairs of rival firms. This test statistic is new to the literature as it expunges not only the influence of priced risk factors on stock returns, but also the industry index return itself. As a result, our comovement statistic more directly identifies cross-firm effects of the competition shock.

For example, the competition shock may be good news for one rival but bad news for another, which in turn drives differential rival reactions and cause changes in their bi-firm idiosyncratic return comovement (what's good for Sprite may be bad for Pepsi). We use this property to test two broad and mutually exclusive hypotheses. The first (H1) holds that rivals react by increasing product differentiation, while the second (H2) holds that rivals instead choose to lower product differentiation and/or reduce costs to capture scale economies. While H1 predicts a comovement decrease, H2 implies a comovement increase. Moreover, as rival reactions likely depend on their levels of quasi-rents, we condition our comovement tests on the firms' within-industry position as leaders or followers.

Using a difference-in-difference regression approach, and based on changes in millions of idiosyncratic bi-firm correlation coefficients, we find that rival firms on average react so as to increase their return comovement. In other words, rivals tend to react by becoming less differentiated (more similar) in terms of their underlying operating strategies and cash flows. Also important, this effect is most pronounced among the within-industry followers. This finding makes intuitive sense as relatively low-rent rival firms may have the most to lose from tariff cuts and hence more likely to respond to increased competition by cutting costs. We also provide corroborating evidence that cash-flow measures of cost efficiencies increase significantly following the tariff cuts, which supports our hypothesis H2 that tariff cuts trigger product standardization strategies.

Finally, because the comovement changes that we document do not directly identify the underlying reaction channels adopted by the rival firms, we investigate one such potential channel: M&A transactions. We uncover evidence that industry followers are targeted by M&A activity in the wake of tariff cuts. Moreover, using a triple differences-in-differences approach, this shock-induced M&A activity itself is shown to generate an increase in future return comovement. This last finding corroborates our conclusion of a causal effect running from increased competition to rival reactions primarily in the form of product standardization and cost-reduction strategies.

The methodological innovation of this paper—using idiosyncratic return comovement to decipher the nature corporate rivalry—has several other interesting applications, which 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 intraindustry corporate rivalry, particularly in industries that are relatively vulnerable to social distancing.

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Figure I: **Predicted change in idiosyncratic return comovement of shocks to competition**

The change in idiosyncratic stock return comovement is caused by changes in firm-specific cash flows as rival firms react to a positive shock to industry competition. Rivals become "more differentiated" when they react to the industry shock by dropping overlapping products and/or adding new and more differentiated products. Rivals become "less differentiated" when they lower differentiation of existing products and streamline production costs vis-a-vis rival firms to take advantage of scale economies. $\triangle|\rho_{ij}|$ is the absolute value of the change in the idiosyncratic comovement caused by the industry shock, while $\triangle\rho_{ij}$ is the change in the signed value of ρ_{ij}.

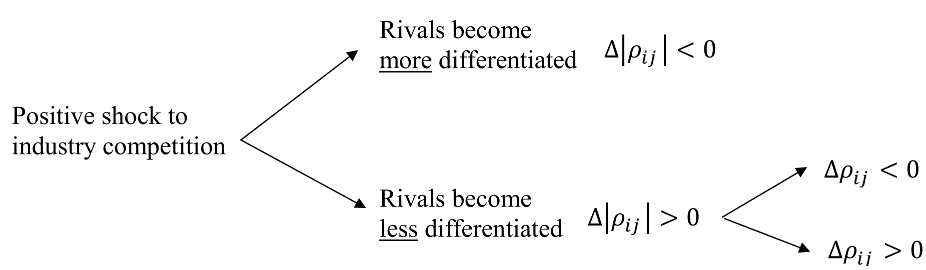

Figure II: **Frequency distribution of annual bi-firm idiosyncratic return comovement**

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.

