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Christina Kolerus, Papa N'Diaye, and Christian Saborowski

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CHINA'S FOOTPRINT IN GLOBAL COMMODITY MARKETS

This paper assesses empirically the role Chinese activity plays in global commodities markets. It shows that the strength of China's economic activity has a significant bearing on commodity prices. But the impact differs across commodity markets, with industrial production shocks having a substantial impact on metals and crude oil prices, and less so on food prices. The size of the impact of China's activity on the prices of specific commodities varies with China's footprint in that market. The empirical estimates indicate that, over a one-year horizon, a 1 percent increase in industrial production leads to a 5–7 percent rise in metals and fuel prices. The surprise component in Chinese industrial production announcements has a bearing on commodity prices that is comparable in magnitude to that of industrial production surprises in the United States, and this impact is much larger when global risk aversion is high.

Overview

China's footprint in global commodities markets has grown considerably over the past three decades. Between the mid-1990s and 2014, China's demand for metals (iron ore, copper, nickel, lead, and tin) rose from about 3 percent to some 40 percent of global demand; its imports of soybeans increased from 1 percent to 60 percent; and its demand for crude oil jumped from about 1 percent to 11 percent of global demand. However, the rapid increase in Chinese commodity demand is unlikely to persist as the country shifts to a more balanced and slower growth path that relies more on consumption and less on investment, relies more on services and less on manufacturing, and is accompanied by an attendant slowdown in commodity import-intensive industries. A waning Chinese thirst for commodities has the potential to leave considerable marks on global commodities markets, as illustrated by the dramatic drop in commodity price since 2014.

This paper assesses empirically the role Chinese activity plays in global commodities markets. It shows that the strength of China's economic activity has a significant bearing on commodity prices. But the impact differs across commodity markets, with industrial production shocks having a substantial impact on metals and crude oil prices, and less so on food prices. The size of the impact of China's activity on the prices of specific commodities varies with China's footprint in that market. The empirical estimates indicate that, over a one-year horizon, a 1 percent increase in industrial production leads to a 5–7 percent rise in metals and fuel prices. The surprise component in Chinese industrial production announcements has a bearing on commodity prices that is comparable in magnitude to that of industrial production surprises in the United States, and this impact is much larger when global risk aversion is high.

Introduction

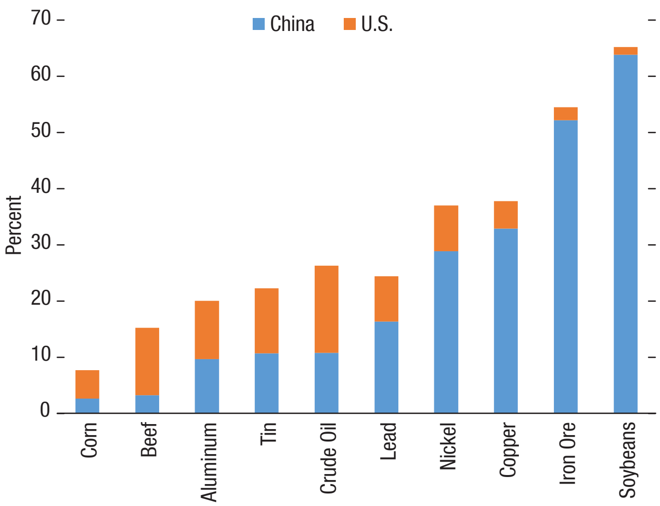
China's footprint in global commodities markets has grown considerably over the past three decades. Between the mid-1990s and 2014, China's demand for metals (iron ore, copper, nickel, lead, and tin) rose from about 3 percent to some 40 percent of global demand; imports of soybeans increased from 1 percent to 60 percent; and its demand for crude oil jumped from about 1 percent to 11 percent of global demand (Figure 1). The concomitant commodity price boom has often been attributed to the rapid rise in demand from China (Aastveit, Bjørnland, and Thorsrud, 2015; IMF, 2015). However, this rapid increase in Chinese commodity demand is unlikely to persist as the country shifts to a more balanced and slower growth path that relies more on consumption and less on investment, relies more on services and less on manufacturing, and is accompanied by an attendant slowdown in commodity import-intensive industries. A waning Chinese thirst for commodities has the potential to leave considerable marks on global commodities markets, as illustrated by the recent dramatic commodity price declines that analysts have attributed, at least partly, to the slowdown in China's growth (Gauvin and Rebillard, 2015; IMF, 2015).

This paper assesses empirically the role Chinese activity plays in global commodities markets using

We are grateful to Gillian Adu, Wang Ruosi, and Tessy Vasquez Baos for excellent assistance. The note benefited from useful discussions with Patrick Blagrave, Vikram Haksar, Petya Koeva Brooks, and Esteban Vesperoni; we also thank the IMF Spillover Task Force for their insightful comments.

Figure 1. Global Commodity Import Shares

(Percent of total, 2014)



Sources: Gruss (2014); and IMF staff estimates.

two complementary methodologies. It analyzes, in a high-frequency setting, the effects of surprises relative to expectations, and in a lower-frequency setting, the impact of actual Chinese demand. More specifically, the first approach analyzes the impact of surprises about Chinese industrial production on commodities markets by regressing daily price changes on the deviation of industrial production growth from the median Bloomberg consensus estimate prior to the announcement. This approach uncovers the relationship between these two variables without having to resort to restrictive identification assumptions. The second approach uses a structural vector autoregression (SVAR) framework to estimate the reaction of commodity prices to Chinese demand using quarterly data.

The two-pronged approach helps show the magnitude of market movements resulting from news about Chinese industrial production (IP), including for different states of the world (e.g., high risk aversion), and assess the degree to which these effects are economically relevant.

The findings are as follows. First, we find that IP shocks have a significant impact on metals and crude oil prices, but not on food prices. The size of the effects on commodity prices varies with China's footprint in the specific commodity market. Second, the magnitude of the impact of Chinese IP surprises on commodity prices is broadly in line with those of similarly sized U.S. IP surprises. Third, the effects of economic surprises are significantly larger in the presence of elevated risk aversion in global financial markets, especially for negative surprises. Finally, over a one-year horizon, a 1 percent increase in industrial production leads to a 5–7 percent rise in metals and fuel prices, an impact commensurate to China's current footprint in global commodities markets.

The remainder of the note is structured as follows. Section 2 analyzes the effects of IP announcement surprises on global commodity prices. Section 3 estimates the effects of China's economic activity on commodity prices. Section 4 concludes the paper.

Impact on Commodity Prices of Surprises about the Strength of China's Economy

In this section, we analyze the impact of surprises about Chinese industrial production on commodities markets using daily data.[1] The data sample ranges from 2006 to 2016 and covers metals, oil, and food commodities in which China accounts for a large share in global imports—namely, iron ore, copper, nickel, lead, tin, aluminum, crude oil, soy, corn, and beef.

The empirical approach we follow in this section is consistent with existing literature and spelled out in detail in Annex I.[2] The analysis runs both linear regressions for individual commodities and fixed effects regressions for all commodities together. The dependent variable is the percent change in a given commodity price future. The main regressor of interest is the surprise variable, which is defined to be zero on non-IP-announcement days and, on IP-announcement days, is given by the scaled deviation of year-on-year IP growth from the median Bloomberg consensus estimate immediately prior to the announcement. The scaling factor is the sample's standard deviation of the surprise (Roache and Rousset, 2015).

In each of the regressions, we include the contemporaneous value of the surprise variable and a number of lagged values to allow for delayed impacts. We also

[1]The analysis in this note doesn't seek to uncover the potential impact of speculative trading on global commodity prices. To the degree that these trades are uncorrelated with the variables used in the various regressions, their effects may be found in the unexplained (residuals) components of the regressions.

[2]The current literature on the impact of macroeconomic announcements focuses mainly on bond, stock, and currency markets, and confirms that macroeconomic news announcements can have significant price effects (e.g., Andersen et al., 2003; Galati and Ho, 2003). Various studies have confirmed the existence of a link between macroeconomic news and commodity prices (Roache and Rossi, 2009), although results are more mixed than in more liquid financial markets (e.g., Kilian and Vega, 2008; Hess, Huang, and Niessen, 2008).

experiment with a variety of control variables, including economic surprises in the United States and proxies for activity in other countries that are major players in global commodities markets.

Metals

The empirical results show that surprises in China's IP announcements generally have significant impacts on metals prices. For example, adding up the coefficients on the surprise variable and its lags in the first three regressions of Table 1 suggests that a one standard deviation surprise in IP leads to a copper price change of just above 1 percent. While the contemporaneous term is not significant, its first and second lags are, signaling that it takes between two and three days on average for the news impact to be fully reflected in prices.[3] Iron ore is the exception among metals, with results that are inconclusive and even counterintuitive a times. This is perhaps not so surprising given that iron ore markets were financialized particularly late, with spot and futures markets only reflecting a fraction of the global transactions volume until late in our sample period (IMF, 2015).[4,5]

The qualitative conclusion above is robust to the inclusion of a number of additional variables in the regressions to control for the potential effect of other contemporaneous factors on commodity prices.[6] Control variables such as the percent change in advanced economies' stock market valuations, the Chicago Board Options Exchange Volatility Index (VIX), and the percentage change in the U.S. nominal effective exchange rate (NEER) are all highly significant, and their coefficients have the expected signs: rising stock market valuations in advanced economies boost commodity prices while rising risk aversion in financial markets and an appreciating U.S. NEER depress commodity prices.

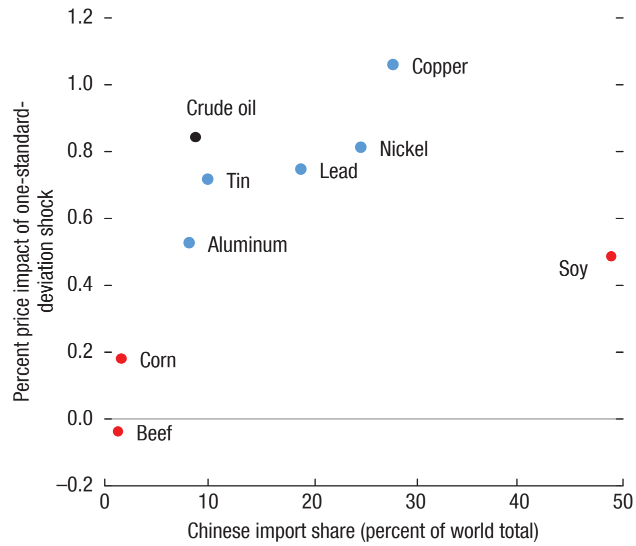
[3]The delayed impact on metals prices could reflect the fact that commodities markets have been late to become financialized, and may thus be less efficient in pricing in new information as it arrives.

