Corporate rivalry and return comovement*

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Abstract

Industrial organization theory suggests that rivals react to industry-specific competition shocks in primarily one of two ways: by increasing product differentiation to capture additional revenue or lowering product differentiation to reduce costs. Since rival reactions affect intra-industry cash-flow correlations, they also cause changes in idiosyncratic (extra-factor, within-industry) return comovement. Consistent with cost-reducing rival reactions, we find that competition shocks increase idiosyncratic comovement, which in turn is associated with higher levels of firm-specific cost-efficiency measures. The higher post-shock bi-firm rival comovement also increases the likelihood that the two firms will merge.

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1 Introduction

Financial economics provides rich evidence of industry effects in stock returns. The return comovement across rivals within an industry reflects common shocks to consumer preferences, production technologies, and investment opportunities. These effects, which are well known, create industry-specific return comovement that is unrelated to macroeconomic risk factor exposures.[1] In this paper, we delve one level deeper and study how individual rival firms react to common industry-level shocks to competition. For this purpose, we expunge not only the influence of common risk factors in stock returns but also the industry factor itself. This extra-factor, extra-industry return allows us to identify changes in *within-industry* return comovement as industry competition increases. We then use observed changes in this idiosyncratic comovement to address a long-standing question in industrial economics: when industry competition increases, do rival firms tend to react by adopting business strategies that make the rivals more "similar" or more "differentiated" in economic terms?

We do not, of course, attempt to identify the particular business strategies (other than merger activity) that rival firms actually implement in reaction to competition shocks. The difficulty in observing and classifying those basic strategies is the very reason why existing empirical evidence on specific competitive strategies is sparse even in studies focused on a single industry. Instead, we argue that the change in idiosyncratic (extra-factor) stock return comovement among rival firms caused by an exogenous shock to industry competition, which are readily estimated from publicly available large-sample data, is highly informative about rival reactions.

For example, if firms react to increased competition by lowering product differentiation vis-a-vis their rivals (in order to lower costs), rivals become "more similar" in their operating strategies. In this case, the within-industry cash flow correlation and therefore idiosyncratic return comovement increases. Or, if the optimal profit-maximizing reaction is to develop a new product line that is more differentiated from the product lines of their competitors, rivals become "less similar" and the intra-industry cash flows and idiosyncratic returns become less correlated. Below, we discuss these and other implications for return comovement and subject the associated empirical predictions to large-sample testing.

Our rationale for removing even the average industry return (when computing bi-firm idiosyncratic return comovement) is that it masks the firm-level competitive reactions to industry-level shocks. For

[1] For example, Fama and French (2015) and Hou, Xue, and Zhang (2015) discuss evidence that the cross-section of average returns is in part explained by corporate investment, which is itself industry specific.

example, 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 shock may be negative for some rivals (what's good for Apple may be bad for Samsung). Thus, identifying within-industry effects is facilitated by removing the industry-level factor in returns. As another example, the European restrictions on diesel engines in the wake of the recent "dieselgate" scandal likely benefit producers of hybrid and electric car engines (Tesla, Toyota and Nissan) at the expense of producers of diesel engines (Volkswagen, Peugeot, Citroën, Opel).[2] Our empirical method is designed to control for industry-wide effects so as to reveal these and other differences in firm-level sensitivities to industry shocks.

We tackle the high complexity of the effect of rival reactions on stock return comovement by comparing the effect of the various competition shocks on samples of treated and control firms. That is, in addition to extracting the 3-digit SIC industry index return when estimating the idiosyncratic return comovement, we use a difference-in-difference (DID) approach to control for changes in bi-firm return comovement that are unrelated to the competition shock itself. The competition shocks that we focus on include US import tariff reductions (Frésard, 2010; Frésard and Valta, 2016), China's entry into the WTO (Hombert and Matray, 2017), and the North American Free Trade Agreement (NAFTA), all of which increased competition from foreign producers. Moreover, we examine effects of the 1994 Riegle-Neal Interstate Banking and Braching Efficiency Act (IBBE) on competition among US banks. Finally, we include a potentially negative shock to competition caused by the 2007 Foreign Investment and National Securities Act (FINSA). By reducing foreign direct investment through merger (Godsell, Lel, and Miller, 2018; Frattaroli, 2019), FINSA may have also lowered the level of competition among domestic companies.

In order to identify *persistent* idiosyncratic comovement, we estimate the bi-firm correlations annually, using one year of daily stock returns from the period 1965–2014. We confirm that adjacent one-year return correlations are positively and significantly correlated. Panel regressions, where the idiosyncratic return comovement is estimated over an entire decade (with firm and decade fixed effects), show that the idiosyncratic comovement depends on a range of industry and firm characteristics—as one would expect when these correlations reflect underlying business strategies. In particular, the comovement is higher when the two firms have relatively similar input-output mix.

Our main empirical findings are as follows. First and foremost, we show that idiosyncratic return comovement between pairs of rivals on average *increases* in response to positive competition shocks (tariff

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

reductions, IBBE, NAFTA and China's entry into WTO) and *decreases* after negative shocks (FINSA). As expected, this average hides a substantial cross-sectional heterogeneity in correlation changes. Nonetheless, our evidence suggests—to our knowledge for the first time—that rivals' unobserved operational changes in response to increased competition tend to make the rivals "more similar" in terms of return comovement. Second, consistent with this interpretation, we uncover evidence of significant cash-flow effects related to cost efficiencies when focusing on the subset of industries that experience a significant change in idiosyncratic return comovement after tariff reductions, NAFTA and the China-WTO entry—and more so when this return-comovement change is positive.

Third, to further link our evidence on return comovement to firms' operations, we show that two rivals with relatively high idiosyncratic return correlation tend to produce closely related products as measured by the product-similarity score (SS) of Hoberg and Phillips (2010). Focusing on the China-WTO entry and FINSA events (which occur in the time period when SS data are available), interacting the treatment effect with SS reveals that the treatment effect is stronger for rival pairs with high SS scores. That is, shocks to competition drive a greater increase in the return comovement when the two rivals are more closely related in product markets.

Finally, while firms' reactions to competition shocks are largely unobservable, those reactions may involve "circling the wagons" through, say, mergers and joint ventures. Asset complementarities, scale economies and product similarity are all factors in the pairing of bidder and target firms and so may both drive and affect merger likelihood.[3] We present substantial evidence that competition shocks increases merger likelihood and, as a consequence, affect rival firm comovement.

The remainder of the paper is organized as follows. Section 2 introduces our conceptual framework, predictions and the basic identification strategy. Section 3 explains the data, present evidence of persistence in return comovement, and identifies cross-sectional determinants of decade-long return correlations. Section 4 examines changes in return comovement (treatment effects) following shocks to industry competition, while Section 5 document industry heterogeneity in the treatment effect. Section 6 presents evidence on the relation between return comovement and Hoberg and Phillips (2010) product-similarity scores. Finally, in Section 7, we study how increased return comovement among rival firms interact with merger activity—one observable form of a strategic rival reaction to increased competition. Section 8

[3]See, e.g., Klein, Crawford, and Alchian (1978), Hart (1995), Gomes and Livdan (2004), Levis (2011), and Hoberg and Phillips (2010). Betton, Eckbo, and Thorburn (2008) review much of the empirical merger literature.

concludes the paper.

2 Concepts, predictions, and identification strategy

In this section, we first introduce the concept of idiosyncratic return comovement between two firms i and j in period t (ρ_{ijt}), and provide a simple but powerful example of how the industry-average ρ_{ijt} responds to a significant industry-specific shock. We then outline competing hypotheses for the effect on ρ_{ijt} of shocks to industry competition more generally. Finally, we outline the DID regression specification that forms the basis for our large-scale empirical tests.

2.1 The idiosyncratic return comovement concept

Let ρ_{ijt} denote the annual correlation coefficient of the idiosyncratic stock returns ϵ_i and ϵ_j of firms i and j in period t:

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

where σ_ϵ denotes the standard deviation of the residuals ϵ in the following return generating factor model:

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

$\mathbf{F}$ is a vector of risk and industry factors and $\beta_{\mathbf{i}}$ is the (transposed) vector of factor exposures. The risk and industry factors are: $\mathbf{F} = [r_m - r_f,\ smb,\ hml,\ i_{sic3}]$, where $r_m - r_f$ is the excess return on the Center for Research in Security Prices (CRSP) value-weighted market portfolio, *smb* and *hml* are the returns on the Fama-French long-short size and book-to-market portfolios (Fama and French, 1993).[4]

The industry index is included in the model generating expected return so as to remove also the average industry-wide effect of industry-specific shocks to competition. For example, when the 1973 oil embargo dramatically increased the oil price—a case illustrated next using changes in rival airline return comovement—the airline industry index removes the negative average industry return so as to identify the (idiosyncratic) return component ϵ that is driven solely by within-industry airline competition. Our main hypotheses below concern how various exogenous industry shocks affects this idiosyncratic residual

[4]The main results of this paper are robust to adding lead- and lag values of the factor portfolios as a check on non-synchronous trading (Scholes and Williams, 1977; Dimson, 1979).

return component. Adding the industry index, which is unique to this study, thus allows us to focus our empirical tests on the nature of direct within-industry cross-firm rival reactions.

The industry index i_{sic3} that we use is a value-weighted portfolio of all CRSP firms (excluding firm i) that are in i's 3-digit Standard Industrial Classification (SIC) industry and that survive the data filtering described below (results are unchanged if we perform the analysis with a 4-digit SIC industry index instead). The exclusion of individual firms from the industry index is, of course, particularly important when there are few members in firm i's industry. The factor model is estimated using a minimum of 90 daily returns within one calendar year.

2.2 A treatment effect illustration

Before turning to our main predictions, it is instructive to visualize a straightforward example that caused a dramatic change in the industry average ρ_{ijt}: the effect on the airline industry of the OPEC-driven fuel price hike in 1973. By lowering the price-cost margin in the airline industry, the OPEC embargo acts much like the competition shocks in our main analysis below, where the shocks are instead coming from the demand (price) side. Figure 1, which is centered on 1973, plots the annual average ρ_{ijt} across eleven publicly listed national US airlines that survived over the nine years from 1969 through 1977 (the figure ends just prior to the 1978 Airlines Deregulation Act).

In this illustration, 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.[5] Prior to 1973, ρ_{ijt} averages -0.047. A negative correlation 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 likely created a zero-sum game between airlines, in which increased market share of one airline reduces the market share of another.

More important, the average ρ_{ijt} increases from -0.047 to 0.156 after 1973—a dramatic increase due to OPEC's oil embargo in October of 1973, which caused the oil price to increase from $3 to $12 per barrel. Recall from Eq. (1) that we remove the industry-wide impact of this shock to fuel prices by subtracting the 3-digit airline industry return in the estimation of ρ_{ijt}. Hence, we maintain throughout the paper that the change in annual average ρ_{ijt} is driven by the individual firms' reactions to the industry-wide shock.

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

A consistent interpretation of Figure 1 is that, as airlines raced to lower other input costs to survive the surge in the oil price, their cash flows to shareholders became more highly and positively correlated. That is, the industry-specific shock caused individual airlines to react in ways that made these rivals "more similar" as evidenced by the dramatic increase in ρ_{ij}.

In our main empirical analysis, the trade-based industry-wide shocks are less dramatic than the oil-price effect of the OPEC's embargo. However, the trade-based shocks generally open up for more complex rival reactions than what may be feasible in the relatively homogenous airline industry. As discussed next, this additional complexity may cause ρ_{ij} to increase or decrease depending on whether rival reactions primarily affect the revenue-side (product line) or the cost-side (efficiency) of firm operations—a central empirical question of this paper.

2.3 Rival reactions and predicted change in return comovement

The industry shocks that we study range from import tariff reductions (85 tariff cuts in 74 unique 4-digit Standard Industrial Classification (SIC4) manufacturing industries between 1974 and 2005), state-by-state adoptions of the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBE), the North American Free Trade Agreement (NAFTA) in 1994, China's entry into the World Trade Organization (WTO) in 2001 and, finally, the Foreign Investment and National Security Act (FINSA) enactment in 2008.

The menu of rivals' strategic responses to these shocks is potentially wide ranging and complex (Shapiro, 2012). Referring to classical theory of industrial organization, we suggest that the strategic responses fall into one of two distinct groups. As indicated in the introduction, rivals may strive to become more differentiated from (less similar to) their peers. This strategy puts emphasis on protecting or even enhancing revenues by increasing product differentiation (Hotelling, 1929; Arrow, 1962; Salop, 1979). Product differentiation is enhanced by (1) adding new features to existing products (e.g., a camera to the smart-phone), (2) introducing an entirely new product (e.g., Tesla's electric car), and (3) 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. This scenario underlies the upper branch of the Figure 2, where a positive shock to industry competition leads to rivals becoming more differentiated. The lower cash-flow correlation also lowers the absolute value of the idiosyncratic return comovement: $\Delta|\rho_{ij}| < 0$. In other words, with greater differentiation, rival i's firm-specific information is less relevant to the equity pricing of rival i.

In the second group, depicted in the lower-left branch of the Figure 2, firms respond by becoming less differentiated. The traditional example is one where rivals respond to increased industry competition by lowering costly product differentiation and increase cost efficiencies to take advantage of scale economies (Schumpeter, 1943; Spence, 1984). 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 rivals but has the benefit of reducing 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.[6]

As rival firms become less differentiated, their cash flows become more highly correlated. 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: $\Delta|\rho_{ij}| > 0$. Moreover, as indicated by the two arrows in the lower right of the figure, there are now two scenarios to consider as the signed value of the change in $|\rho_{ij}|$ 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 other. For example, information about a patent violation or a consumer class-action suit may affect both firms in the same direction, $\Delta\rho_{ij} > 0$. On the other hand, when the two firms' products are close substitutes, firm-specific information that increases the demand for one may reduce the demand for the other, $\Delta\rho_{ij} < 0$.

With reference to Figure 2, the following combinations of estimates $|\Delta\rho_{ij}|$ and ρ_{ij} identify whether rivals respond by becoming more or less differentiated:

(1) Rivals become *more* differentiated (less similar) if $\Delta|\rho_{ij}| < 0$.

(2) Rivals become *less* differentiated (more similar) if $\Delta\rho_{ij} > 0$, or if $\Delta|\rho_{ij}| > 0$ and $\Delta\rho_{ij} < 0$.