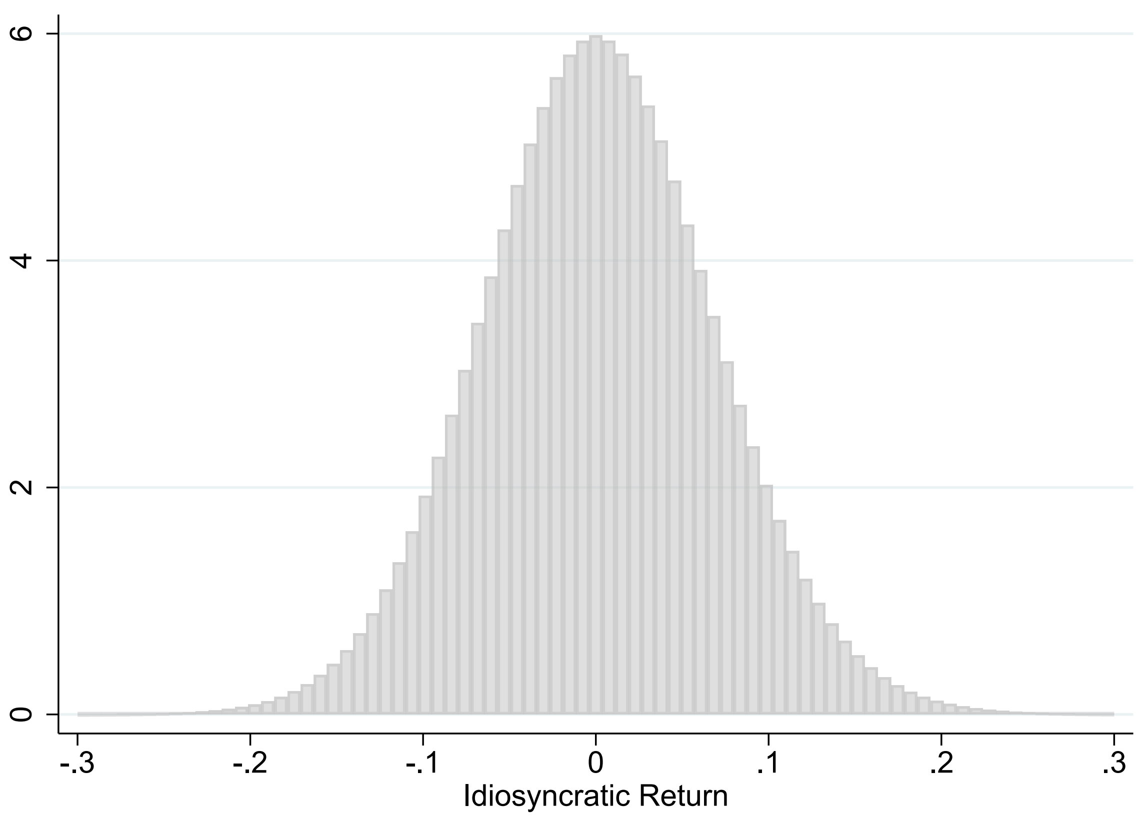

Figure III: **Significant import tariff cuts in 4-digit SIC manufacturing industries, 1975–2005**

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 ρ_{ijt}, 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.