[4]For decades, the iron ore market was characterized by overcapacity, with iron ore making up only a fraction of the final price of steel. In this environment, iron ore pricing was based on gentleman's agreements linked to yearly benchmarks. A push toward increased financialization—and disruption of the yearly benchmarks as the global pricing mechanism for iron ore—has come only since about 2007–09 as buyers and sellers increasingly refused to accept price offers and resorted to purchasing iron ore on the spot market.

[5]We therefore exclude iron ore from the remaining analysis in this section.

[6]As discussed in Annex 1, adding some of these controls may come at the cost of potentially biasing downward the coefficient of interest.

Figure 2. Cumulative Impact of a One Standard Deviation Positive Chinese Industrial Production Surprise on Commodity Futures



Source: IMF staff estimates.

Oil and Food

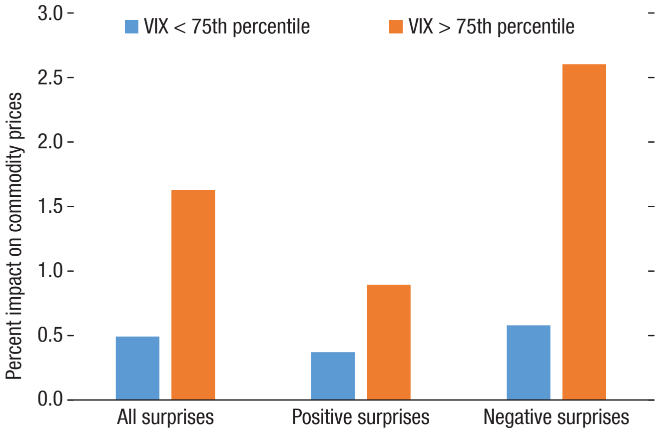
The empirical evidence of a statistically significant impact of surprises about the strength of activity in China on oil and food (soy, corn, and beef) prices is less robust than that for metals (Annex Tables 1.1d and 1.1e). IP surprises have significant effects on crude oil and soy futures in the baseline specification, but the statistical significance wanes once we include controls in the regression (less so for the cumulative coefficients). Nevertheless, and unlike for metals, most of the impact on oil and soy prices materializes during the day of the IP announcement. At the same time, IP surprises have no statistically significant impact on corn and beef prices.

Comparison across Commodities

The effects of China's activity on commodity prices are larger the higher China's footprint is in each individual market. Figure 2 plots the impact of a one standard deviation IP surprise across commodities against the share of Chinese imports in global imports of the respective commodity.[7] A few results are noteworthy. First, for metals (the blue dots on Figure 2), the chart

[7]In particular, the chart shows the cumulative impact of the IP shock by adding up the coefficients on the surprise variable and its lags in Annex Tables 1.1a–1.1e, using the regressions without controls (first column for each commodity).

Figure 3. Cumulative Impact of Surprise Announcements



Source: IMF staff estimates.

shows an intuitive positive correlation between the effects of IP surprises and the share of China's demand for commodities in global markets. Second, the magnitude of the impact on crude oil is somewhat larger than that on metals, and is what one would expect based on the share of China's demand in global markets. Finally, food prices generally respond less to IP announcements than metals prices; this is also an intuitive result given that rising IP growth does not necessarily imply significantly higher demand for food. The only food commodity that does show a statistically significant response is soy, a market in which China accounts for more than half of global demand across our sample period.

Comparison to U.S. IP Announcements

The analysis shows that Chinese IP surprises have a comparable, albeit slower to manifest, impact on commodity prices to U.S. IP surprises. A 1 percentage point surprise in Chinese IP moves commodity prices by about ½ percent, similar to U.S. IP surprises. The results hold despite the fact that China has a larger footprint in the global commodity markets than the United States, with the average shares in total imports across the commodities amounting to about 16 percent for China and 9 percent for the United States during our sample period. The large impact on global commodity prices of U.S. demand relative to its share in global markets may reflect the role the United States plays as a bellwether for global growth.

Effects of Surprises and Risk Aversion

We now explore whether the impact of surprises in Chinese IP announcements on commodity prices varies with the degree of risk aversion in global financial markets (as measured by the VIX).[8] To do so, we split the sample into negative and positive surprises and interact them with the VIX. Our hypothesis is that the interaction terms, or at least some of them, would enter the regression with positive coefficients, implying that Chinese IP surprises have larger impacts when risk aversion is high. We investigate the role of various levels of risk aversion.

For levels of risk aversion above the median—that is, when there is fear in global markets but no panic—we find that the interaction terms have positive signs in both regressions, though only in Regression 2 does one of the interaction terms enter significantly (Columns 1 and 2 of Annex Table 1.3a).[9] In other words, there is only limited evidence that IP surprises have larger impacts when the VIX is higher than its median.

For levels of risk aversion in the upper quartile—that is when there is panic in global markets—we find that the impact of IP surprises on commodity prices increases substantially. Indeed, two out of the three interaction terms in each regression are highly significant with the expected positive coefficients, and the cumulative coefficient on the three interaction terms is strongly positive. In other words, when market participants are particularly nervous and hesitant to take risks, news about Chinese demand for commodities has an especially large impact on prices.[10]

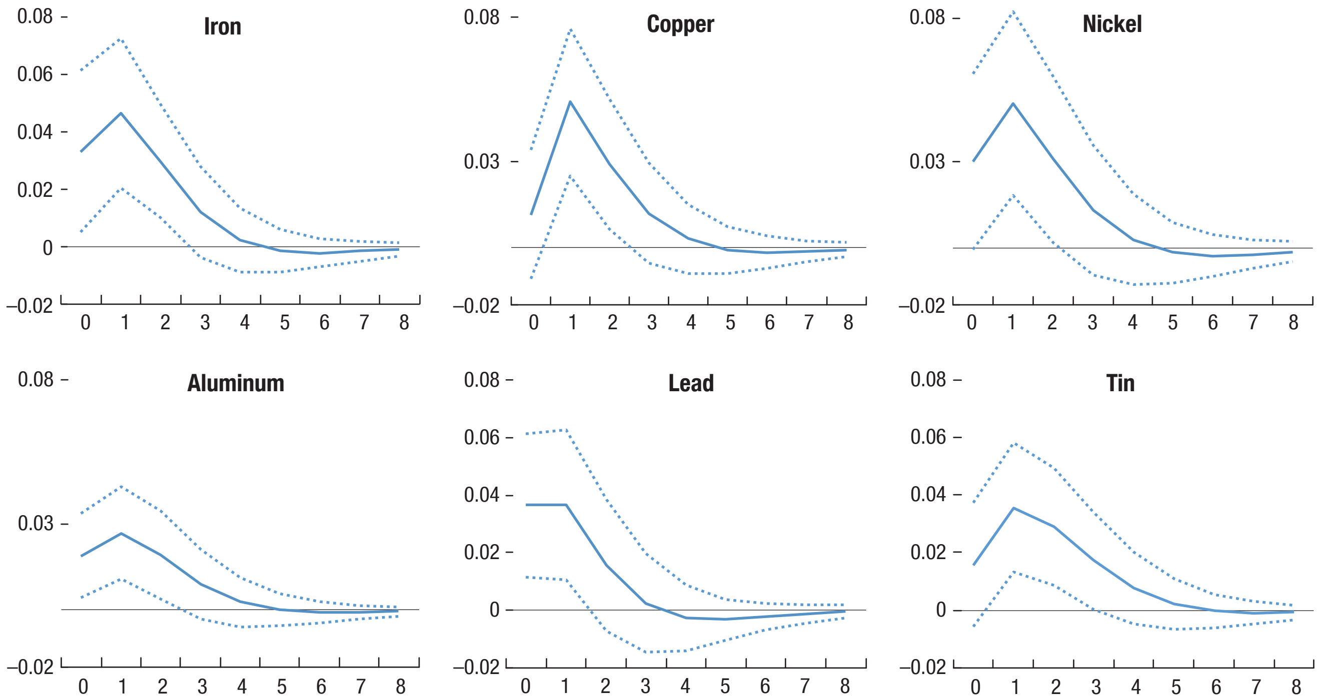
An interesting question related to the finding of a nonlinear effect of Chinese IP surprises on commodity prices is whether the nonlinearity differs with the type of IP surprise (negative vs. positive surprises). We therefore redo the analysis in Annex Table 1.3a while distinguishing positive from negative surprises. Figure 3 illustrates the results presented in Annex Table 1.3b. When the VIX is below its 75th percentile, a one standard deviation positive IP surprise lifts commodity prices on average by less than ½ percent. When the VIX is above the threshold, however, the magnitude of the impact is more than twice as large. Strikingly, for negative surprises, the impact increases

[8]Previous studies have found evidence of state-dependent impacts of macroeconomic news announcements, for example in the context of stock prices (e.g., Boyd, Hu, and Jagannathan, 2005; McQueen and Roley, 1993) but also for commodity prices (e.g. Hess, Huang, and Niessen, 2008).

[9]The median VIX in our sample is 17, the 75th percentile is 23, and the 90th percentile is 30.

[10]The regressions in Columns 5 and 6 of Annex Table 1.3a set the value of the dummy variable to 1 only for observations in the upper decile of the distribution of the VIX. While the results once again confirm the hypothesis that surprise effects are larger when the VIX is high, there is no evidence that IP surprises have even larger impacts in the upper decile of the VIX than in the upper quartile.

Figure 4a. Choleski Impulse Responses for Metals Prices



Source: IMF staff estimates.
Note: Orthogonalized responses of real commodity prices to an impulse in China IP; 95 percent confidence bands are shown. Numbers on the horizontal axis are months.

even more when risk aversion is elevated: when the VIX is in its lower three quartiles, a one standard deviation IP surprise increases commodity prices on average by about half a percent while the impact rises to some 2.5 percent when uncertainty is high.