To reiterate, Part (1) says that observing a decline in the absolute value of the rival firm return comovement ($\Delta|\rho_{ij}| < 0$)—whether the signed value of the pre-shock comovement is positive or negative—is

[6]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, US 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.

sufficient to conclude that the competition shock caused the two firms to become *less* similar (more differentiated) and so less correlated. In Part (2), observing an increase in the the bi-firm comovement ($\Delta\rho_{ij} > 0$) is sufficient to conclude that the two rivals have become *more* similar (less differentiated) and so more correlated. Moreover, the same inference holds if the absolute value of the comovement increases while the signed comovement decreases ($\Delta|\rho_{ij}| > 0$ and $\Delta\rho_{ij} < 0$). The latter case is relevant when the two firms are negatively correlated (what's good for Apple is bad for Samsung) and the competition shock causes this correlation to be even more negative, so as to increase the absolute value of the correlation.

Our empirical analysis focuses primarily on predictions (1) and (2). In addition, we provide direct estimates of cash-flow effects for a subset of industries experiencing *significant* treatment effects ($\Delta\rho$) from competition shocks. These cash-flow effects include changes in sales-to-cost ratios, working capital changes, and changes in R&D expenditures. The latter is also interesting since R&D plays a role in both product- and process-based innovation (Bellstam, Bhagat, and Cookson, 2017; Bena, Ortiz-Molina, and Simintzi, 2018; Hoberg and Maksimovic, 2019). While evidence of an *increase* in R&D intensity does not indicate whether the additional R&D effort is used to develop new products or new lower-cost production processes, a *decrease* R&D tends to rule out that rivals' average strategic response is one of new product development.

2.4 Identification strategy

We use the parameter λ in the following DID regression to identify the average treatment effect ($\Delta\rho_{ij}$):

$$y_{ijt} = \alpha_i + \beta_j + \gamma_t + \delta Treated_j + \lambda(Post_{it} \times Treated_j) + \mathbf{Controls}'\mu + \epsilon_{ijt}, \tag{3}$$

where y_{ijt} is either the absolute value or the signed value of ρ, α_i, β_j and γ_t are firm i, firm j and year-fixed effects, $Treated_j = 1$ if firms i and j are in the same industry (and zero otherwise), $Post_{it} = 1$ in all periods after a shock to firm i's industry (and zero otherwise), and standard-errors are clustered at the firm i level. The control variables in the vector **Controls** (market-to-book ratio, leverage, cash and intangibles financial ratios, logarithm of total assets) are described in more detail below.

This DID specification allows for multiple shocks across calendar time (e.g., as for the import tariff reductions and the state-by-state implementation of the 1994 IBBE Act). Note also that 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 and firm j is in either this industry or in another industry. This restriction ensures that we isolate the treatment effect on ρ_{ij} as the difference between ρ_{ij} when firm j is in the shocked industry and ρ_{ij} when firm j is *not* in the shocked industry. This approach also rules out the possibility that changes in ρ_{ijt} for firm pairs unaffected by competition shocks may drive our empirical results.

While the parameter λ estimates the average (cross-industry) impact of the competition shock, we also report on the industry-specific treatment effect ν for individual 3-digit SIC industries using the following expanded version of Eq. (3):

$$y_{ijt} = \alpha_i + \beta_j + \gamma_t + \delta Treated_j + \lambda(Post_{it} \times Treated_j) + (Post_{it} \times Treated_j \times \mathbf{SIC3})'\nu + \mathbf{Controls}'\mu + \epsilon_{ijt}. \quad (4)$$

Here, ν is a vector of coefficients capturing the industry-specific deviation from the average response in ρ_{ij} already reflected in λ. Below, we use the vector of parameters ν to illustrate the substantial heterogeneity in the treatment effect at the 3-digit SIC industry level. While we estimate ν for all 3-digit SIC industries in our sample, given the large number of such industries, we report results for industries with significant ν-coefficient estimates only.

3 Data sources and determinants of return comovement

3.1 Data and sample selection

The sample is drawn from the population of firms on the daily CRSP database, January 1965 through December 2014. The entire population ranges from 2,271 firms in 1965 to 7,432 firms in 2014, with a maximum of 10,036 in 1997 and an annual average of 6,656. We exclude a return record if (1) the share code is not 10 or 11 (common stocks), (2) the stock exchange code is not 1 (NYSE) 2 (Amex) or 3 (Nasdaq), (3) the price is less than \$1 (penny stock), and (4) the return or the number of shares or the industry code is missing (we include returns computed from bid/ask spreads, as indicated by a negative price). These filters reduce the total number of firms by 18% and the number of return records by 17%. Finally, in any given calendar year, firms with less than 90 available returns are eliminated. This last filter reduces the sample of firms further by 7% to an annual average of 4,307 and an annual average number of return records by 3% to 1,085,553.

Figure 3 displays histograms for the total sample of ρs estimated by decade, which reduces the number of ρs from about five hundred million to about ten million over the five decades. Table 1 lists several moments of the ρ distribution across decades. The figure and the table also show simple return correlations computed from raw returns, which reflect global risk exposures and is therefore highly skewed to the right. A successful extraction of all common factors should yield an average ρ that is close to zero, which Figure 3 clearly shows is the case. In Table 1, the return comovement using raw returns averages 0.11 in the first decade (1965-1975), hovering around 0.08 thereafter until the last decade (2005-2014) where it averages as much as 0.26. In contrast, the average four-factor ρ ranges from 0.001 to 0.003. While not tabulated, switching the industry from 3-digit SIC to 4-digit SIC industries, or focusing on ρ scaled by its standard error rather than the raw value of ρ, yield the same conclusions.

3.2 Persistence in annual return comovement

Stock returns and idiosyncratic residuals are random variables driven by an underlying stochastic process resulting from market pricing. In contrast, firm production technologies and product differentiation strategies are non-random and highly persistent. If two rival firms i and j react to shocks to their respective firm-specific technologies and degree of product differentiation in a relatively similar manner over time, the reaction will create a degree of persistence in ρ as well. In this case, ρ_{ijt} will be correlated with $\rho_{ij,t-1}$.

To examine this type of persistence, we estimate the following cross-sectional (OLS) regression model:

$$\rho_{ijt} = \alpha + \beta\rho_{ij,t-1} + \epsilon_{ijt}. \tag{5}$$

We begin the estimation using firm pairs ij existing in the data in the two years 1965 and 1966, and repeat the estimation over successive two-year periods until 2014. While not tabulated, the estimates of β, and of β standardized by its estimated standard error, are highly significant with the annual average t-value exceeding 15 over the entire sample period. Thus, $\rho_{ij,t-1}$ significantly predicts ρ_{ijt}—there is significant persistence in the idiosyncratic return comovement.

The annual estimate of β jumps significantly in the sample period after year 2000. This is likely related to the general time trend in average stock return variance and covariance documented by Campbell, Lettau, Malkiel, and Xu (2001), Brandt, Brav, Graham, and Kumar (2010) and Nam, Khaksari, and Kang (2017). While our sample of firms differ from that literature, we checked but find no evidence of an underlying time-trend in our average annual estimate of ρ. Thus, any such time trend is likely offset by the numerator and denominator in the ratio used to generate ρ.[7] Also, as we include year fixed effects in our DID regressions below, we are controlling for possible time trends in ρ.

3.3 Determinants of decade-long return comovement

If ρ truly reflects direct within-industry (idiosyncratic) cross-firm effects, the cross-sectional variation in ρ ought to be a function of bi-firm-specific factors. To examine this, we use the following unbalanced panel estimation across decades, with decade and firm-fixed effects, to capture cross-sectional heterogeneity at the firm level:

$$\rho_{ijt} = \alpha_i + \beta_j + \gamma_t + \mathbf{x}'_{\mathbf{ijt}}\delta + \epsilon_{ijt}. \tag{6}$$

Here, the time period t is a decade, $\mathbf{x}$ is a vector of determinants, γ_t is the decade-fixed effect, and α_i and β_j are firm-i and firm-j fixed effects (which also absorbs firm i industry fixed effects). The regression does not include firm-pair ij fixed effects since i and j do not necessarily belong to the same industry. The cross-sectional; determinants in $\mathbf{x}$ are defined in Table 2. Standard errors are clustered at the firm-pair level. Recall from above that, on a daily basis, the number of sample firms (N) typically ranges from 2,000 to 6,000, while the number of daily return observations is less than T=255 when estimating ρ. Since $N > T$, regression (6) must use the coarser time-period of a decade in order to avoid mechanical correlation across firm-pair ρ estimates.

Beginning in 1965, we group the sample firms by decade and include firm i in the regression only if it has available CRSP/Compustat information in every year of the decade. The decade-long survivorship restriction eliminates about half of the sample firms, with the annual number of firms averaging 1,790. Within each decade, the number of firms is at most N=2,145 while the number of daily stock returns is $T \approx$ 2,500. We impose the decade-long survivorship restriction for the cross-sectional determinant analysis in this section only. Notwithstanding the sample size reduction, this decade analysis is informative in that it helps identify relatively persistent—and thus fundamental—drivers of ρ.[8]

[7] As reported in an earlier draft of this paper, there is a strong upward time-trend after year 2000 also in the regression R^2 of the risk-factor model used to generate ρ. This increase is robust as it holds whether the risk-factors include the market return only, the market return plus the two Fama-French factors and momentum, and industry indices based on either 3-digit SIC or 4-digit-SIC codes. These findings are available upon request.

[8] While not tabulated, we also performed decade-by-decade cross-sectional regressions without firm-fixed effects, and using White's heteroscedastic-robust standard errors. The main inferences are unchanged from those reported below for regression (6).

The coefficient estimates are reported in Table 3. The results strongly support our notion that more "similar" firm-pairs ij will have higher ρ_{ij}. With the exception of *I/O quartile*, all variables in $\mathbf{x}$ receive positive and highly significant coefficient estimates in all of the regressions in the table. For *I/O quartile*, which is a measure of the distance between the vectors of inputs of firms i and j, the coefficient estimates are negative and significant.

In columns (1) and (2) of Table 3, firms i and j belong to the same industry if they share the same 3-digit SIC industry code while in columns (3) and (4), firms belong in the same 4-digit SIC industry. In columns (1) and (3), the *I/O quartile* variable is excluded because data availability reduces the sample size by 90%, while in columns (2) and (4), it is included to obtain an estimate of the corresponding coefficient. A variable name that includes the word "quartile" is a dummy indicating that firms i and j are in the same quartile of the sample distribution in decade t. The remaining four determinants (defined without the word "quartile") measure industry and location controls.[9]

The coefficient estimates in Table 3 support the notion that stock prices of two firms with similar characteristics behave similarly. Here, being "similar" is based on firm characteristics commonly featured in finance and industrial economics. Thus, in addition to industry belonging, the quartile indicators *Age* (public listing age), *BM* (book-to-market ratio),[10] *Lev* (leverage ratio based on long-term debts plus current liabilities), *Cash* (ratio of cash plus short term investment to total assets) and *Intg* (ratio of intangible assets) all confirm that stock returns comove more across firms with similar structures. Table 3 also shows that the inclusion of an industry in the stock return factor model does not remove all industry-level effects: the 3-digit SIC industry (SIC3) is significant in columns (1) and (2). Investigating this residual effect of SIC3 further, we re-estimated the industry return factor using only the subsample of firms included in the decade-analysis in Table 3, and we examined a value-weighted 3-digit SIC industry factor. In these alternative specifications (not tabulated), the coefficient estimate on SIC3 remains positive and significant. This residual industry impact likely reflects our restrictive assumption that each sample firm may be fully represented by a single SIC code that is updated only infrequently, at discrete points in time.

[9] Recall that we exclude firm i from the industry index when estimating Eq. (2). To check whether this exclusion affects the estimation when the industry has few members, we also limit the sample to industry-years with at least 20 firms as well as to single-segment firms (identified using the Compustat Segment database). The conclusions (untabulated) are unchanged.

[10] As in Fama and French (1993), 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.

Industry indicators include *Leader* (firms i and j are both among the top three SIC3 firms by sales), *HHI* (i and j are both in a SIC3 industry where $HHI > 1,500$, which is the threshold in the antitrust merger guidelines issued by the Department of Justice), and *I/O quartile* (i and j are both in top quartile of the I/O distance distribution, where I/O distance is the absolute value of the sum of differences between the input vectors of i and j using the Bureau of Economic Analyses USE tables) and *Location* is equal to one for i and j having headquarters in the same state. Location is less commonly used in the empirical industrial economics literature but 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.

Columns (1) to (4) of Table 3 show that ρ_{ij} increases significantly in *Leader*, *HHI* and *Location*, whether or not we include *I/O quartile*. Moreover, columns (2) and (4), which include *I/O quartile*, show that ρ_{ij} decreases significantly when the two firms are in the top quartile of the I/O-distance measure. In other words, bi-firm return correlation declines when the two firms' input-output mix becomes less similar. Finally, to check whether the p-values are overly influenced by the extraordinary large number of observations (Lin, Lucas, and Shmueli, 2013; Harvey, 2017), we replicate the first specification reported in Table 3 on 1,000 sub-samples. Each subsample consists of a random selection of 1% of the observations in the original sample (about 100,000 observations). Table 3 lists the resulting average Student statistic an in Column (5). The significance levels are confirmed for all coefficient estimates.[11]

4 Treatment effects of competition shocks

In this section, we present estimates of the average treatment effect of shocks to industry competition—in the form of λ in regression Eq. (3) above. As suggested by the conceptual discussion around Figure 2 above, we provide estimates for the absolute value (Table 5) as well as the signed value of ρ_{ijt} (Table 6).

Before turning to the λ estimates, it is instructive to consider informally the parallel trend assumption for the average values of ρ_{ijt} for the various sets of treated and control firms shown in Figure 4. The event-window for these trend lines is the five-year period (-2,2) centered on the year of the competition shock caused by China WTO entry, NAFTA and FINSA.[12] In addition to the trend lines themselves, the

[11] While not tabulated, joint tests of the significance of the coefficients in the full model and the restricted model using Bayesian inference (Bayes factors) confirms the statistical inferences reported above.

[12] The figure excludes the multi-year shocks caused by tariff reductions and the IBBE due to the overlapping event-windows.

bars in the figure show the annual trend-line spread. There are two sets of treated firms associated with each of the China WTO and NAFTA shocks: firms in the treated 3-digit SIC industries with import shares above the median or in the top quartile, respectively, of the distribution of US industries' import shares in 1996 and in 1989, respectively.