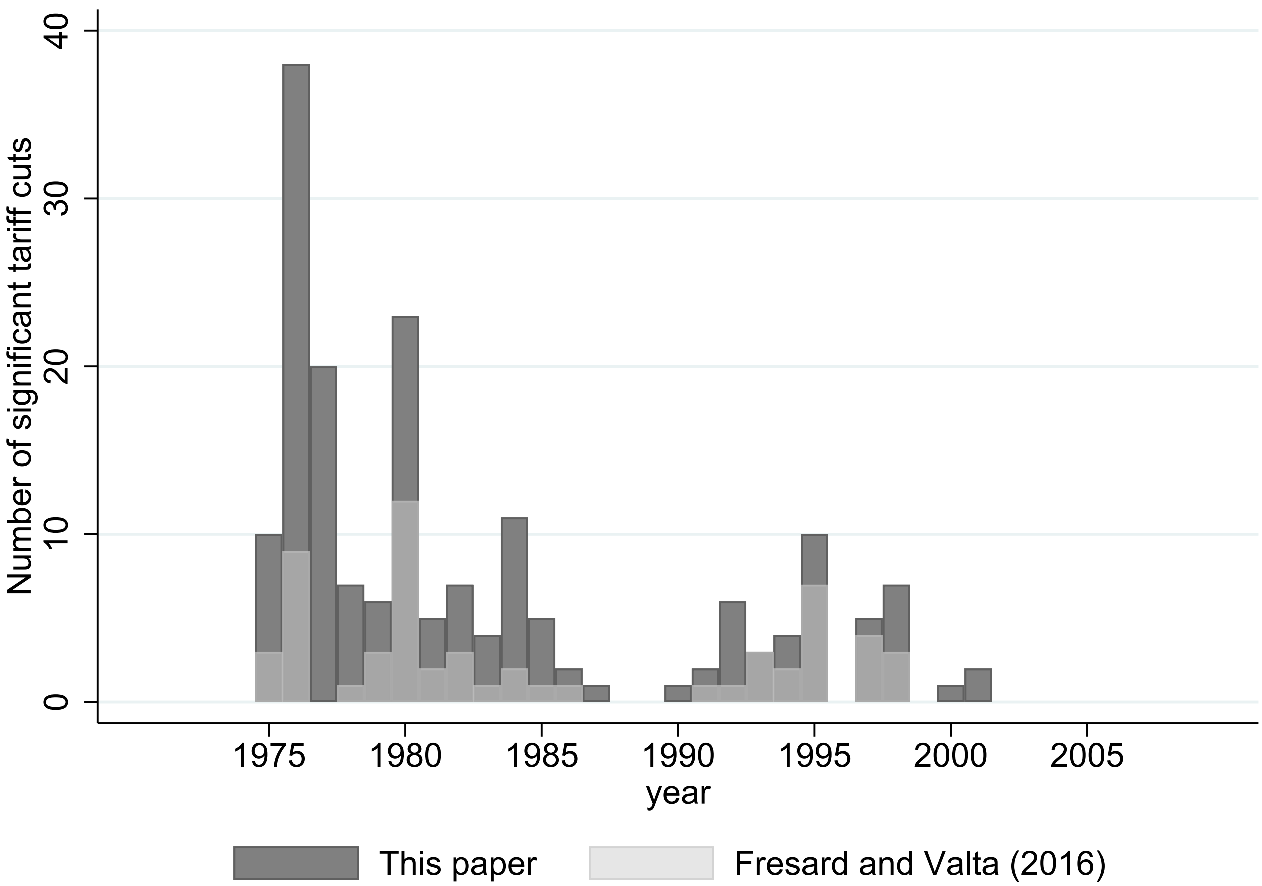

Figure IV: **Annual comovement in event time in tests of the parallel assumption**

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

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

where ρ_{ijt} is the idiosyncratic return correlation coefficient between firms i and j in year t, 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 (experiencing a significant tariff cut in event-year 0), and zero otherwise. The horizontal line means that the divergence between the comovement of the treatment and control groups remain unchanged through event time, which is equivalent to parallel developments of the two groups ($\gamma_\tau = 0$). The series of the estimated values of γ_τ in event time therefore provides a graphical test of the parallel trend assumption behind our difference-indiffference test approach. "99% C.I." denotes the 1% 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).

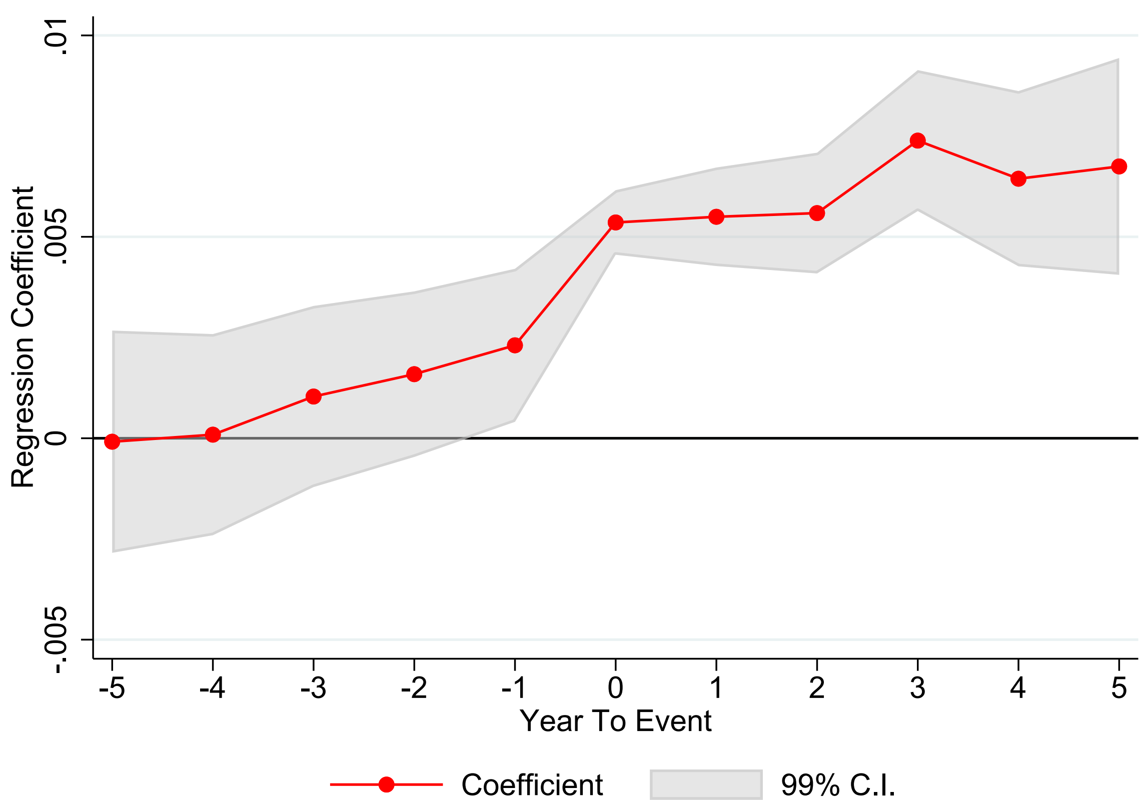

Figure V: Distribution of the two-ways (2×2) DID estimator for the tariff-cut treatment effect

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

$$\rho_{ijt} = \alpha_{ij} + \beta_t + \gamma(Treated_{ij} \times Post_t) + \epsilon_{ijt}$$

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.