The Effect of China's Demand on Commodity Price: Evidence from a Vector Autoregression Model

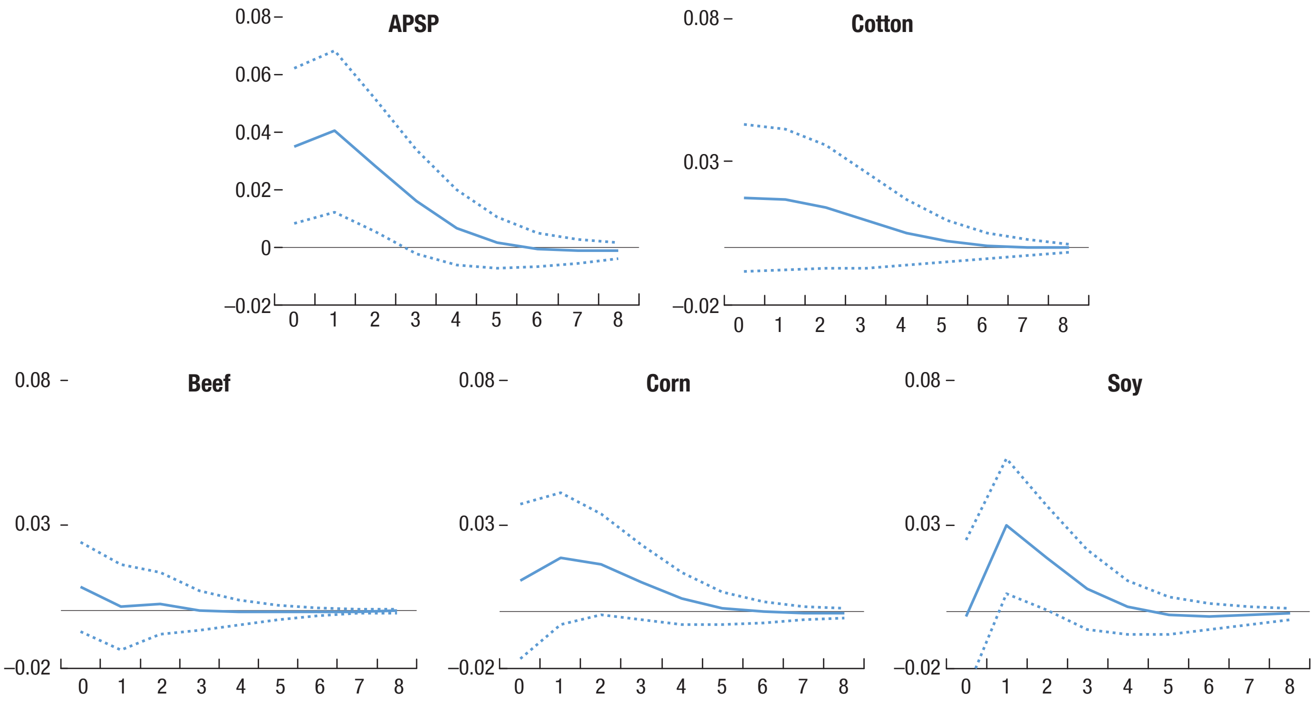
This section estimates the impact of China's economic activity on the commodity prices using an SVAR framework (see Annex II) with recursive shock identification.

The baseline SVAR specification broadly follows Roache and Rousset (2015) and includes world industrial production excluding China; China's industrial production (as a proxy for real aggregate demand for commodities); the U.S. real effective exchange rate to capture the effects of exchange rates and relative price changes other than commodity prices on the demand for commodities; the VIX to capture market sentiment and risk-related factors that could influence commodity prices; and, alternately, the prices of aluminum, copper, iron, nickel, tin, lead, oil (average petroleum spot price, or APSP), cotton, beef, soy, and corn.

The VAR analysis shows that activity in China has a statistically significant impact on global metals and oil prices. The impact is largely instantaneous for all metals, except copper and tin, increases to about 3 to 5 percent in the first quarter, and wanes after one year (see Figures 4a and 4b for a one standard deviation change in innovation in IP, which is close to a 1 percent change in IP). Copper and nickel prices show the strongest peak impact of about 5 percent, and aluminum the smallest with about 3 percent. Lead displays a slightly different pattern, with a contemporaneous and first-quarter impact roughly similar and an effect that becomes insignificant after the second quarter.

As is the case for the evidence based on high-frequency data in the previous section, China's economic activity has no significant impact on food prices (Figure 4b). The only exception remains soy, reflecting the fact that China's imports for soy make up about half of the global market demand for this commodity.

Figure 4b. Choleski Impulse Responses for Oil, Cotton, and Food Prices



Source: IMF staff estimates.
Note: Orthogonalized responses of real commodity prices to an impulse in China IP; 95 percent confidence bands are shown. Numbers on the horizontal axis are months. APSP = average petroleum spot price.

Cumulative Impact on Commodity Prices

The cumulative one-year impact of a 1 percent shock to Chinese IP reaches 5 to 7 percent for metals prices, and 7 percent for oil prices. These results are broadly in line with recent estimates in the literature (Table 1).[11]

[11]Earlier studies that use sample periods before the 2010s tend to find lower estimates.

Similar to the results from the analysis of IP surprises, the magnitude of these elasticities mainly reflects the importance of China's demand in each commodity market. Figure 5 shows that the impact of China's economic activity on metals prices is larger the larger China's footprint is in the respective markets. The price sensitivity is largest for iron and smallest for aluminum, consistent with China's import shares of over 30 percent for iron ore, and below 10 percent for aluminum. Interestingly, oil prices (APSP as

Table 1. One Year Horizon Commodity Price Effects from Shocks to China Demand Variables

Study	Sample Period	Shock Variable	Commodity Prices		
			Metals	*Oil*	*Food*
Roache and Roussett (2015	2002–15	Industrial Production (1 ppt)	6.5%–7.5%	9%	…
Roache (2012)	2002–11	Industrial Production (1 ppt)	1%–2%	2%	…
IMF (2016)	2002–14	Industrial Production (1 ppt)	8%	8%	…
IMF (2011)	2002–10	Industrial Production (1 std or 1 ppt)	6%	6%	…
Ahuja and Nabar (2012)	2002–11	Fixed Assets Investment (1 std), peak	3%–9%	not significant	3%

Source: IMF staff estimates.

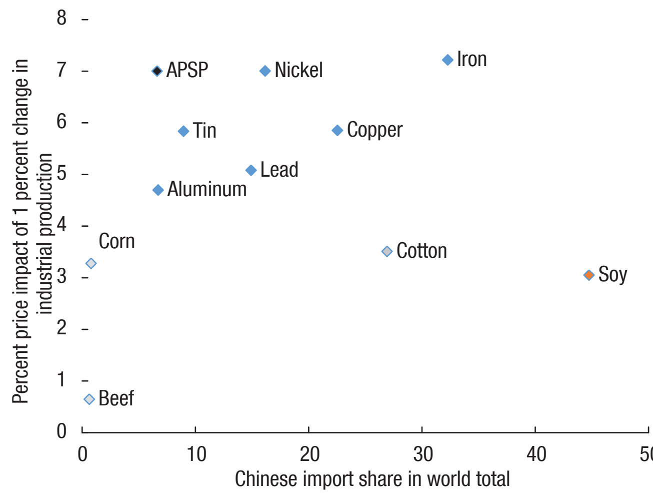
Note: ppt = percentage point; std - standard deviation.

well as Brent and West Texas Intermediate, or WTI) tend to react more strongly than suggested by the world market share, a result also found in the event study. A possible explanation could be that in oil markets, the strength of China's economy is perceived as more of a bellwether for the strength of global demand than in metals markets.

Looking Back in Time: The Upward Path of Price Elasticities

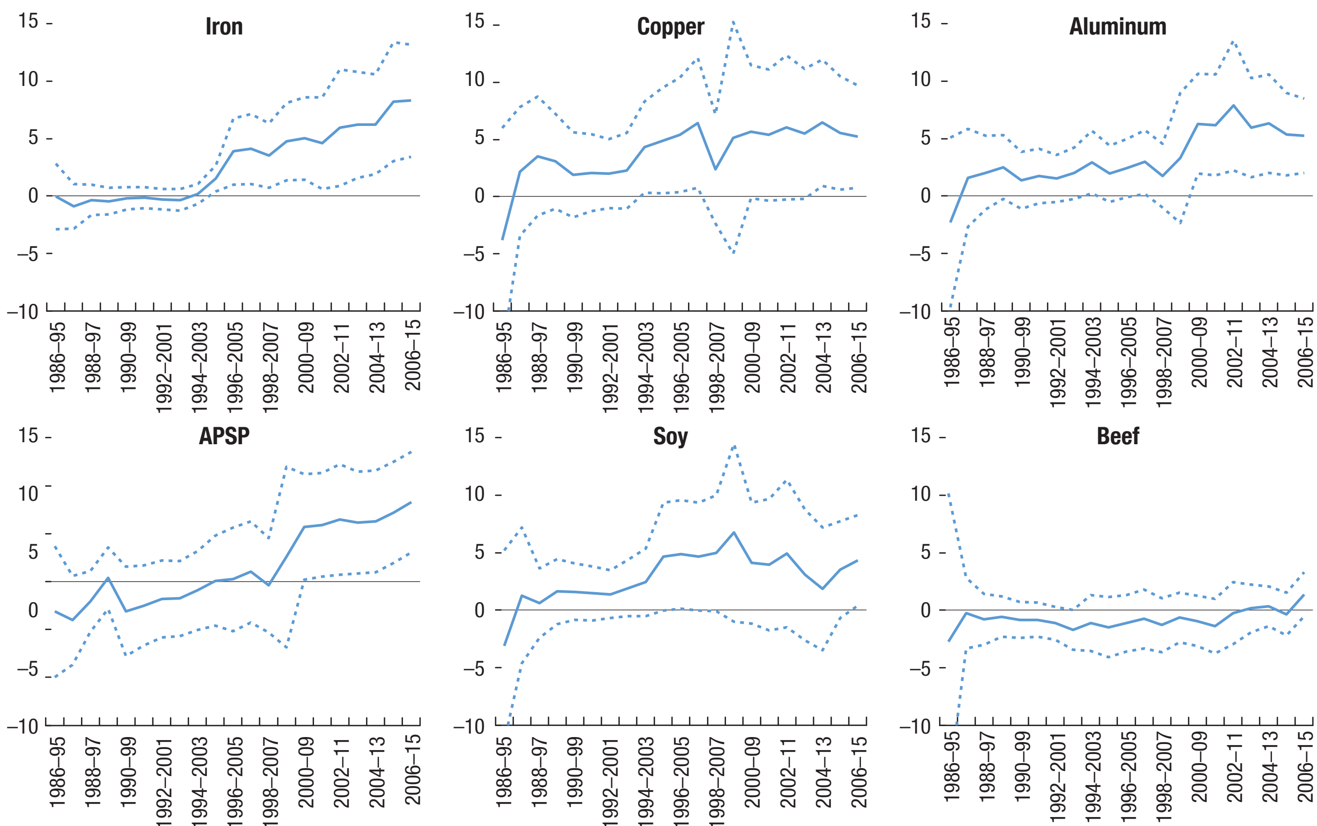
The influence of China's economic activity on global commodity prices has evolved over time, in tandem with China's rise as an economic powerhouse and integration in global trade. Figure 6, which displays estimates of one-year price elasticities to China's demand over a rolling window of 10 years (spanning from 1986 to 2015), shows that the sensitivity of commodity prices to China's demand was negligible