Four of the five panels in Figure 4 show parallel trends for treated and control firms prior the event, providing substantial (heuristic) support for the identifying assumption behind our DID estimation approach (Angrist and Pischke, 2009). The exception is "NAFTA Median", where the trend lines are parallel for Top Quartile but not for the Median set of treated firms. In tables (5) and (6) below, we therefore provide λ-estimates for both the Median and Top Quartile firms.

4.1 Effects of import tariff reductions

Frésard (2010) and Frésard and Valta (2016) identify 91 significant import tariff reduction events in 74 unique SIC4 manufacturing industries between 1974 and 2005. For a given industry, their definition of a significant event is that the tariff reduction is at least three times larger than the industry's average tariff change (positive or negative) over their pre-event sample period. We are able to use 85 of their 91 significant events (for the remaining six events, the event industry contains only a single firm).

Column (1) of tables 5 and 6 show the λ-estimates for the interaction term $Post_{it} * Treated_j$, with standard errors clustered at the firm i level. Recall that $Treated_j = 1$ when firms i and j are in the same treated industry, and that $Post_{it} = 1$ in periods after the shock to firm i's industry has occurred (and zero otherwise). Thus, λ measures the average impact of the 85 tariff reduction events on $|\rho_{ijt}|$ (Table 5) and ρ_{ijt} (Table 6) for treated relative to control firms. In Table 5, the treatment effect λ for the absolute value of the return comovement is positive and statistically significant whether we use the 3-digit SIC industry index in our risk factor model (Panel A) or the 4-digit SIC index (Panel B). Similarly, in Table 6, λ for the signed value of the return comovement is also positive and highly statistically significant whether using the 3-digit or the 4-digit SIC industry indices.

In terms of the conceptual framework in Section 2 above, the λ-estimates in tables 5 and 6 are consistent with 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. Again, while we do not observe the reactions themselves, this type of response would increase pairwise correlation of the rivals' cash flows and thus the bi-firm idiosyncratic return comovement (we return to actual cash-flow effects in Section 5 below).

4.2 Additional positive competition shocks

Columns (2)-(6) of tables 5 and 6 report treatment effects of the three additional positive shocks to competition in our sample. We discuss each of these individually.

(1) The 1994 Riegle-Neal Interstate Banking Act (IBBE)

The 1994 federal Reigle-Neal Interstate Banking and Branching Efficiency Act ($IBBE$) removed the previous prohibition on interstate banking. By permitting banks to take advantage of scale economies and other forms of streamlining cross-state operations, this deregulation likely increased competition in the US financial industry. Bos, Kolari, and van Lamoen (2013) use this regulatory shock to examine the causal effect of changes in banking competition on corporate innovation. Using regression (3), we instead test whether state-adoptions of $IBBE$ affect the bi-firm idiosyncratic return comovement of financial institutions in the SIC60 and SIC61 industries (banks and credit institutions). The estimation period is 1990-2010.

In Eq. (3), the post-event period for firm i ($Post_{it} = 1$) now starts with the date of the *initial* adoption by the state where bank i's headquarter is located (from Compustat).[13] Moreover, subscript i refers to banks located in a state that adopts the $IBBE$ regulation. Firm j is located either inside ($Treated_j = 1$) or outside the treated state ($Treated_j = 0$).

In Panel A of Table 5, Column (2) shows that the treatment effect λ on the absolute value of the return comovement is positive and significant when the risk-factor model is based on the 3-digit SIC industry index, while it is positive but statistically insignificant when using the 4-digit SIC industry index in Panel B. In Column (2) of Table 6, λ for the signed value employs the of the return comovement is positive and highly significant whether one employs the 3-digit or the 4-digit SIC industry index. In sum, these estimates support the hypothesis that IBBE Act implementations on average led to higher idiosyncratic return comovement among treated rival banks (relative to control firms). Again, it appears that the treated rival banks have become more (not less) similar.

[13]Information from the internet site of the Federal Deposit Insurance Corporation (FDIC) show that all fifty states had adopted to $IBBE$ by the end of 1997. Several states revised their initial adoption, with a total of seventeen such revisions until 2005. We ignore these subsequent revisions.

(2) The 1994 North American Free Trade Agreement (NAFTA)

NAFTA—the free-trade accord between US, Mexico and Canada—was passed in 1994. In regression (3), the pre- and post-event periods are now the ten years centered on 1994: 1989-1993 and 1995-1999, respectively. Moreover, the treated industries are those with the largest import shares from Canada and Mexico in percent of total US imports. The regression results are reported in columns (3) and (4) of tables 5 and 6. In Column (3), the treated SIC3 industries have import shares above the median of the distribution of US industries' import shares in 1989, while in Column (4) the treated SIC3 industries are in the top quartile of this distribution. All estimated values of λ are positive and they are statistically significant in six of eight cases listed in the two tables. Overall, this suggests that US rivals may have responded to the increased import-competition caused by NAFTA by implementing corporate policies that increased their pairwise idiosyncratic return comovement on average.

(3) China's 2001 entry in to the World Trade Organization (China-WTO)

China entered the World Trade Organization (WTO) in 2001. While Autor, Dorn, Hanson, Shu, and Pisano (2016) and Hombert and Matray (2017) link innovation to import competition from China, we instead examine the impact of this import competition on the rival firm return comovement ρ_{ij}. The estimation procedure is similar to that for NAFTA above, except that the estimation period is now centered on 2001 (five years on each side). As for NAFTA, we report two alternative sets of treated industries: those with import shares from China above the US median for SIC3 manufacturing industries or in the top quartile in 1996, respectively. The resulting estimates of λ are reported in columns (5) and (6) of tables 5 and 6, respectively. As shown, much like for NAFTA, the λ-estimates for China-WTO are positive and statistically significant in seven of the eight categories reported.

4.3 A negative competition shock

Finally, to help validate the significantly positive estimate of λ for the positive competition shocks reported above, we examine a shock that tends to *lower* industry competition in some industries. This negative shock is the 2009 implementation of the 2007 Foreign Investment and National Security Act (FINSA). FINSA reinforces the powers of the Committee on Foreign Investment in the United States (CFIUS). The origin of CFIUS is the Defense Production Act of 1950, which was passed in response to the Korean

War. The Act permits the US President to reject foreign investments that threatens national security. CFIUS assesses potential threats to national security from foreign ownership and control of US assets.

FINSA imposes costs on foreign acquirers in the form of delays, political uncertainty, forced deal restructuring and penalties, all of which reduce foreign acquirers incentives to acquire US targets. Godsell, Lel, and Miller (2018) report that, since FINSA began to be fully enforced in 2009, foreign takeovers of FINSA-affected firms have declined by 68% relative to a control group of US firms that are unlikely to be constrained by FINSA. In our analysis, FINSA therefore represents a negative exogenous shock—albeit somewhat indirect—to industrial competition.

We follow Godsell, Lel, and Miller (2018) and group FINSA enforcement into fourteen industry groups obtained from the 2008 CFIUS Annual Report to Congress.[14] We then apply the above estimation procedure for NAFTA and China-WTO to FINSA, estimating Eq. (3) on an eleven-year estimation period centered on year 2009 (i.e., using five years on each side of the event year 2009). Again, $Treated_j = 1$ when firm j is in the same industry as i (a FINSA industry), while $Post_{it} = 1$ indicates the period 2009-2014. The vector of controls is as before.

Interestingly, the λ-estimates in panels A and B of Column (7) of tables 5 and 6 are negative and highly significant. That is, FINSA lowers bi-firm idiosyncratic return comovement among rivals in the treated industries relative to control firms. While the negative competition-shock caused by FINSA is not as pervasive as the positive shocks caused by tariff reductions and trade agreements—it affects only the subset of potential target firms in the affected industries—this result complements our earlier conclusion that the competition shocks cause rival firms to become more (not less) similar in terms of idiosyncratic return comovement.

5 Industry heterogeneity and firm-level cash-flows

Naturally, rival reactions to exogenous changes in industry competition will depend on industry-specific factors such as market structure (concentration and barriers to entry), consumer preferences (substitutes), resource specialization and technological sophistication. For each industry, the estimated treatment effect (λ) represents the sum impact of these industry-specific factors on changes in rival firms' cash

[14]The groups are Advanced materials and processing, Chemicals, Advanced Manufacturing, Information Technology, Telecommunications, Microelectronics, Semiconductor Fabrication Equipment, Electronics Military Related, Biotechnology, Professional/Scientific Instruments, Aerospace and Surface Transportation, Energy, and Space Systems, Marine Systems. The CFIUS Annual Report to the Congress provides the corresponding 3-digit SIC codes.

flow and therefore idiosyncratic return comovement. Moreover, the global (cross-industry) estimate of the treatment effect in Section 4 above shows the tendency for rival firms to react by becoming more similar across broad swaths of the US economy. While this broad effect is important—and new to the literature—we are also interested in how this effect breaks down across industries. In this section, we therefore identify industries with statistically significant (positive or negative) treatment effects. We examine whether those industries exhibit cash-flow changes that are consistent with our inference that rivals react to competition shock by becoming more similar.

5.1 Industries with a significant treatment effect

We begin by estimating the vector ν of industry-specific treatment effects in Eq. (3) using all of the exogenous shocks to competition in Table 5. We then single out the elements in ν that are statistically significant at the 10% level or higher (t-value $\geq |1.64|$). Figure 5 shows the industries and the corresponding t-values of the treatment effect ν_i when the competition shock is coming from a tariff cut. The vertical bars in the figure indicate critical t-values for significance levels of 10%, 5% and 1%.

A total of forty-four different 3-digit SIC industries in our sample receive tariff shocks. Perhaps surprising, as many as twenty of these industries (44%) receive estimated values of ν_i with t-value $\geq |1.64|$. Moreover, of these twenty industries, eleven experience a positive treatment effect. The five industries with the most significant treatment effect—absolute t-values of four or higher—are SIC 367, 602 and 612 ($\nu_i > 0$) and SIC 222 and 334 ($\nu_i < 0$).[15] Thus, while the aggregate treatment effect is positive, there is substantial heterogeneity across industries. We obtain similar evidence of industry heterogeneity for the other competition shocks (IBBE, NAFTA, China WTO entry and FINSA).[16]

5.2 Cash-flow changes when the treatment effect is significant

As discussed in Section 2 above, our evidence of a positive treatment effect suggests that rival firms are adopting various cost-cutting strategies and/or product line simplifications in response to increased competition. In this section, we examine whether evidence on direct cash-flow variables corroborates or

[15]The three SIC industries with t-value $\geq$ 4. are: 367 Electron Tubes, Printed Circuit Boards, Semiconductors and Related Devices, Electronic Capacitors, etc; 602 National Commercial Banks, State Commercial Banks, Commercial Banks, Not Elsewhere Classified; and 612 Wireless telecommunication activities. The two industries with t-value ≤ -4. are 222 Broadwoven Fabric Mills, Manmade Fiber and Silk, and 334 Secondary Smelting and Refining of Nonferrous Metals.

[16]These are not tabulated due to space limitations. In the case of FINSA, $\nu_i < 0$ and statistically significant for Advanced Materials and Processing, Chemicals, Information Technology, Telecommunications, Microelectronics, Biotechnology, Professional/Scientific Instruments and Space Systems industries.

refutes such strategies. We do so by estimating the following DID regression:

$$y_{it} = \alpha_i + \beta_t + \gamma Post_{it} + \mathbf{Control}'\delta + \eta_{it}, \tag{7}$$

where α_i and β_t are firm i and year t fixed effects, $Post_{it}$ indicates that firm i is treated in year t and **Control** is, as before, our vector of control variables. We use three different dependent variables, y_{it}: Sales divided by the cost of goods sold (COGS), R&D divided by Total Assets, and Working capital divided by property, plants and equipment (PPE). In the regression, the competition shocks are the set of 85 import tariff reductions, the NAFTA agreement, and the China WTO Entry.[17]

Table 7 displays the regression results using a panel composed of Compustat firms from 1970 (five years before the first shock) to 2007 (three years after the last shock). Treated firms are identified as belonging to industries where the treatment effect has an absolute Student t-value of at least 1.64. $Post_{it}$ takes a value of $+1$ when the treatment effect is positive, a value of -1 when the treatment effect is negative, and zero otherwise, during a period of 3 years(Panel A) and 5 years after the shock (Panel B). Standard-errors are clustered at the firm i level.

The results in Table 7 are interesting. The main coefficient of interest, γ, is highly significant in all six regression specifications in both panels and whether or not the full set of control variables is included. The significant industry treatment effects are positively associated with Sales/COGS and negatively associated with R&D/Total Assets and Working Capital/PPE. These coefficient estimates are consistent with cost-cutting strategies driving the positive industry treatment effect. The positive coefficient on Sales/COGS suggest that this cost cutting has increased the spread between revenues and sales (the price-cost margin), while the negative coefficient on Working Capital/PPE suggest that it has also reduced the need for costly working capital (perhaps by lowering inventories).

Last, but not least, the negative coefficient on R&D/Total Assets suggests that the rival cost-cutting strategies also lowered expenses on innovative activities. This is of particular interest because is clarifies that the positive industry treatment effect is more likely to reflect a trend towards *lower* product differentiation among rivals. In other word, the evidence points to rivals becoming more (not less) similar following the significant competitive industry shocks.

[17] BBE is excluded from this analysis since it represents state-level (not industry) shocks. Moreover, we exclude FINSA as it represents a negative competition shock.

6 Return comovement and product similarity

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 measures firm similarity driven by market expectation of future cash flow. In this section, we first investigate the extent to which ρ and SS provide overlapping categorization of bi-firm similarity. We then interact SS and the treatment effect of competition shocks.

6.1 Overlapping classifications of bi-firm similarity

We begin by matching SS to ρ for firm ij pairs year by year. SS scores are publicly available starting in 1996 for a subset of Compustat firm pairs. This results in a total of 4,708,736 matches with our sample of firm-years. The univariate sample correlation between ρ_{ijt} and SS_{ijt} is a statistically significant 0.2 (p-value < 0.01).

Table 8 show the results of panel estimations, beginning in year 1996, with idiosyncratic comovement as dependent variable and SS as the single regressor (with standard errors clustered at the firm-pair ij level). In panel A, the dependent variable is ρ_{ijt} while in panel B it is ρ_{ijt}^{scaled} (ρ divided by its unconditional standard error SE_ρ). In both panels, the coefficient estimate γ on SS is positive and highly significant. Moreover, the estimate of γ increases in Column (3) where we add both firm- and year fixed effects. Thus, there is, on average, a significant and positive relation between SS and our measure of idiosyncratic comovement, which further supports the notion that our designated industry rivals operate in overlapping product markets.