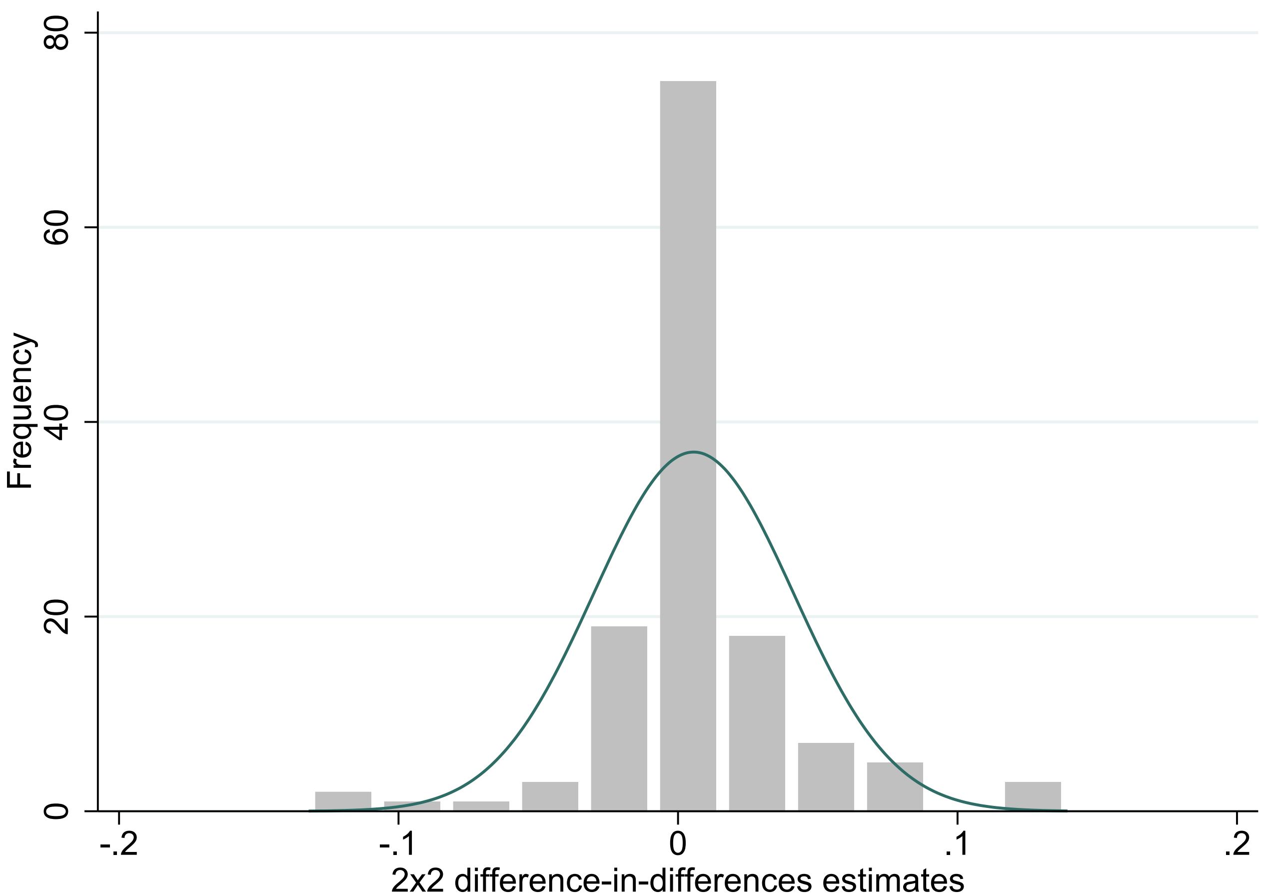

Figure VI: **Effect of the 1973 oil embargo on comovement among U.S. airlines**

The solid line plots the annual within-industry idiosyncratic bi-firm return comovement ρ_{ijt} for airlines i and j, where the daily return factors include the Fama and French (2015) risk factors (long-short size, book-to-market, profitability and investment portfolios) and the daily return on a value-weighted airline industry index 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 risk factors).