Figure 5. China Market Share and Price Elasticities



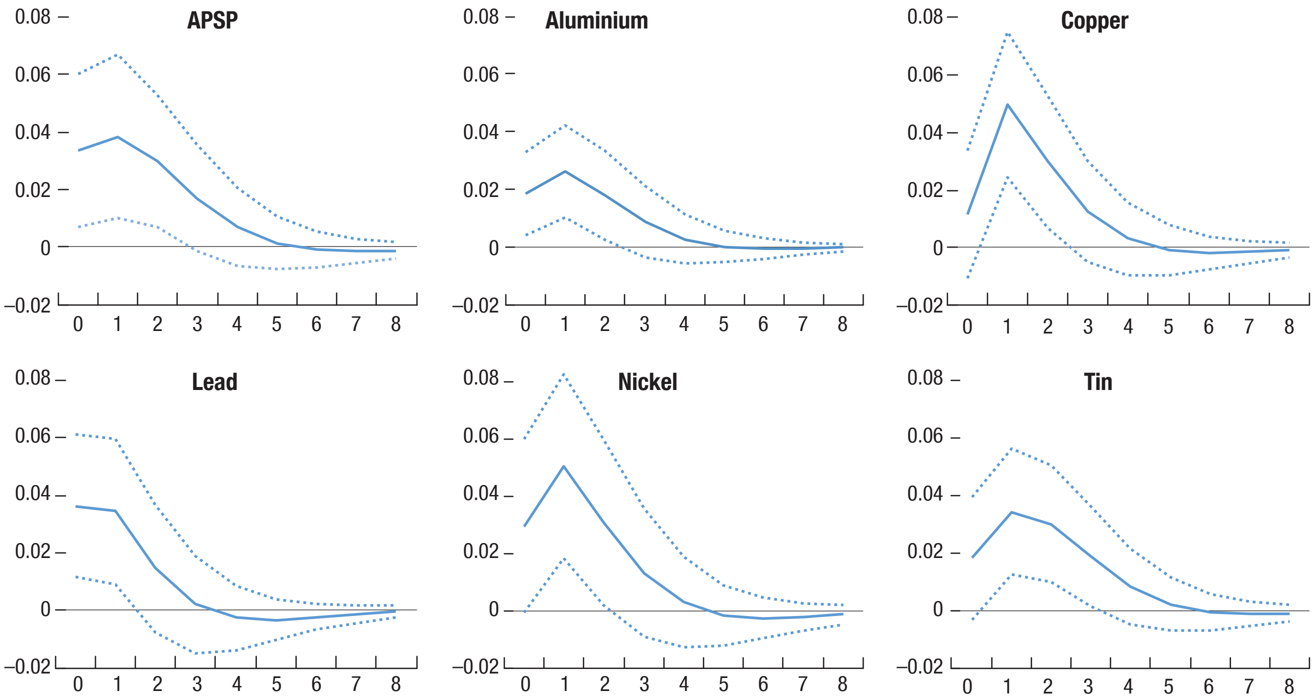
Source: IMF staff estimates.
Note: APSP = average petroleum spot price.

Figure 6. One-Year Price Elasticities to a 1 Percent Shock in China Industrial Production by Subperiod



Source: IMF staff estimates.
Note: Cumulative, orthogonalized impulse responses to a cumulative 1 percent shock in China industrial production. APSP = average petroleum spot price.

Figure 7. Choleski Impulse Responses for Metals Prices in a Demand and Supply Model



Source: IMF staff estimates.
Note: Orthogonalized impulse responses to a 1 percent shock in China industrial production. Numbers on the horizontal axis are months. APSP = average petroleum spot price.

prior to China's accession to the World Trade Organization (WTO) in early 2000s. But from the early 2000s onward, the sensitivity of oil and metals prices to China's demand became statistically significant and rising. For instance, the price elasticity of iron ore rose throughout the sample period, in line with China's import of iron ore (from 3.5 percent in 1986 to 52 percent in 2015). Similar patterns are observed for copper and aluminum, though the effects of China's demand on these metals markets seemed to have changed relative to the decade prior to the global financial crisis.[12] In both cases, China's market share stagnated between 2003 and 2008, even dropping slightly in 2006 before increasing strongly in 2008.

The significant impact of China's demand on soy prices is a recent phenomenon. After being not statistically significant for most time windows, it was significant during 2006–15. At the same time, while the sensitivity of beef prices to China's demand remains small and statistically not significant, there has been some uptick recently, possibly reflecting a shift in the consumption patterns of China's middle classes as the country develops.

Robustness

Ordering of the VAR

The results are robust to various ordering of the variables in the VAR, notably reversing real effective exchange rate (REER) and VIX, as well as advancing commodity prices before these two variables. Dropping the VIX does not change the thrust of the results, though the impact of China's activity on commodity prices is slightly larger than presented above, mainly due to a stronger second-quarter effect.

Supply Factors

Adding supply factors—that is, the growth in the production of each commodity—to the analysis doesn't affect the results above, with responses of prices to China's demand having similar shapes and sizes as those in earlier results (Figure 7). Please note that there are fewer commodities in our sample due to data restrictions on production levels.

[12]In the case of copper, China's market share stagnated between 2003 and 2008, even dropping slightly in 2006.

Alternative Demand Variables

Estimating the baseline VAR specification alternatively with real GDP and real total domestic demand as proxy measures of China's demand for commodities, in lieu of industrial production, shows a significant impact of China's demand on metals, oil, cotton, and food prices (Figure 8). However, the estimated price elasticities based on the VAR model with real GDP and real domestic demand are larger than those obtained using industrial production. This is in part because industrial production captures only about 1/3 of China's economy and displays a larger volatility than real GDP and real domestic demand. As shown in Figure 8, right panel, metals price elasticities with respect to real GDP range between 6 percent (aluminum) and 12 percent (nickel, closely followed by iron). For oil, the sensitivity to real GDP and real domestic demand is about 9 percent for every percent change in China's real GDP or domestic demand. For cotton, corn, and soy, the estimates vary between 4 and 6 percent when using the VAR model with real GDP growth, and 7–10 percent when using real domestic demand. Interestingly, beef remains insignificant.

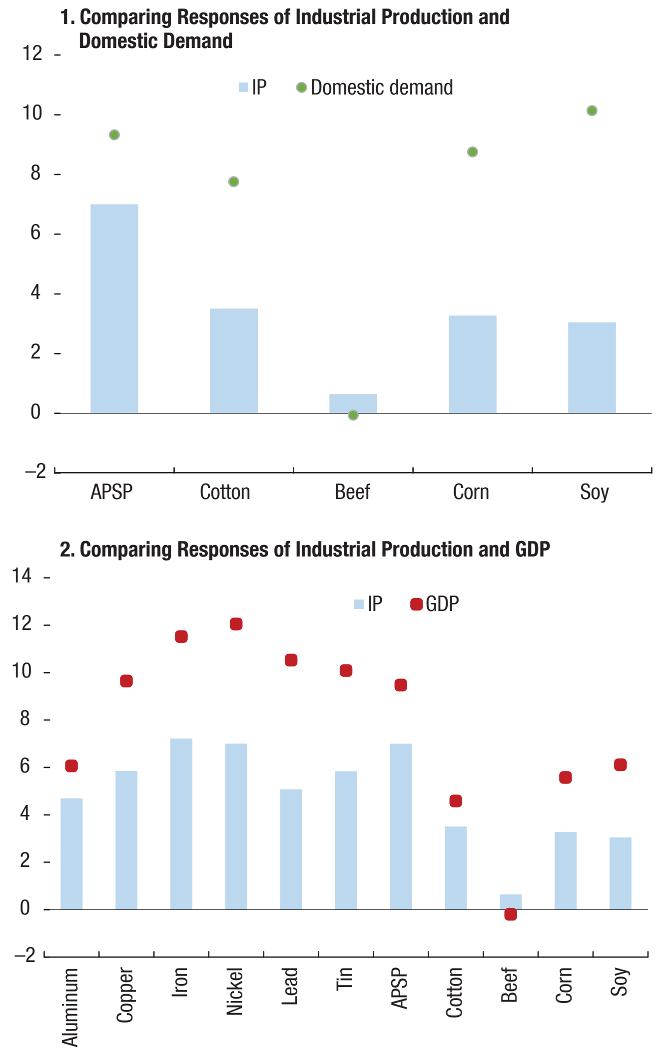
Conclusion

The empirical analysis above has shown that the strength of China's economic activity has significant impact on commodity prices. But the impact differs across commodity markets, with IP shocks having a substantial impact on metals and crude oil prices, and less of an impact on food prices. The size of the impact of China's activity on the prices of specific commodities varies with China's footprint in that market. The analysis also showed that the effects on global commodity prices of news about the strength of activity in China are similar in magnitude to those of news about U.S. activity and are significantly larger when global risk aversion is high, especially when the news is bad.

Annex 1. Data and Empirical Approach for Analyzing the Effects of IP Surprises on Commodity Prices

The sample includes daily data ranging from 2006 to 2016 and covers metals, oil, and food commodities in which China represents a relatively large share in total global imports—namely, iron ore, copper, nickel, lead, tin, aluminum, crude oil, soy, corn, and beef. The dependent variable is the percentage change in a given commodity price future. The main regressor of interest

Figure 8. One-Year Price Elasticities to Industrial Production, Total Domestic Demand, and GDP Shocks



Source: IMF staff estimates.
Note: APSP = average petroleum spot price; IP = industrial production.

is the IP announcement surprise. The latter is defined to be zero on non-announcement days and, on announcement days, is given by the scaled (by the sample standard deviation in the surprises) deviation of year-on-year IP growth from the median Bloomberg consensus estimate immediately prior to the announcement. The surprises can thus be interpreted as standard deviations from the consensus. Since announcements are generally made on a monthly basis, the sample provides us with 117 surprises, 56 of which are positive and 61 of which are negative.[13]

[13]Note that information on the median survey expectation is missing on Bloomberg for a few months in the sample period.