We also examine the annual cross-sectional correlation between ρ and SS by estimating, year-by-year, the first of the three regression specifications in Table 8. While not tabulated, 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 significantly) but not the Hoberg-Phillips SS score. We do not pursue this issue further as, again, our inclusion of year fixed effects accounts for time trends and common shocks in ρ.

6.2 Interacting competition shocks with similarity scores

We use the following regression to test whether SS affects the intensity of the treatment effect (λ) of shocks to industry competition:

$$\rho_{ijt} = \alpha_i + \beta_j + \gamma_t + \delta Treated_j + \lambda(Post_{it} \times Treated_j) + \mu(Post_{it} \times Treated_j \times SS_{ijt}) + \mathbf{Controls'}\mu + \epsilon_{ijt}. \quad (8)$$

Since SS is publicly available starting in 1996, Eq. (8) is estimated for the China-WTO and FINSA shocks only. As before, for China-WTO, the treated 3-digit SIC industries have import shares above the median of the distribution of US industries' China-import shares in 1996.

The results are reported in Table 9, where the coefficients of interest are λ and μ. In columns (1) and (3), we first re-estimate our baseline regression Eq. (3)—without the triple interaction term—using the smaller sample of firms with available data on SS. As for the larger sample in Table 6 above, these two regressions show that the positive shock to competition caused by China-WTO results in a significantly positive λ, while the negative shock caused by FINSA produces a negative λ-estimate.

We then estimate Eq. (8) where SS is added, with the coefficient estimate μ shown in columns (2) and (4) in Table 9. In both columns, the estimate of μ is highly significant and of the same sign as the estimate of λ. In Column (2), adding SS drives the λ-estimate for China-WTO to become statistically insignificant. This does not happen in Column (4), where the estimates of λ and μ in response to the FINSA shock are both significant. In sum, Table 9 further validates that increased comovement between rivals caused by greater industry competition is driven by firms neighbouring in the product market space.

7 Return comovement and merger activity

The above evidence is consistent with the hypothesis that reactions by rival firms to increased competition on average make these firms' more similar in terms of idiosyncratic stock returns (the treatment effect). Moreover, for a subset of industries with significant treatment effects, the evidence shows that firms experience cash flow changes consistent with lower production costs—including lower working capital and R&D expenses. This evidence shows the typical *consequence* of rival reactions for cash flows and return comovement—not the form of the reaction itself. In this section, we investigate one potential form of rival firm reaction: merger activity designed to make the combined firm better able to survive in the new competitive environment. We are particularly interested in whether (lagged) merger activity helps explain the industry treatment effect document above.

We begin the analysis with merger activity between banks in the wake of state-by-state IBBE adoptions. This is because IBBE, by legalizing interstate banking, increased the incentive of banks in one state (j) to enter another state (i), in part trough merger. We subsequently examine whether greater rival firm comovement (the treatment effect of competition shocks) affect the likelihood of becoming a target and pairing with a correlated rival firm more generally. We conclude this section by investigating how ρ reacts to increased M&A activity in the wake of tariff cuts.

7.1 Interstate bank mergers following IBBE

The state-by-state IBBE adoptions represent exogenous shocks to entry-barriers in local (state level) bank markets. As such, the post-IBBE interstate bank merger activity offers an interesting window into local-bank entry and its effect on bank rivalry. We sample interstate bank mergers from the Thomson-Reuters SDC M&A database (SDC). We then replicate DID analyses developed in Section 4 and estimate λ using Eq. (3) with our standard set of control variables but with alternative measures of treatment intensity:

$$Y_{ijt+1} = \alpha_i + \beta_j + \gamma_t + \delta Treated_{jt} + \lambda(Post_{it} \times Treated_{jt}) + \mathbf{Controls}'\mu + \epsilon_{ijt}, \tag{9}$$

where Y_{ijt+1} is either ρ_{ijt+1} or ρ^{scaled}_{ijt+1} (ρ divided by its unconditional standard error SE_ρ) estimated year by year using daily returns, α_i, β_j and γ_t are bank i, bank j and year-fixed effects. $Post_{it} = 1$ in the post-IBBE-enactment period for the state of bank i. and zero otherwise. In columns (1) and (2), $Treated_{jt} = 1$ when (i) bank state j is different from bank state i and (ii) there has been an acquisition by a bank located in bank state j of a bank located in bank state i, and zero otherwise. However, in columns (3) and (4), $Treatment_{jt}$ records the *cumulative number* of such acquisitions, and it is the logarithm of the *cumulative value* of acquisitions in columns (5) and (6), two alternative measures of treatment intensity.

The results are shown in Table 10. Consistent with the evidence reported earlier in Table 5, the λ-coefficient is positive and highly significant in each specification. That is, we find that increased competition caused by new entries into the local banking market—driven by IBBE adoptions—increases rival comovement. This finding is noteworthy since it suggests that merger activity represents a significant channel through which banks react to increased competition, and that this reaction results in increased rival-bank comovement.

7.2 Comovement and merger activity: who buys who?

Next, we test whether greater *average* comovement within firm i's 3-digit SIC industry at time $t-1$ ($\bar{\rho}_{i,t-1}$) increases the likelihood of firm i becoming a target at time t. Expanding on the extant merger literature investigating "who buys who", we test whether greater lagged comovement between two firms ($\rho_{ij,t-1}$) increases the likelihood of the two firms merging. The merger literature traditionally examines who-buys-who through the lens of Tobin's Q and the market-to-book ratio (M/B) of the merging firms. The theoretical motivation for this traditional approach goes back to Gort (1969) and Jovanovic and Rousseau (2002, 2008), where capital is reallocated from under-performing low-Q targets to high-Q bidders with superior management skills and productive resources ("high buys low" in terms of market-to-book ratios).[18]

Alternatively, property rights arguments (Klein, Crawford, and Alchian, 1978; Hart, 1995) lead Rhodes-Kropf and Robinson (2008) and Hoberg and Phillips (2010) to argue that bidders may be seeking out targets with complementary assets (similar M/B ratios—"like buys like").[19] To the extent that idiosyncratic return comovement captures the distance between firms in terms of cash-flows, we argue that ρ likely complements both M/B and the Hoberg-Phillips SS score as predictors of merger activity.

We sample 3,272 merger bids (both successful and unsuccessful) from SDC, 1992-2014. The sample period starts in 1992 for computational purposes—to reduce the large number of idiosyncratic correlations—and we require the bidder and target firms to be US-domiciled and publicly traded. Furthermore, the bidder must own less than 50% of the target shares prior to the merger, and SDC must provide information on the deal value. Table 11 shows the results of estimating the likelihood that firm i becomes

[18] Yang (2008) reformulates this tendency to firms with rising productivity buying assets of firms with falling productivity, or "rising buys falling".

[19] Levis (2011) also builds on the idea of complementarities: firms with high revenue growth opportunities but high operating costs, become targets of firms with lower growth prospects but higher cost efficiency. In Gomes and Livdan (2004), synergies emanate from economies of scope which allow merged firms to lower their fixed cost of production by eliminating redundant and inefficient activities. Morellec and Zhdanov (2005) model the option value of merger in industry equilibrium, while David (2011) and Dimopoulos and Sacchetto (2013) examine industry dynamics resulting from mergers, exit and entry.

a target in period t. Columns (1) and (2) report the coefficient estimates using a probit model while columns (3) and (4) use a linear probability (OLS) estimation that allows us to include firm fixed-effects, as follows:

$$Target_{it} = \Phi(\alpha + \beta_t + \gamma\bar{\rho}_{i,t-1} + \delta\bar{\rho}^{10}_{i,t-1} + \mathbf{Controls}'\mu + \epsilon_{it}) \tag{10}$$

and

$$Target_{it} = \alpha_i + \beta_t + \gamma\bar{\rho}_{i,t-1} + \delta\bar{\rho}^{10}_{i,t-1} + \mathbf{Controls}'\mu + \epsilon_{it}. \tag{11}$$

Here, $Target_{it} = 1$ if firm i becomes a target in year t and zero otherwise, and $\Phi(.)$ stands for the standard normal cumulative distribution function. $\bar{\rho}_{i,t-1}$ is the equally-weighted average $\rho_{ij,t-1}$ across all firms j in firm i's 3-digit SIC industry. $\bar{\rho}^{10}_{i,t-1}$ is the average $\rho_{i,t-1}$-value of firm i's ten nearest neighbors in terms of $\rho_{i,t-1}$: the greater the value of $\bar{\rho}^{10}_{i,t-1}$, the more closely is the comovement between firm i and its top-ten nearest neighbors. Thus, $\bar{\rho}^{10}_{i,t-1}$ serves as a proxy for the potential supply of high-value targets in industry i. This proxy is inspired by Hoberg and Phillips (2010) who use the average value of the ten highest SS scores as their proxy for potential target supply.

We predict $\gamma > 0$ because greater within-industry average similarity likely means higher net merger synergies (Betton, Eckbo, and Thorburn, 2008; **?**). Moreover, we expect $\delta < 0$: the greater the supply of potential high-value targets the smaller the likelihood of firm i being targeted. These predictions are largely borne out by the estimates in Table 11. That is, the estimate of γ is positive and significant, indicating that likelihood of becoming a target increases with $\bar{\rho}_{i,t-1}$. Moreover, the coefficient δ on $\bar{\rho}^{10}_{i,t-1}$ is negative and significant, suggesting that greater supply lowers within-industry target likelihood. As the table also shows, these estimates are robust to using $\bar{\rho}_{i,t-1}$ scaled by its standard error. In sum, Table 11 indicates that higher within-industry average similarity is associated with a higher likelihood of rival firms becoming targets of takeover attempts.

We next estimate the likelihood that two firms i and j merge in year t (at the extensive margin):

$$Merger_{ijt} = \alpha + \beta_t + \gamma_1\rho_{ij,t-1} + \gamma_2(|M/B_{i,t-1} - M/B_{j,t-1}|) + \mathbf{Controls}'\mu + \epsilon_{ijt}. \tag{12}$$

Here, $Merger_{ijt} = 1$ if firms i and j are involved in a merger bid in year t and zero otherwise, and $|M/B_{i,t-1} - M/B_{j,t-1}|$ is the absolute value of the difference between the M/B of i and j. Since the number of possible ijt pairs–from which the 3,272 merger bids ultimately emerged—is prohibitively large (almost 300 million), we split the estimation period into two parts: 1992-2000 and 2001-2014 (before and after the internet bubble). While not tabulated, results are similar if we include firm ij fixed effects.

We predict $\gamma_1 > 0$ (greater return comovement increases the likelihood that the firm-pair ij will merge), which is strongly supported by the estimates in Panel A of Table 12 whether using $\rho_{ij,t-1}$ or $\rho_{ij,t-1}$ scaled by its standard error. Panel B reports the corresponding coefficient size effects.[20] A size effect is the percentage change in merger likelihood from a one standard deviation increase in the variable of interest.[21] As shown, the size effects for both ρ and scaled ρ are substantial, ranging from 27%/28% in the first period to 64%/68% in the second period. In columns (3) and (7) of Table 12, we replace ρ with the text-based similarity score SS. Consistent with the finding of Hoberg and Phillips (2010), who study merger bids from the period 1997-2006, the coefficient estimate on SS is positive and significant here as well. While not tabulated, and notwithstanding the fact that ρ_t and SS are positively correlated (shown in Section 2.2 above), ρ_t and SS both receive positive and significant coefficient estimates when included in the same regression.

Table 12 also reveals interesting information about the association between $|M/B_{i,t-1} - M/B_{j,t-1}|$ and merger likelihood. As noted above, the relative M/B of bidders and targets figures prominently in theories for who-buys-who. Also, M/B is consistently reported to be a statistically significant determinant of merger likelihood (Betton, Eckbo, and Thorburn, 2008). Columns (1)-(3) and (5)-(7) of Table 12 show the estimate of γ_2 for $|M/B_{i,t1} - M/B_{j,t1}|$, our specification of relative M/B in Eq. (12). As shown, when including ρ or ρ^{Scaled} on the right-hand side of the regression, γ_2 is positive and statistically significant only for the 1992-2000 period. Moreover, when we include SS in the regression in columns (3) and (7), $|M/B_{i,t1} - M/B_{j,t1}|$ loses its explanatory power, producing an insignificant estimate of γ_2.

Columns (4) and (8) of Table 12 investigate further the effect of breaking down $|M/B_{i,t1} - M/B_{j,t1}|$ into quartiles. In these two columns, we estimate the following linear probability model without a constant term and with standards errors clustered at the firm level:

$$Merger_{ijt} = \delta_1 M/B_{q1,t-1} + \delta_2 M/B_{q2,t-1} + \delta_3 M/B_{q3,t-1} + \delta_4 M/B_{q4,t-1} + \epsilon_{ijt} \tag{13}$$

[20]We do not report size effects for SS because this variable is left-censored due to Hoberg and Phillips (2010)'s exclusion of firms with SS score below a certain threshold.

