The Markets of Metals: Determinants, Predictors, and Interrelations

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Abstract

Metals, the markets they are traded at, and in particular metal prices are of great importance to the global economy. On the one hand, many developing countries, where metals are usually mined, are heavily dependent on revenues from commodity exports. On the other hand, industrialized countries consume these metals on a large scale and hence fear the inflationary pressure caused by rising commodity prices. While metals are often considered a unified group or asset class, they are in fact very heterogeneous, both in terms of usage within different industries and the characteristics of their markets. The objective of this thesis is therefore to provide an in-depth analysis of metal markets, their determinants, predictors, and interrelations.

Metal prices are believed to be primarily demand-driven, while this demand is again driven by numerous microeconomic, macroeconomic, and financial market conditions. Monetary policy of central banks in general, and the policy of the Federal Reserve in particular, affects several of these demand channels and is therefore considered to have a significant impact on commodities in general and metals in particular.

In the first part of this thesis, we investigate whether and how the impact of monetary policy on metal prices has changed, as a result of the implementation of unconventional policy actions. While we observe the policy channel, as well as the direction of relation have shifted, the policies' impact on metals remains valid over time.

In the second part of this thesis, we analyze the forecastability, as well as the metal-specific price predictors and determinants of three precious, six industrial, as well as fifteen minor metals. We find strong predictability for the minor metals, as well as changes in the price predictors and determinants over time, where we additionally observe effects of the financialization of commodity markets.

Given the similar price determinants of the industrial metals in this empirical analysis, as well as their theoretical relationship via the co-production, co-consumption, as well as the co-trading on exchanges, we proceed to model the industrial metal markets jointly in the third part of this thesis. We therefore connect multiple metal markets via a global vector autoregression and reveal numerous linkages within and across the individual metal markets, especially between prices.

Overall, this thesis reveals the individuality of each metal market, their increasing connection with financial markets and the global economy, as well as their interrelations.

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List of Variables

$\mathbf{A}$	Coefficient matrix in the GVAR model
$\mathbf{B}_{\mathsf{p}}$	Coefficient matrix for the MA representation of a VAR model
BIC_i	Bayesian Information Criterion
$BM_{i,t}$	Basis-Momentum of metal i
β_{i,K_i}	Regression parameter for co-variate K_i of metal i
$\hat{\beta}_{i,K_i}$	Estimated regression parameter for co-variate K_i of metal i
$CY_{i,t}$	Convenience yield per metal i
$\mathbf{demand}_i$	Demand vector per metal i
$\boldsymbol{\delta}$	Shock size in the IRF and GIRF
$\hat{e}_j$	Sub-sample error term in the structural break test
$\mathbf{e}$	Exogenous variables in the GVAR model
$exports_{i,t}$	U.S. Exports vector per metal i
ε	Error term
$\hat{\varepsilon}_{ss1,j}$	Error term in the regression of co-variate j for sub-sample 1
$\hat{\varepsilon}_{ss2,j}$	Error term in the regression of co-variate j for sub-sample 2
$\mathbf{E}$	Lower triangular matrix of $\mathbf{V}$
$\mathbb{E}$	Expected value
FUT_{i,t,T_1}	Futures contract of metal i with maturity at time T_1
$\mathbf{G}$	Parameter matrix in the final GVAR model
$\mathbf{GIR}$	Generalized Impulse Response Function
$\mathbf{H}$	Coefficient matrix in the GVAR model
$\mathbb{H}$	Matrix used to analyze stability of the VAR model
$HHI_{i,t}$	Production concentration per metal i
i	Metal index
$\tilde{\imath}$	Additional metal index
$\mathbf{I}_K$	Identity matrix of dimension K
$imports_{i,t}$	U.S. Imports vector per metal i
$\mathbf{IR}$	Regular Impulse Response Function
j	Co-variate index in the VAR model
K	Total number of metal specific variables, aggregated over all metals in the GVAR model
K_i	Number of covariates for metal i
K_i^*	Number of starred, external variables in the GVAR model
$\mathcal{K}$	Number of variables in the VAR model
K_{exog}	Number of exogeneous variables in GVAR
$\hat{L}_i$	Estimator of the Likelihood function