The analysis runs both simple linear regressions for individual commodities (equation (1)) and panel regressions for the sample as a whole (equation (2)). In the case of some of the panel regressions, interaction terms between the IP surprise and the VIX, an indicator of risk aversion in global financial markets, are included. The two equations are given by

$$dP_t = \alpha + \beta_1 dP_{t-1} + \sum_{s=0}^{S}(\gamma_s \text{Surprise}_{t-s}) + \sum_{p=0}^{P} \theta_p \text{Controls}_{pt} + \varepsilon_{it} \quad (1)$$

$$dP_{it} = \alpha + \sum_{s=0}^{S}\big(\gamma_s \text{Surprise}_{t-s} + \delta_s \text{Surprise}_{t-s} * \text{VIX}_{t-(S+1)}\big) + \sum_{p=0}^{P} \theta_p \text{Controls}_{pt} + \varepsilon_{it} \quad (2)$$

where $i \epsilon I$ is the panel dimension of equation (2), representing the various commodities in our sample; t is the time dimension; and $t = 0$ is the day of the announcement. dP_{it} is the percentage price change in commodity i on day t; *Surprise* is the surprise component in the IP announcement, scaled by the sample standard deviation in the surprises; *Controls* is a vector of control variables; and ε_{it} is the error term that, in the case of the panel regressions, includes the fixed effect.

The annex tables define all variables used in the analysis and reference their sources. We obtained data on commodities prices from Bloomberg. For all commodities, we use futures rather than spot prices, as the former have been shown to lead the latter in the price discovery (Antoniou and Foster, 1992; Yang, Balyeat, and Leatham, 2011). We made an effort to choose those futures that, to our knowledge, represent the nearest contract that is generally used as the benchmark for that commodity and traded on exchanges in the United States.

We obtained data on Chinese and U.S. economic data announcements from Bloomberg. While the main announcement of interest is Chinese IP, we also experiment with Chinese Purchasing Managers Index (PMI) and Fixed Asset Investment (FAI) surprises. We further compare their effects on commodity prices to those of U.S. IP, U.S. PMI surprises, and surprises in Nonfarm Payrolls, Chicago Business Barometer, Durable Goods Orders, and Philadelphia Fed Business Outlook announcements. All of these are defined in the same way as the Chinese IP surprise and are scaled by their own standard deviation. The analysis thereby makes use of information provided by Bloomberg, including the announcement itself, the median survey expectation immediately preceding the announcement, and the announcement time. The latter is important for the analysis as it allows us to determine on what day the announcement would have first had a chance to impact the relevant exchanges in the United States.

While we chose the event-study-type setting precisely to avoid identification problems, we also experiment with control variables. The choice of regressors reflects a tradeoff between controlling for other influences on commodity prices and limiting collinearity with the IP surprise. In particular, the concern is that the IP surprise might influence the control variables, which would then pick up part of the effect that we are aiming to capture in our regressor of interest. The set of control variables we experiment with includes, first, the percent daily change in the composite developed country stock market index; second, the daily percent change in the VIX; and, third, the daily percent change in the U.S. NEER. We include the U.S. NEER because various studies have shown commodity prices—which are traded in dollars—to fall as the dollar rises. At the same time, the U.S. NEER is perhaps the variable for which the collinearity issue weighs most strongly, given that news about Chinese activity would likely influence the bilateral exchange rates with the United States of countries for which China is an important trading partner. Thus, we use the variable mostly to show that our results are qualitatively insensitive to its inclusion while leaving it out of the baseline specifications. Finally, we include the lagged dependent variable as a control in some of the regressions.

Baseline Regressions

We begin by running simple linear regressions for individual commodities by estimating equation (1) using ordinary least squares (OLS). In each of the regressions, we include the contemporaneous surprise variable as well as a number of its lags to allow any effect to propagate in a delayed fashion. We experimented with lag structures of up to five lags, but found that effects tend to materialize with the second lag at most for all commodities in our sample. In the results reported in the text, we included two lags in each of the regressions to ensure comparability across commodities.

The first column of Annex Table 1.1a presents the results from estimating equation (1) for $S = 2$ using the daily percentage change in copper futures as the dependent variable. The regression does not include any control variables. The first thing to note is that the

Annex Table 1.1a. Regressions by Commodity: Copper and Nickel
Ordinary Least Squares
Dependent Variable: Percent Daily Change in Commodity Price

	Copper	Copper	Copper	Copper	Nickel	Nickel	Nickel	Nickel
One-standard-deviation IP surprise	0.083	0.146	0.228	0.163	–0.07	–0.024	0.164	0.067
	–0.18	–0.182	–0.197	–0.18	–0.231	–0.231	–0.26	–0.249
First lag	0.341*	0.371**	0.244	0.283	0.351	0.369	0.292	0.36
	–0.177	–0.181	–0.196	–0.178	–0.223	–0.23	–0.258	–0.248
Second lag	0.636***	0.693***	0.639***	0.564***	0.532**	0.528**	0.438*	0.374
	–0.176	–0.177	–0.191	–0.173	–0.223	–0.221	–0.246	–0.235
Lagged dependent variable		–0.084***	–0.098***	–0.115***		0.006	–0.004	–0.009
		–0.019	–0.018	–0.017		–0.019	–0.019	–0.018
Percent change AM stock market			0.193***	0.112***			0.150***	0.078***
			–0.016	–0.015			–0.022	–0.021
Percent change in VIX			–0.041***	–0.025***			–0.050***	–0.036***
			–0.005	–0.004			–0.006	–0.006
Percent change in U.S. NEER				–2.389***				–2.156***
				–0.102				–0.142
Constant	0.034	0.025	0.024	0.05	0.01	0.013	0.019	0.042
	–0.036	–0.037	–0.035	–0.031	–0.046	–0.046	–0.045	–0.043
R^2	0.01	0.01	0.11	0.26	0	0	0.06	0.14
N	2,753	2,645	2,606	2,606	2,742	2,629	2,590	2,590

Source: IMF staff estimates.

Note: AM = advanced markets; IP = industrial production; NEER = nominal effective exchange rate; VIX = Chicago Board Options Exchange Volatility Index.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

regression's explanatory power is very limited with an R^2 of 0.01. This is not surprising since the IP surprise variable takes values different from zero in only 117 of the 2,753 observations in the sample. In other words, this simple specification can aim to explain the variation in the dependent variable on only about 4 percent of the days in the sample.

Moving to the explanatory variable of interest, the surprise variable has a positive coefficient, both contemporaneously and on its first and second lag. While the contemporaneous term is not significant, its first and second lags are, signaling that it takes between two and three days on average for the news impact to be fully reflected in copper prices. While this finding is perhaps somewhat surprising, we see it confirmed in the cases of a number of other commodities in our sample. Our interpretation is that commodities markets have been late to become financialized, and may thus be less efficient in pricing in new information as it arrives. Adding up the three coefficients on the surprise variable and its lags, the results would suggest that a one standard deviation surprise in IP leads to a copper price change of just above 1 percent.

Regressions 2 to 4 in Annex Table 1.1a show the results when including the control variables discussed above. We first include the lagged dependent variable only and then add the percentage change in developed economy stock market valuation and the VIX and, finally, the percentage change in the U.S. NEER. The control variables are all highly significant and their coefficients carry the expected signs: rising AM stock markets boost commodity prices while rising risk aversion in financial markets and an appreciating U.S. NEER depress commodity prices. Interestingly, the lagged dependent variable is also significant with a negative coefficient. As discussed above, including these control variables has the advantage of allowing us to control for additional influences on commodity prices at the cost of potentially biasing the coefficient of interest due to the controls' likely responsiveness to Chinese IP surprises. Nevertheless, the results presented in Regressions 2–4 are generally very similar

Annex Table 1.1b. Regressions by Commodity: Lead and Tin
Ordinary Least Squares
Dependent Variable: Percent Daily Change in Commodity Price

	Lead	Lead	Lead	Lead	Tin	Tin	Tin	Tin
One-standard-deviation IP surprise	–0.121	–0.092	0.066	–0.01	0.124	0.147	0.332	0.312
	–0.216	–0.215	–0.236	–0.221	–0.189	–0.199	–0.227	–0.216
First lag	0.279	0.349	0.275	0.335	0.334*	0.387**	0.32	0.315
	–0.209	–0.214	–0.236	–0.221	–0.184	–0.189	–0.212	–0.202
Second lag	0.589***	0.566***	0.573**	0.495**	0.259	0.272	0.429**	0.364*
	–0.209	–0.207	–0.226	–0.212	–0.184	–0.184	–0.205	–0.195
Lagged dependent variable		0.068***	0.055***	0.041**		0.026	0.018	0.009
		–0.019	–0.019	–0.018		–0.02	–0.02	–0.019
Percent change AM stock market			0.196***	0.114***			0.103***	0.041**
			–0.02	–0.019			–0.018	–0.018
Percent change in VIX			–0.041***	–0.025***			–0.046***	–0.032***
			–0.006	–0.005			–0.005	–0.005
Percent change in U.S. NEER				–2.435***				–1.896***
				–0.127				–0.119
Constant	0.049	0.022	0.024	0.049	0.046	0.042	0.047	0.063*
	–0.043	–0.043	–0.042	–0.039	–0.038	–0.039	–0.038	–0.037
R^2	0	0.01	0.08	0.19	0	0	0.06	0.15
N	2,748	2,637	2,600	2,600	2,681	2,513	2,476	2,476

Source: IMF staff estimates.

Note: AM = advanced markets; IP = industrial production; NEER = nominal effective exchange rate; VIX = Chicago Board Options Exchange Volatility Index.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

to those in Regression 1: the regressors of interest are always jointly significant and the cumulative coefficient remains very close to 1.

The remainder of Annex Table 1.1a shows results from estimating the same regressions as in the case of copper for nickel futures, while Annex Table 1.1b does the same for lead and tin and Annex Table 1.1c for aluminum and iron ore prices. For all metals besides iron ore, we find strong evidence of a positive link between Chinese IP surprises and commodity futures. We also consistently find that commodities markets appear to take two to three days to price in the relevant news content. In general, the control variables we use affect neither the cumulative coefficients of our variables of interest much, nor their significance. The big exception to these findings is iron ore, for which the results are inconclusive and often counterintuitive. The reason is likely the fact that iron ore markets were particularly late to financialize, with spot and futures markets only reflecting a fraction of iron ore transactions until late in our sample, as the market remained dominated by large players that made use of reference prices that varied only at a low frequency. For these reasons, the remainder of the analysis in this section will exclude iron ore.

Annex Tables 1.1d and 1.1e show the results of running the same regressions as in Annex Tables 1.1a, 1.1b, and 1.1c for crude oil and food (soy, corn, and beef) prices. We find that IP surprises have significant impacts on crude oil and soy futures, although significance (less so cumulative coefficients) wanes as more control variables are included in the regressions. Interestingly, a larger share of the cumulative impact on oil and soy prices appears to materialize during the same day of the announcement than was the case for metals prices. In the case of corn and beef prices, there is no evidence of an important role for IP surprises.