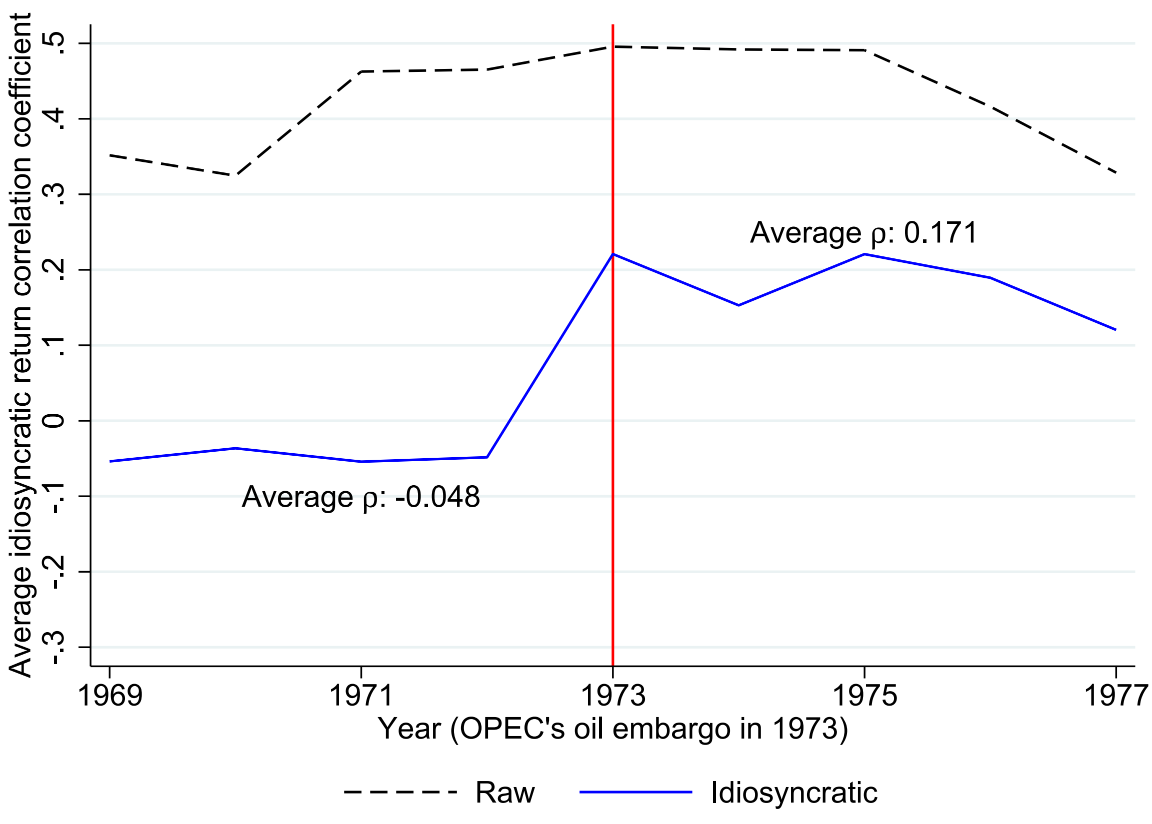

Table I: Annual return comovement: descriptive statistics

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:

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

where $\mathbf{F} = [r_m - r_f,\ smb,\ hml,\ rmw,\ cma,\ i_{sic3}]$. 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. The sample of firms 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

Table II: **Return comovement and Hoberg-Phillips product similarity scores**

The table shows the coefficient estimates of the coefficient γ in the following panel 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 1989–2010. ρ_{ijt} is the idiosyncratic return correlation coefficient between firm i and firm j, estimated using the residuals from regression Eq. (2). 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 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)
A: All firms			
SS_{ijt}: γ	0.070***	0.069***	0.012***
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
B: Single-segment firms only			
SS_{ijt}: γ	0.070***	0.068***	0.012***
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 III: **Stock-return comovement as predictor of cash-flow comovement**

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. 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 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)			
Coefficient	$\rho^{ROA}_{ij,t+1}$ (1)	$\rho^{ROA}_{ij,t+1}$ (2)	$\rho^{ROA^{Resi}_{Mkt}}_{ij,t+1}$ (3)	$\rho^{ROA^{Resi}_{SIC3}}_{ij,t+1}$ (4)
A: all years				
Predictor ρ_{ijt} : γ	0.053***	0.005***	0.005***	0.003***
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
B: Non-overlapping five-year windows only				
Predictor ρ_{ijt} : γ	0.075***	0.038***	0.037***	0.018***
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 IV: Definition of cross-sectional determinants of annual return comovement

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%
Age quartile	i and j are in same quartile of CRSP listing-age distribution	30.36%
BM quartile	i and j are in same quartile of the book to market distribution	22.44%
Lev quartile	i and j are in same quartile of the leverage distribution	23.10%
R&D quartile	i and j are in same quartile of the R&D distribution	32.92 %
Cash quartile	i and j are in same quartile of the cash ratio distribution	22.88%
Intg quartile	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/O quartile	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 V: Cross-sectional determinants of annual 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. 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). In both cases, the vector $\mathbf{x}$ contains the determinants defined in Table IV. In Column (1), I/O quartile 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. *** indicates significance at the 1% level of confidence.

