

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.

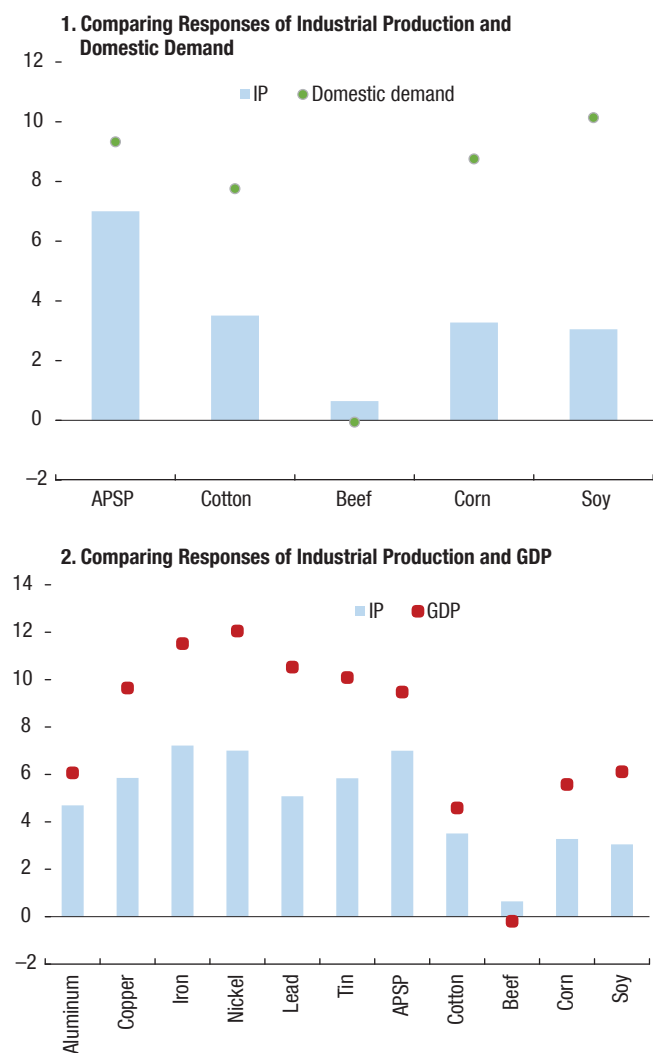
Conclusion

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

¹³Note 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

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

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

where $i \in I$ 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 transac-

tions 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
R ²	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,