[21]$Size_\rho \equiv \frac{\Delta\rho * \gamma}{Prob(merger)}$ where $\Delta\rho$ is a one standard deviation increase in ρ, γ is the coefficient estimate on ρ in Eq. (12) and $Prob(merger)$ is the unconditional merger probability ($\frac{\#Mergers}{\#FirmPairs}$) over the sample period.

where $M/B_{q1,t-1}$, $M/B_{q2,t-1}$, $M/B_{q3,t-1}$ and $M/B_{q4,t-1}$ are dummy variables indicating the quartile of $|M/B_i - M/B_j|$ in which the firm-pair ij belongs in year $t-1$. Quartile 1 represents the lowest absolute difference in M/B. As shown, all coefficients are positive and highly significant, with point estimates decreasing from quartile one to quartile four (roughly divided by a factor of two per quarter). Thus, the greater absolute difference in M/B, the lower the impact on merger likelihood, which tends to support the notion that "like buys like" in terms of M/B.[22]

7.3 Merger activity and return comovement following tariff shocks

In this section, we explore the association between current merger activity in an industry experiencing a tariff cut and the *subsequent* level of average rival firm comovement in that industry, $\overline{\rho}_{i,t+1}$. While not tabulated, we first confirm the conclusion of Srinivasan (2017) that merger activity tends to increase at the industry level in the wake of import tariff cuts. We then estimate the following DID regression:

$$\overline{\rho}_{i,t+1} = \alpha_i + \gamma_t + \beta_1(Post_{it} \times Treated_{it}) + \beta_2 M\&A_{it}^{Agg} + \beta_3(Post_{it} \times Treated_{it} \times M\&A_{it}^{Agg}) + \epsilon_{it} \quad (14)$$

where $M\&A_{it}^{Agg}$ is the aggregate number of merger transactions in industry i, and $Post_{it} \times Treated_{ij}$ indicates that year t is post-import tariff reduction for industry i. The coefficient of main interest is β_3, which captures the effect of the triple interaction term $Post_{it} \times Treated_{it} \times M\&A_{it}^{Agg}$. Specifically, β_3 measures the impact on $\overline{\rho}_{i,t+1}$ of an increase in aggregate industry merger activity after a tariff cut.[23]

Table 13 shows that β_3 is positive and significant, for the acquirer industry (Column 1), the target industry (Column 2) and when the transaction is horizontal (Column 3). Moreover, β_3 is statistically insignificant in non-horizontal transactions. This indicates that positive shocks to industry competition in terms of tariff cuts for the most part increase not only current return comovement (Section 4 above) but also *future* idiosyncratic return comovement through the merger-channel. In sum, merger activity is both affected by and affects return comovement between rival firms: higher idiosyncratic return comovement increases the probability of a merger transaction (tables 11 and 12), while an increase in the number of merger transactions in a particular industry increases future industry average return comovement (Table

[22] The results in Table 12 are robust to sub-samples of horizontal merger (where the acquirer and the target share the same SIC4 industry code), of non-horizontal merger, and to sub-sample of industry peers, defined at the 3-digit SIC industry level. Results are qualitatively similar, both in terms of point estimates and statistical significance.

[23] The estimation period here is 1980 (the start of the SDC database) through 2005. The number of import tariff reductions is 69, down from 85 in Section 4 above due to the shorter sample period.

13).

8 Summary and conclusions

We use changes in idiosyncratic return comovement to examine the nature of rival firm reactions to exogenous competition shocks. This return comovement expunges influences of *both* risk- and industry factors in stock returns and so are likely to be dominated by direct cross-firm effects. When rivals react, they adopt business strategies that change operating cash flows, with concomitant changes in idiosyncratic return comovement. We exploit this simple idea to provide novel tests of whether rivals react by adopting more similar or more differentiated business strategies (they generally cannot do both). In the theory of industrial organization, rivals become less similar if they react by increasing product differentiation, while rival similarity increases if they instead reduce product differentiation and/or reduce costs to capture scale economies. The latent nature of cash flow changes caused by a change in business strategy has prevented prior research from directly illuminating on a large-scale basis which of the two effects tends to dominates in the data.

Our focus on idiosyncratic return comovement helps resolve this measurement problem. Not only are stock returns readily available for publicly traded rivals, the theoretical prediction is also relatively straightforward. If industry rivals react to a positive shock to competition by reducing product differentiation and streamlining production, return comovement among rival firms will increase. Conversely, if rivals increase product differentiation, rival firm return comovement decreases. Also, since stock prices capitalize future cash flow changes, the magnitude of the change in return comovement is larger the more persistent are the cash-flow changes cause by the underlying changes in business strategy.

Our main empirical finding is that idiosyncratic return comovement on average increases significantly in response to a battery of industry-specific competition shocks (import tariff cuts, China's WTO entry, NAFTA, and IBBE). Moreover, it decreases significantly in response to the passage of FINSA, which tends to reduce competition in certain industries by deterring foreign entry. These intra-industry effects, which are based on changes in millions of idiosyncratic bi-firm correlation coefficients, are striking. We also provide evidence that firms increase their operating efficiency in industries that react significantly to import tariff cuts, China's WTO entry and NAFTA agreements. This corroborates the notion that rival firms react to competition shocks by implementing cost-cutting strategies, which lead rival firms to become more cash-flow similar and therefore exhibit greater return comovement. The notion that the changes in return comovement is rooted in actual product- and cost-strategies is further supported by our evidence that the idiosyncratic return comovement is significantly and positively related to the Hoberg and Phillips (2010) product-based similarity scores.

The estimated change in rival return comovement captures complex rival firm reactions to increased competition (the treatment effect). We also study one such strategic reaction: merger activity. Beginning with the effect if state-by-state IBBE enactment on local bank entries via merger, we document a significant positive relation between return comovement and interstate merger activity among banks. We then test whether rival firm comovement *itself* drives merger activity. The motivation for this test is that the potential for realizing cost-efficiencies is likely to be higher among two firms with highly correlated cash flows. Consistent with this argument, we find that the probability of becoming a target at the extensive margin—and the likelihood that two firms pair up—are both increasing in the average return comovement between rivals in the target's industry. We also demonstrate that greater industry merger activity increases *future* within-industry idiosyncratic return comovement.

The empirical approach of this paper—using estimated idiosyncratic return comovement to decipher the nature of direct within-industry cross-firm rivalry—can be used to address other interesting empirical questions in finance and economics that we leave for future research. For example, since we find that rivals react to positive competition shocks by becoming more similar, it would be interesting to correlate these changes with direct evidence on business strategies that affect comovement, such as joint ventures, technological innovations, etc.. Also, our approach can be used to expand on prior work using stock returns to identify anticompetitive effects (if any) of horizontal merger, where the alternatives are efficiency effects from scale economies and other types of cost savings.

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Figure 1: **Idiosyncratic return comovement for U.S. airlines around the OPEC's 1973 oil embargo**

The figure plots the annual average value of the bi-firm idiosyncratic return correlation coefficient ρ_{ijt}, centered on the year the OPEC cartel was formed, where

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

Here, σ indicates standard deviation and ϵ_{it} is a residual from the following four-factor model estimated using daily returns over the year in question:

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

The daily return factors are $\mathbf{F} = [r_m - r_f,\ smb,\ hml,\ i_{sic3}]$, where $r_m - r_f$ is the excess return on the value-weighted market portfolio, smb and hml are the returns on the Fama-French long-short size and book-to-market portfolios. i_{SIC3} is the return on a value-weighted airline industry index formed using public firms in SIC industry 451 and excluding firm i. Pairs of firms i and j are among eleven publicly traded national US domiciled airlines that survived for the entire nine-year period (American, Braniff, Continental, Delta, Eastern, National, Northeast, Northwest, Pan American, and TWA).

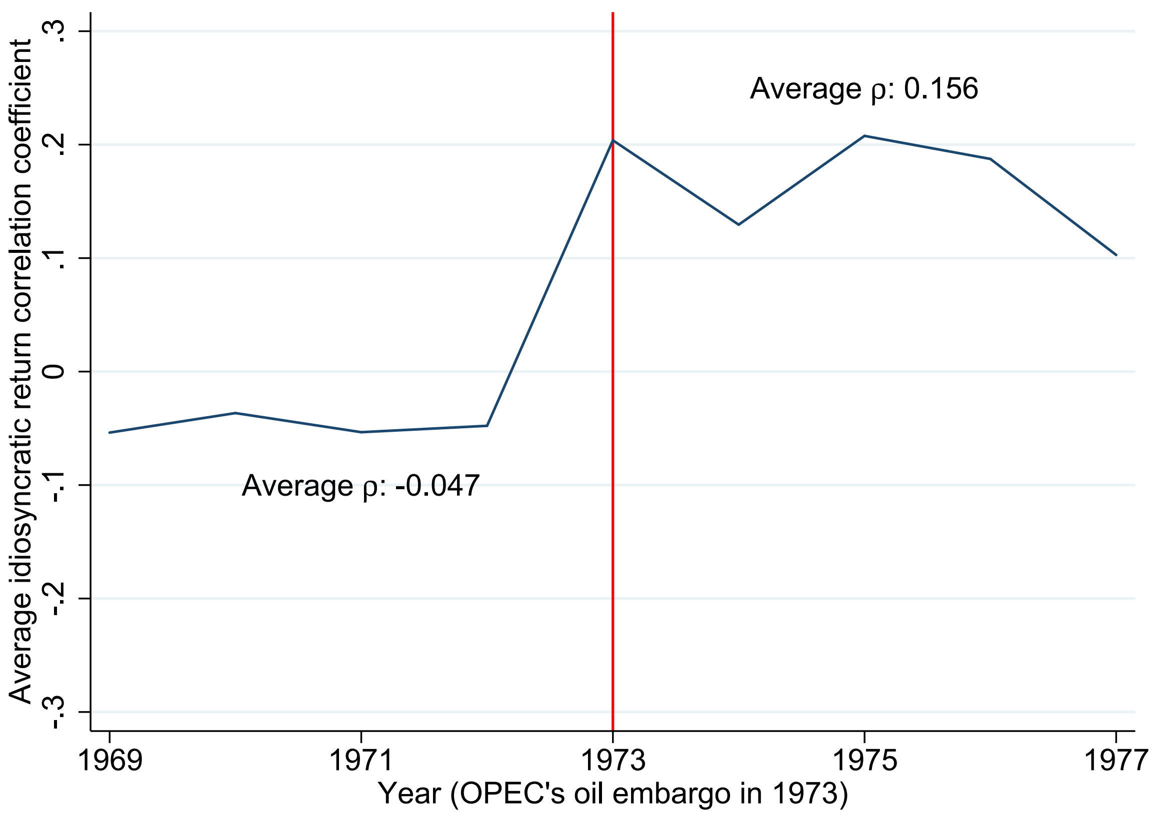


Figure 2: **Predicted change in idiosyncratic return comovement of shocks to competition**

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}.

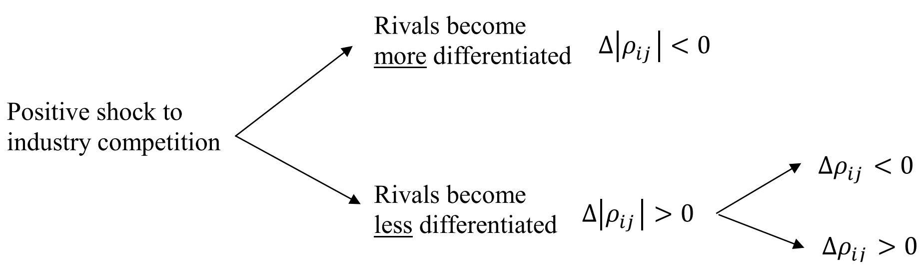


Figure 3: **Frequency distribution of idiosyncratic and raw return comovement**

The figure plots frequency distribution of bi-firm idiosyncratic return correlation coefficients ρ_{ijt} using either daily raw returns or the residuals ϵ_{it} from the four-factor model, and estimated using a minimum of 90 daily returns within a calendar year:

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

where σ indicates standard deviation, and the four-factor model is

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

The daily return factors are $\mathbf{F} = [r_m - r_f,\ smb,\ hml,\ i_{sic3}]$, where $r_m - r_f$ is the excess return on the value-weighted market portfolio, *smb* and *hml* are the returns on the Fama-French long-short size and book-to-market 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. The sample period is 1965-2014, and the annual average number of sample firms is 4,307.

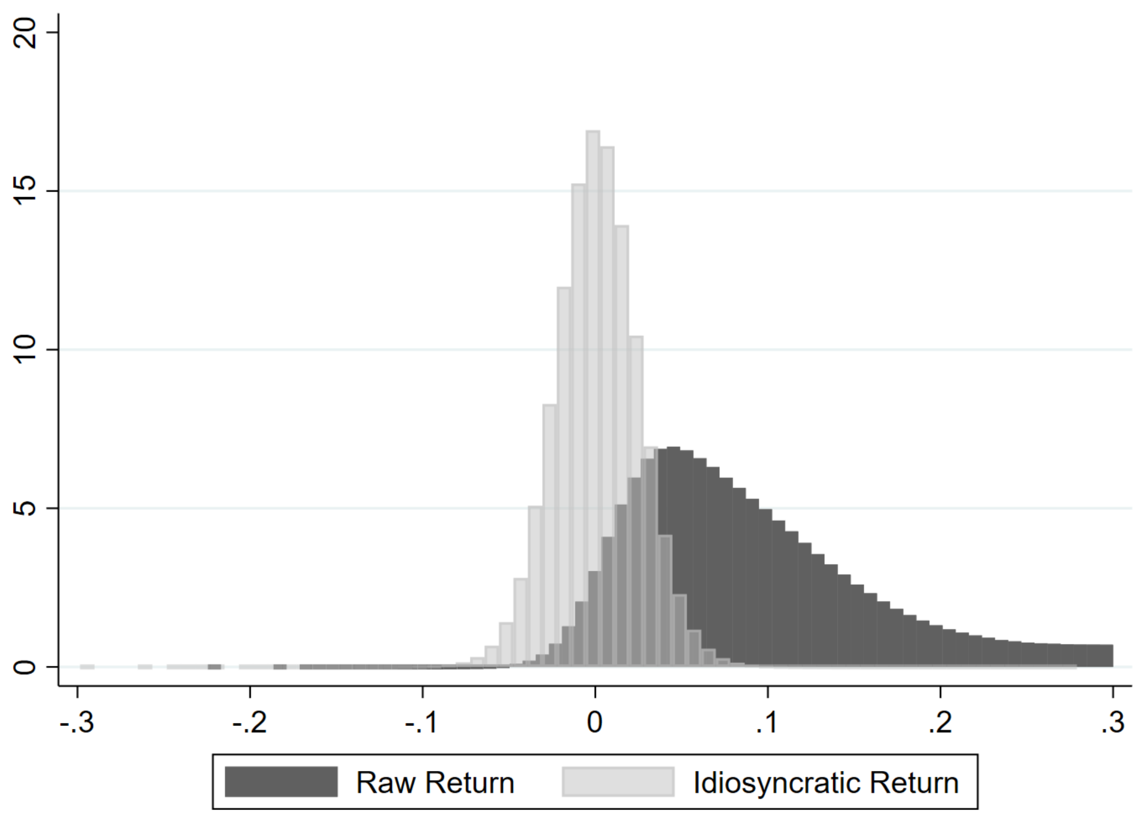
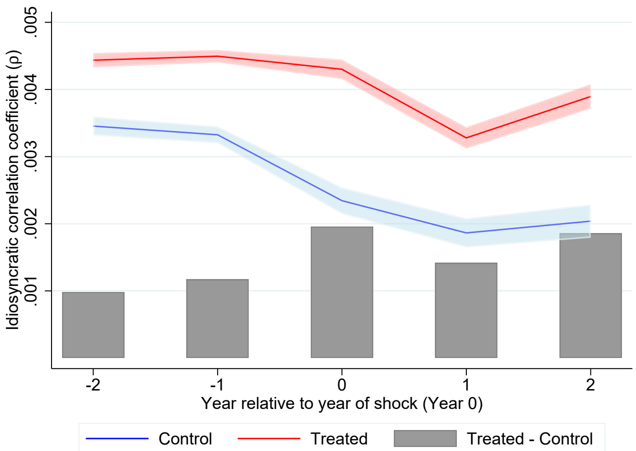


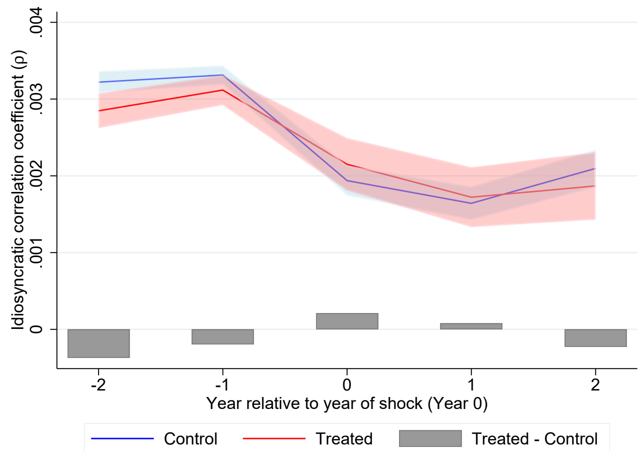
Figure 4: **Trends in idiosyncratic return comovement of treated and control firms**

The figure plots the annual average value of the bi-firm idiosyncratic return correlation coefficient ρ_{ijt} for treated and control firms, over a five-year window centered on the year the competitive shock.