In order to put these results into context, Figure 2 compares the impact of a one standard deviation IP surprise across commodity futures. In particular, the

Annex Table 1.1c. Regressions by Commodity: Aluminum and Iron Ore
Ordinary Least Squares
Dependent Variable: Percent Daily Change in Commodity Price

	Aluminum	Aluminum	Aluminum	Aluminum	Iron	Iron	Iron	Iron
One-standard-deviation IP surprise	0.106	0.101	0.149	0.094	0.116	0.042	0.028	–0.013
	–0.137	–0.137	–0.151	–0.14	–0.391	–0.33	–0.33	–0.327
First lag	0.165	0.166	0.157	0.181	1.219***	–0.043	–0.044	–0.054
	–0.137	–0.136	–0.15	–0.14	–0.374	–0.322	–0.322	–0.319
Second lag	0.256*	0.264*	0.305*	0.266*	–1.381***	–1.438***	–1.452***	–1.467***
	–0.141	–0.14	–0.156	–0.145	–0.37	–0.307	–0.307	–0.304
Lagged dependent variable		–0.052***	–0.059***	–0.069***		–0.045**	–0.044*	–0.046**
		–0.019	–0.019	–0.018		–0.023	–0.023	–0.023
Percent change AM stock market			0.093***	0.035***			0.047	0.016
			–0.013	–0.013			–0.03	–0.03
Percent change in VIX			–0.033***	–0.021***			–0.008	0.002
			–0.004	–0.004			–0.008	–0.008
Percent change in U.S. NEER				–1.700***				–1.046***
				–0.084				–0.185
Constant	0.004	0	0.002	0.018	0.023	–0.034	–0.036	–0.02
	–0.028	–0.029	–0.028	–0.026	–0.065	–0.055	–0.055	–0.054
R2	0	0	0.07	0.19	0.01	0.02	0.02	0.04
N	2,752	2,647	2,608	2,608	1,882	1,686	1,684	1,684

Source: IMF staff estimates.

Note: AM = advanced markets; IP = industrial production; NEER = nominal effective exchange rate; VIX = Chicago Board Options Exchange Volatility Index.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

chart shows the cumulative impact of the IP shock by adding up the coefficients on the surprise variable and its lags in Annex Tables 1.1a–1.1e.[14] As a point of reference, the x-axis shows the average (across our sample period) share of Chinese imports in global imports of the respective commodity. Focusing on metals commodities only—the blue dots—the chart shows a quite intuitive positive correlation between shock impacts and the Chinese footprint in the relevant commodity market. The magnitude of the impact on crude oil is somewhat larger than that on metals, conditional on Chinese import shares. Finally, food prices generally respond less to IP announcements than metals prices; this is also an intuitive result given that rising IP growth does not necessarily imply significantly higher demand for food. The only food commodity that does show a statistically significant response is soy, a market in which China captures more than half of global demand across our sample period.

Comparison to U.S. IP Announcements

In the regressions in Annex Table 1.2, we used a fixed effects estimator to control for any persistent differentials in price growth rates across commodities. Because our findings in Table 1 have shown only limited evidence for a link between IP surprises food prices, we limit ourselves to metals and oil in the analysis.[15] The results are, however, qualitatively insensitive to including the full set of commodities.

The first regression in Annex Table 1.2 includes only the Chinese IP surprise and its first and second lags. All three terms enter the regression significantly. Their cumulative coefficient amounts to about 0.75,

[14]The chart uses the regression without controls (the first column) for each commodity.

[15]We also continue to exclude iron ore for the reasons discussed above.

Annex Table 1.1d. Regressions by Commodity: Crude Oil and Soy
Ordinary Least Squares
Dependent Variable: Percent Daily Change in Commodity Price

	Brent oil	Brent oil	Brent oil	Brent oil	Soy	Soy	Soy	Soy
One-standard-deviation IP surprise	0.566***	0.560***	0.183	0.123	0.371**	0.373**	0.281	0.238
	–0.197	–0.196	–0.209	–0.199	–0.157	–0.156	–0.176	–0.171
First lag	0.155	0.184	0.167	0.19	0.033	0.026	0.133	0.151
	–0.196	–0.196	–0.209	–0.199	–0.157	–0.156	–0.176	–0.171
Second lag	0.122	0.132	0.322	0.262	0.083	0.08	–0.059	–0.091
	–0.196	–0.195	–0.208	–0.198	–0.158	–0.157	–0.177	–0.173
Lagged dependent variable		–0.065***	–0.072***	–0.089***		0.013	0.013	0
		–0.019	–0.018	–0.017		–0.019	–0.019	–0.019
Percent change AM stock market			0.205***	0.141***			0.057***	0.017
			–0.018	–0.017			–0.015	–0.015
Percent change in VIX			–0.048***	–0.034***			–0.027***	–0.019***
			–0.005	–0.005			–0.005	–0.004
Percent change in U.S. NEER				–1.977***				–1.280***
				–0.117				–0.105
Constant	0.017	0.013	0.016	0.036	0.033	0.028	0.022	0.029
	–0.04	–0.04	–0.037	–0.036	–0.032	–0.033	–0.032	–0.032
R^2	0	0.01	0.1	0.19	0	0	0.03	0.08
N	2,846	2,805	2,763	2,763	2,761	2,635	2,595	2,595

Source: IMF staff estimates.

Note: AM = advanced markets; IP = industrial production; NEER = nominal effective exchange rate; VIX = Chicago Board Options Exchange Volatility Index.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

which, unsurprisingly, comes close to the average of the effects for the commodities included in Figure 2. As in the individual regressions in Table 1, adding our set of control variables does not alter the results much (Regression 2).

Regressions 3 and 4 add the U.S. IP surprise and its first two lags as additional regressors. Regression 3 includes our control variables while Regression 4 does not, with only very limited impact on the significance and coefficients of the variables of interest. Importantly, the inclusion of the U.S. IP surprise does not affect the results for the Chinese IP surprise much. Neither the coefficients nor the p-values of the Chinese IP surprise variables change substantially. Moreover, it appears that the U.S. IP surprise term is also a significant determinant of commodity prices, with a cumulative coefficient of about 0.33 in Regression 3 and 0.25 in Regression 4. Interestingly, U.S. IP surprises seem to be priced into commodity prices more rapidly than their Chinese counterparts.

With a cumulative coefficient of about 0.25 in Regression 4, the average U.S. IP surprise moves average commodity prices only about a third as much as the average Chinese IP surprise (cumulative coefficient of 0.8). Note, however, that Chinese IP surprises are generally larger (standard deviation of 1.4) than their U.S. counterparts (standard deviation of 0.5). In order to ask the question whether a 1 percentage point surprise in Chinese IP would have a larger impact than a 1 percentage point surprise in U.S. IP, we need to multiply the respective cumulative coefficients with the relevant standard deviations. Doing so, we find that a 1 percentage point IP surprise in China would move commodity prices by about 0.6 percent while a 1 percentage point surprise in U.S. IP would move commodity prices by about 0.5 percent. In other words, Chinese IP shocks have only marginally larger impacts than U.S. IP shocks of the same magnitude. Interestingly, the ratio of one to the other is not far from the relative footprints

Annex Table 1.1e. Regressions by Commodity: Corn and Beef
Ordinary Least Squares
Dependent Variable: Percent Daily Change in Commodity Price

	Corn	Corn	Corn	Corn	Beef	Beef	Beef	Beef
One-standard-deviation IP surprise	0.145	0.101	–0.154	–0.191	0.012	0.036	0.022	0.023
	–0.176	–0.172	–0.196	–0.192	–0.066	–0.057	–0.065	–0.065
First lag	–0.036	–0.052	–0.074	–0.062	–0.019	–0.024	–0.017	–0.017
	–0.176	–0.17	–0.193	–0.189	–0.066	–0.057	–0.065	–0.065
Second lag	0.072	0.076	0.077	0.046	–0.03	–0.022	–0.032	–0.031
	–0.176	–0.17	–0.193	–0.189	–0.066	–0.057	–0.065	–0.065
Lagged dependent variable		0.034*	0.036*	0.026		0.511***	0.509***	0.509***
		–0.019	–0.019	–0.019		–0.017	–0.017	–0.017
Percent change AM stock market			0.064***	0.02			–0.006	–0.005
			–0.018	–0.019			–0.006	–0.006
Percent change in VIX			–0.027***	–0.021***			0.003*	0.003
			–0.005	–0.005			–0.002	–0.002
Percent change in U.S. NEER				–1.193***				0.035
				–0.118				–0.039
Constant	0.039	0.052	0.049	0.056	0.019	0.001	–0.002	–0.002
	–0.037	–0.037	–0.037	–0.036	–0.013	–0.012	–0.012	–0.012
R^2	0	0	0.02	0.06	0	0.26	0.26	0.26
N	2,645	2,472	2,433	2,433	2,786	2,702	2,658	2,658

Source: IMF staff estimates.

Note: AM = advanced markets; IP = industrial production; NEER = nominal effective exchange rate; VIX = Chicago Board Options Exchange Volatility Index.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

of China and the United States in the commodity markets used in the regression. Indeed, the average shares in total imports across the commodities included here amount to about 16 percent for China and 9 percent for the United States during our sample period.

Regression 5 in Annex Table 1.2 further adds Chinese and U.S. PMI surprises as well as those from the remaining data announcements that may be important regressors for commodity prices. Comparing the magnitudes of the cumulative impacts of PMI surprises broadly corroborates the result we found in the case of IP. The cumulative impacts of an average PMI surprise amount to 0.34 percent both in China and the United States. The standard deviation in the U.S. data, however, is larger (1.9) than that in the Chinese data (0.7). Hence, a 1 percentage point surprise in the Chinese PMI boosts commodity prices on average by about 0.5 percent while a 1 percentage point surprise in the U.S. PMI increases them by 0.2 percent.

Among the remaining data surprises included in Regression 5 in Annex Table 1.2, U.S. Nonfarm Payrolls and Philadelphia Fed Business Outlook surprises appear to matter most for commodity prices. Most other announcements have limited or even counterintuitive impacts.