$\mathbf{\Lambda}$	Coefficient matrix for the starred, external variables in the GVAR model
$MAPE_i$	Mean absolute prediction error for metal i
$MOM_{i,t}$	Momentum factor of metal i
$MSPE_i$	Mean squared prediction error for metal i
$MSPE_{i,2,adj}$	Adjusted MSPE of the tested model in the Clark-West test for metal i
n	Number of steps ahead in the IRF/OIRF/GIRF analysis
N	Number of metals
OIR	Orthogonalized Impulse Response Function
$\mathbf{\Omega}$	Information set
$\mathbf{price}_i$	Price vector per metal i
P	Number of lags in the (G)VAR model
p	Time index for the MA representation of the VAR model
P	Out-of-sample length
$prod_{i,t,r}$	Production per metal i and country r
$\mathbf{\Phi}$	Coefficient matrix for endogenous variables in the VAR model
$\mathbf{\Psi}$	Coefficient matrix of the exogenous variables with in the VAR model
Q	In-sample length
r	Index of production country
R	Number of production countries
$\mathcal{R}_i^2$	R^2 - Coefficient of determination
$\mathcal{R}_{i,adj}^2$	Adjusted R^2 - Adjusted coefficient of determination
$\mathfrak{s}_\mathsf{j}$	Selection vector with $\mathfrak{s}_\mathsf{j} = 1$ as j-the element and 0 else
$\mathbf{supply}_i$	Supply vector per commodity i
SSE_i	Explained sum of squares by the model for metal i
SST_i	Total sum of squares in the data for metal i
$stocks_{i,t}$	U.S. stocks vector per metal i
t	Time Index
t_0	Time of structural break
$\underline{\mathsf{t}}$	Lower bound for t_0 in structural break test
$\bar{\mathsf{t}}$	Upper bound for t_0 in structural break test
T	Time span of the analysis
τ	Time index for the out-of-sample window
$\mathbf{V}$	Covariance matrix of error terms
$VAL_{i,t}$	Value factor of metal i
$\mathbf{w}$	Weight matrix between the metals in the GVAR model
$\mathsf{x}_{i,K_i,t}$	Co-variate K_i for metal i at time t
$\mathbf{x}$	Vector of all metal-specific variables
$\mathsf{y}_{i,t}$	Price of metal i
y_i^{rw}	Random walk benchmark for metal i
y_i^{rwd}	Random walk with drift benchmark for metal i
$\mathbf{y}_t$	Vector of variables in the VAR model
$\boldsymbol{\upsilon}_t$	Error term / shock in the VAR model
$\mathbf{\Upsilon}$	Coefficient matrix for the exogenous variables in the GVAR model
z	Modulus of matrix $\mathbb{H}$
$\mathbf{z}$	Vector of metal-specific and external variables per metal in the GVAR model
$\mathbf{Z}$	Link matrix for each metal

List of Abbreviations

ADF	Augmented Dickey Fuller
AR	Autoregressive
BDI	Baltic Dry Index
BMK	Benchmark
BIC	Bayesian Information Criterion
CFTC	U.S. Commodity Futures Trading Commission
CIF	Cost, Insurance and Freight
CME	Chicago Mercantile Exchange
CPI	U.S. Consumer Price Index
FED	Federal Reserve
FOMC	Federal Open Market Committee
GDP	Gross Domestic Product
GIRF	Generalized Impulse Response Function
HHI	Herfindahl-Hirschman Index
IRF	Impulse Response Functions
JB	Jarque-Bera
LME	London Metal Exchange
LSAP	Large-Scale Asset Purchasing Program
MA	Moving Average
MAPE	Mean Absolute Prediction Error
MSCI	Morgan Stanley Capital International
MSPE	Mean Squared Prediction Error
MP	Monetary Policy
NWE	NorthWest Europe
OIRF	Orthogonalized Impulse Response Function
RICI	Rogers International Commodity Index
RW	Random Walk
RWD	Random Walk with Drift
SHFE	Shanghai Futures Exchange
VAR	Vector Autoregressive
VIF	Variance Inflation Factor
ZLB	Zero Lower Bound

