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Business groups and the incorporation of firm-specific shocks into stock prices☆

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ABSTRACT

Firm-specific information has a damped effect on business group-affiliated firms' stock prices. Such firms' idiosyncratic stock returns are less responsive to idiosyncratic commodity price shocks than are the idiosyncratic returns of otherwise similar unaffiliated firms in the same country and commodity-sensitive industry. Using global commodity shocks means we assess responses to common idiosyncratic shocks of the same magnitude, frequency, and observability. Further identification follows from difference-in-difference tests exploiting successful and matched exogenously failed control block transactions. We conclude that business group firms' stock prices provide less firm-specific information to capital providers and managers.

1. Introduction

A fundamental role of the stock market is to incorporate firm-specific (idiosyncratic) information into stock prices (Grossman, 1976), which provide feedback to firms' managers and capital providers (Bond et al., 2012) so that their capital allocation decisions are more economically efficient (Tobin, 1984). We find that business groups damp this stock-price feedback mechanism because investors' expectations about intra-group risk sharing and transfers confound stock price responses to idiosyncratic shocks.[1] Given that the efficiency of capital allocation and productivity growth are impaired when stock prices move less idiosyn-

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[1] We define business groups as collections of listed firms under common control through equity blocks.

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cratically (Wurgler, 2000; Durnev et al., 2004a), our results suggest that more businesses belonging to groups could damp the efficiency of capital allocation and productivity growth in an economy.

We hypothesize that business group member firms' stock prices incorporate less firm-specific information because investors expect intragroup risk-sharing and resource transfers. Business groups, which are ubiquitous around the world, can spread risk across their member firms (Hoshi et al., 1990, 1991; Friedman et al., 2003; Khanna and Yafeh, 2005; Gopalan et al., 2007) and can shift resources from member firms with excess free cash flow to low-earnings firms with unfinanced profitable investments (Almeida and Wolfenzon, 2006a), fund private benefits for their top insiders (Johnson et al., 2000; Bertrand et al., 2002), or prop up ill-run affiliates (Morck and Nakamura, 1999). Investors, expecting business groups to behave in any or all of these ways, would rationally expect idiosyncratic shocks to have less impact on the share price of a group affiliate than on the share price of an otherwise comparable unaffiliated firm.

Ascertaining whether or not business groups cause their member firms' share prices to move less idiosyncratically is a difficult econometric challenge because idiosyncratic shocks to different firms vary in frequency, magnitude, and observability. One would ideally like to observe the responses of group-affiliated and unaffiliated firms to the same shock. This is what we do by introducing a novel methodology that focuses on how shocks to global commodity prices are incorporated into stock prices of firms in the same commodity-sensitive industries. These shocks are observable by all market participants; affect all commodity-sensitive firms in the same country and industry with the same magnitude, permanence, and frequency; and are measured prior to any risk sharing, propping, or tunneling activities.

Our identification strategy relies on matching commodities to industries and, thus, to firms. We do this in three main ways. The first approach uses statistically estimated out-of-sample sensitivities of stocks in U.S. industries to commodity shocks, emulating the Rajan and Zingales (1998) methodology for flagging external finance-sensitive sectors. The major advantage of the statistical method is that it gauges the sensitivity of stocks in an industry to commodity price-related shocks through all possible channels, including supply and demand effects, linkages to untraded commodities, or other factors (Anderson and Danthine, 1981). The second approach, constrained statistical matches, selects commodity-industry links that best satisfy the criterion of the statistical method subject to the requirement that the matched industry also be a direct user or producer of the commodity in the Bureau of Economic Analysis (BEA) input-output (I-O) tables. The third approach simply links industries to commodities that constitute large fractions of their inputs or outputs in the BEA input-output tables. Because business groups are relatively unimportant in the US (La Porta et al., 1999a; Masulis et al., 2011), our use of U.S. data as benchmarks for the statistical method and constrained statistical method mitigates attenuation bias due to group-affiliated firms possibly being less responsive to commodity shocks that would result if we used groups' domestic country data instead. The third method sidelines this problem by focusing on commodity inputs and outputs instead of estimating sensitivities in sample.

Our main finding is that the idiosyncratic returns of business group-affiliated firms are less responsive to idiosyncratic commodity price shocks than are the idiosyncratic returns of unaffiliated firms after controlling for time-varying country-industry level latent variables. The results are not driven by firm-level observable characteristics such as hedging, diversification across industries, a firm's equity ownership of other firms, leverage, size, or research and development (R&D) activity. The results are robust to battery of tests.[2]

Further identification follows from difference-in-difference tests exploiting changes in group affiliation, control block acquisitions, and failed control block bids. When previously unaffiliated firms become group-affiliated, their stocks become less sensitive to commodity price shocks. Likewise, when previously affiliated firms cease to be group-affiliated, their stocks become more sensitive to such commodity price shocks. Further identification tests preclude potential selection problems in control block transactions by comparing successful control block acquisitions with matched control block bids that failed for exogenous reasons (Seru, 2014), and reaffirm our results.

We also show that when a group affiliate in a commodity-sensitive sector is hit by a commodity price shock, the stocks of the group's other affiliates in sectors not sensitive to that commodity react to the shock nonetheless. These results are consistent with investors expecting risk sharing or income shifting within business group firms to spread firm-specific stock return volatility associated with idiosyncratic commodity shocks across affiliates.

Group affiliation attenuates share price responses to commodity shocks, so it may well attenuate share price responses to other firm-specific shocks and increase stock price synchronicity across all the firms in the business group. Attenuated firm-specific shocks should increase a stock's co-movement with its market, measured by its market model R^2. Firm-level tests show business group affiliates' stocks co-moving more with their markets than do otherwise similar unaffiliated firms' stocks. This is consistent with our results generalizing to other idiosyncratic shocks, i.e. investor's expectations of intra-group transactions confounding the effects of other idiosyncratic shocks on stock prices.

We contribute to the literature in several ways. First, the novel methodology we develop, tracking the responses of investors to the same idiosyncratic commodity shock, could have broader applications. An important feature of this shock is that it is globally determined, observed by all investors and, unlike commonly used accounting measures, unaffected by ex-post actions, such as wealth transfers. We posit that differences in group firms' stock price responses to these idiosyncratic shocks could provide a

[2] We vary industry-commodity matching, business group affiliate identification, regression specifications, samples and the asset pricing model used in calculation of idiosyncratic returns.

Panel A: R^2 (vertical axis) versus per capita GDP *Panel B: The incidence of business groups (vertical axis) versus per capita GDP* *Panel C: R^2 (vertical axis) versus incidence of business groups*

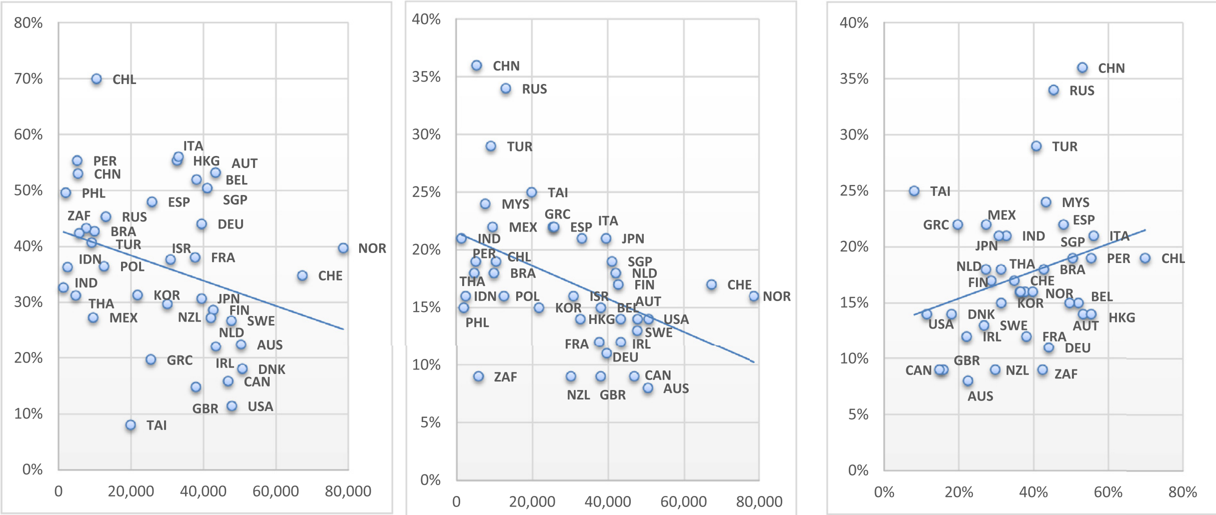

Fig. 1. Stock return co-movement, economic development, and the importance of business groups.

The R^2s are from Morck et al. (2013), averaged across 1995–2010. Gross domestic product (GDP) per capita, from the International Monetary Fund's World Economic Outlook dataset [https://www.imf.org/external/pubs/ft/weo/2019/02/weodata/index.aspx] is in current US dollars and is averaged across all sample years. The country abbreviations are from the same dataset. Fraction of group-affiliated observations (incidence of business groups) is from Table 1. The sample contains 40 countries that are in Morck et al. (2013) and in Table 1.

measure of investors' expectation about the internal operations of business groups with different structures, in different economic conditions, or in eras or countries with different laws or regulations.

Second, the results highlight a salient consequence to engaging in activities such as risk sharing, income shifting, and propping: damping the feedback that stock prices provide to managers and shareholders about each individual group firm's investment decisions and opportunities. Business groups may arise to substitute group-level centrally planned resource allocation for stock market directed resource allocation in countries whose stock markets work poorly (Khanna and Yafeh, 2007). However, our results show a feedback effect: expected resource allocation at the business group-level damps individual stock price reactions to firm-specific events, making stock prices less informative as guides to firm-level resource allocation. Business groups can thus be a cause as well as a consequence of impaired information flow in the stock market.

Third, we show business group prevalence to be a complementary explanation, in addition to others surveyed by Morck et al. (2013), of market-level stock synchronicity. Our firm-level tests affirm a causal role for business groups in damping firm-specific stock price movements. Fig. 1 shows that stock returns are more synchronous in economies where more firms are group-affiliated.

Fourth, we causally link two seemingly unrelated findings in the literature. Stock prices move less idiosyncratically in lower income economies (Morck et al., 2000) and business groups are also more prominent in lower income economies (R. La Porta et al., 1999b; Fogel, 2006; Khanna and Yafeh, 2007; Masulis et al., 2011). This pattern is evident in Fig. 1 as well, but income levels could proxy for any number of factors associated with both stock return synchronicity and the prevalence of business groups. Our study connects these two lines of research by showing that business group affiliation causes stock prices to react less to idiosyncratic shocks.