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

¹⁵We 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
First lag	-0.079	-0.087	-0.087	-0.079	-0.083
Second lag	0.270***	0.212**	0.195**	0.258***	0.352***
Percent change in AM stock market	-0.077	-0.085	-0.085	-0.077	-0.081
Percent change in VIX	0.400***	0.437***	0.487***	0.417***	0.482***
One-standard-deviation U.S. IP surprise at t	-0.078	-0.085	-0.085	-0.078	-0.079
First lag		0.157***	0.156***		
Second lag		-0.007	-0.007		
One-standard-deviation PMI surprise at t		-0.045***	-0.045***		
First lag		-0.002	-0.002		
Second lag			0.365***	0.335***	0.297***
One-standard-deviation U.S. PMI surprise at t			-0.069	-0.071	-0.072
First lag			-0.091	-0.068	-0.097
Second lag			-0.069	-0.071	-0.072
One-standard-deviation China FAI at t			0.054	-0.013	-0.056
First lag			-0.07	-0.072	-0.073
Second lag					0.432***
One-standard-deviation U.S. Nonf. surprise at t					-0.102
First lag					0.012
Second lag					-0.098
One-standard-deviation U.S. Philly surprise at t					-0.104
First lag					-0.099
Second lag					0.058
One-standard-deviation China FAI at t					-0.078
First lag					0.179**
Second lag					-0.077
One-standard-deviation U.S. Nonf. surprise at t					0.101
First lag					-0.074
Second lag					-0.003
One-standard-deviation U.S. Philly surprise at t					-0.078
First lag					-0.034
Second lag					-0.081
One-standard-deviation U.S. Nonf. surprise at t					-0.325***
First lag					-0.08
Second lag					0.202***
One-standard-deviation U.S. Philly surprise at t					-0.074
First lag					0.074
Second lag					-0.074
One-standard-deviation Chicago at t					0.257***
First lag					-0.074
Second lag					0.243***
One-standard-deviation Durables at t					-0.073
First lag					0.146*
Second lag					-0.076
One-standard-deviation Chicago at t					0.165**
First lag					-0.077
Second lag					-0.06
One-standard-deviation Durables at t					-0.072
First lag					0.065
Second lag					-0.079
One-standard-deviation U.S. Nonf. surprise at t					-0.092
First lag					-0.079
Second lag					-0.266***
One-standard-deviation U.S. Philly surprise at t					-0.073
First lag					0.183**
Second lag					-0.074
Constant	0.027*	0.033**	0.036**	0.030*	0.038**
R^2	-0.016	-0.015	-0.015	-0.016	-0.016
N	0	0.07	0.08	0	0.01
	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
First lag	-0.147	-0.141	-0.101	-0.096	-0.097	-0.092
Second lag	0.104	0.138	0.102	0.087	0.158*	0.111
Interaction Surprise and L3.VIX > 50th percentile	-0.144	-0.138	-0.1	-0.095	-0.095	-0.09
Interaction L_Surprise and L3.VIX > 50th percentile	0.436***	0.432***	0.274***	0.262***	0.358***	0.341***
Interaction L2_Surprise and L3.VIX > 50th percentile	-0.144	-0.138	-0.101	-0.096	-0.095	-0.091
Dummy for L3.VIX > 50th percentile	0.218	0.432**				
Percent change in AM stock market	-0.175	-0.179				
<i>Percent change in VIX</i>	0.235	0.118				
Interaction Surprise and L3.VIX > 75th percentile	-0.171	-0.175				
Interaction L_Surprise and L3.VIX > 75th percentile	-0.049	0.008				
Interaction L2_Surprise and L3.VIX > 75th percentile	-0.171	-0.175				
Dummy for L3.VIX > 75th percentile	0.036	-0.006				
Interaction Surprise and L3.VIX > 90th percentile	-0.032	-0.031				
Interaction L_Surprise and L3.VIX > 90th percentile		0.157***		0.156***		0.156***
Interaction L2_Surprise and L3.VIX > 90th percentile		-0.007		-0.007		-0.007
Dummy for L3.VIX > 90th percentile		-0.045***		-0.045***		-0.045***
Constant		-0.002		-0.002		-0.002
<i>R</i> ²			-0.127	0.269		
N			-0.162	-0.224		
			0.426***	0.600***		
			-0.158	-0.209		
			0.313**	0.801***		
			-0.158	-0.206		
			0.03	-0.006		
			-0.036	-0.036		
					-0.187	0.284
					-0.167	-0.268
					0.346**	0.761***
					-0.165	-0.258
					0.132	0.716***
					-0.165	-0.259
					-0.128**	-0.145***
					-0.052	-0.054
	0.01	0.037*	0.019	0.037**	0.040**	0.048***
	-0.022	-0.021	-0.018	-0.018	-0.017	-0.016
	0	0.07	0	0.08	0	0.08
	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***	
Pct change in VIX	-0.007		-0.007	
One-standard-deviation negative IP surprise at t	-0.045***		-0.045***	
First lag	-0.002		-0.002	
Second lag	0.205*	0.176	0.078	0.101
One-standard-deviation positive IP surprise at t	-0.108	-0.113	-0.121	-0.127
First lag	0.12	0.176	-0.042	-0.069
Second lag	-0.106	-0.111	-0.123	-0.129
One-standard-deviation positive IP surprise at t	0.682***	0.790***	0.528***	0.564***
First lag	-0.107	-0.112	-0.124	-0.13
Second lag	0.041	0.063	0.133	0.281*
Interaction Negative Surprise and L3.VIX > 75th percentile	-0.148	-0.111	-0.159	-0.166
Interaction Negative L_Surprise and L3.VIX > 75th percentile	0.378***	0.362***	0.281*	0.361**
Interaction Negative L2_Surprise and L3.VIX > 75th percentile	-0.142	-0.109	-0.151	-0.158
Interaction Positive Surprise and L3.VIX > 75th percentile	0.01	0.031	-0.143	-0.169
Interaction Positive L_Surprise and L3.VIX > 75th percentile	-0.142	-0.109	-0.153	-0.16
Interaction Positive L2_Surprise and L3.VIX > 75th percentile			0.598**	0.369
Dummy for L3.VIX > 75th percentile			-0.263	-0.275
Constant			0.634***	0.975***
R^2			-0.244	-0.255
N			0.595**	0.891***
			-0.244	-0.256
			-0.72	-0.405*
			-0.443	-0.224
			0.786*	-0.007
			-0.434	-0.218
			1.034***	0.360*
			-0.401	-0.218
			0.001	0.071*
			-0.037	-0.037
	0.039**	0.036**	0.041**	0.021
	-0.016	-0.016	-0.018	-0.019
	0.08	0	0.08	0.01
	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	Philadelphia 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	lmmnds03 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 vari-

able 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), 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:

$$Z^i = [\Delta \ln(IP_t^w) \quad \Delta \ln(IP_t^C) \quad \Delta \ln(REER_t) \\ \Delta \ln(VIX_t) \quad \Delta \ln(P_i)]$$

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:

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

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

$$Z_t^i = [\Delta \ln(X_t^i) \quad \Delta \ln(IP_t^w) \quad \Delta \ln(IP_t^c) \\ \Delta \ln(REER_t) \quad \Delta \ln(VIX_t) \quad \Delta \ln(P_t^i)]$$

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.

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