List of Co-Authored Papers

Over the course of this thesis' writing, I have (co-)written the following five papers:

1. *Commodities and monetary policy - the role of interest rates revisited
   Working Paper - Available at SSRN: http://ssrn.com/abstract=4365481, 2023
   with Amelie Schischke and Andreas Rathgeber

2. *Factors of Predictive Power for Metal Commodities
   Working Paper - Available at SSRN: https://ssrn.com/abstract=3860107, 2021
   with Amelie Schischke and Andreas Rathgeber

3. *Using the Three Co's to Jointly Model Commodity Markets: Co-Production, Co-Consumption and Co-Trading
   Working Paper -Available at SSRN: https://ssrn.com/abstract=3860004, 2022
   with Amelie Schischke and Andreas Rathgeber

4. Sustainable energy transition and its demand for scarce resources: Insights into the German Energiewende through a new risk assessment framework
   Renewable and Sustainable Energy Reviews, 176, pp. 113190, 2023
   with Amelie Schischke, Max Brem, Paul Kurz and Andreas Rathgeber

5. Wie nachhaltig ist die deutsche Energiewende wirklich? Eine Analyse der sozialen Bedingungen des Rohstoffabbaus
   Die Unternehmung, 76(2), pp. 164 - 191, 2022
   with Amelie Schischke and Hendrik Mihai

The three papers indicated with an asterisk (*) build the foundation for this thesis, while the respective sections of the papers have been revised and extended. Paper 1 comprises the foundation for the Sections 4.2, 5.1, and 6.1, paper 2 for the Sections 2.1, 3.3, 4.1, 5.2, and 6.2. Moreover, paper 3 comprises the foundation for Sections 2.4, 3.6, 4.4, 5.3, and 6.3.

1 Introduction

Commodities are a cornerstone of many economies, for commodity exporters as well as importers. As many countries are so dependent on commodities and their prices, much interest of academic research has centered on the determinants and forecasts of commodity prices. Ben Bernanke, the former chairman of the Federal Reserve (FED) and 2022 Nobel Memorial Prize Laureate in Economic Sciences, highlighted at the Federal Reserve Bank of Boston's 53rd Annual Economic Conference, see Bernanke (2008):

> *"Policymakers and other analysts have often relied on quotes from commodity futures markets to derive forecasts.(...) The poor recent record of commodity futures markets in forecasting the course of prices raises the question of whether policymakers should continue to use this source of information and, if so, how."*

while he further generally pointed out:

> *"(...) the importance for policy of both forecasting commodity price changes and understanding the factors that drive those changes."*

To achieve this, an in-depth analysis of commodity prices, their drivers, predictors and interrelations is inevitable. While traditionally mainly the food and, especially the energy commodities were at the focus of attention, the worldwide restructuring of energy systems, from traditional fossil-fuel based systems towards green, CO_2 neutral ones, will require the build-up of large-scale renewable energy production and storage technologies, which in turn require massive amounts of metals. Further, rapidly growing economies such as China and India further elevate the demand for metals. According to Frankel and Rose (2010), this demand increase by emerging economies is, among loose monetary policy conditions and other factors, responsible for the price increases across a wide range of commodities during the last financial crisis in 2007-2009.