In summary, group firms' stocks moving less than do the stocks of otherwise similar unaffiliated firms on the same commodity price shock event can be viewed as each individual group firm's stock price providing less firm-specific feedback to capital providers and managers (Bond et al., 2012). Business groups can be a second-best response to high capital market information and transactions costs (Khanna and Yafeh, 2007). However, our findings show that business groups can also exacerbate such costs by confounding the incorporation of idiosyncratic information into group firms' stock prices, which can reduce the value and, therefore, the production of firm-specific information (Veldcamp, 2006), creating a lock-in effect. Given that idiosyncratic information incorporated into stock prices correlates highly with economy-level efficiency of capital allocation (Wurgler, 2000), business groups could trap an economy in a state of inefficient capital allocation. We posit that business groups could help explain the stability of the middle income trap (Rajan and Zingales, 2004; Almeida and Wolfenzon, 2006b; Eichengreen et al., 2013), in which many economies' growth slows and stalls after a first generation of large businesses rises, an issue of first-order importance in financial and economic development.

Section 2 describes the data and methods of isolating commodity shocks and identifying commodity-sensitive industries. Section 3 presents the baseline results associating business group affiliation with reduced stock price sensitivity to commodity shocks. Section 4 explains causal inference and Section 5 discusses robustness. Section 6 discusses economy level implications and Section 7 concludes.

2. Data and methodology

Several steps are involved in the construction of our sample. First, we identify group-affiliated firms. Next, we calculate idiosyncratic components of stock returns and idiosyncratic components of commodity shocks. Finally, we identify which industries (and, hence, firms) should be sensitive to shocks to the prices of key commodities using three methods of matching.

2.1. Group affiliation

Ownership data for publicly traded firms worldwide are from three sources: Worldscope for 1993 through 2009, Thomson Reuters Ownership for 2005 through 2012, and Datastream Asset-4 Universe for 2002 through 2013.[3] For an economy to be included in our sample, it must have at least 50 publicly traded firms for which we have ownership data at any time during the entire sample period. This leaves a sample of 43 economies.

Each of these data sources provides the name and the cash flow (i.e., ownership) rights of each firm's largest shareholder. We presume that the largest blockholder has a controlling stake if her ownership stake in the firm is at least 20%. This cut-off is also employed by La Porta et al. (1999b) to infer control.[4] Using this relatively high ownership threshold minimizes problems due to cross-economy differences in the precise threshold that triggers ownership disclosure. Our data provide ownership stakes, not voting control stakes, which depend on control enhancement devices such as dual-class shares, golden shares, reserved board seats, or pyramiding via unlisted affiliates. This almost certainly leads to misclassifying some group affiliates as unaffiliated and, therefore introduces an attenuation bias, i.e., biasing point coefficient estimates on measures of group affiliation towards zero.

Controlling shareholders are classified as governments, corporations, investment funds or individuals (including families), using lists of words and abbreviations commonly found in the names of each sort of entity. Faccio et al. (2011) provide a list of terms commonly found in the names of government shareholders (in various languages), and Faccio and O'Brien (2020) supply an analogous list for corporate entities. For example, a controlling shareholder whose name contains the term "Ltd," or its equivalent in another language, is presumed to be a corporation, and a controlling shareholder whose name contains the term "municipal" is presumed to be a government entity. Investment funds are flagged using an analogous list we develop for this purpose. Terms such as "fund" identify investment funds.[5] Any controlling shareholder not classified as a government, corporation, or investment fund is presumed to be an individual.

Firms whose controlling shareholder is a government entity are dropped from the sample because soft budget constraints of state-owned enterprises (SOEs) (Kornai, 1986) could affect the link between their fundamentals and stock returns. SOEs' public shareholders could anticipate bailouts to smooth earnings fluctuations, and natural monopoly SOEs could pass shocks to consumers, partially immunizing shareholders. SOE shares' reactions thus can resemble those of group affiliates even if the SOEs are not formal affiliates of state-controlled groups of listed firms, such as existed in Austria and Italy until recently and remain important in China.

We classify a firm as group-affiliated if its controlling shareholder is a corporation, if its controlling shareholder is an individual who controls at least one other firm in our sample, or if the firm itself is the controlling shareholder of at least one other firm in our sample. All other firms, including those controlled by investment funds, are designated as unaffiliated. This classification algorithm follows prior studies (e.g. Faccio et al., 2001; Bae et al., 2002; Bertrand et al., 2002; Baek et al., 2006; Masulis et al., 2011) in defining business groups as collections of separate legal entities under common control through equity blocks.

To identify controlling shareholders who own control blocks in multiple firms in the sample, the names of controlling shareholders are matched by Levenshtein (1965) distance: the minimum number of single character edits (excluding punctuation, multiple consecutive spaces, and spaces at the beginning or at the end) required to change one name into the other, normalized by the length of the shorter name. If the Levenshtein distance between two names is 20% or less, the algorithm infers a match. The algorithm allows for minor name variations that exact matching would miss, but it is far from perfect.

False and missed matches are inevitable. The vagaries of languages and the complexities of control chains (see Almeida et al., 2011) combined with a relatively stringent (20%) threshold likely leave missed matches predominating. Our approach misses group affiliates controlled via multiple control chains that sum to over 20% if each fall

[3] All three datasets have been discontinued.

[4] Robustness tests in Section 5.2 use a 15% ownership threshold.

[5] In some countries, business families control business groups via pension funds [e.g., Brazil (Perkins, Morck and Yeung, 2014)], closed-end mutual funds [e.g., Sweden (Högfeldt, 2005)], or other institutional investment funds. In recent years, increasing numbers of US firms have investment funds as common equity blockholders (Gilje, Gormley and Levit, 2018). The Investment Companies Act of 1940 proscribes US investment companies from intervening in listed firms' management decisions except as shareholders operating via channels legally open to shareholders, so the effects we explore are less likely to be evident in such cases. Disputed findings (e.g., Rock and Rubinfeld., 2017; Schmalz, 2018) nonetheless associate common institutional investor ownership with coordinated corporate strategies, notably price fixing. To avoid counting US exchange-traded funds or investment funds as controlling shareholders in defining business groups, common blockholders are screened for English terms associated with institutional investors. This presumes that English terms flag US-based institutional investors and miss those based in other countries. Robustness tests (not shown) that retain investment companies associated with a business family (using a list of keywords such as "family," "estate," etc.) as common controlling shareholders for the purpose of detecting business groups yields results (not shown) similar to those in the tables. The list of words used to identify investment funds of business families is available upon request.

below that threshold as well as those controlled via control enhancement devices. This further potential misclassification of group affiliates as unaffiliated also adds attenuation bias to the tests. An opposite problem arises if we misidentify targets in the process of being acquired or divisions in the process of being divested as group affiliates. This is a potentially more serious problem in economies, such as the US, with more merger and divestiture activity.[6]

Our procedure yields 55,671 unique firms and 390,186 firm-years of ownership data. Table 1, Panel A, summarizes firm-year observations classified as group-affiliated versus unaffiliated, by economy. Consistent with prior studies, business groups are prevalent around the world, and more prevalent in some economies than others. For example, group-affiliated firms account for large fraction of firms in Chile, Hong Kong, Italy, and Peru, but lower fractions of firms in Canada, Taiwan, the United Kingdom, and the United States. Stulz (2005) shows how the percentage of shares held by control block holders varies across economies. Although presence of a control blockholder does not imply business group affiliation, the Stulz (2005) ranking of economies by percentage of shares held by blockholders is consistent with our ranking by the prevalence of business groups: Canada, Taiwan, the United Kingdom, and the United States rank low, while Chile and Peru rank high.

2.2. Firm-level control variables

Table 1, Panel B, summarizes the means of key firm-level characteristics across group-affiliated and unaffiliated firms. The panel reports statistics both from the entire sample and from the sample excluding US firms. We report both because in some tests we exclude US firms. Firm diversification is minus one times the Herfindahl Index of the firm's industrial focus, measured using Datastream annual segment-level revenues in up to ten product segments, so a value of minus one indicates an undiversified firm.[7] Leverage is book value of total debt divided by book value of total assets. Hedging activity is an indicator variable equal to 1 if Datastream reports that the firm discloses financial data associated with hedging or derivative usage: Comprehensive Income Hedging Gain/Loss, Unrealized Valuation Gains/Losses Hedges/Derivatives, Derivative Assets Current, Derivative Liabilities Current, Derivative Assets Non-Current, and Derivative Liabilities Non-Current. The proxies for firm size, market capitalization in millions of US dollars and total assets in thousands of US dollars, enter the regressions as logs. R&D activity is R&D expenses over total assets. If R&D expenses are missing, R&D spending is presumed insubstantial and set to zero.

[6] Many instances of listed US firms holding equity blocks exceeding 20% in other listed firms could be corporate control transactions in progress. Acquirers often begin with toehold acquisitions followed by bids for all the target's shares (Betton, Eckbo and Thorburn, 2009). Lasting toeholds exist, for example between firms undertaking a joint venture, but the stakes are typically far smaller than 20% and do not indicate common control (Ouimet, 2013).

[7] If segment-level sales are unreported we assume the firm's sales are in one segment.

Compared with unaffiliated firms, group-affiliated firms are on average smaller, more leveraged, less invested in R&D, more diversified, and less actively hedging. Our tests thus must allow for these differences between group-affiliated and unaffiliated firms in contrasting their responses to idiosyncratic shocks.

2.3. Firm-specific shocks

For each firm, Datastream weekly (Wednesday-to-Wednesday) total returns are used. These include price changes and dividends and are adjusted for stock splits, reverse splits, and stock dividends. Stocks that trade for fewer than 12 weeks during our sample period are dropped, as are firm-week observations with three or more missing daily returns in the week. Following prior literature, in particular Jin and Myers (2006), we use a version of the international capital asset pricing model (CAPM) to define firm-specific shocks. For the sake of transparency, we like to avoid changing methodology. However, in robustness tests, we consider an alternative asset pricing model based on the Fama and French (2015) global 5-factor model.

Firm-specific shocks are the residuals from separate regressions for each firm in the sample period:

$$r_{i,t}=\alpha_i+\sum_{l=-2}^{2}\left(\beta_{1,i,t+l}r_{m,t+l}+\beta_{2,i,t+l}\left(r_{US,t+l}+e_{US,m,t+l}\right)\right)+\varepsilon_{i,t}. \tag{1}$$

The explained variable, $r_{i,t}$, is the total return of firm i's stock in week $t$in the local currency. The explanatory variables are $r_{m,t+l}$, the stock market return of economy m (where firm i's stock trades) in local currency, $r_{US,t+l}$is the US stock market return (in US dollars), and $e_{US,m(i),t+l}$is the return from buying US dollars at the beginning of the week and selling at the end of the week in m's domestic currency. Including leads and lags, l,of −2,−1, 0, 1, and 2 weeks for the explanatory variables accounts for differences in time zones, illiquidity, and nonsynchronous trading. The residual, $\varepsilon_{i,t}$, is the firm-specific shock of stock $i$in week t. We focus on how shocks to the idiosyncratic component of stock returns, $\varepsilon_{i,t}$, react to idiosyncratic shocks to commodity prices.