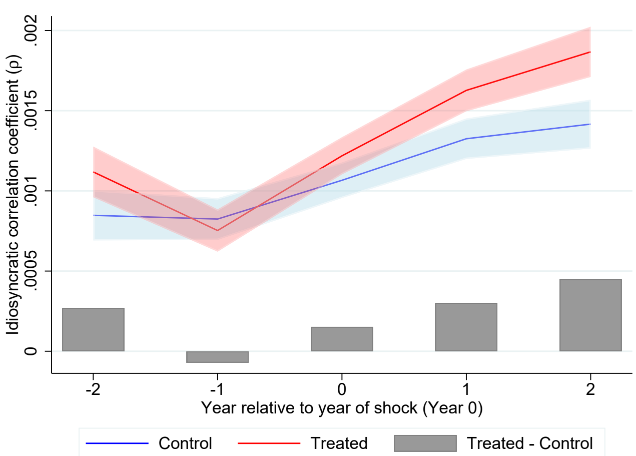
(a) China Median



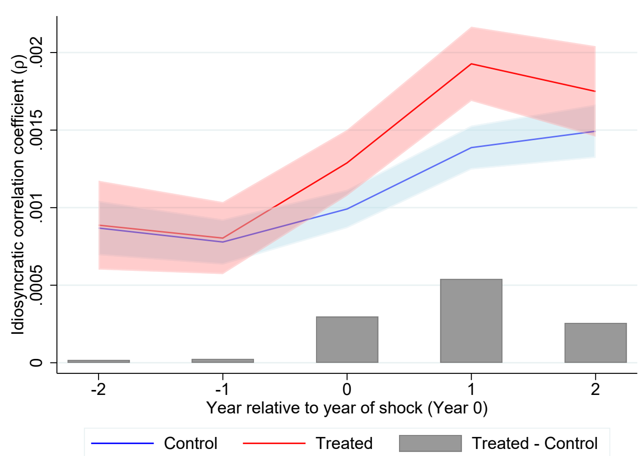
(b) China Top Quartile



(c) Nafta Median



(d) Nafta Top Quartile



(e) FINSA

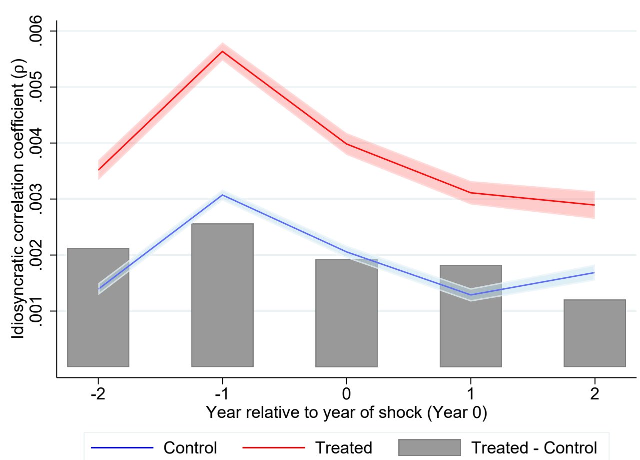


Figure 5: **Industry-heterogeneity in the effect of tariff cuts**

This figure displays the t-values of the individual estimates in the vector ν for twenty different industries (listed on the vertical axis) covered by the sample of tariff-reductions. ν is estimated using the following regression:

$$\rho_{ijt} = \alpha_i + \beta_j + \gamma_t + \delta Treated_j + \lambda(Post_{it} \times Treated_{jt}) + (Post_{it} \times Treated_{jt} \times \mathbf{SIC3})'\nu + \mathbf{Controls}'\mu + \epsilon_{ijt},$$

where α_i, β_j and γ_t are firm i, firm j and year-fixed effects, $Treated_j$ indicates that firm j belongs to the same industry as firm i (an industry subject to tariff reduction), $Post_{it}$ indicates the post-tariff-reduction period for the industry of firm i, and **Controls** is the vector of control variables. ρ_{ijt} is estimated year by year using daily returns. The plotted t-values are ν scaled by the standard errors of ν, and the figure reports only those with t-values of 1.64 or higher i absolute value. Of the total of 44 different industries in the sample with tariff shocks, 20 (44%) have such t-values. The vertical dotted, dashed and solid lines indicate t-values corresponding to significance levels of 10%, 5% and 1%.

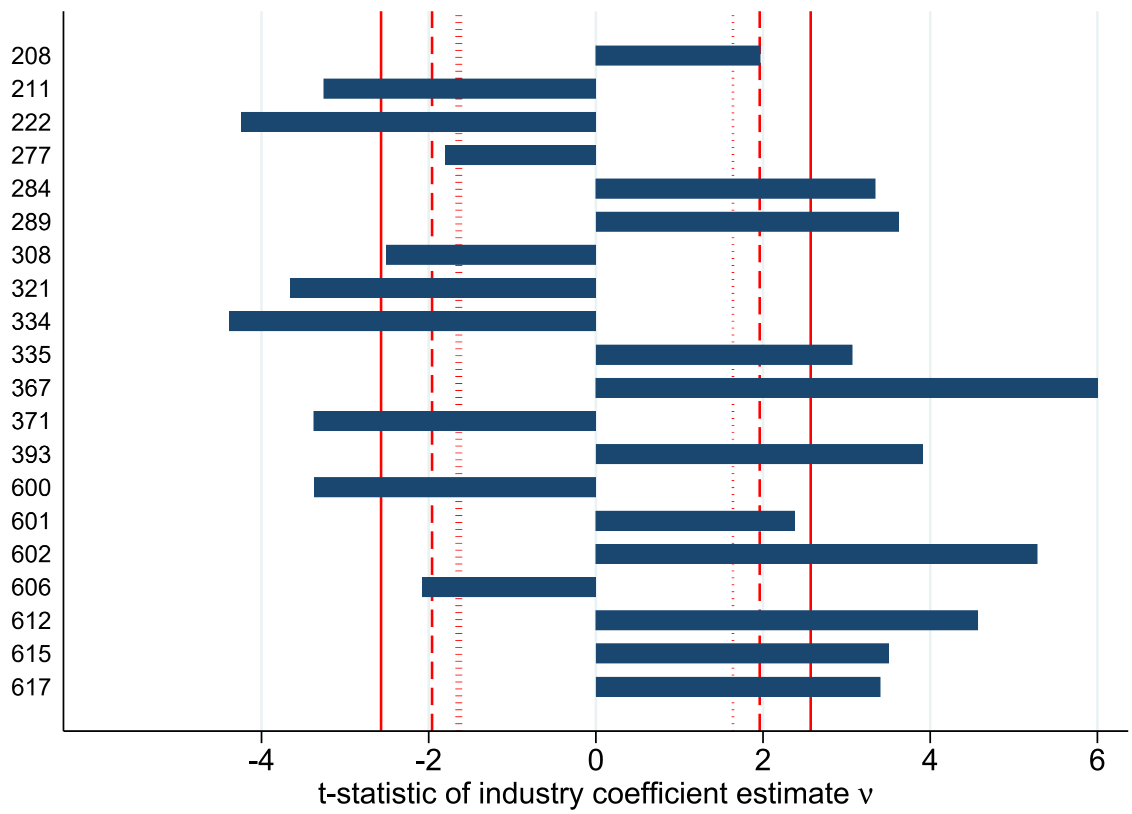


Table 1: Descriptive statistics for annual idiosyncratic return comovement

The table reports characteristics of the cross-sectional distribution of the idiosyncratic return correlation coefficient ρ between firms i and j, estimated using a minimum of 90 daily returns observations within each calendar year, as follows:

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

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

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

The daily return factors are $\mathbf{F} = [r_m - r_f,\ smb,\ hml,\ i_{sic3}]$, where $r_m - r_f$ is the excess return on the value-weighted market portfolio, smb and hml are the returns on the Fama-French long-short size and book-to-market 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. The table reports the "Raw" ρ, the idiosyncratic ρ, the scaled ρ and the illiquidity robust ρ. The "Raw" ρ is computed using daily raw returns within the year. The scaled ρ is obtained by dividing ρ by its standard error and the illiquidity robust ρ by applying the Dimson (1979) correction of the the return generating factor model. The sample period is 1965-2014, and the annual average number of sample firms is 4,307.

Period	Mean	Median	Stdev	Skewness	Kurtosis
1965-1974					
Raw ρ	0.107	0.101	0.056	0.682	4.237
Idiosyncratic ρ	0.001	0.001	0.024	0.154	4.820
Scaled ρ	0.065	0.055	1.185	0.172	5.311
Illiquidity robust ρ	0.001	0.001	0.025	0.060	5.534
1975-1984					
Raw ρ	0.083	0.076	0.055	0.999	5.161
Idiosyncratic ρ	0.002	0.001	0.023	0.181	5.670
Scaled ρ	0.080	0.066	1.141	0.454	27.951
Illiquidity robust ρ	0.002	0.001	0.023	0.120	5.856
1985-1994					
Raw ρ	0.079	0.063	0.069	1.319	5.507
Idiosyncratic ρ	0.001	0.001	0.023	0.214	6.32
Scaled ρ	0.051	0.039	1.169	0.314	10.398
Illiquidity robust ρ	0.001	0.001	0.025	0.164	6.405
1995-2004					
Raw ρ	0.078	0.062	0.070	1.3322	6.156
Idiosyncratic ρ	0.004	0.003	0.025	0.585	10.730
Scaled ρ	0.201	0.166	1.277	1.073	40.390
Illiquidity robust ρ	0.004	0.003	0.026	0.527	10.430
2005-2014					
Raw ρ	0.260	0.279	0.153	-0.025	2.121
Idiosyncratic ρ	0.003	0.002	0.036	0.906	10.573
Scaled ρ	0.168	0.087	1.830	1.324	26.927
Illiquidity robust ρ	0.003	0.002	0.040	0.896	10.174

Table 2: **Cross-sectional determinants: variable definitions**

Name	Indicator (dummy) definition	Percentage
A. Capital structure controls for firm-pairs i and j		
SIC3	i and j are in same SIC3 industry	1.58%
Age quartile	i and j are in same quartile of CRSP listing-age distribution	49.18%
BM quartile	i and j are in same quartile of the book to market distribution	32.89%
Lev quartile	i and j are in same quartile of the leverage distribution	24,96%
R&D quartile	i and j are in same quartile of the R&D distribution	41,16 %
Cash quartile	i and j are in same quartile of the cash ratio distribution	24,98%
Intg quartile	i and j are in same quartile of the ratio of intangible-asset distribution	36.06%
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)	4,65 %
HHI	i and j are in a highly concentrated SIC3 industry (HHI exceeds 1,500)	19,80%
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)	4.74%

Table 3: Cross-sectional determinants of decade-long idiosyncratic return comovement

The table reports coefficient estimates based on the following panel data regression with a decade-long idiosyncratic correlation coefficient ρ as dependent variable:

$$\rho_{ijt} = \alpha_i + \beta_j + \gamma_t + \mathbf{x}'_{\mathbf{ijt}}\delta + \epsilon_{ijt},$$

where ρ_{ij} is as defined in Table 1 but estimated here over a decade so that the number of time periods exceeds the number of firms ($T > N$). The vector $\mathbf{x}$ contains the determinants defined in Table 2, γ_t is the decade-fixed effect, and α_i and β_j are firm-i and firm-j fixed effects. In Column (5), we report the average Student t-statistic obtained on 1,000 replications on randomly selected sub-samples of one percent the observations. Standard errors are clustered at the firm-pair level. Below coefficient estimates between parentheses are reported corresponding size effects, computed as $\Delta x_{ijt}\delta_{ijt}/\bar{\rho}$, where Δx_{ijt} is a one standard deviation increase in x_{ijt}, δ_{ijt} is the coefficient of x_{ijt} and $\bar{\rho}$ is the grand average of ρ_{ijt}. *** indicates significance at the 1% level of confidence. The sample period covers the five decades 1965-2014.