Hence, this thesis focuses on metal markets, while the structure of this thesis is threefold. First, we show the channels of relation between the prices of storable commodities and monetary policy instruments changed since, in response to the big financial crisis of '07-'09, the monetary policy went from a conventional interest rate policy towards the implementation of unconventional policy actions, such as large scale asset purchase programs and forward guidance. However, we are able to determine effects of similar or even larger magnitude at times of unconventional policy, but of reverse direction, indicating the channels as well as the causality changed. Second, we analyze the factors further determining the prices of metals, while additionally analyzing their predictive abilities for prices, where we observe substantial differences within and across the metal categories. Subsequently, we perform one-month ahead forecasts for the three precious metals gold, silver and platinum, the six industrial metals, as well as fifteen minor metals. While the forecast performance is evaluated in comparison to several benchmark models, we highlight the increases in forecast performance via a metal-specific variable selection. While the predictors and determinants are in fact differing across the metals, we see a common pattern across the industrial metal markets. Given this finding, as well as the large literature strand on the co-movement of commodity prices, we develop and implement, in the third part of this thesis, a model that incorporates metal-specific supply and demand conditions within metal-specific market models, while simultaneously linking multiple of these market models via information on the co-production, co-consumption and co-trading of the metals.

Metal Prices and Monetary Policy

Metal prices are assumed to be the result of supply and demand conditions, where much interest centers on the economic conditions that reduce or increase the demand for metals. The monetary policy of central banks is among the most important factors affecting prices in this regard, since it has long been, and still continues to be, one of the determining factors of general economic conditions, nowadays primarily acting through financial markets. In theory, an expansionary monetary policy, usually implemented through interest rate cuts, should increase metal prices through several channels, according to Akram (2009) and Frankel and Rose (2010). First, lower interest rates increase the demand for commodities through a portfolio reallocation of investors, from bonds to alternative asset classes, such as commodities, according to Calvo (2008). Second, lower storage costs increase the demand for inventories, which in turn contributes to higher metal prices, given a fixed supply in the short run. Third, producers of metals will, over time, reduce their supply, as it is less profitable for them to invest the proceeds from extraction in times of low interest rates. While the third channel might only affect markets with a lag, the market participants' expectations on the future actions of the supply side are hypothesized be priced immediately. Additionally, monetary policy and prices are interrelated further. On the one hand, commodity prices are, as outlined above, influenced by central banks actions, while on the other hand, commodity prices, especially energy prices, contribute to the level of inflation, which is monitored by central banks. Therefore, central banks adjust their policy partly in response to the developments in commodity markets, see

Frankel (2014).

While lower interest rates are assumed to have a stimulating effect on the entire economy, as lower funding costs create incentives for firms to undertake new projects or expand their current activities, interest rates close to zero are subject to a natural constraint, as central banks cannot lower interest rates below the so called zero lower bound (ZLB). Within the financial crisis of 2007-2009, the federal funds rate was lowered to this zero bound in the fourth quarter of 2008. Since the crisis was far from over at that point, the Federal Reserve (FED)implemented unconventional monetary policy measures to further stimulate the economy. In this process, the central bank buys assets from market participants, which increases demand for these assets, leading to rising prices in the face of fixed supply. Since bond prices are inversely related to the interest rates on these contracts, this allows the central bank to further lower the implied interest rates in the bonds. In addition, the FED introduced forward guidance, a practice where FED communicates its further actions. In general, the FED communicates its actions eight times a year at meetings of the Federal Open Market Committee (FOMC), which are closely followed by capital market participants. Forward guidance is a practice whereby the FED not only communicates its current actions at such an FOMC meeting, but also discloses some of its plans for future actions, such as committing itself not to raise the federal funds rate for a specific period in time, thereby influencing the expectations of markets participants.

Therefore, the question arises whether and how the relationship between monetary policy and metal prices changed during and after the big financial crisis, given the resulting policy change, which we analyze in the first part of this thesis. Although the relationship between monetary policy and commodity prices is certainly a very important one, monetary policy is far from being the only determinant of metal prices. Therefore, within the second part of this thesis, we analyze the metal-specific price determinants and forecasting factors in more detail.