	Cross-sectional average coefficient estimates		
	Total sample		Random sub-samples
Regressors	(1)	(2)	(3)
SIC3	0.00319***	0.00253***	0.00323***
I/O quartile		−0.00060***	
Age quartile	0.00064***	0.00045***	0.00066***
BM quartile	0.00109***	0.00123***	0.00115***
Lev quartile	0.00043***	0.00055***	0.00035***
R&D quartile	0.00091***	0.00067***	0.00100***
Cash quartile	0.00045***	0.00037***	0.00036***
Intg quartile	0.00038***	0.00053***	0.00049***
Location	0.00122***	0.00212***	0.00121***
Leader	0.00277***	0.00265***	0.00315***
HHI	0.00071***	0.00094***	0.00088***
Firm i & j FE	Yes	Yes	Yes
Average R^2	0.92		
Average N	1,781,439		

Table VI: **Effect of tariff cuts on return comovement**

The table shows coefficient estimates of tariff-cut treatment effects using the following two panel regressions, estimated over the period 1970–2010:

$$
\begin{aligned}
(1)\ \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{Controls'}\mu + \gamma(Treated_{ij} \times Post_{ijt}) + \epsilon_{ijt} \\
(2)\ \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{Controls'}\mu \\
&\quad + \gamma_1(Treated_{ij} \times Post_{ijt} \times D_{Follower_i}) + \gamma_2(Treated_{ij} \times Post_{ijt} \times D_{Leader_i}) \\
&\quad + \gamma_3(Treated_{ij} \times Post_{ijt} \times (1 - D_{Follower_i}) \times (1 - D_{Leader_i})) + \epsilon_{ijt}
\end{aligned}
$$

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. 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 $(1 - Follower_i) \times (1 - Leaders_i)$. 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 V as significant determinants of ρ_{ijt} (book-to-market, leverage, R&D, cash, intangibles quartiles 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 in parentheses. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the p-value of a Fisher test of equality of coefficients and N is the number of observations. *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Treatment coefficient	**All firms** (1)	(2)	**Followers v. Leaders** (3)
A: Signed value of ρ_{ijt}			
All firms: γ	0.003***	0.003***	
	(0.045)	(0.045)	
Followers: γ_1			0.004***
Leaders: γ_2			−0.002*
In between: γ_3			−0.000
Controls	No	Yes	Yes
R^2	0.223	0.223	0.223
F	7.012	18.090	7.841
$\gamma_1 = \gamma_2$			0.00
N	14,549,529	14,549,529	14,549,529
B: Absolute value of ρ_{ijt}			
All firms: γ	0.006***	0.006***	
	(0.13)	(0.13)	
Followers: γ_1			0.003***
Leaders: γ_2			0.001**
In between: γ_3			0.005***
Controls	No	Yes	Yes
R^2	0.221	0.221	0.221
F	47.26	25.08	19.908
$\gamma_1 = \gamma_2$			0.02
Obs.	14,549,529	14,549,529	14,549,529

Table VII: **Direct cost-efficiency effect of tariff cuts**

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

$$
\begin{aligned}
(1)\quad y_{it} &= \alpha + \mathbf{Controls}'\mu + \beta_1 Treated_i + \beta_2 Post_t + \gamma(Treated_i \times Post_t) + \epsilon_{it} \\
(2)\quad y_{it} &= \alpha + \mathbf{Controls}'\mu + \beta_1 Treated_i + \beta_2 Post_t \\
&\quad + \gamma_1(Treated_i \times Post_t \times D_{Follower_i}) + \gamma_2(Treated_i \times Post_t \times D_{Leader_i}) \\
&\quad + \gamma_3(Treated_i \times Post_t \times (1 - D_{Follower_i}) \times (1 - D_{Leader_i})) + \epsilon_{it}.
\end{aligned}
$$