Effects of Surprises and Risk Aversion

We investigate the effects of surprises and risk aversion using the panel framework in equation (1), estimating it using fixed effects. We include the same commodities in the sample as in Annex Table 1.2. Our proxy for risk aversion in global financial markets is the VIX. Column 1 of Annex Table 1.3a uses the basic specification from Annex Table 1.2 but adds four variables: the first is a dummy that takes the value 1 if the five-day moving average of the VIX takes a value greater than its sample median. In calculating the dummy, we lag the VIX by three periods to avoid it

Annex Table 1.2. Comparison to U.S. Industrial Production Surprises
Panel Regression with Fixed Effects
Dependent Variable: Percent Daily Change in Commodity Price

	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
One-standard-deviation IP surprise at *t*	0.119	0.148*	0.138	0.116	0.117
	–0.079	–0.087	–0.087	–0.079	–0.083
First lag	0.270***	0.212**	0.195**	0.258***	0.352***
	–0.077	–0.085	–0.085	–0.077	–0.081
Second lag	0.400***	0.437***	0.487***	0.417***	0.482***
	–0.078	–0.085	–0.085	–0.078	–0.079
Percent change in AM stock market		0.157***	0.156***		
		–0.007	–0.007		
Percent change in VIX		–0.045***	–0.045***		
		–0.002	–0.002		
One-standard-deviation U.S. IP surprise at *t*			0.365***	0.335***	0.297***
			–0.069	–0.071	–0.072
First lag			–0.091	–0.068	–0.097
			–0.069	–0.071	–0.072
Second lag			0.054	–0.013	–0.056
			–0.07	–0.072	–0.073
One-standard-deviation PMI surprise at *t*					0.432***
					–0.102
First lag					0.012
					–0.098
Second lag					–0.104
					–0.099
One-standard-deviation U.S. PMI surprise at *t*					0.058
					–0.078
First lag					0.179**
					–0.077
Second lag					0.101
					–0.074
One-standard-deviation China FAI at *t*					–0.003
					–0.078
First lag					–0.034
					–0.081
Second lag					–0.325***
					–0.08
One-standard-deviation U.S. Nonf. surprise at *t*					0.202***
					–0.074
First lag					0.074
					–0.074
Second lag					0.257***
					–0.074
One-standard-deviation U.S. Philly surprise at *t*					0.243***
					–0.073
First lag					0.146*
					–0.076
Second lag					0.165**
					–0.077
One-standard-deviation Chicago at *t*					–0.06
					–0.072
First lag					0.065
					–0.079
Second lag					–0.092
					–0.079
One-standard-deviation Durables at *t*					–0.266***
					–0.073
First lag					0.183**
					–0.074
Second lag					0.061
					–0.075
Constant	0.027*	0.033**	0.036**	0.030*	0.038**
	–0.016	–0.015	–0.015	–0.016	–0.016
R^2	0	0.07	0.08	0	0.01
N	16,522	16,276	16,276	16,522	16,522

Source: IMF staff estimates.

Note: AM = advanced markets; FAI = fixed-assets investment; IP = industrial production; PMI = purchasing manager index; VIX = Chicago Board Options Exchange Volatility Index.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Annex Table 1.3a. Impact of Industrial Production Surprises Conditional on Risk Aversion

Panel Regression with Fixed Effects

Dependent Variable: Percent Daily Change in Commodity Price

	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5	Regression 6
One-standard-deviation IP surprise at t	−0.035	−0.121	0.167*	0.098	0.184*	0.107
	−0.147	−0.141	−0.101	−0.096	−0.097	−0.092
First lag	0.104	0.138	0.102	0.087	0.158*	0.111
	−0.144	−0.138	−0.1	−0.095	−0.095	−0.09
Second lag	0.436***	0.432***	0.274***	0.262***	0.358***	0.341***
	−0.144	−0.138	−0.101	−0.096	−0.095	−0.091
Interaction Surprise and L3.VIX > 50th percentile	0.218	0.432**				
	−0.175	−0.179				
Interaction L_Surprise and L3.VIX > 50th percentile	0.235	0.118				
	−0.171	−0.175				
Interaction L2_Surprise and L3.VIX > 50th percentile	−0.049	0.008				
	−0.171	−0.175				
Dummy for L3.VIX > 50th percentile	0.036	−0.006				
	−0.032	−0.031				
Percent change in AM stock market		0.157***		0.156***		0.156***
		−0.007		−0.007		−0.007
Percent change in VIX		−0.045***		−0.045***		−0.045***
		−0.002		−0.002		−0.002
Interaction Surprise and L3.VIX > 75th percentile			−0.127	0.269		
			−0.162	−0.224		
Interaction L_Surprise and L3.VIX > 75th percentile			0.426***	0.600***		
			−0.158	−0.209		
Interaction L2_Surprise and L3.VIX > 75th percentile			0.313**	0.801***		
			−0.158	−0.206		
Dummy for L3.VIX > 75th percentile			0.03	−0.006		
			−0.036	−0.036		
Interaction Surprise and L3.VIX > 90th percentile					−0.187	0.284
					−0.167	−0.268
Interaction L_Surprise and L3.VIX > 90th percentile					0.346**	0.761***
					−0.165	−0.258
Interaction L2_Surprise and L3.VIX > 90th percentile					0.132	0.716***
					−0.165	−0.259
Dummy for L3.VIX > 90th percentile					−0.128**	−0.145***
					−0.052	−0.054
Constant	0.01	0.037*	0.019	0.037**	0.040**	0.048***
	−0.022	−0.021	−0.018	−0.018	−0.017	−0.016
R^2	0	0.07	0	0.08	0	0.08
N	16,522	16,276	16,522	16,276	16,522	16,276

Source: IMF staff estimates.

Note: AM = advanced markets; IP = industrial production; L, L2, L3 = one-, two-, and three-period lag, respectively; VIX = Chicago Board Options Exchange Volatility Index.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

responding to the IP surprise or its first or second lag; then, the specification includes three interaction terms between said dummy and the three IP surprise terms.

Columns 1 and 2 of Annex Table 1.3a show the results of estimating equation (2) with the four additional variables. We find that the interaction terms carry positive signs in both regressions, but only in Regression 2 does one of the interaction terms enter significantly. In other words, there is only limited evidence that IP surprises have larger impacts when the VIX is higher than its median.

Columns 3 and 4 show the same two regressions again, except that the dummy variable now takes the value 1 only when the VIX is in its upper quartile. In other words, we are now testing whether surprises have larger impacts when the VIX is not only somewhat elevated but very high. Indeed, the results now give very strong backing to our hypothesis: two out of the three interaction terms in each regression are highly significant with the expected positive coefficients, and the cumulative coefficient on the three interaction terms is strongly positive. At the same time, the coefficients on the IP surprise and its first and second lags are still positive and some of the terms are significant. In other words, positive IP surprises always have positive effects on commodity prices but the magnitude of the impact

Annex Table 1.3b. Distinguishing Positive and Negative Surprises Conditional on Risk Aversion

Panel Regression with Fixed Effects

Dependent Variable: Percent Daily Change in Commodity Price

	Regression 1	Regression 2	Regression 3	Regression 4
Percent change in AM stock market	0.157***		0.156***	
	–0.007		–0.007	
Pct change in VIX	–0.045***		–0.045***	
	–0.002		–0.002	
One-standard-deviation negative IP surprise at *t*	0.205*	0.176	0.078	0.101
	–0.108	–0.113	–0.121	–0.127
First lag	0.12	0.176	–0.042	–0.069
	–0.106	–0.111	–0.123	–0.129
Second lag	0.682***	0.790***	0.528***	0.564***
	–0.107	–0.112	–0.124	–0.13
One-standard-deviation positive IP surprise at *t*	0.041	0.063	0.133	0.281*
	–0.148	–0.111	–0.159	–0.166
First lag	0.378***	0.362***	0.281*	0.361**
	–0.142	–0.109	–0.151	–0.158
Second lag	0.01	0.031	–0.143	–0.169
	–0.142	–0.109	–0.153	–0.16
Interaction Negative Surprise and L3.VIX > 75th percentile			0.598**	0.369
			–0.263	–0.275
Interaction Negative L_Surprise and L3.VIX>75th percentile			0.634***	0.975***
			–0.244	–0.255
Interaction Negative L2_Surprise and L3.VIX>75th percentile			0.595**	0.891***
			–0.244	–0.256
Interaction Positive Surprise and L3.VIX>75th percentile			–0.72	–0.405*
			–0.443	–0.224
Interaction Positive. L_Surprise and L3.VIX>75th percentile			0.786*	–0.007
			–0.434	–0.218
Interaction Positive L2_Surprise and L3.VIX>75th percentile			1.034***	0.360*
			–0.401	–0.218
Dummy for L3.VIX > 75th percentile			0.001	0.071*
			–0.037	–0.037
Constant	0.039**	0.036**	0.041**	0.021
	–0.016	–0.016	–0.018	–0.019
R^2	0.08	0	0.08	0.01
N	16,276	16,522	16,276	16,522

Source: IMF staff estimates.

Note: AM = advanced markets; IP = industrial production; L, L2, L3 = one-, two-, and three-period lag, respectively; VIX = Chicago Board Options Exchange Volatility Index.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

rises when uncertainty is high. Figure 3 illustrates this finding: when the VIX is below its 75th percentile, a one standard deviation IP surprise lifts commodity prices on average by somewhat less than 0.5 percent. When the VIX is above the threshold, however, the magnitude of the impact is some four times higher, at about 2 percent.

The regressions in Columns 5 and 6 of Annex Table 1.3a define the dummy to the value 1 only in the upper decile of the distribution of the VIX. While the results once again confirm the hypothesis that surprise effects are larger when the VIX is high, there is no evidence that IP surprises have even larger impacts in the upper decile of the VIX than in the upper quartile.

An interesting follow-up question is whether uncertainty matters only for negative surprises, only for positive surprises, or for both. We therefore redo the analysis in Annex Table 1.3a while distinguishing positive from negative surprises. In doing so, we create two new variables: the positive surprise variable is equal to the IP Surprise when the latter is positive and zero otherwise; the negative surprise variable is equal to the IP Surprise when the latter is negative and zero otherwise. Columns 1 and 2 of Annex Table 1.3b show the baseline regressions when replacing the IP surprise variable with the two new variables. Somewhat surprisingly, the coefficients on the negative surprise variables are larger in the aggregate than those on the positive one. Taken at face value, this result would imply that negative surprises have larger impacts on commodity prices. However, we do not pursue this finding further as our main interest is in the interaction of the surprise variables with the VIX dummy.