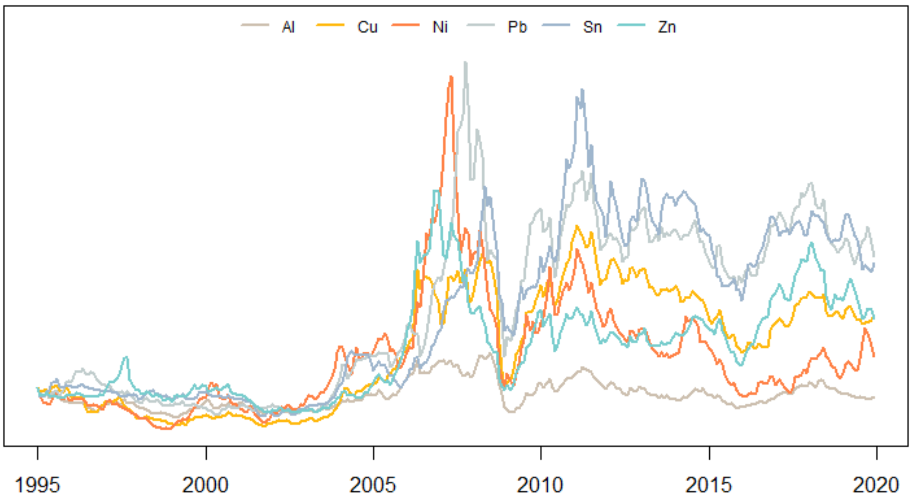
Metal Price Forecasts, Predictors and Determinants

Many studies that analyze commodity price determinants focus on commodity indices, rather than on individual commodity or metal prices, see Vansteenkiste (2009) and Groen and Pesenti (2011), for example. Since metals differ substantially in their applications, ranging from components in the transportation and construction sector for aluminum and copper, over fine applications of metals like germanium in electronics all the way to gold, which is mostly used as a store of value, regarded as currencies and asset class itself, see The World Gold Council (2022) and Belousova and Dorfleitner (2012), we hypothesize the determinants influencing the prices of these metals should be differing as well. Hence, we analyze the precious metals silver, gold and platinum, the six industrial metals aluminum, copper, nickel, lead, tin and zinc, as listed on the London Metal Exchange (LME), as well as 15 minor metals in this regard. We start with an overview over potential determinants and the theory behind those, originating from studies which either consider only a selection of attributes or apply them only to specific commodities or commodity indices, while we further review studies on the prediction of commodity prices.

As mentioned above, metals still mark a cornerstone for many modern economies, as they are required for a large field of applications in commodity importing countries and are a central export good for commodity exporters, see Byrne et al. (2013) among others. The literature review of metal price determinants and forecasting factors yields in a set of 28 variables, which we cluster in several groups. The metal-specific supply and demand conditions, which could affect prices, followed by metal-specific information extracted from the metal price time-series and, where available, the corresponding futures price series. Subsequently, the next category includes monetary policy measures like interest rates and monetary aggregates, while specifically including variables from China, due to the nations ever growing impact in the metal production and consumption. In addition to the U.S. Dollar Index as exchange rate, we include various indicators of economic activity, as well as financial and commodity indices.

However, the analysis of forecasting factors reveals a degree of relation between metals of the same group, i.e. the industrial metals. This is also observable in the progression of the prices, as displayed in Figure 1.1. This common pattern in prices, referred to as

Figure 1.1: Price-Series of the Industrial Metals



This figure displays the LME spot price series of the six industrial metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn), in the period from 1995 to 2019. The individual price series have been indexed in January 1995 to foster the visual comparability.

co-movement, is larger than the amount that would be explainable by common macroeconomic conditions, which simultaneously influence all metal prices, as already found by Pindyck and Rotemberg (1990). Hence, within the third part of this thesis, we analyze the possible linkages between markets and subsequently use these links to model the markets jointly. Hereby, we empirically analyze the relations within and across the markets of the six industrial metals.