	δ estimates from: $\rho_{ijt} = \alpha_i + \beta_j + \gamma_t + \mathbf{x}'_{\mathbf{ijt}}\delta + \epsilon_{ijt}$				
$\mathbf{x}$-variable	(1) SIC3	(2) SIC3	(3) SIC4	(4) SIC4	(5) SIC3
SIC	0.0103***	0.0073***	0.0067***	0.0055***	8.07
	(4.25)	(3.02)	(2.85)	(2.37)	
I/O quartile		−0.0011***		−0.0015***	
		(-0.44)		(-0.66)	
Age quartile	0.0007***	0.0010***	0.008***	0.008***	3.72
	(0.31)	(0.42)	(0.32)	(0.37)	
BM quartile	0.007***	0.0010***	0.0007***	0.0010***	3.42
	(0.29)	(0.42)	(0.29)	(0.43)	
Lev quartile	0.0005***	0.0007***	0.0005***	0.0007***	2.56
	(0.22)	(0.28)	(0.21)	(0.30)	
R&D quartile	0.0012***	0.0007***	0.0014***	0.0008***	6.02
	(0.51)	(0.27)	(0.59)	(0.34)	
Cash quartile	0.0006***	0.0005***	0.0007***	0.0007***	2.49
	(0.23)	(0.22)	(0.24)	(0.29)	
Intg quartile	0.0008***	0.0009***	0.0008***	0.0011***	4.01
	(.32)	(0.37)	(0.34)	(0.48)	
Location	0.0012***	0.0027***	0.0014***	0.0028***	2.68
	(0.51)	(1.11)	(0.57)	(1.21)	
Leader	0.0024***	0.0030***	0.0027***	0.0031***	4.60
	(0.99)	(1.25)	(1.14)	(1.34)	
HHI	0.0009***	0.0010***	0.0010***	0.001***	3.31
	(0.36)	(0.40)	(0.39)	(0.46)	
Constant	−0.0012***	0.0017***	−0.0036***	0.0023***	
Decade FE	Yes	Yes	Yes	Yes	Yes
Firm i FE	Yes	Yes	Yes	Yes	Yes
Firm j Ind. FE	Yes	Yes	Yes	Yes	Yes
R^2	0.014	0.023	0.012	0.022	
Adj. R^2	0.014	0.021	0.011	0.020	
F	479.9	71.02	403.4	67.46	
Obs.	9,478,816	721,545	8,606,416	632,167	

Table 4: Number of firm-pairs and treated pairs for five categories of competitive shocks

In each year, Column (1) shows the total number of firm pairs in our sample, while Columns (2)-(7) lists the number of treated firm-pairs across the five categories of shocks to competition used in this paper. The number in square brackets (next to the number of treated firm-pairs) is the number of SIC4 industries subject to the shock (for IBBE, it is the number of states adopting the banking regulation law). In Column (2), the total number of import tariff reductions is 85. In Column (3), IBBE is the 1994 Reigle-Neal Interstate Banking and Branching Efficiency Act. NAFTA in Column (4) is the 1994 North American Free Trade Agreement, while China-WTO in Column (5) is China's 2001 entry into the World Trade Organization. For both NAFTA and China-WTO, the treated industries have import shares above the median of the distribution of US industries import shares five years before the shock. FINSA in Column (6) is the Foreign Investment and National Security Act (enforced in 2009), while Column (7) adds all of the shocks across Columns (2)-(6).

		Number of treated firm-pair observations [treated SIC4 industries][a]					
Year	**Total firm-pairs** (1)	**Tariffs** (2)	**IBBE[a]** (3)	**NAFTA** (4)	**China WTO** (5)	**FINSA** (6)	**Total** (7)
1976	463,598	867[3]	0	0	0	0	867
1977	454,116	1,034[16]	0	0	0	0	1,034
1978	419,270	1,020[14]	0	0	0	0	1,020
1979	389,178	1,090[14]	0	0	0	0	1,090
1980	384,985	972[15]	0	0	0	0	972
1981	420,281	1,450[31]	0	0	0	0	1,450
1982	424,831	1,523[33]	0	0	0	0	1,523
1983	453,775	2,041[38]	0	0	0	0	2,041
1984	544,027	2,968[38]	0	0	0	0	2,968
1985	539,430	3,583[42]	0	0	0	0	3,583
1986	431,893	1,820[35]	0	0	0	0	1,820
1987	374,301	1,883[42]	0	0	0	0	1,883
1988	333,166	1,975[38]	0	0	0	0	1,975
1989	2,182,844	1,666[38]	0	0	0	0	1,666
1990	2,000,268	1,563[37]	0	0	0	0	1,563
1991	2,020,556	1,442[36]	0	0	0	0	1,442
1992	2,532,715	1,422[38]	0	0	0	0	1,422
1993	2,946,296	1,480[38]	0	0	0	0	1,480
1994	3,505,900	1,596[44]	0	0	0	0	1,596
1995	3,662,850	766[38]	0	228,826[120]	0	0	229,592
1996	7,579,489	1,784[53]	0	243,951[120]	0	0	245,735
1997	7,944,670	1,990[53]	10,153[22]	247,456[119]	0	0	259,599
1998	7,442,369	2,072[57]	10,878[21]	243,951[119]	0	0	256,901
1999	6,786,168	2,058[58]	62,128[25]	216,811[119]	0	0	280,997
2000	3,366,845	2,789[59]	54,285[25]	0	0	0	57,074
2001	2,785,540	4,641[55]	52,650[28]	0	0	0	57,291
2002	2,256,317	4,381[52]	50,721[27]	0	109,278[112]	0	164,380
2003	2,168,403	4,529[54]	50,086[27]	0	108,345[112]	0	162,960
2004	12,786,279	7,613[51]	43,956[27]	0	103,740[109]	0	155,309
2005	12,276,098	9,031[48]	42,195[28]	0	90,525[104]	0	141,751
2006	11,865,602	0	31,626[28]	0	93,096[100]	0	124,722
2007	9,885,019	0	30,628[28]	0	0	0	30,628
2008	8,713,743	0	28,680[28]	0	0	0	28,680
2009	7,083,871	0	24,976[28]	0	0	314,821[54]	339,797
2010	7,147,119	0	19,701[28]	0	0	336,610[54]	356,311
2011	6,604,795	0	0	0	0	322,806[54]	322,806
2012	6,105,765	0	0	0	0	280,126[49]	280,126
2013	5,984,070	0	0	0	0	283,128[51]	283,128
2014	6,392,100	0	0	0	0	289,180[53]	289,180
Total	159,658,542	73,049	512,663	1,180,995	504,984	1,826,671	4,098,362

[a] In Column (3), the number in square brackets is the number of states adopting IBBE

Table 5: Treatment effects (λ) on the absolute value of idiosyncratic return comovement

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

$$|\rho_{ijt}| = \alpha_i + \beta_j + \gamma_t + \delta Treated_j + \lambda(Post_{it} \times Treated_j) + \mathbf{Controls}'\mu + \epsilon_{ijt},$$

where α_i, β_j and γ_t are firm i, firm j and year-fixed effects, $Treated_j$ indicates that firm j belong to the same 3-digit SIC industry as firm i (an industry subject to the competitive shock), $Post_{it}$ indicates the post-shock period for the industry of firm i and **Controls** is the vector of control variables (market-to-book ratio, leverage, cash and intangibles financial ratios, logarithm of total assets). ρ_{ijt} is estimated year by year using daily returns. The shocks are consist of 85 import tariff reductions (Column 1), individual states' adoption of the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBE, Column 2), the North American Free Trade Agreement of 1994 (NAFTA, columns 3 and 4), China's entry into the World Trade Organization in 2001 (China-WTO, columns 5 and 6) and the competition-reducing Foreign Investment and National Security Act enforced in 2009 (FINSA, Column (7)). For NAFTA and China-WTO, the treated SIC3 industries either have import shares above the median of the distribution of US industries' import shares in 1989 (columns 3 and 5), or are in the top quartile of this distribution (columns 4 and 6). Panel A reports results obtained with SIC3 industry indices to estimate idiosyncratic returns while in Panel B, SIC4 industry indices are used. Standard-errors are clustered at the firm i level. Size effects, computed as the coefficient scaled either by the unconditional average of the ρ_{ij} or by it's standard error, respectively, are reported in parentheses. F is the Fisher test statistic for the joint significance of the regression coefficients and Obs is the number of observations. *, **, *** indicate significance at the 10%, 5%, and *** 1% levels of confidence.

	Competition increase						**Competition decrease**
			NAFTA		China WTO		
	Tariffs	IBBE	Median	Top quartile	Median	Top quartile	FINSA
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A: Idiosyncratic comovement based using SIC3 industry index							
$Post * Treated$	0.0029***	0.0006***	0.0004*	0.0012***	0.0002***	0.0003***	0.00019***
	(1.881/0.044)	(0.07/0.008)	(0.032/0?006)	(0.09/0.001)	(0.087/0.003)	(0.122/0.005)	(0.084/0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.003	0.020	0.001	0.001	0.003	0.002	0.008
F	47.53	64.81	68.44	36.74	98.85	39.76	99.38
Obs.	15.414.123	3.056.948	14.444.163	8.072.688	14.781.609	6.986.128	16.422.134
B: Idiosyncratic comovement based using SIC4 industry index							
$Post * Treated$	0.0045***	0.0003	0.00001	0.0020***	0.0004	0.0003***	0.0002***
	(2.812/0.066)	(0.06/0.004)	(0.009/0.0001)	(0.114/0.002)	(0.016/0.0006)	(0.102/0.004)	(0.102/0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.003	0.010	0.002	0.002	0.003	0.003	0.008
F	47.94	70.98	61.05	32.38	96.13	35.98	100.75
Obs.	14.442.211	3.027.647	13.104.972	7.298.116	13.582.792	6.197.534	15.603.254

Table 6: Treatment effects (λ) on the signed value of idiosyncratic return comovement

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

$$\rho_{ijt} = \alpha_i + \beta_j + \gamma_t + \delta Treated_j + \lambda(Post_{it} \times Treated_j) + \mathbf{Controls}'\mu + \epsilon_{ijt},$$

where α_i, β_j and γ_t are firm i, firm j and year-fixed effects, $Treated_j$ indicates that firm j belong to the same 3-digit SIC industry as firm i (an industry subject to the competitive shock), $Post_{it}$ indicates the post-shock period for the industry of firm i and **Controls** is the vector of control variables (market-to-book ratio, leverage, cash and intangibles financial ratios, logarithm of total assets). ρ_{ijt} is estimated year by year using daily returns. The shocks are consist of 85 import tariff reductions (Column 1), individual states' adoption of the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBE, Column 2), the North American Free Trade Agreement of 1994 (NAFTA, columns 3 and 4), China's entry into the World Trade Organization in 2001 (China-WTO, columns 5 and 6) and the competition-reducing Foreign Investment and National Security Act enforced in 2009 (FINSA, Column (7)). For NAFTA and China-WTO, the treated SIC3 industries either have import shares above the median of the distribution of US industries' import shares from the concerned countries five years before the shock (columns 3 and 5), or are in the top quartile of this distribution (columns 4 and 6), respectively. Panel A reports results obtained with SIC3 industry indices to estimate idiosyncratic returns while in Panel B, SIC4 industry indices are used. Standard-errors are clustered at the firm i level. Size effects, computed as the coefficient scaled either by the unconditional average of the ρ_{ij} or by it's standard error, respectively, are reported in parentheses. F is the Fisher test statistic for the joint significance of the regression coefficients and *Obs* is the number of observations. *, **, *** indicate significance at the 10%, 5%, and *** 1% levels of confidence.

	Competition increase						**Competition decrease**
			NAFTA		China WTO		
	Tariffs	IBBE	Median	Top quartile	Median	Top quartile	FINSA
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A: Idiosyncratic comovement based using SIC3 industry index							
$Post \times Treated$	0.0033***	0.0017***	0.0002***	0.0001	0.0006***	0.0004**	−0.0006***
	(2.09/0.05)	(0.21/0.02)	(0.15/0.003)	(0.09/0.002)	(0.23/0.01)	(0.14/0.002)	(-0.25/0.007)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.001	0.010	0.001	0.001	0.003	0.003	0.002
F	13.27	29.96	26.29	13.20	47.07	19.89	34.34
Obs.	15.414.123	3.056.948	14.444.163	8.072.688	14.781.609	6.986.128	16.422.134
B: Idiosyncratic comovement based using SIC4 industry index							
$Post \times Treated$	0.0034***	0.0010***	0.0001*	0.0003**	0.0005***	0.0004**	−0.0004**
	(2.11/0.05)	(0.19/0.01)	(0.10/0.007)	(0.23/0.004)	(0.19/00.1)	(0.17/0.006)	(-0.15/-0.004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.001	0.004	0.001	0.001	0.003	0.003	0.002
F	14.17	26.95	22.09	12.23	36.96	16.00	31.24
Obs.	14.442.211	3.027.647	13.104.972	7.298.116	13.582.792	6.197.534	15.603.254

Table 7: Treatment effects on operating efficiency and profitability

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

$$y_{it} = \alpha_i + \beta_t + \gamma Post_{it} + \mathbf{Controls}'\delta + \eta_{it}$$

where α_i and β_t are firm i and year t fixed effects, $Post_{it}$ indicates that firm i is treated in year t and **Controls** is a vector of control variables. y_{it} is sales divided by the costs of goods sold (Columns (1) and (2)), R&D divided by total assets (Columns(3) and (4)), working capital divided by property, plants and equipment (Columns (5) and (6)). In Columns (2), (4), and (6),in addition to firm and year fixed-effects, control variables include the market-to-book, leverage, cash and intangibles financial ratios as well as the logarithm of total assets. The set of shocks to competition is composed of 85 import tariff reductions, NAFTA agreement and China WTO Entry. Treated firms are belonging to industries that display a statistically significant change in ρ (a t-value of of at least ± 1.64) to the competitive shock. $Post_{it}$ is equal to $+1$ in case of increase, -1 in case of decrease and 0 otherwise during a period of 3 years(Panel A) and 5 years after the shock (Panel B). The analyzed period goes from 1970 (five years before the first shock) to 2007 (three after the last shock). 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 *Obs.*, the number of observations. *, **, *** indicate significance at the 10%, 5%, and *** 1% levels of confidence.

	Sales/COGS		**R&D/Total Assets**		**Working Capital/PPE**	
	(1)	(2)	(3)	(4)	(5)	(6)
A: 3-years post-shock window						
Post	0.0748**	0.0777**	−0.0079***	−0.0072***	−0.6621***	−0.608***
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
R^2	0.706	0.708	0.671	0.684	0.578	0.600
F	1.83	4.81	6.13	17.87	5.62	21.24
Obs.	121,765	121,765	121,988	121,988	108,810	108,810
B: 5-years post-shock window						
Post	0.0734**	0.0758**	−0.0072***	−0.0063***	−0.559**	−0.455**
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
R^2	0.706	0.708	0.671	0.684	0.578	0.600
F	1.82	4.77	6.05	17.78	5.57	20.98
Obs.	121,765	121,765	121,988	121,988	108,810	108,810

Table 8: **Idiosyncratic return comovement and Hoberg-Phillips product similarity scores**

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

$$Y_{ijt} = \alpha + \gamma SS_{ijt} + \epsilon_{ijt}$$

$$Yijt = \alpha + \beta_t + \gamma SS_{ijt} + \epsilon_{ijt}$$

$$Yijt = \alpha_{ij} + \beta_t + \gamma SS_{ijt} + \epsilon_{ijt}$$

where Y_{ijt} is either ρ_{ijt} in Panel A or, in Panel B, ρ_{ijt}^{scaled} (ρ_{ijt} divided by its unconditional standard error SE_ρ). α_{ij} are firm pairs fixed-effects, β_t are year fixed-effects and SS_{ijt} is the Hoberg-Phillips product similarity score. Panel A reports results obtained using ρ_{ijt} defined as in Table 1 and Panel B, results obtained using ρ_{ijt} scaled by it standard-error. The 3-digit SIC industry indices are used to estimate idiosyncratic returns in both cases. 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 Obs, the number of observations. *, **, *** indicate significance at the 10%, 5%, and *** 1% levels of confidence.