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. 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 $(1 - Follower_i) \times (1 - Leaders_i)$. $Treated_i$ 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 V as significant determinants of ρ_{ijt} (book-to-market, leverage, R&D, cash, intangibles quartiles as well as the leader, HHI and location dummy variables). The dependent variable y_{it} takes one of four forms: sales divided by the costs of goods sold and administrative expenses (Sales/COGSX), R&D divided by total assets (R&D/AT), working capital divided by property, plants and equipment (WC/PPE), and employees divided by total assets (Emp/AT). 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-Wolf (2005) test for multiple hypotheses with 1,000 bootstrap replicates. $\gamma_1 = \gamma_2$ reports the p-value of a Fisher test of equality of coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Treatment coefficient	**Sales/COGSX** (1)	**R&D/AT** (2)	**WC/PPE** (3)	**Emp/AT** (4)
A: All firms				
All firms: γ	0.0221***	−0.025***	−0.893***	0.006***
Controls	Yes	Yes	Yes	Yes
R^2	0.108	0.327	0.189	0.298
F	113.9	474.0	181.7	541.1
Romano-Wolf p-val	0.00	0.00	0.00	0.00
N	44,844	48,063	42,657	42,043
B: Industry followers versus Leaders				
Followers: γ_1	−0.017***	−0.013***	−0.113	0.007***
Leaders: γ_2	0.0718***	−0.011***	−1.161***	0.002**
Controls	Yes	Yes	Yes	Yes
R^2	0.109	0.326	0.189	0.297
F	96.15	370.9	77.15	419.4
$\gamma_1 = \gamma_2$	0.00	0.02	0.00	0.00
N	44,844	48,063	42,657	42,043

Table VIII: **Robustness: Effect of tariff cuts with treated firms only**

The table shows coefficient estimates of tariff-cut treatment effects using the following two panel regressions, with year t running from 1970–2010:

$$
\begin{aligned}
(1)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{Controls}'\mu + \gamma Post_{ijt} + \epsilon_{ijt} \\
(2)\quad \rho_{ijt} &= \alpha_{ij} + \beta_t + \mathbf{Controls}'\mu \\
&\quad +\gamma_1(Post_{ijt} \times D_{Follower_i}) + \gamma_2(Post_{ijt} \times D_{Leader_i}) \\
&\quad +\gamma_3(Post_{ijt} \times (1 - D_{Follower_i}) \times (1 - D_{Leader_i})) + \epsilon_{ijt}
\end{aligned}
$$

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. 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 $(1 - Follower_i) \times (1 - Leaders_i)$. 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 V as significant determinants of ρ_{ijt} (book-to-market, leverage, R&D, cash, intangibles quartiles 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 in parentheses. F is the Fisher test statistic for the joint significance of the regression coefficients. $\gamma_1 = \gamma_2$ reports the p-value of a Fisher test of equality of coefficients and N is the number of observations. *, **, *** indicate significance at the 10%, 5%, and 1% levels of confidence.

Treatment coefficient	**All firms** (1)	(2)	**Followers v. Leaders** (3)
A: Signed value of ρ_{ijt}			
All firms: γ	0.003^{**}	0.003^{**}	
	(0.039)	(0.040)	
Followers: γ_1			0.003^{***}
Leaders: γ_2			-0.001^{*}
In between: γ_3			-0.002
Controls	No	Yes	Yes
R^2	0.413	0.413	0.413
F	3.443	3.316	3.404
$\gamma_1 = \gamma_2$			0.00
N	189,592	189,592	189,592
B: Absolute value of ρ_{ijt}			
All firms: γ	0.003^{***}	0.003^{***}	
	(0.059)	(0.058)	
Followers: γ_1			0.001
Leaders: γ_2			0.000
In between: γ_3			0.002^{*}
Controls	No	Yes	Yes
R^2	0.467	0.468	0.468
F	11.38	9.558	9.064
$\gamma_1 = \gamma_2$			0.12
Obs.	189,592	189,592	189,592

Table IX: Effect of tariff cuts on the likelihood of becoming an M&A target

The table shows coefficient estimates of tariff-cut treatment effects using the following two panel regressions, with year t running from 1981–2007:

$$
\begin{aligned}
(1)\quad ln(1+Int_{it}^{M\&A[t,t+\tau]}) &= \alpha_i+\beta_t+\mathbf{Controls'}\mu+\gamma(Treated_i\times Post_t)+\epsilon_{it}\\
(2)\quad ln(1+Int_{it}^{M\&A[t,t+\tau]}) &= \alpha_i+\beta_t+\mathbf{Controls'}\mu\\
&\quad +\gamma_1(Treated_i\times Post_t\times D_{Follower_i})+\gamma_2(Treated_i\times Post_t\times D_{Leader_i})\\
&\quad +\gamma_3(Treated_i\times Post_t\times(1-D_{Follower_i})\times(1-D_{Leader_i}))+\epsilon_{it}
\end{aligned}
$$