2.4. Idiosyncratic commodity shocks

We construct economy-specific idiosyncratic commodity price shocks by considering how different commodities' prices can affect different economies' fundamentals differently. For example, an oil price increase can have a more widespread impact across all sectors in a heavily oil export-dependent economy, such as Norway, than a more diversified economy such as Germany.

Datastream provides daily price indexes for major commodities, whose prices are globally determined, starting in 1993.[8] Tables 2 and 3 list these and their Datastream iden-

[8] Commodities such as natural gas, whose pricing is subject to segmented markets problems, are excluded from the sample.

Table 1
Group-affiliated firms.
The Panel A tabulates the count of firm-year observations in our final ownership sample during 1993–2013. Panel B reports mean characteristics of group-affiliated and unaffiliated firms averaged across all available firm-year observations. We classify firms as group-affiliated if they satisfy one of the following criteria: the controlling shareholder is a corporation (with the exclusion of investment funds), the controlling shareholder is an individual who controls at least one other firm in our sample, or the firm itself is the controlling shareholder of at least one other firm in our sample. Firms are otherwise classified as unaffiliated firms. State-owned enterprises are excluded from the sample. Market size and total assets are in millions of US dollars.

Panel A: Incidences and fractions of group-affiliated firm-year observations, by economy

Economy name	Unaffiliated firm-year	Group-affiliated firm-year	Total	Fraction of group-affiliated observations
Australia	14,847	4292	19,139	0.22
Austria	533	606	1139	0.53
Belgium	1115	1206	2321	0.52
Brazil	2069	1544	3613	0.43
Canada	19,601	3687	23,288	0.16
Chile	735	1713	2448	0.70
China	6661	7519	14,180	0.53
Croatia	280	339	619	0.55
Denmark	2330	513	2843	0.18
Egypt	508	189	697	0.27
Finland	1358	545	1903	0.29
France	7674	4718	12,392	0.38
Germany	6718	5290	12,008	0.44
Greece	1893	464	2357	0.20
Hong Kong	5493	6817	12,310	0.55
India	9751	4730	14,481	0.33
Indonesia	2252	1284	3536	0.36
Ireland	866	245	1111	0.22
Israel	2427	1467	3894	0.38
Italy	1468	1871	3339	0.56
Japan	36,392	16,110	52,502	0.31
Jordan	700	294	994	0.30
Kuwait	518	362	880	0.41
Malaysia	6251	4770	11,021	0.43
Mexico	922	346	1268	0.27
Netherlands	1947	729	2676	0.27
New Zealand	910	385	1295	0.30
Norway	1647	1086	2733	0.40
Peru	424	526	950	0.55
Philippines	897	883	1780	0.50
Poland	1612	925	2537	0.36
Russian Federation	1091	905	1996	0.45
Singapore	3965	4035	8000	0.50
South Africa	2804	2062	4866	0.42
South Korea	9026	4117	13,143	0.31
Spain	1361	1256	2617	0.48
Sweden	3252	1186	4438	0.27
Switzerland	2475	1322	3797	0.35
Taiwan	9549	834	10,383	0.08
Thailand	2824	1284	4108	0.31
Turkey	1385	951	2336	0.41
United Kingdom	29,987	5203	35,190	0.15
United States	73,582	9476	83,058	0.11
Total	282,100	108,086	390,186	0.28

Panel B: Mean characteristics of group-affiliated and unaffiliated firm-year observations

	All economies		All economies except US	
Firm characteristic	Group-affiliated	Unaffiliated	Group-affiliated	Unaffiliated
Diversification	−0.77	−0.80	−0.75	−0.78
Leverage	0.23	0.21	0.23	0.21
Hedging activity	0.17	0.19	0.17	0.18
Market size	1049	1596	1048	1349
Total assets	3048	6324	3081	6448
R&D activity	0.02	0.05	0.01	0.02

Table 2
Commodity-industry matches using the statistical and the constrained statistical methods.
The table displays the commodities matched to industries using the statistical method (Column 3) and the constrained statistical methods (Column 6). In Column 4, "all" refers to all SIC four-digit industries classified under the FF-30 industry in the same row. To determine the matches we use out-of-sample US firms that are in the lowest quartile of stock market capitalization at the beginning of each month in each industry. The following commodities, which are priced globally, and return series that are available in Datastream are considered: Gold (GOLDBLN), Silver (SILVERH), Aluminum (LAHCASH), Copper (LCPCASH), Nickel (LNICASH), Zinc (LZZCASH), Lead (LEDCASH), Tin (LTICASH), Crude oil (CRUDWTC), Corn (CORNUS2), Wheat (WHEATSF), Lumber (LUMRLF1), Feeder cattle (CFCINDX), Lean hog index (CLHINDX), Cotton (COTTONM), Soybean (SOYBEAN), Cacao (COCINUS), Coffee (COFDICA), Sugar (WSUGDLY). FF = Fama and French; SIC = Standard Industrial Classification.

(1) FF-30 industry	(2) FF-30 industry description	(3) Statistical method: matched commodity	(4) SIC four-digit industries	(5) SIC four-digit industry description	(6) Constrained statistical method: matched commodity
1	Food products	None	100–199	Agriculture production - crops	Corn
			200–299	Agriculture production – Livestock	Feeder Cattle
			2010–2019	Meat Products	Feeder Cattle
			2040–2046	Flour and other grain mill	Wheat
			2050–2059	Bakery products	Wheat
			2060–2063	Sugar and confectionery	Sugar
			2095	Roasted coffee	Coffee
4	Recreation	Feeder cattle			None
8	Healthcare, medical equipment, pharmaceutical products	Feeder cattle			None
11	Construction and construction materials	None	2400–2439	Lumber and wood products	Lumber
12	Steel works (metals) etc.	Silver	All		Silver
13	Fabricated products and machinery	Feeder cattle			None
17	Precious metals, non-metallic, and industrial metal mining	Gold	1020–1029	Copper ores	Copper
			1030–1039	Lead and zinc ores	Zinc
			1050–1059	Bauxite & aluminum ore	Aluminum
			1040–1049	Gold and silver ores	Gold
			All others		Gold
19	Petroleum and natural gas	Crude oil	All		Crude oil
21	Communication	Feeder cattle			None
22	Personal and business services	Crude oil			None
23	Business equipment	Crude oil			None
25	Transportation	Feeder cattle			None
26	Wholesale	Lead			None
27	Retail	Feeder cattle	5210–5219	Lumber & building materials	Lumber

tifiers. Following Gorton and Rouwenhorst (2004), commodity returns are changes in spot prices. Economy-level commodity shocks are the residuals from separate regressions of the form Eq. (2) for each commodity economy pair:

$$r_{c,m,t} = \alpha_c + \sum_{l=-2}^{2} \left(\beta_{1,c,t+l} r_{m,t+l} + \beta_{2,c,t+l}\left(r_{US,t+l} + e_{US,m,t+l}\right)\right) + \varepsilon_{c,m,t}. \tag{2}$$

The explained variable $r_{c,m,t}$ is commodity c's weekly (Wednesday-to-Wednesday) return in economy m's local currency at time t. The explanatory variables are as in [1]. The idiosyncratic shock to commodity c's price change in economy $m$in week t is the residual, $\varepsilon_{c,m,t}$.

2.5. Identifying industry-commodity matches

Our tests require identifying industries that are sensitive to shocks to the price of each commodity. In-sample estimation of these sensitivities is problematic because our hypothesis is that group affiliation could damp the observable effects of commodity shocks on share prices. Three alternative methods of matching industries to commodities are employed to circumvent this problem.

2.5.1. Statistical method

The statistical method reapplies the methodology of Rajan and Zingales (1998), who use US data to estimate external finance dependence across industries in the US and infer that the same industries are apt to require external financing elsewhere. We likewise use US data for out-of-sample benchmarks in tests using this methodology, to estimate commodity price dependence across industries in the US and infer that the same industries are commodity price sensitive in other economies, too.

Following Rajan and Zingales (1998) in using US data to identify industry-commodity matches has several advantages. First, because business groups are relatively rare in the US (La Porta et al., 1999b; Villalonga and Amit, 2009; Masulis et al., 2011), group affiliation is relatively less likely to damp the observable effects of commodity shocks on share prices there. US industries' com-

Table 3
Commodity-industry matches using the Bureau of Economic Analysis (BEA) data.
The table lists industries at the input-output (I-O) six-digit code level matched with commodities by utilizing the 2002 industry commodity use table from the BEA website (https://www.bea.gov/industry/benchmark-input-output-data). Primary industries are in italics.

I-O six-digit industry code	Industry definition	Matching commodity
31161A	*Animal (except poultry) slaughtering, rendering, and processing*	Feeder cattle
111,335	Tree nut farming	Feeder cattle
1113A0	Fruit farming	Feeder cattle
112,120	*Dairy cattle and milk production*	Feeder cattle
115,000	Support activities for agriculture and forestry	Feeder cattle
31151A	Fluid milk and butter manufacturing	Feeder cattle
1121A0	*Cattle ranching and farming*	Feeder cattle
311,514	Dry, condensed, and evaporated dairy product manufacturing	Feeder cattle
316,100	Leather and hide tanning and finishing	Feeder cattle
311,410	Frozen food manufacturing	Feeder cattle
311,513	Cheese manufacturing	Feeder cattle
111,200	Vegetable and melon farming	Feeder cattle
311,520	Ice cream and frozen dessert manufacturing	Feeder cattle
112A00	*Animal production, except cattle and poultry and eggs*	Lean hog index
311,320	*Chocolate and confectionery manufacturing from cacao beans*	Cacao
311,920	*Coffee and tea manufacturing*	Coffee
311,210	Flour milling and malt manufacturing	Corn
311,615	Poultry processing	Corn
112,300	Poultry and egg production	Corn
311,221	*Wet corn milling*	Corn
311,830	Tortilla manufacturing	Corn
311,119	Other animal food manufacturing	Corn
311,111	Dog and cat food manufacturing	Corn
1111B0	*Grain farming*	Corn
313,240	Knit fabric mills	Cotton
111,920	*Cotton farming*	Cotton
313,100	Fiber, yarn, and thread mills	Cotton
314,110	Carpet and rug mills	Cotton
486,000	Pipeline transportation	Crude oil
213,112	*Support activities for oil and gas operations*	Crude oil
325,182	Carbon black manufacturing	Crude oil
221,200	Natural gas distribution	Crude oil
114,100	Fishing	Crude oil
311,700	Seafood product preparation and packaging	Crude oil
481,000	Air transportation	Crude oil
324,121	Asphalt paving mixture and block manufacturing	Crude oil
324,110	*Petroleum refineries*	Crude oil
325,130	Synthetic dye and pigment manufacturing	Crude oil
561,700	Services to buildings and dwellings	Crude oil
324,191	*Petroleum lubricating oil and grease manufacturing*	Crude oil
325,181	Alkalies and chlorine manufacturing	Crude oil
213,111	*Drilling oil and gas wells*	Crude oil
335,991	Carbon and graphite product manufacturing	Crude oil
325,310	Fertilizer manufacturing	Crude oil
211,000	*Oil and gas extraction*	Crude oil
324,199	*All other petroleum and coal products manufacturing*	Crude oil
324,122	Asphalt shingle and coating materials manufacturing	Crude oil
325,910	Printing ink manufacturing	Crude oil
2122A0	*Gold, silver, and other metal ore mining*	Gold
335,911	Storage battery manufacturing	Gold
331,419	Primary smelting & refining of nonferrous metal (excluding copper and aluminum)	Gold
33131A	*Alumina refining and primary aluminum production*	Aluminum
332,430	Metal can, box, and other metal container (light gauge) manufacturing	Aluminum
312,110	Soft drink and ice manufacturing	Aluminum
331,314	*Secondary smelting and alloying of aluminum*	Aluminum
331,520	Nonferrous metal foundries	Aluminum
336,212	Truck trailer manufacturing	Aluminum
33131B	*Aluminum product manufacturing from purchased aluminum*	Aluminum
331,420	*Copper rolling, drawing, extruding, and alloying*	Copper
335,920	Communication and energy wire and cable manufacturing	Copper
331,411	*Primary smelting and refining of copper*	Copper
337,110	Wood kitchen cabinet and countertop manufacturing	Lumber
32121B	Engineered wood member and truss manufacturing	Lumber