Annex Table 2.1. Data Definitions and Sources
Panel Regression with Fixed Effects
Dependent Variable: Percent Daily Change in Commodity Price

	Description	Frequency	Source	Ticker
Chinese announcements				
IP	Value added of industry; YoY percent growth rate	Daily, including time of announcement	Bloomberg	chvaioy index
PMI	Manufacturing PMI, in percent	Daily, including time of announcement	Bloomberg	cpmindx index
FAI	Fixed assets investment; YoY growth rate	Daily, including time of announcement	Bloomberg	cnfayoy index
U.S. announcements				
IP	Value added of industry; MoM percent growth rate	Daily, including time of announcement	Bloomberg	
PMI	Manufacturing PMI; in percent	Daily, including time of announcement	Bloomberg	
Nonfarm	Nonfarm payrolls, in thousand jobs	Daily, including time of announcement	Bloomberg	
CBB	Chicago Business Barometer, in percent	Daily, including time of announcement	Bloomberg	
DGO	Durable Goods Orders, MoM percent growth rate	Daily, including time of announcement	Bloomberg	
PHBO	Philadephia Fed Business Outlook	Daily, including time of announcement	Bloomberg	
Commodity futures				
Iron ore	SGX Asiaclear Iron Ore cfr Chi	Daily	Bloomberg	OREXIO3M Index
Copper	LME COPPER 3MO ($)	Daily	Bloomberg	LMCADS03 Comdty
Nickel	LME NICKEL 3MO ($)	Daily	Bloomberg	lmnids03 comdty
Brent	Generic 1st 'CO' Future	Daily	Bloomberg	CO1 COMDTY
Tin	LME TIN 3MO ($)	Daily	Bloomberg	lmsnDS03 comdty
Lead	LME LEAD 3MO ($)	Daily	Bloomberg	lmpbds03 comdty
Aluminum	LME ALUMINUM 3MO ($)	Daily	Bloomberg	lmahDS03 Comdty
Soy	Generic 1st 'S ' Future	Daily	Bloomberg	s 1 comb comdty
Beef	Generic 1st Future	Daily	Bloomberg	GOLDLNPM Comdty
Corn	Generic 1st Future	Daily	Bloomberg	CORNLA2Y Comdty
Control variables				
VIX	Chicago Board Options Exchange (CBOE) Volatility Index	Daily	Haver	SPVIX@DAILY
US NEER	U.S. nominal effective exchange rate	Daily	Haver	FXDUSB@DAILY
Import share	Chinese share of imports of a commodity in world total	Annual	Gruss (2014)	
EMBI Global	Emerging market bond index	Daily	Haver	S200GI@INTDAILY
GS commodity all	Goldman Sachs commodity price index	Daily	Haver	PZALL@DAILY
CRB commodity all	CRB commodity price index	Daily	Haver	PFALL@DAILY
EM stock markets	Emerging market stock market index	Daily	Haver	S200ACD@INTDAILY

Columns 3 and 4 proceed to interact the six IP surprise terms with the VIX dummy (taking the value 1 when the VIX was within the upper quartile of its distribution). The findings suggest that both negative and positive surprises have larger impacts when the VIX is very high, although the evidence in the case of the negative surprises is stronger. In particular, in the regression with controls (Regression 3), we find that all three interaction terms with the negative surprise variable are highly significant, and their coefficients carry the expected positive sign. In Regression 4, the same is true, except that one of the interaction terms is insignificant. In the case of positive surprises, the regression with controls (Regression 3) provides evidence of an important role for the VIX while the regression without controls (Regression 4) does not.

Figure 3 summarizes the information in Annex Tables 1.3a and 1.3b by averaging the coefficients

across the respective regressions with and without controls. For instance, the first two bars reflect the averages of the coefficients in Regressions 3 and 4 in Annex Table 1.3a. As can be seen, the effect of a positive surprise on commodity prices is more than twice as large when the VIX is in its upper quartile than when it is not. Strikingly, for negative surprises, the impact increases even more when risk aversion is elevated: when the VIX is in its lower three quartiles, a one standard deviation IP surprise increases commodity prices on average by about half a percent while the impact rises to some 2.5 percent when uncertainty is high.

Annex 2. Vector Autoregression Model

Identification and Data

The baseline VAR specification broadly follows Roache and Rousset (2015) and includes world industrial production excluding China (IP_t^{w}), and China industrial production (IP_t^{C}) as a proxy for real aggregate demand for commodities (see Annex Table 2.1). We also include the U.S. real effective exchange rate ($REER_t$) to capture shifts in the U.S. exchange rate given the dollar denomination of all commodities, and the VIX (VIX_t) to capture market sentiment and risk-related factors that could influence commodity prices. Finally, we include the price of the commodity i (P^i_t), with i = (aluminum, copper, iron, nickel, tin, lead, APSP, cotton, beef, soy, corn). All variables are in log first differences. For each commodity i, the baseline vector of endogenous variables is defined with the following order:

$$Z^{i\,\prime} = [\Delta\ln(IP_t^{w})\ \Delta\ln(IP_t^{C})\ \Delta\ln(REER_t)\ \Delta\ln(VIX_t)\ \Delta\ln(P^i_t)]$$

Specification tests show a short lag order (Akaike information criterion and others) of one for all commodities when including the VIX. The VAR is stable and Granger causality tests are mixed for most variables, but Chinese demand variables cause commodity price changes.

The impulse response functions are derived based on a Choleski decomposition using the above order. We assume that demand in the rest of the world, in the baseline specification proxied by industrial production, is not affected by demand in China in the same quarter. Changes in the U.S. dollar effective exchange rate affect industrial production in the world and in China with a lag of at least one quarter but could change the VIX contemporaneously. While the first two assumptions are straightforward, the behavior of the VIX and the U.S. dollar exchange rate is presumably a more critical assumption and different orders are tested in alternative specifications. Finally, commodity prices can be affected by all variables contemporaneously, but price changes alter demand variables only after at least one quarter.

We use quarterly data, which are seasonally adjusted when appropriate, and the baseline period covers the years 2000 to 2015, and 1986 to 2015 for the time-varying results. Commodity prices and exchange rates are taken from the April 2016 *World Economic Outlook* (WEO); industrial production from Haver; and commodity production levels, used in the robustness section, from the World Bureau of Metal Statistics (WBMS) with the exception of oil production, which is sourced from Haver. While IP is often used in the literature as a measure for real aggregate demand, we also test alternative measures of demand in the robustness section, all taken from the April 2016 WEO.

Price Elasticities

To better understand the magnitude of price changes and compare the effects with other results in the literature, including those using different techniques, we compute price elasticities for each commodity. Precisely, a one-year price elasticity $\varepsilon_4^{P_i}$ for each commodity i is calculated using the orthogonalized cumulative price response to an orthogonalized cumulative impulse in China IP:

$$\varepsilon_4^{P_i} = \frac{\sum_{t=0}^{4}\beta_t^{P_i}}{\sum_{t=0}^{4}\beta_t^{IP^C}}$$

Robustness: Supply Factors and Alternative Demand Variables

We re-run the above baseline specification during the period 2000–15 simply adding supply factors to the analysis. As data on world commodity production are more limited, our set of commodities is restricted to metals (except iron) and fuel prices, excluding food and other commodities. For the specification, we assume that world supply of commodity i is not affected by contemporaneous changes in demand vari-

ables, price, and risk variables. The vector of endogenous variables is then described as

$$Z^{i\,'} = [\Delta\ln(X_t^{\,i})\ \ \Delta\ln(IP_t^{\,w})\ \Delta\ln(IP_t^{\,w})\ \Delta\ln(IP_t^{C})$$
$$\Delta\ln(REER_t)\ \Delta\ln(VIX_t)\ \Delta\ln(P^i_{\,t})]$$

with $\Delta\ln(X_t^{\,i})$ being total world production of commodity i. For specifications with alternative demand variables, we simply replace China IP and world IP by GDP for both aggregates or by total domestic demand.

References

Aastveit, K., H. Bjørnland, and L. Thorsrud. 2015., "What Drives Oil Prices? Emerging versus Developed Economies." *Journal of Applied Econometrics* 30 (7): 1013–28.

Ahuja, A., and M. Nabar. 2012. "Investment-Led Growth in China: Global Spillovers." IMF Working Paper 12/267, International Monetary Fund, Washington, DC.

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega. 2003. "Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange." *American Economic Review* 93: 38–62.

Antoniou, Antonios, and Andrew J. Foster. 1992. "The Effects of Futures Trading on Spot Price Volatility: Evidence for Brent Crude Oil Using GARCH." *Journal of Business Finance and Accounting* 19(4): 473–84.

Boyd, J., J. Hu, and R. Jagannathan. 2005. "The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks." *Journal of Finance* 60(2): 649–72.

Galati, G., and C. Ho. 2003., "Macroeconomic News and the Euro/Dollar Exchange Rate." *Economic Notes* 32(3): 371–98.

Gauvin, L., and C. Rebillard. 2015. "Towards Recoupling? Assessing the Global Impact of a Chinese Hard Landing through Trade and Commodity Price Channels." Working Paper 562, Bank of France, Paris.

Gruss, B. 2014. "After the Boom—Commodity Prices and Economic Growth in Latin America and the Caribbean." IMF Working Paper 14/154, International Monetary Fund, Washington, DC.

Hess, D., H. Huang, and A. Niessen. 2008. "How Do Commodity Futures Respond to Macroeconomic News?" *Journal of Financial Markets and Portfolio Management* 22(2).

International Monetary Fund. 2011. "China Spillovers: Global Commodity Markets." In *China Spillover Report 2011*. Washington, DC: International Monetary Fund.

———. 2015. "Special Feature: Commodity Market Developments and Forecasts, with a Focus on Metals in the World Economy." Chapter 1 in *World Economic Outlook*. Washington, DC: International Monetary Fund, October.

———. 2016. *Regional Economic Outlook: Asia and Pacific.* Washington, DC: International Monetary Fund, April.

Kilian, L., and C. Vega. 2008. "Do Energy Prices Respond to U.S. Macroeconomic News? A Test of the Hypothesis of Predetermined Energy Prices." International Discussion Paper 957, Federal Reserve, Washington, DC.

McQueen, G., and V. Roley. 1993. "Stock Prices, News and Business Conditions." *Review of Financial Studies* 6 (3): 683–707.

Roache, S. K. 2012. "China's Impact on World Commodity Markets." IMF Working Paper 12/115, International Monetary Fund, Washington, DC.

———, and M. Rossi. 2009. "The Effects of Economic News on Commodity Prices: Is Gold Just Another Commodity?" IMF Working Paper 09/140, International Monetary Fund, Washington, DC.

Roache, S. K., and M. Rousset. 2015. "China: Credit, Collateral, and Commodity Prices." HKIMR Working Paper 27/2015, Hong Kong Institute for Monetary Research.

Yang, Jian, R. Brian Balyeat, and David J. Leatham. 2005. "Futures Trading Activity and Commodity Cash Price Volatility." *Journal of Business Finance and Accounting* 32(1): 297–323.

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