The dependent variable, $Int_{it}^{M\&A[t,\tau]}$, is the M&A activity targeting firms in firm i's 3-digit SIC industry between year t and $t+\tau$ scaled by the number of firms in firm i's 3-digit SIC industry. α_i and β_t are firm and year fixed-effects respectively. $Treated_i$ 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. $Follower_i$ ($Leader_i$) is an indicator variable identifying industry followers (leaders) in their 3-digit SIC industry using a combination of market shares, cash and return-on-assets financial ratios (details in the text). **Controls** is the vector of control variables (return on assets, market-to-book ratio, leverage, cash and intangibles financial ratios, logarithm of total assets). The sample of M&A transactions is from SDC Refinitiv and contains all completed acquisitions of partial interests, acquisitions of assets, acquisitions and mergers by private and public U.S. acquirers of U.S. listed targets (a total of 2,274 transactions). The sample of firms encompasses the Compustat-CRSP universe of manufacturing industries (4-digit SIC codes 2000 to 3999) with more than five firms in a given year. 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.

	M&A event window (0=year of tariff cut)			
Treatment	[t=0,τ=0]	[t=0,τ=+1]	[t=0,τ=+2]	[t=0,τ=+3]
coefficient	(1)	(2)	(3)	(4)
A: M&As targeting any firm in treated industries				
γ	0.001^{*}	0.002^{**}	0.003^{*}	0.003
Controls	Yes	Yes	Yes	Yes
R^2	0.258	0.344	0.410	0.453
F	2.60	2.52	2.86	2.61
N	36,463	31,334	27,011	23,365
B: M&As targeting industry followers versus leaders				
Followers: γ_1	0.001^{**}	0.002^{**}	0.003^{**}	0.003
Leaders: γ_2	-0.001^{**}	-0.001^{*}	-0.001	-0.002^{*}
Controls	Yes	Yes	Yes	Yes
R^2	0.258	0.345	0.410	0.453
F	2.53	2.47	2.76	2.57
N	36,463	31,334	27,011	23,365

Table X: Triple treatment effect of M&As on future return comovement, 1981–2007

The table shows the coefficient estimates from the following regression:

$$\begin{aligned} y_{ij,t+\tau} \quad = \quad & \alpha_{ij} + \beta_t + \mathbf{Controls'}\mu + \gamma_1(Treated_{ij} \times Post_{ijt}) + \gamma_2 M\&A_{it} \\ & + \gamma_3(M\&A_{it} \times Treated_{ij}) + \gamma_4(M\&A_{it} \times Post_{ijt}) + \gamma_5(Treated_{ij} \times Post_{ijt} \times M\&A_{it}) + \epsilon_{it} \end{aligned}$$

where the dependent variable, $y_{ij,t+\tau}$, is either $\rho_{ij,t+1}$ (the one-year-ahead return comovement) or $\overline{\rho_{ij,t+3}}$ (the three-years-ahead annual average comovement). α_{ij} and β_t are firm pair ij and year fixed-effects respectively. $Treated_{ij}$ is an indicator variable equal to one if the firm pair ij is treated, $Post_{ijt}$ is an indicator variable equal to one for the post-event periods. $M\&A_{it}$ is the frequency of M&A transactions computed as the ratio of the number of M&A transactions in the 3-digit SIC industry of firm i divided by the number of listed firms in the industry. **Controls** is the vector of control variables (market-to-book ratio, leverage, cash and intangibles financial ratios, logarithm of total assets). The sample of M&A transactions is from SDC Refinitiv and contains all completed acquisitions of partial interests, acquisitions of assets, acquisitions and mergers by private and public U.S. acquirers of U.S. private and public targets (64,597 transactions). The sample of firms encompasses all Compustat-CRSP universe manufacturing firms that contains more than five firms in a given year). 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 $y_{ij,t+\tau}$			
	$\rho_{ij,t+1}$	$\overline{\rho_{ij,t+3}}$	$\rho_{ij,t+1}$	$\overline{\rho_{ij,t+3}}$
Treatment effect on ρ_{ij}	(1)	(2)	(3)	(4)
Post-treatment effect: γ_1	-0.0095^{**}	-0.0040	-0.0095^{**}	-0.0040
M&A effect: γ_2	-0.0002	-0.0004^{***}	-0.0002	-0.0004^{***}
M&A-treatment effect: γ_3	-0.0067^{***}	-0.0076^{***}	-0.0067^{***}	-0.0076^{***}
M&A-Post effect: γ_4	0.0002	0.0002	0.0002	0.0003^{*}
Triple treatment effect: γ_5	0.0237^{***}	0.0277^{***}	0.0237^{***}	0.0277^{***}
Controls	No	No	Yes	Yes
R^2	0.270	0.497	0.270	0.497
F	13.19	11.31	10.36	8.37
N	3,213,512	1,738,033	3,213,512	1,738,033