(*continued on next page*)

Table 3 (*continued*)

I-O six-digit industry code	Industry definition	Matching commodity
321,100	Sawmills and wood preservation	Lumber
321,999	All other miscellaneous wood product manufacturing	Lumber
33721A	Wood television, radio, and sewing machine cabinet manufacturing	Lumber
322,110	Pulp mills	Lumber
113A00	*Forest nurseries, forest products, and timber tracts*	Lumber
321,920	Wood container and pallet manufacturing	Lumber
321,992	Prefabricated wood building manufacturing	Lumber
337,122	Non-upholstered wood household furniture manufacturing	Lumber
321,219	Reconstituted wood product manufacturing	Lumber
321,910	Wood windows and doors and millwork	Lumber
32121A	Veneer and plywood manufacturing	Lumber
113,300	*Logging*	Lumber
212,230	*Copper, nickel, lead, and zinc mining*	Zinc
1111A0	*Oilseed farming*	Soybean
311,225	Fats and oils refining and blending	Soybean
31122A	*Soybean and other oilseed processing*	Soybean
1119B0	*All other crop farming*	Wheat
311,910	Snack food manufacturing	Wheat
311,940	Seasoning and dressing manufacturing	Wheat
311,313	*Beet sugar manufacturing*	Sugar
1119A0	*Sugarcane and sugar beet farming*	Sugar
31131A	*Sugar cane mills and refining*	Sugar

modity price sensitivities are thus a useful out-of-sample benchmark, against which to gauge how business group affiliation could dampen commodity price-sensitivity in economies in which business groups are important. Second, US stock prices appear to incorporate more firm-specific information (broadly defined) than do stocks in most other economies (Bartram et al., 2012). Third, because the US has, on average, more listed firms per industry, US data provide more precise point estimates.

Firm-level US data are from Compustat and the Center for Research in Security Prices. Using 30 Fama and French (FF-30) industries ensures a large number of firms in each industry to estimate industry sensitivity to commodities. Firms that hedge commodity risk can exhibit a lower sensitivity to commodity shocks. However, smaller US firms are less likely to hedge (Nance et al., 1993; Geczy et al., 1997; Carter et al., 2006; Rampini et al., 2014). We therefore use the smallest quartile (by market capitalization) of US firms in each industry at the beginning of each month to match industries to commodities.

Each US industry is matched to one commodity by assessing how sensitive firm-specific return shocks in an industry are to idiosyncratic shocks in the prices of different commodities. This is accomplished by estimating the following three sets of equations:

$$\forall\,\text{firms}\,i,\quad r_{i,t} = \alpha_i + \sum_{l=-2}^{2}\left(\beta_{i,t+l} r_{US,t+l}\right) + \varepsilon_{i,t}, \tag{3}$$

$$\forall\,\text{commodities}\,c,\quad r_{c,US,t} = \alpha_c + \sum_{l=2}^{2}\left(\beta_{c,t+l} r_{US,t+l}\right) + \varepsilon_{c,US,t}, \tag{4}$$

and

$$\forall\,\text{industries}\,j,\quad \varepsilon_{i(j),t} = \alpha_j + \sum_{c=1}^{19}\left(\beta_{c,j}\varepsilon_{c,US,t}\right) + \tau_{i,t}. \tag{5}$$

Eqs. (3) and (4) adapt Eqs. (1) and (2) to US firms. Eq. (5), which runs pooled regressions for each industry j, explains residuals $\varepsilon_{i,t}$from Eq. (3) with contemporaneous residuals $\varepsilon_{c(US),t}$ from Eq. (4). That is, Eq. (5) explains variation in the firm-specific shocks in week t stock return of small US firms i in industry j with variation in the US economy-specific idiosyncratic components of the return to holding commodity c that week. The $\tau_{i,t}$are regression residuals in Eq. (5). A tighter link between commodity c and industry j is inferred from a more statistically significant loading $\beta_{c,j}$in the regression Eq. (5) for that industry.

We require a minimum threshold of three for the absolute value of the t-statistic of the loading $\beta_{c,j}$and then select the commodity-industry pair with the highest absolute t-statistic among these as a potential match. We then run a univariate second pass regression analogous to Eq. (5) – namely, $\varepsilon_{i,t} = \beta_{c,j}\varepsilon_{c(US),t} + \tau_{i,t}$ – for the potential match. We declare a match between industry j and commodity c only if the commodity's coefficient has the same sign as in the first pass regression and the t-statistic in this second pass regression also exceeds three in absolute value. This extra step is done to cull false matches due to multicollinearity (no false matches are identified).

The major advantage of the statistical method is that it gauges an industry's sensitivity to commodity prices through all possible channels. For example, a shock to oil prices could affect the auto industry by affecting input prices (supply shock) or consumer preferences as to the type of car (demand shock). The commodity matches identified with this procedure could proxy for the prices of goods that affect an industry, but for which no global commodity market exists (Anderson and Danthine, 1981), other fundamental shocks that affect an industry, substitutes for industry's main product, or other such factors. In all such cases, the industry-commodity match is valid for our analysis as long as the shock to the matched commodity is a good proxy for the unobserved fundamental shock to the matched industry.

The major disadvantages of statistical matching are that type one and type two errors inevitably arise, missing genuine matches and declaring spurious matches. Spurious or missed matches are likely to induce attenuation bias in the tests that follow. We therefore test whether industry commodity matches are valid out-of-sample (see Section 3).

The third Column of Table 2 reports the industry-commodity matches detected using the statistical method. Some matches are intuitive, such as that between the Precious metals, non-metallic, and industrial metal mining industry and Gold and between the Petroleum and natural gas industry and Crude oil. Others link seemingly unrelated industries and commodities, such as Fabricated products and machinery, and Feeder cattle. Closer investigation provides economic intuition for some of these. For example, farm equipment is included in the Fabricated products and machinery industry. Regardless, validating matches intuitively is subject to ex post justification bias. We therefore take the matches as determined by the data.

We supplement tests using this approach with tests using matches based on a constrained statistical matching method and on Bureau of Economic Analysis (BEA) input-output tables that list industries direct dependence on commodities.

2.5.2. Constrained statistical method

The statistical method generates statistically highly significant matches between some industries and commodities that perhaps are not directly related. If these commodities capture genuine supply and demand, cross-industry, or latent factor effects, the method is useful. If these matches are false positives, tests using them suffer from attenuation bias.

The modified statistical method is designed to mitigate any such bias. This method uses the same algorithm as the statistical matching method, but it adds the requirement that the commodity and industry be directly related. This retains the matches between Petroleum and natural gas and Crude oil, and between Precious metals and Gold, but drops several matches with Feeder cattle and adds matches at finer [four-digit Standard Industrial Classification (SIC)] industry levels between industries and commodities they directly produce or consume. We verify that, in the univariate second pass regression analogous to Eq. (5), the t-statistic of the loading $\beta_{c,j}$ on commodity shocks exceeds three in absolute value for the additional industry-commodity matches introduced in this way. This adds matches between Roasted coffee and Coffee, Meat products and Feeder cattle, Lumber and wood products and Lumber etc. The sixth Column of Table 2 reports industry-commodity matches determined by this method.

The constrained statistical matching method potentially mitigates concerns about noise-driven matches and mismatches, but it reduces the sample size by 74% because fewer firms end up in industries matched to a commodity. This could give rise to issues related to power in regressions. Therefore, we view this method as a robustness test.

2.5.3. BEA method

An alternative and qualitatively different approach uses Bureau of Economic Analysis (BEA) input-output tables. These list every industry's use of inputs produced by every other industry for approximately 56 thousand industry pairs in the US. This matching method is not statistical-based and, thus, avoids noise-driven matches and mismatches. However, it does not capture all possible channels through which commodity price shocks could affect an industry. For example, an increase in oil prices can boost the profits of coal mines, which produce a substitute for oil but do not use much oil as input.

To employ the BEA matching method, we begin by determining a set of basic commodity-linked industries by identifying industries that produce each given commodity or use it as their predominant input. For example, Cotton farming is linked to the commodity Cotton; Cattle ranching and farming to Feeder cattle; Petroleum refineries to Crude oil; and so on. We declare these base industries matched to that commodity.

We then identify industries that depend on a commodity by summing each industry's inputs from the base industries that are already linked to the commodity. If at least 10% of an industry's inputs are from industries already linked to the commodity, we match that industry to the same commodity. For example, the base industries matched to Crude oil provide 22% of the inputs of Asphalt shingle and coating materials manufacturing, so we also match that industry to Crude Oil. We repeat this matching process for two additional rounds, increasing the threshold for declaring a match to 20% in the second and 30% in third round because the number of industries matched to each commodity increases prior to each round.[9] Table 3 lists the 86 matches of (six-digit I-O classification) industries to commodities.[10]

3. The incorporation of idiosyncratic commodity shocks into stock prices

Eq. (6) tests whether or not group-affiliated firms' stock returns incorporate idiosyncratic information differently *vis-à-vis* unaffiliated firms. Following Jin and Myers (2006), we employ a variant of Fama-MacBeth estimation, which Petersen (2009) finds appropriate in panel regressions explaining abnormal returns. The regressions explain weekly shocks to firm-specific stock returns with idiosyncratic components of weekly shocks to the prices of matched commodities, calculated separately for each economy:

$$\varepsilon_{i,t} = b_1\varepsilon_{c(j)m,t}\mathrm{sgn}\left(\beta_{c,j}\right) + b_2G_{i,t} + b_3G_{i,t}\varepsilon_{c(j),m,t}\mathrm{sgn}\left(\beta_{c,j}\right) + \sum_{v=4}^{N} b_vX_{i,t} + \delta_{j,m} + u_{i,j} \tag{6}$$

[9] Alternative thresholds and additional rounds of matching generate similar results (unreported). We stop at the third round because a fourth adds only two matches.