	Regression specification		
	(1)	(2)	(3)
A: dependent variable ρ_{ijt}			
γ	0.032***	0.027***	0.037***
Year FE	No	Yes	Yes
Firm pairs FE	No	No	Yes
R^2	0.001	0.006	0.372
F	4,492	1,503	831
Obs.	5.043.182	5.043.182	5.043.182
B: dependent variable ρ_{ijt}^{scaled}			
γ	0.546***	0.465***	0.618***
Year FE	No	Yes	Yes
Firm pairs FE	No	No	Yes
R^2	0.001	0.006	0.372
F	3,745	1,535	858
Obs.	5.043.182	5.043.182	5.043.182

Table 9: Treatment effects on idiosyncratic return comovement interacted with Hoberg-Phillips similarity scores

The table shows the coefficient estimates of λ and μ in the following specification:

$$\rho_{ijt} = \alpha_i + \beta_j + \gamma_t + \delta Treated_j + \lambda(Post_{it} \times Treated_j) + \mu(Post_{it} \times Treated_j \times SS_{ijt}) + \mathbf{Controls}'\mu + \epsilon_{ijt}$$

where α_i, β_j and γ_t are firm i, firm j and year-fixed effects, $Treated_j = 1$ if j is in the same industry as firm i (an industry subject to the competitive shock), $Post_{it} = 1$ in the post-shock period for the industry of firm i, SS_{ijt} is the Hoberg and Phillips similarity scores (available from 1996-2014), and **Controls** is the vector of control variables (market-to-book ratio, leverage, cash and intangibles financial ratios, logarithm of total assets). ρ_{ijt} is estimated year by year using daily returns as explained in Table 1. Results are obtained with SIC3 industry indices to estimate idiosyncratic returns. The shocks consist of China's entry into the World Trade Organization in 2001 (China-WTO, columns 1 and 2) and the competition-reducing Foreign Investment and National Security Act enforcement in 2009 (FINSA, columns 3 and 4). For China-WTO, the treated 3-digit SIC industries have import shares above the median of the distribution of US industries' import shares in 1989. In Column (4), we use $1 - SS_{ijt}$ in place of SS_{ijt} as measure of dissimilarity. Standard-errors are clustered at the firm i level. F is the Fisher test statistic for the joint significance of the regression coefficients and Obs, the number of observations. *, **, *** indicate significance at the 10%, 5%, and *** 1% levels of confidence..

	Competition increase		**Competition decrease**	
	China-WTO		FINSA	
Variable	(1)	(2)	(3)	(4)
$Post \times Treated$	0.0006**	0.0017	−0.001***	−0.0011***
$Post \times Treated * SS$		0.2880***		−0.2460***
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls FE	Yes	Yes	Yes	Yes
R^2	0.001	0.001	0.004	0.004
F	37.71	43.81	29.02	34.69
Obs.	14,781,608	14,781,608	16.422.13	16.422.13

Table 10: Post-IBBE effects (λ) on idiosyncratic return comovement of interstate bank entries

This table reports λ coefficient estimates using the following regression, estimated around IBBE enactment at state level:

$$Y_{ijt+1} = \alpha_i + \beta_j + \gamma_t + \delta Treated_{jt} + \lambda(Post_{it} \times Treated_{jt}) + \mathbf{Controls'}\mu + \epsilon_{ijt}$$

where Y_{ijt+1} is either ρ_{ijt+1} or ρ^{scaled}_{ijt+1} (estimated year by year using daily returns), α_i, β_j and γ_t are bank i, bank j and year-fixed effects. $Post_{it} = 1$ indicates the post-IBBE-enactment period for the state of bank i. In columns (1) and (2), $Treated_{jt} = 1$ indicates that (i) bank state j is different from bank state i and (ii) there has been an acquisition by a bank located in bank state j of a bank located in bank state i. In columns (3) and (4) $Treated_{ij}$ records the *cumulative number* of such acquisitions (*Num Entries*), while it is the logarithm of the *cumulative value* of acquisitions in columns (5) and (6) (*Val Entries*). **Controls′** is a set of control variables (market-to-book ratio, leverage, cash and intangibles financial ratios, logarithm of total assets). Information on merger activity is from Thomson-Reuters SDC M&A database. F is the Fisher test statistic for the joint significance of the regression coefficients and Obs is the number of observations. *, **, *** indicate significance at the 10%, 5%, and *** 1% levels of confidence.

	Dummy Entry		**Num Entries**		**Val Entries**	
	(1)	(2)	(3)	(4)	(5)	(6)
	ρ_{ij}	ρ_{ij}^{Scaled}	ρ_{ij}	ρ_{ij}^{Scaled}	ρ_{ij}	ρ_{ij}^{Scaled}
$Post \times Treated$	0.003***	0.004***	0.001**	0.02**	0.001***	0.01***
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.047	0.048	0.047	0.048	0.047	0.048
F	132.2	135.6	132.2	135.5	133.2	136.5
Obs.	932,918	932,918	932,918	932,918	932,918	932,918

Table 11: **Idiosyncratic return comovement and the likelihood of becoming a target**

The table reports the coefficient estimates of γ and δ in the following probit and linear probability model:

$$Target_{it} = \Phi(\alpha + \beta_t + \gamma\bar{\rho}_{i,t-1} + \delta\bar{\rho}^{10}_{i,t-1} + \mathbf{Controls}'\mu + \epsilon_{it})$$

$$Target_{it} = \alpha_i + \beta_t + \gamma\bar{\rho}_{i,t-1} + \delta\bar{\rho}^{10}_{i,t-1} + \mathbf{Controls}'\mu + \epsilon_{it},$$

where $Target_{it} = 1$ if firm i becomes a target in year t and zero otherwise, $\bar{\rho}_{i,t-1}$ is the equally-weighted average $\rho_{ij,t-1}$ across all firms j in firm i's 3-digit SIC industry, $\bar{\rho}^{10}_{i,t-1}$ is the average $\rho_{ij,t-1}$-value of firm i's ten nearest neighbors in terms of $\rho_{ij,t-1}$, **Controls** is the vector of control variables (market-to-book ratio, leverage, cash and intangibles financial ratios, logarithm of total assets) and $\Phi(.)$ stands for the standard normal cumulative distribution function. Columns (1) and (2) report the coefficients estimates for the probit model while columns (3) and (4) report results from the linear probability mode. In columns (2) and (4), $\bar{\rho}_{i,t-1}$ and $\bar{\rho}^{10}_{i,t-1}$ are replaced by their values scaled by their respective standard errors. The merger sample includes 3,272 listed targets over the 1992-2014 period. Size effects, reported in brackets, are computed as $Size_x = \frac{\triangle x * \beta_x}{Prob(Merger)}$, where $\triangle x$ is a one standard deviation increase in x, β_x is the coefficient of x and the unconditional probability of being a target is $Prob(Target) = \frac{\#Target}{\#Firm}$ over the sample period. Standard errors are clustered at the firm level. F is the Fisher test statistic for the joint significance of the regression coefficients and Obs is the number of observations. *, **, *** indicate significance at the 10%, 5%, and *** 1% levels of confidence.

	Coefficient estimates			
	Probit model		**Linear probability model**	
Variable	(1)	(2)	(3)	(4)
$\overline{\rho}$	6.751***		0.251*	
	[0.055]		[0.031]	
Scaled $\overline{\rho}$		0.4171***		0.015*
		[0.053]		[0.029]
$10^{th}\overline{\rho}_{nn}$	−0.8511***		−0.085***	
	[-0.076]		[-0.114]	
Scaled $10^{th}\overline{\rho}_{nn}$		−0.052***		−0.004***
		[-0.089]		[-0.102]
Constant	−1.074***	−1.078***	−0.062***	−0.067***
Firm FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
$PseudoR^2$	2.93	2.94		
R^2			0.9	0.29
F			31.58	31.48
Obs.	84,642	84,642	84,642	84,642

Table 12: Idiosyncratic return comovement and merger-pair likelihood

Panel A of the table reports coefficient estimates in the following linear probability model estimated using OLS:

$$Merger_{ijt} = \alpha + \beta_t + \gamma_1 \rho_{ij,t-1} + \gamma_2(|M/B_{i,t-1} - M/B_{j,t-1}|) + \mathbf{Controls}'\mu + \epsilon_{ijt}, \tag{15}$$

where $Merger_{ijt} = 1$ if firms i and j are involved in a merger bid in year t and zero otherwise, α is a constant, β_t are year fixed-effects, $\rho_{ij,t-1}$ is the idiosyncratic return correlation between firm pair i and j, and $|M/B_{i,t-1} - M/B_{j,t-1}|$ is the absolute value of the difference between the market-to-book ratios of i and j. **Controls** is a set of control variables (market-to-book ratio, leverage, cash and intangibles financial ratios, logarithm of total assets). Columns (2) and (6) replace ρ with ρ scaled by its standard error. In Columns (3) and (7), we replace ρ with Hoberg and Phillips (2010)'s text-based product similarity score SS. Columns (4) and (8) report the results of the following model:

$$Merger_{ijt} = \delta_1 M/B_{q1,t-1} + \delta_2 M/B_{q2,t-1} + \delta_3 M/B_{q3,t-1} + \delta_4 M/B_{q4,t-1} + \epsilon_{ijt}$$

where $M/B_{q1,t-1}$, $M/B_{q2,t-1}$, $M/B_{q3,t-1}$ and $M/B_{q4,t-1}$ are dummy variables indicating the quartile of $|M/B_i - M/B_j|$ to which the firm pair i, j belong in year $t-1$. Panel B reports the size effects for ρ, ρ scaled by its standard deviation and $|MB_i - MB_j|$, which provide the percentage change in the unconditional merger likelihood from a one standard deviation increase in the listed variable (Panel B excludes the effect of the SS score since it is left-censored). The M&A sample comprises 3,272 pairs of listed bidders and targets, 1992-2014. Standard errors are clustered at the firm level. F is the Fisher test statistic for the joint significance of the regression coefficients and Obs is the number of observations. *, **, *** indicate significance at the 10%, 5%, and *** 1% levels of confidence.

Variable	**1992-2000**				**2001-2014**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Coefficient estimates								
ρ ($\times 10^{-4}$)	0.39***				0.85***			
Scaled ρ ($\times 10^{-4}$)		0.026***				0.058***		
SS			0.003***				0.003***	
$\|M/B_i - M/B_j\|$ ($\times 10^{-4}$)	0.015***	0.015***	−0.002		0.067	0.068	−0.040	
M/B $q1$ ($\times 10^{-4}$)				0.135***				0.151***
M/B $q2$ ($\times 10^{-4}$)				0.119***				0.117***
M/B $q3$ ($\times 10^{-4}$)				0.092***				0.087***
M/B $q4$ ($\times 10^{-4}$)				0.075***				0.065***
Constant ($\times 10^{-4}$)	−0.058***	−0.058***	−0.002		−0.078***	−0.078***	−0.046***	
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Controls	Yes	Yes	Yes	No	Yes	Yes	Yes	No
B: Size effects								
Size ρ	0.27				0.64			
Size Scaled ρ		0.28				0.68		
Size M/B	0.06	0.06			0.02	0.03		
F	28.19	28.17	25.53	229.3	18.56	18.54	18.73	160.9
Obs. (million)	172	172	108	140	120	120	124	104

Table 13: **Impact of import tariff reductions and merger activity on future idiosyncratic return comovement**

Table 13 reports the coefficient estimates of the following regression equation:

$$\overline{\rho}_{i,t+1} = \alpha_i + \gamma_t + \beta_1(Post_{it} \times Treated_{it}) + \beta_2 M\&A_{it}^{Agg} + \beta_3(Post_{it} \times Treated_{it} \times M\&A_{it}^{Agg}) + \epsilon_{it}$$

where $\overline{\rho}_{i,t+1}$ is the equally-weighted industry average idiosyncratic return comovement between firm-pair ij for industry i and year $t+1$, α_i and γ_t are industry- and year-fixed effects, $M\&A_{it}^{Agg}$ is the aggregate number of merger transactions in industry i, $Post_{it} * Treated_{ij}$ indicates that year t is post-import tariff reduction for industry i and $Post_{it} * Treated_{it} * M\&A_{it}^{Agg}$ is a triple interaction term. The estimation period is from 1980 (the beginning of the Thomsom-Reuters SDC database coverage) through 2005 (the last year that witnessed a significant tariff reduction in our sample). Significant import tariff reductions are from Frésard (2010) and Frésard and Valta (2016), restricted to 69 tariff reductions after 1979. An import tariff reduction is considered significant by the original authors if it is at least three times larger than the industry's average tariff change (positive or negative) over the pre-event period. A horizontal merger (Column 3) is one where the acquirer and target operate in the same 4-digit SIC industry. Size effects are reported between brackets below coefficients of interest. Standard errors are clustered at the industry level. F is the Fisher test statistic for the joint significance of the regression coefficients and Obs is the number of observations. *, **, *** indicate significance at the 10%, 5%, and *** 1% level of confidence.

Variable	**Acquirer industry** (1)	**Target industry** (2)	**Horizontal transaction** (3)	**Non-horizontal transaction** (4)
$M\&A_{it}^{Agg}$	0.00012**	0.00013**	0.00014**	0.00016***
$Post_{it} \times Treated_{it}$	−0.00021	−0.00027	−0.00014	−0.00012
$Post_{it} \times Treated_{it} \times M\&A_{it}^{Agg}$	0.00008**	0.00012**	0.00013**	0.00014
	[0.023]	[0.029]	[0.019]	[0.015]
Constant	0.0021***	0.0021***	0.0021***	0.0021***
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.40	0.41	0.40	0.39
F	30.95	30.06	30.81	29.7
Obs.	9,482	9,482	9,482	9,482