[10] A concordance table provided by the BEA matches its I-O industry classification system with the North American Industry Classification System (NAICS), and a second concordance table provided by the US Bureau of the Census links NAICS industries to the SIC system available in Datastream.

The explained variable $\varepsilon_{i,t}$is the firm-specific shock to the return of stock *i* in week *t* from Eq. (1). The first explanatory variable, $\varepsilon_{c(j),m,t}$is the idiosyncratic commodity shock $\varepsilon_{c,m,t}$to country *m* from Eq. (2) that is matched to firm *i*'s industry *j*. Multiplying the idiosyncratic component of commodity shock by $sgn(\beta_{c,j})$,which is one or minus one as $\beta_{c,j}$in Eq. (5) is positive or negative, respectively, sgnensures that expected sign of $b_1$is positive regardless of whether shocks to the price of commodity *c*affect industry *j*positively or negatively.[11] If firm *i*'s industry *j* is not matched with any commodity *c*, the firm is dropped from the sample. The second explanatory variable is an indicator variable, denoted $G_{i,t}$, set to one if firm *i*is group-affiliated at time *t* and to zero otherwise.

In some specifications, we include firm-specific control variables, $X_{i,t}$ and industry-economy fixed effects, denoted $\delta_{j,m}$, based on 30 Fama-French industries. Industry-economy fixed effects subsume all latent factors with variation at the industry, economy, or industry-economy level. Moreover, the estimates in the tables are the means of week-by-week Fama-MacBeth regressions, so the coefficients of the industry-economy fixed effects take different values each week, effectively leaving the regressions subsuming all time-varying industry-, economy-, and industry-economy-level latent factors as well. In this context, Fama-MacBeth estimation has the advantage of mitigating potential bias due to cross-sectional correlation in the firm-specific stock returns. The dependent variables are estimated idiosyncratic returns and so ought not to be autocorrelated. To err on the side of underestimating significance levels, we allow for any potential autocorrelation in the firm-specific stock returns by assessing the significance of the means of the coefficients in Eq. (6) using Newey-West t-statistics, adjusted for four-week lags.

The coefficient $b_1$can be estimated if industry-economy fixed effects are not introduced. A positive and significant coefficient for $b_1$implies that, on average, commodities are correctly matched to industries. The coefficient of interest in Eq. (6) is b_3, the sign-adjusted interaction of the commodity shock measure $\varepsilon_{c(j),m,t}$with the group affiliation indicator, G_{it}. A negative and significant $b_3$implies that group-affiliated firms exhibit a muted response to economy-specific commodity shocks as compared with unaffiliated firms.

Table 4 summarizes the main regression results. Regressions 1 and 2 use the variant of $\varepsilon_{c(j),m,t}$calculated in Eq. (2) and matched to industries using the statistical method. Regressions 3 and 4 use the variant of $\varepsilon_{c(j),m,t}$matched to industries using the constrained statistical method, and Regressions 5 and 6 use the variant of $\varepsilon_{c(j),m,t}$matched to industries using the BEA matching method. Regressions 2, 4, and 6 include industry-economy fixed effects.

In Regressions 1, 3 and 5, the coefficient $b_1$on the commodity shock measure is positive and statistically significant. These out-of-sample tests affirm that, on average, all three industry-commodity matching procedures successfully identify commodity shocks relevant to the firm-specific shocks. The coefficient $b_1$in Regression 1 links a 1 percentage point idiosyncratic shock to commodity prices to a 5 basis points idiosyncratic shock to the stock prices of unaffiliated firms.

The key coefficient of interest is b_3,on the interaction of the commodity shock measure with the group affiliation indicator. This is negative and statistically significant in all specifications, indicating a muted incorporation of commodity shocks into the idiosyncratic stock returns of group-affiliated firms on average. The interaction coefficient in Regression 1 links a 1 percentage point shock to commodity prices to a 3 (5.82 – 2.46 = 3.36) basis point shock to the firm-specific stock returns of group-affiliated firms. This is about 40% less than the shock to unaffiliated firms' share prices, and the difference between the two is highly statistically significant across all specifications. The regressions in Table 4 demonstrate a statistically and economically significant damping of the impact of idiosyncratic commodity price shocks on the idiosyncratic return of group-affiliated firms relative to unaffiliated firms.

4. Identification of group affiliation as the culprit

The results show that group-affiliated firms' stocks are less responsive to a given economy-specific commodity shock than are unaffiliated peer firms in the same economy, industry, and time. The primary vulnerability of the findings in Table 4 that remains is that group-affiliated and unaffiliated firms could differ along other firm-level dimensions, some perhaps unobservable given data constraints. This section presents tests designed to mitigate these concerns.

4.1. Mitigating omitted variables

Table 1, Panel B, shows group-affiliated and unaffiliated firms differing from each other in diversification, leverage, hedging activity, size, and R&D activity. We therefore next include these control variables to mitigate concerns that group affiliation could be proxying for these other differences in firm characteristics.

A firm diversified across industries can exhibit a muted response to a commodity shock that affects only some of its industry segments. We also control for each firm's leverage. The stock prices of more leveraged firms are plausibly more sensitive to shocks. Group-affiliated firms could hedge commodity risk more aggressively to shield the wealth of their controlling block holders (Tufano, 1996). We proxy for hedging activity in two ways. One is a hedging indicator set to 1 if Datastream reports that the firm has financial accounts related to hedging or derivative usage. The second is firm size, reflecting prior findings showing that larger firms employ more extensive hedging strategies (Nance et al., 1993; Geczy et al., 1997; Carter et al., 2006; Rampini et al., 2014). The log of market capitalization or log of total assets proxies for firm size. We also control for each firm's R&D spending each year. R&D-intensive firms' valuations are thought to depend more on future growth opportunities than on current conditions (and shocks that primarily affect current cash

[11] The sign of $\beta_{c,j}$is similarly calculated using the regression specification Eq. (5) for the BEA matched industry-commodity pairs.

Table 4
Incorporation of idiosyncratic information into stock prices.
The Table reports mean coefficients from Fama-MacBeth cross-section regressions, run separately for each of 1095 weeks. Industries are matched to commodities using the statistical matching in Regressions 1 and 2, modified statistical matching in Regression 3 and 4 and Bureau of Economic Analysis (BEA) matching in Regressions 5 and 6. US firms are excluded from the sample in the first 4 regressions as they are used to identify the industry-commodity links. US firms are included in the sample in Regressions 5 and 6. The dependent variable is the weekly idiosyncratic stock return in local currency, measured from Wednesday to Wednesday. Coefficients are multiplied by one hundred. The numbers in parentheses are *p*-values. Significance levels of means of coefficients from weekly cross-sectional regressions are adjusted for potential autocorrelation using Newey-West methodology with 4 lags. Boldface indicates coefficients significant at 10% or better in two-tailed tests.

	Statistical Matching		Constrained Statistical Matching		BEA Matching	
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
Idiosyncratic commodity return	**5.82** **(0.00)**		**7.11** **(0.00)**		**2.54** **(0.00)**	
Group-affiliated firm	**0.06** **(0.01)**	**0.06** **(0.00)**	**0.14** **(0.00)**	**0.09** **(0.01)**	0.04 (0.14)	0.02 (0.51)
Idiosyncratic commodity return * group-affiliated firm	**−2.46** **(0.01)**	**−1.84** **(0.04)**	**−1.85** **(0.02)**	**−1.91** **(0.07)**	**−1.64** **(0.03)**	**−1.90** **(0.03)**
Intercept	−0.03 (0.29)		**−0.09** **(0.06)**		−0.04 (0.18)	
Economy * industry fixed effects	No	Yes	No	Yes	No	Yes
Firm * week observations	5,767,175	5,767,175	1,491,947	1,491,947	1,057,725	1,057,725
Number of economies	42	42	42	42	43	43
Average adj. R^2	0.01	0.05	0.01	0.04	0.01	0.11

flows). All variables are measured annually at the prior fiscal year-end.

Table 5 summarizes these regressions, all of which expand Regression 2 in Table 4 by including diversification, leverage, R&D activity, total assets, or market capitalization and their interactions with the industry-economy specific commodity shock. Industries and commodities are matched using the statistical matching method. Regressions 1–6 of Table 5 incorporate the new control variables and matching interactions one pair at a time, and Regression 7 includes them all. No interaction is statistically significant in Regressions 1–6, and some interactions are significant in Regression 7. More important, the interaction between the group affiliation indicator and the commodity shock measure remains uniformly negative and statistically significant. This suggests that omitting these firm-level characteristics in the previous analyses cannot explain group-affiliated firms' muted stock price responses to commodity shocks.

Clearly, the tests in this section cannot mitigate all potential concerns about sources of confounding variation. The conclusions are subject to the caveat that group-affiliated and unaffiliated firms could differ along other dimensions that are unobservable due to data limitations.

4.2. Changes in group affiliation: difference-in-difference tests

An alternative identification strategy is based on a difference-in-difference setting, where changes in group affiliation act as the treatment. These difference-in-difference tests explore how the sensitivities of firms' stock prices to commodity price shocks change before versus after the firms' status as group-affiliated changes (the treatment group). These changes are contrasted against contemporaneous changes in sensitivities of firms' stock prices to commodity price shocks for firms whose group affiliation status does not change (the control group). Identification comes from firms whose group affiliation status does not change serving as a counterfactual for how treated firms' firm-specific stock returns would have responded to the commodity shocks had their affiliation status not changed. As in all difference-in-difference tests, the identification assumptions are that omitted firm-level characteristics do not significantly change around the treatment and that the change in group affiliation is exogenous. Relaxing these identification assumptions is explored in Section 4.3.

The treatment group consists of firms that are unaffiliated in one year and group-affiliated in the following year (positive treatment firms) or affiliated in one year and unaffiliated in the following (negative treatment). These tests require that the firms we designate as treated genuinely do change affiliation status. Group affiliation is inferred from a firm having another firm as its controlling shareholder, controlling another firm, or being controlled by a controlling shareholder who controls another firm. We use a 20% minimum threshold for designating any given equity block sufficient to exercise control and, thus, to make a firm a group affiliate. We do not want blocks that either meet or fail to meet the threshold briefly or by small margins to count as changes in group affiliation status. The treatment group therefore is restricted to firms whose group affiliate status changes because the control block(s) relevant to its status change(s) by at least 5 percentage points and whose status does not change during the prior or sub-

Table 5
Group affiliation versus other firm-level characteristics.
The Table revisits the mean coefficients from Fama-MacBeth cross-section Regression 2 of Table 4, run separately for each of 1095 weeks but including additional control variables and their interactions with the group affiliation indicator. The dependent variable is firm-specific stock return in local currency, measured from Wednesday to Wednesday, for stocks in 42 economies. Coefficients are multiplied by one hundred. Numbers in parentheses are *p*-values, adjusting for time series autocorrelation of 4 weeks in successive cross-section estimates using the Newey-West methodology. Boldface indicates mean coefficients significant at 10% or better in two-tailed tests. R&D = research and development.

Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Idiosyncratic commodity return * group-affiliated firm	**−1.87** **(0.04)**	**−1.69** **(0.06)**	**−1.81** **(0.04)**	**−1.79** **(0.05)**	**−1.86** **(0.04)**	**−1.95** **(0.03)**	**−1.80** **(0.05)**
Idiosyncratic commodity return * diversification	0.94 (0.59)						0.51 (0.74)
Idiosyncratic commodity return * leverage		−3.01 (0.15)					**−4.35** **(0.04)**
Idiosyncratic commodity return * hedging activity			1.58 (0.37)				1.66 (0.37)
Idiosyncratic commodity return * log market size				0.66 (0.13)			**0.69** **(0.09)**
Idiosyncratic commodity return * log total assets					0.20 (0.57)		
Idiosyncratic commodity return * R&D activity						−28.2 (0.23)	−33.0 (0.17)
Group-affiliated firm	**0.06** **(0.00)**	**0.06** **(0.00)**	**0.06** **(0.00)**	**0.06** **(0.00)**	**0.05** **(0.00)**	**0.06** **(0.00)**	**0.06** **(0.00)**
Diversification	−0.01 (0.81)						**−0.06** **(0.04)**
Leverage		**0.19** **(0.00)**					**0.15** **(0.01)**
Hedging activity			−0.03 (0.31)				1.66 (0.36)
Log market size				**−0.07** **(0.00)**			**−0.08** **(0.00)**
Log total assets					**−0.02** **(0.05)**		
R&D activity						0.03 (0.96)	0.28 (0.60)
Economy* industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average adj. R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.06

sequent two-year periods. This effectively excludes, from the treatment group, firms attached to their groups due to stakes varying around the threshold because such fluctuations could reflect seasoned equity issues, share buybacks, stock dividends, or share creation associated with stock options, not genuine changes in group affiliation status. The data exclude firms that either list or delist within the same windows because differences in betas cannot be calculated for these firms.

We use propensity scores matching to match each treatment firm with a control firm, whose group affiliation status does not change, within the same industry, economy, and year using the nearest neighbor matching (Abadie et al., 2004) by firm size, leverage, R&D over assets, and commodity beta in the prior year. If no match is available from the same country-industry-year, we default to a global match from the same industry-year. We require differences in propensity scores to be within the 0.05 range. Positively and negatively treated firms are matched separately. Matching is done with replacement to preclude the order of the observations from affecting the results.

Commodity betas for each treatment firm and control firm are estimated with respect to the industry-matched commodity return for each year. This entails estimating a variant of Regression Eq. (5) separately for each firm. The explained variable is firm-level idiosyncratic return shocks and the explanatory variable is the idiosyncratic shock to the commodity matched with the firm's industry. Firms with fewer than 24 weeks of data are dropped from the sample, and betas are symmetrically winsorized at the 5% level to mitigate the impact of outliers. First differences in the commodity betas of each firm are calculated. The tests then focus on the difference-in-difference between treatment and control firms' commodity betas.

These difference-in-difference tests, summarized in Table 6, align with the findings in Tables 4 and 5. Group affiliation mitigates the sensitivity firm-specific stock returns to industry-specific commodity price shocks. The commodity beta of unaffiliated firms that become affiliated (positively treated firms) on average falls significantly, by −3.96 (p-value = 0.00), and the commodity beta of their nearest neighbor firms, whose group affiliation does not change, remains constant on average. The commodity beta of affiliated firms that become unaffiliated (negatively treated firms) on average rises significantly, by 2.88 (p-value = 0.07), and the average commodity beta of their nearest neighbor firms displays a statistically insignificant decline of −0.45. The difference-in-difference point estimate for negatively treated firms is a statistically significant 3.33 (*p*-value = 0.08). Because the first differences of

Table 6
Firms changing group affiliation status.
The table reports a difference-in-difference analysis of changes in the sensitivity of firm-specific stock returns to commodity price shocks. The treatment group consists of firms experiencing a change in affiliation status between year t-1 and year $t+1$, by either becoming group-affiliated (positive treatment) or ceasing to be affiliated with a business group (negative treatment). Group affiliates have a controlling shareholder with a block of 20% or more; unaffiliated firms do not. Block acquisitions or sales that change a firm's group affiliation status must be for at least 5% of the firm's shares. The firm's group affiliation must be stable going forward 1 year. The difference is the sensitivity of firms' firm-specific stock returns to commodity shocks after the change in group affiliation status minus that before the change in status. The matched group contains firms that did not experience a change in group affiliation status and that are in the same economy-industry selected using the nearest neighbor matching on total assets, leverage, research and development expenses divided by total assets and commodity beta in the year prior to the event. The sample covers all economies. Coefficients are multiplied by one hundred. When both positive and negative treated observations are pooled, the difference-in-difference coefficients of negatively treated observations are multiplied by −1. Industry-commodity matching is by statistical method. The left hand side variable is winsorized at the 5% level. Boldface indicates coefficients significance at 10% or better in two-tailed tests.

		Commodity beta (sensitivity of firm-specific stock returns to commodity price shocks)			
Treatment	Compared groups	12 Months Before	12 Months After	Difference	Difference-in-difference
Positive treatment (unaffiliated transition to affiliated)	Treated (transition) firms	**7.46**	**3.50**	**−3.96**	**−3.76**
		(0.00)	**(0.00)**	**(0.00)**	**(0.03)**
	Matched firms	**6.65**	**6.46**	−0.19	
		(0.00)	**(0.00)**	(0.89)	
	Number of observations	2,855	2,855	2,855	2,855
Negative treatment (affiliated transition to unaffiliated)	Treated (transition) firms	**6.35**	**9.22**	**2.88**	**3.33**
		(0.00)	**(0.00)**	**(0.07)**	**(0.08)**
	Matched firms	**6.34**	**5.89**	−0.45	
		(0.00)	**(0.00)**	(0.76)	
	Number of observations	2,302	2,302	2,302	2,302
Pooled treatment (positive treatment and sign-inverted negative treatment)	Treated (transition) firms			**−3.47**	**−3.57**
				(0.00)	**(0.00)**
	Matched firms			0.09	
				(0.93)	
	Number of observations			5,157	5,157

treated firms are always in the predicted direction and statistically significant, while those of the nearest neighbor firms are statistically insignificant, the results are driven by the changes in treated firms, not changes in the control group.

Pooling positively and negatively treated firms (after multiplying negatively treated firms' differences in commodity beta by minus one) generates a highly statistically significant difference-in-difference estimate of about −3.57 (p-value = 0.00).

Thus, shocks to the firm-specific returns of group-affiliated firms that become unaffiliated are more sensitive to commodity price shocks, and shocks to the firm-specific returns of unaffiliated firms that become affiliated are less sensitive to commodity price shocks.

4.3. Placebo tests exploiting failed merger and acquisition transactions

Identification in Section 4.2 relies on the assumption that firms become affiliated or unaffiliated for exogenous reasons. If changes in group affiliation status are endogenous, a sample selection bias problem arises. The results would be also consistent with, for example, groups taking on firms that are expected to become less sensitive to commodity shocks and divesting firms expected to become more sensitive to commodity shocks. One approach to mitigating such concerns follows Seru (2014) in comparing successful control block acquisition attempts with (unsuccessful) acquisition attempts that failed for plausibly exogenous reasons. If control block targets are selected *in anticipation of* changes in their sensitivity to commodity risk, instead of group affiliation being the cause of those changes, changes would be evident in the sensitivity to commodity risk also among targets of unsuccessful acquisition attempts.

Control block acquisition attempts recorded in the Thomson One database are merged with our ownership data. We require that the bidder seek to own at least 20% of the target's shares after the transaction and that the target be classified as unaffiliated in the year prior to the bid. Instances of firms purchasing their own shares are dropped.

The treatment group consists of target firms that are unaffiliated prior to the acquisition announcement, become group-affiliated as a result of a *successful* acquisition, and continue to be publicly traded so their commodity betas can be estimated after the acquisition. The last requirement is especially important in this context because acquisitions in most economies entail acquiring a sufficient block of stock to exercise effective control and are not bids for all of the target firm's shares as is generally the case in the US.

The control group consists of targets that are unaffiliated prior to the acquisition announcement, *remain unaffiliated* because the acquisition attempt failed due to a plausibly exogenous reason, and continue to be publicly traded after the failed acquisition attempt. Acquisition bids that

Table 7
Targets of successful control block bids versus bids that failed due to plausibly exogenous reasons.
The table reports a difference-in-difference analysis of changes in the sensitivity of firm-specific stock returns to commodity price shocks. The treated group consists of targets of successful control block acquisitions, in which targets were unaffiliated in the year prior to the bid announcement, which left the acquirer owning 20% or more of the target's shares after the transaction. The matched group consists of targets of similar bids that failed for plausibly exogenous reasons. The targets were unaffiliated in the year prior to the bid announcement and the acquirer sought to own at least 20% of the target's shares after the transaction. Firms in the matched group are selected using nearest neighbor matching criteria based on total assets, leverage, research and development expenses divided by total assets, and commodity beta in the year prior to the acquisition or failed acquisition attempt, and are, when possible, from the same economy-industry-year as each target of successful bid. The sample covers all economies. Industry-commodity matching is by the statistical method. Coefficients are multiplied by one hundred. The dependent variable is winsorized at the 5% level. Boldface indicates coefficients significance at 10% or better in two-tailed tests.

		Commodity beta (sensitivity of firm-specific stock returns to commodity price shocks)			
Treatment	Compared groups	12 Months Before	12 Months After	Difference	Difference-in-difference
Positive treatment (unaffiliated transition to affiliated)	Treated (successful transition) firms	**4.99**	0.61	**−4.38**	**−6.65**
		(0.00)	(0.71)	**(0.02)**	**(0.00)**
	Matched (unsuccessful transition) firms	**4.70**	**6.97**	**2.28**	
		(0.00)	**(0.00)**	**(0.01)**	
	Number of observations	5284	5284	5284	5284

failed due to plausibly exogenous reasons consist of acquisition attempts, as reported in *Thomson One*, that failed because of intervention by regulatory bodies (Savor and Lu, 2009; Seru, 2014; Faccio and Hsu, 2017), court decisions (Seru, 2014; Faccio and Hsu, 2017), employee opposition, or unexpected adverse market-wide conditions [e.g., the 2007–2009 financial crisis, the 1997 Asian financial crisis, etc., as in Seru (2014)]. Acquisition bids that failed due to fluctuations in commodity prices are excluded, as are takeovers that failed because a rival bidder acquired a control block. The latter are excluded because the rival's takeover is included in the treatment group. The reasons behind the failure of each given transaction are determined based on the deal description in Thomson One, Capital IQ, and newspapers articles in Factiva and Lexis-Nexis.

In these tests, identification follows from the targets of unsuccessful acquisition attempts (placebo treatment firms) serving as counterfactuals for how successfully acquired targets' (treatment firms') sensitivities to commodity shocks would have changed had they not been acquired.

As in Section 4.2, we use propensity score matching to pair targets of successful acquisitions with targets of unsuccessful acquisitions within the same economy, industry and year (if possible) using the nearest neighbor matching (Abadie et al., 2004) with total assets, leverage, R&D expenses as a fraction of total assets and commodity beta in the prior year as covariates. If no match is available from the same country, we default to a global match from the same industry-year. As before, the matching is done with replacement.

Commodity betas with respect to industry-matched commodities are estimated for treatment and control firms over the 52 weeks before and 52 weeks after the takeover announcement date, excluding the announcement week. Firms with fewer than 24 weeks of observations are dropped and betas are winsorized at the 5% level.

As Table 7 shows, the results of the tests based on takeover attempts that failed for plausibly exogenous reasons do align with those in Tables 4 and 5. Firm-specific stock returns become significantly less sensitive to commodity shocks after a firm becomes affiliated with a business group following a successful takeover, in contrast to control firms that remain unaffiliated after a takeover attempt that failed for plausibly exogenous reasons. These tests mitigate the concern that our previous results are due to self-selection.

4.4. Within-group risk sharing

If a commodity shock to a one group firm is diffused across the group, other firms in the group would appear sensitive to the shock. Tests for this second-hand commodity shock sensitivity must therefore focus on business groups containing one or more firms in industries sensitive to a given commodity and one or more firms in industries insensitive to that commodity. These tests are best illustrated by a simple example. Consider a business group of three firms: Firm F_1 in an industry sensitive to commodity C_1; firm F_2 in an industry sensitive to commodity C_2; and firm F_3 in an industry insensitive to any commodities. One set of tests explores whether F_1 is sensitive to C_2, F_2 is sensitive to C_1, and F_3 is sensitive to both C_1 and C_2.

We employ a variant of the Fama-MacBeth regressions of Eq. (6):

$$\varepsilon_{i,t} = b_1 \varepsilon_{c(j),m,t} sgn\left(\beta_{c,j}\right) + b_2 \varepsilon_{\neg c(j),m,t} sgn\left(\beta_{\neg c,j}\right) + u_{i,t}. \tag{7}$$

As in Eq. (6), the explained variable $\varepsilon_{i,t}$is the firm-specific shock to the return of stock i in week t from Eq. (1). Unlike in Eq. (6), where the explanatory variable $\varepsilon_{c(j),m,t}$was idiosyncratic shock to the price of commodity $c$matched to i's industry $j$in its economy $m$in week t, in Eq. (5)the explanatory variable of interest, $\varepsilon_{\neg c(j),m,t}$, is shock to the price of a commodity $\neg c(j)$ which is not $c(j)$, but a different commodity matched to the industry of another firm in firm i's group. As in Eq. (6), $sgn(\beta_{\neg c,j})$ is one or minus one as $\beta_{\neg c,j}$is positive or negative, respectively,

Table 8

Within-Group Transmission of Commodity Shocks.

The table tests whether a firm's stock price reacts to commodity shocks to other firms within the same business group that matches with a commodity other than the firm's own matched commodity. For this exercise we use a sample of firms that belong to the same business group, i.e. have a common controlling shareholder, such that at least two firms of the group are in our sample and at least one of the firms matches with a different commodity than matched commodities of other group firms. In Regression 4, we include only cases that a group firm's industry beta does not statistically significantly load on the commodity shocks in regression(5); i.e., we require the absolute value of t-statistics of beta to be less than 0.5 when commodities are entered individually. The dependent variable is the weekly idiosyncratic stock return in local currency, measured from Wednesday to Wednesday. Coefficients are multiplied by one hundred. The numbers in parentheses are *p*-values. Estimation is by weekly Fama-MacBeth regressions in Regressions 1–3 and monthly in Regression 4. In regression 4 low number of observations results in few extreme coefficients when Fama-Macbeth regressions are run for each week. In this case, the average coefficient of idiosyncratic commodity shocks to other group firms is 6.2 and $p = 0.04$. We adjust standard errors for time series autocorrelation of 4 weeks using the Newey-West methodology. Boldface indicates coefficients significance at 10% or better in two-tailed tests.

Shocks	All (1)	All (2)	Top 25% shocks to other group firms (3)	Non-sensitive industry-commodity pairs (4)
Idiosyncratic Commodity Shocks to Other Group Firms	**0.86**	**0.70**	**1.12**	**2.52**
	(0.04)	**(0.10)**	**(0.02)**	**(0.08)**
Own idiosyncratic commodity shocks		**3.80**	2.60	
		(0.00)	(0.11)	
Intercept	−0.01	−0.01	−0.02	−0.01
	(0.44)	(0.59)	(0.33)	(0.84)
Firm * week observations	735,014	735,014	188,636	39,943
Average adj. R^2	0.01	0.02	0.02	0.00

and inverts the sign of the explanatory variable if the industry loads negatively on its matched commodity.

With no risk sharing across groups, shocks to the industries of a firm's fellow group affiliates would not affect its own shares and the regression coefficient $b_2$in Eq. (7) would be zero. If group-level risk sharing or income shifting are important, $b_2$would be significantly positive.

Table 8 summarizes Fama-MacBeth regressions of Eq. (7). Regression 1 considers firm's reaction to all commodities that affect the industries of its fellow group firms but do not affect the firm's own industry. The coefficient of $b_2$is statistically significant and its point estimate, 0.86 is about 25% of the main coefficient in Regression 1 of Table 4, which is 3.36. These point estimates indicate that a second-hand commodity shock, affecting the industry of one or more of a firm's fellow group affiliates, moves its stock by about 25% as much as does a commodity shock to the firm's own industry.

Commodity shocks are on average positively correlated, and even if a firms' industry does not match with the other group firms' commodity a positive coefficient could ensue as a result of this correlation. Regression 2 of Table 8 controls for the shocks to firms' own matched commodity. The coefficient of $b_2$is now 0.7 and barely statistically significant at 10%. Second-hand commodity shocks should stand out more clearly if the shocks they echo are larger. To restrict our analysis to severe second-hand commodity shocks, we sort commodity shocks by their absolute values for each economy and retain only the top quartile of these for each economy. Regression 3 repeats the test with this sample. The coefficient $b_2$increases to 1.1 and becomes statistically significant at the 2% level. More severe commodity shocks to a firm's fellow group affiliates thus tend to affect its own share price more. This indicates that group-level risk sharing intensifies in response to more intense commodity shocks to a group member firm.

Finally, a group affiliate not matched to a commodity could show a stock return response if its industry is somewhat sensitive to that commodity, but not sensitive enough to meet the *t*-statistic greater than three threshold for matching in Eq. (5). Such a high threshold makes sense for our other tests, where misattributing commodity sensitivity to an industry that is not commodity-sensitive must be avoided. In these tests, we instead need to avoid falsely classifying a sector as commodity-insensitive. To address this concern, we focus on firms in industries that do not statistically significantly load on any commodity shocks in Eq. (5) by requiring the absolute value of t-statistics of beta to be less than 0.5 for the firms' industry and commodity to be included in the test in Regression 1 of Table 8. Results are displayed in Regression 4.[12] The coefficient on other group firm shock is 2.5 and is statistically significant with a *p*-value of 0.08.

Overall, we find a statistically significant, albeit attenuated, effect in the idiosyncratic stock returns of group firms to shocks to other firms within the same business group. This is consistent with shocks being spread across firms in the same group.

[12] In this test the total number of observations is less than 40 thousand, which corresponds to about 36 observation per week. We use monthly regressions, instead of weakly, to mitigate concerns related to running cross-sectional regressions with few observations. When we run Fama-Macbeth regressions at the weekly level, we obtain a coefficient of 6.2, which is statistically significant with *p*-value=0.04.

Table 9
Robustness tests.
We repeat the test in Regression 2 of Table 4 using alternative methods and samples. Regression 1 modifies the statistically matching as described in Section 5.1. Regression 2 drops group-affiliated firms that control other firms in the sample. Regression 3 uses a 15% threshold to presume control, and Regression 4 excludes Japan and the UK from the sample. These two economies have the largest number of observations in the sample that already excludes the US. Regression 5 limits the time period to the latest 10 years. Regression 6 uses panel data regression instead of Fama-MacBeth regressions. Regression 7 uses local market returns and Fama-French global 5 factors to estimate the idiosyncratic component of stock and commodity returns. Coefficients were multiplied by one hundred. The numbers in parentheses are *p*-values. When we use Fama-MacBeth regressions, we adjust the standard errors for time series autocorrelation of 4 weeks using the Newey-West methodology. Boldface indicates coefficients significance at 10% or better in two-tailed tests.

Explanatory variable	Statistical and economic significance (1)	Group firms at bottom of ownership pyramid (2)	15% threshold for control (3)	Exclude Japan and UK (4)	Time eriod: 2003–2013 (5)	Panel regression (6)	Fama-French Five-factor model (7)
Group-affiliated Firm	**0.07**	**0.06**	**0.06**	**0.06**	**0.07**	**0.04**	0.02
	(0.00)	**(0.00)**	**(0.00)**	**(0.02)**	**(0.00)**	**(0.00)**	(0.27)
Idiosyncratic commodity return * group-affiliated firm	**−1.29**	**−1.81**	**−2.22**	**−2.40**	**−1.85**	**−0.98**	**−2.48**
	(0.05)	**(0.05)**	**(0.02)**	**(0.04)**	**(0.07)**	**(0.00)**	**(0.01)**
Economy * industry * time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm * week observations	6624,689	5755,866	5753,487	4180,231	4864,415	5767,175	5781,727
Number of economies	42	42	42	40	42	42	42
Number of weeks	1095	1095	1095	1095	574	1095	1095

5. Robustness tests

We run a number of robustness tests using the specification in Regression 2 of Table 4. If the coefficient of the interaction between group affiliation and idiosyncratic commodity shock measure is negative and significant at the 10% level, then we say the tests generate results that are qualitatively similar to those in Table 4.

5.1. Alternative method of matching commodities with industries

An alternative to matching based on statistical significance considers economic significance as well. The statistical matching method assumes that a more statistically significant loading $\beta_{c,j}$on commodity *c* implies a tighter link between the commodity and industry *j*. A plausible variant of the statistical method infers a tighter link if the economic impact of a shock to a commodity price, defined as the standard deviation of shocks to that commodity multiplied by the point estimate $\beta_{c,j}$, is the tightest. This approach matches an industry to the commodity with the highest economic impact, assessed in this way, whose loading $\beta_{c,j}$also has a *t*-statistic exceeding three in absolute value and retains the same sign in the second step single regressions as in the first step multivariate regression, as defined in the description of the statistical matching method. While new matches emerge, most intuitive matches remain (the list of matches are available upon request). For example, the Petroleum and natural gas industry remains matched with the commodity Crude oil because that commodity has both the most statistically significant and most economically important loading for stock returns in that industry. Regression 1 of Table 9, using matches determined by this method, generates results that are qualitatively similar to those in Table 4.

5.2. Diversification through share ownership

We have controlled for firms with sales diversified across industries. Firms that are at the top of the business groups pyramids could be diversified if the firms in which they hold stakes operate in different industries. As a result, firms at the top of pyramids could be less sensitive to commodity shocks. To mitigate this concern, we repeat our main test using only firms that are at the bottom of a pyramid. To do this, we drop group affiliates that control other firms in the sample. Regression 2 in Table 9 shows that our results continue to hold when we focus on firms that are at the bottom of the business group pyramid.

5.3. Alternative ways of identifying business groups

Our main tests in Table 4 use a 20% threshold for designating a firm's largest shareholder as its controlling shareholder. Using a relatively high stake can under-identify group-affiliated firms if smaller stakes suffice to lock in control if other equity is diffusely held and small shareholders do not vote at shareholder meetings. Erroneously classifying some group-affiliated firms as unaffiliated introduces attenuation bias in our tests. To explore the sensitivity of our tests to this concern, we construct an alternative version of the group affiliation indicator variable, $Group_{i,t}$, reclassifying controlling shareholders as those with stakes exceeding 15% and then reassessing group as described in Section 2.1. Regression 3 in Table 9, shows that this change yield results qualitatively similar to those in Table 4. [13]

5.4. Alternative samples

Our results are not driven by a few economies or extreme observations. For example, Regression 4 in Table 9,

[13] The number of observations drops slightly when the 15% threshold is used because the number of firms identified as controlled by governments, which are dropped from the sample, increases.

which is also based on the statistical matching, shows that dropping Japan and the UK (the US is again excluded), which have the largest number of observations, yields qualitatively similar results.

Qualitatively similar results are ensued after winsorizing firm-specific stock returns and economy-specific commodity returns at 1% (unreported).

We have roughly 20 years of ownership data in the sample. Ownership data coverage becomes wider in the latter 10 years. Fama-MacBeth regressions give equal weights to every time period regardless of the number of observations. Dropping the initial 10 years of data and repeating our tests using only the 2003–2013 period yields results, summarized in Regression 5 of Table 9, that are qualitatively similar to those in Table 4.

5.5. Alternative regression specification

We employ Fama-MacBeth estimation following Jin and Myers (2006) and the Petersen (2009) finding that this approach is appropriate in panel regressions explaining abnormal returns. An alternative is to run panel regressions controlling for country * industry * time fixed effects and double-cluster at the country * industry and business-group level. Regression 6 in Table 9 shows that the coefficient of Idiosyncratic commodity return * Group-affiliated firm is negative and statistically significant although the coefficient is −0.98, which is slightly smaller than the corresponding coefficients estimated by Fama-MacBeth regressions.

5.6. Alternative asset pricing model

Because we seek to test whether idiosyncratic shocks are incorporated differently into the stock prices of group-affiliated firms versus non-affiliated ones, we focus on the relation between idiosyncratic shocks to stock returns and idiosyncratic shocks to commodity prices with respect to the international version of CAPM developed by Jin and Myers (2006) to provide such a variance decomposition. A priori, we do not expect the Jin and Myers international CAPM to result in biased estimations of idiosyncratic shocks for group-affiliated versus unaffiliated firms. Nonetheless, testing whether results are affected by the choice of the particular asset pricing model is useful.

We use a global version of the Fama and French (2015) five-factor model, changing specifications (1) and (2) to include local market returns and Fama-French global five factors on the right-hand side in estimating idiosyncratic component of firm and commodity returns, respectively. Regression 7 in Table 9 shows that the coefficient of Idiosyncratic commodity return * Group-affiliated firm is negative, slightly larger in magnitude than in Regression 2 in Table 4 and highly statistically significant.

6. Business groups and R-squared around the world

We interpret the tests above as evidence that business group affiliation damps firm-specific shocks associated with commodity price changes. If business group affiliation similarly buffers other firm-specific shocks, share prices in general could co-move more in economies where business groups are more important. Therefore, we explore whether firm- and economy-level stock price co-movement correlates with the incidence of business groups.

To do this, we define the co-movement of firm *i*'s stock return with its market return in year *t*to be

$$\mathrm{Y}_{\mathrm{i,t}} = \log\left(\frac{R^2_{i,t}}{1 - R^2_{i,t}}\right) \tag{8}$$

where $R^2_{i,t}$is the regression *R*-squared statistic of Eq. (1) run on weekly returns for each firm in each year. The logistic transformation Eq. (8), which follows Morck et al. (2000), generates a variable with a roughly normal distribution and that is more positive for stocks whose shares more closely track market returns and more negative for stocks whose prices move more idiosyncratically.

We then run regressions explaining $\mathrm{Y}_{\mathrm{i,t}}$with firm-level group affiliation controlling for economy-level variables shown elsewhere to correlate with stock return co-movement: log gross domestic product (GDP) per capita (Morck et al., 2000), property rights (Morck et al., 2000), and accounting standards (Jin and Myers, 2006).[14]

Table 10 displays Fama-MacBeth regressions of $\mathrm{Y}_{\mathrm{i,t}}$on these explanatory variables. We use Newey-West estimator with 10 year lags to adjust for persistence in country-level variables. As in prior studies, log GDP per capita attracts a negative coefficient across all specifications and is uniformly significant. Property rights enters insignificantly if alongside other variables but are significant when included alone (not reported). These results accord with the prior literature.

The primary variable of interest, *Group Affiliation*, attracts a positive and significant coefficient in all specifications. Group-affiliated firms' stock returns have significantly higher co-movement with their markets or, in other words, less idiosyncratic volatility as a fraction of total volatility than do unaffiliated firms.

These findings suggest that more pervasive business group affiliation should be added to the list of economy characteristics associated with greater stock return co-movement. Fig. 1, Panel C, confirms this pattern, with economy level co-movement measure from Morck et al. (2013) on the vertical axis and the fraction of observations that are from group affiliates, from Table 1, on the horizontal axis. Stocks in countries with more group-affiliated firm observations have statistically significantly (p=0.09) higher economy-level stock return co-movement. The considerable scatter around the positive correlation line leaves abundant room for other mechanisms. However, our difference-in-difference findings, especially those using failed control block bids, affirm a direction of causation at the firm-level: Business group affiliation damps idiosyncratic stock return volatility, which in return causes share price co-movement. Firm-level data on business groups causing attenuated commodity shock-related firm-specific stock return volatility thus provide new economic intu-

[14] GDP per capita is from the World Bank WDI data set. Property rights index data are from the Heritage Organization website 2013 index of economic freedom. Accounting standards are from La Porta et al. (1998).

Table 10
R-squared around the world.
The dependent variable is a logistic transformation of the R-squared to $Y = \log(\frac{R^2}{1-R^2})$from annual firm-level regressions based on equation [1]. Results summarizes Fama-MacBeth regressions for each year, adjusting for time series autocorrelation over 10 years using the Newey-West methodology. Numbers in parentheses are *p*-values. Boldface indicates coefficients significance at 10% or better in two-tailed tests. GDP = gross domestic product.

Explanatory variable	(1)	(2)	(3)	(4)
Log GDP per capita	**−0.14**		**−0.13**	**−0.15**
	(0.03)		**(0.03)**	**(0.01)**
Group-affiliated firm		**0.09**	**0.06**	**0.08**
		(0.02)	**(0.02)**	**(0.00)**
Property rights				0.00
				(0.94)
Accounting standards				0.00
				(0.17)
Intercept	0.82	**−0.62**	0.74	**0.57**
	(0.20)	**(0.00)**	(0.21)	**(0.10)**
Number of firm * years	321,875	321,875	321,875	299,276
Average adj. R^2	0.02	0.01	0.02	0.02

ition to explain, partially at least, economy-level patterns in stock return co-movement.

7. Conclusions

We use global shocks to commodity prices to ascertain whether business groups' activities, such as risk sharing and internal transfers, cause the stock prices of group-affiliated firms to be less responsive to idiosyncratic shocks. Using global shocks to commodity prices allows us to exclude explanations of different responses being due to differences of shock frequency, magnitude, and observability across firms. We find that business group member firms' stocks are less sensitive to commodity shocks than are otherwise similar unaffiliated firms' stocks at the same time, in the same economy, and in the same commodity-sensitive industry. Difference-in-difference tests exploiting successful and matched exogenously failed control block transactions also confirm our results. Further tests show damped firm-specific volatility more generally in the stocks of business group affiliates, linking cross-economy differences in overall stock return co-movement to differences in the prevalence of business groups.

Business groups, as a second-best hierarchical allocation mechanism (Coase, 1937) in response to inefficient financial and other markets (Morck, Wolfenzon and Yeung, 2005; Khanna and Yafeh, 2007), allocate capital internally within the group (Almeida and Wolfenzon, 2006b; Morck et al., 2011). Internal capital markets can also be used to maximize business groups' controlling shareholders' private benefits (Bertrand et al., 2002), for example, by siphoning off group member firms' firm-specific abnormal earnings (Jin and Myers, 2006). The extent to which business group affiliates' share price responses to commodity price shocks are attenuated relative to unaffiliated firms' share price responses can be a useful empirical variable for measuring the extent to which investors expect business groups to shift resources and risk across their affiliates. We welcome research using shock sensitivity to better discern how business groups are governed.

Where markets expect more extensive resource and risk shifting across group affiliates, their stock prices provide less information feedback to corporate decision makers and capital providers (Bond et al., 2012). That is, by responding to capital market imperfections with more active hierarchical allocation, business groups further impair this important information transmission role of the stock market. Business groups thus could lock in inefficient capital allocation (Wurgler, 2000; Durnev et al., 2004), possibly contributing to the stalled economic growth of middle-income countries, the middle income trap (Rajan and Zingales, 2004; Eichengreen et al., 2013).

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