Linkages Within and Across Industrial Metal Markets

In addition to the common macroeconomic conditions, another possible channel of relation between industrial metals is in the joint supply-side of their markets. Generally, within mining operations rock material is extracted from the ground, to subsequently seperate minerals and finally produce metals from them, while the rock material usually contains multiple ores in differing concentrations at the same time. Hence, if the mine extends its activities, i.e. due to a demand increase in one metal, this potentially translates to a simultaneous supply increase for various other metals. This relation is referred to as the co-production of metals.

Further, industrial metals are inputs for the industry sector and hence, if the industrial sector performs particularly well, this will simultaneously increase the demand for several metals. For example, an increase in the construction sector increases the demand for copper and aluminum at the same time, as both metals are used in the same industry, whereas the same phenomenon applies to metals that are jointly used in alloys. We refer to this aspect as the co-consumption of metals, which testifies another channel of relation between industrial metals.

Moreover, industrial metals are also joint constituents of commodity indices. While the findings of individual studies are mixed, a general consensus within the literature argues index investors significantly increased the amount of capital inflow to commodity markets, which resulted in an increased correlation between the commodities that are included in commodity indices. The explanation of this phenomenon is somewhat trivial, as capital inflow to commodity indices, or ETFs tracking theses indices to be precise, requires the purchase of futures contracts across all commodities included in the index, with the respective weight each, hence driving all prices at the same time. This increased their price co-movement increased significantly, see Tang and Xiong (2012) for example. We therefore propose to additionally consider the co-trading of industrial metals as third channel of relation between their markets.

Given the three channels of relation outlined above, we develop and implement, within the third part of this thesis, a model that connects metal-specific market models of the six industrial metals via information on their co-production, co-consumption and co-trading.

Structure of the Thesis

Given the importance of metal markets to the global economy, for developing and developed nations alike, this thesis aims to provide an in-depth analysis of metal markets, their determinants, predictors, and interrelations. Hereby, Chapter 2 provides an insight into the literature on metal markets, starting with their theoretical relation to price determinants, such as monetary policy or financial markets, followed by an overview of empirical metal market studies. A detailed discussion of selected studies highlights the heterogeneity in the field, while we additionally introduce studies that address the linkages between different commodity prices and markets.

Within Chapter 3, we start by outlining the main applications of the metals considered in this thesis, as well as an analysis of the co-production relation for the industrial metals. Further, we introduce the data that is later analyzed in the empirical analysis, as well as the corresponding data preparation procedures and resulting descriptive statistics. Additionally, we outline the construction for the empirical representation of the connection channels between the industrial metals.

Chapter 4 introduces the models to empirically analyze the hypothesized relations, while Chapter 5 displays the results and corresponding insights gained. Hereby, the threefold structure of the thesis specifically addresses the relation of metal prices to monetary policy, the metal-specific price determinants, predictors and forecasts, as well as the relation between the industrial metal markets. Within Chapter 6, we summarize our findings and compare them to previous empirical findings in the field, as well as to the hypothesized theoretical mechanisms, while Chapter 7 concludes.

2 Literature Overview

The following chapter reviews the various aspects of the literature on metal markets. In Section 2.1, we present a large number of possible factors influencing the price determination and prediction of metals. In addition to the theoretical motivation, we provide an overview of the corresponding empirical evidence for the influence of these factors on prices. Within Section 2.2, we provide a broad overview of the studies on metal price determination and prediction models. In doing so, we highlight the heterogeneity of the studies resulting from the predicted variables, the range of the underlying data sample, the frequency of the data used, as well as the possibly influential variables considered. In Section 2.3, we present in detail four studies that are closely related to the topic of this thesis, highlighting the difficulties associated with commodity price forecasting and the research questions we derive from the current literature. Finally, within Section 2.4, we briefly discuss the phenomenon of different commodity prices moving in sync, often referred to as the co-movement of prices. Further, we discuss possible channels through which this co-movement might be caused.

2.1 Determinants of Metal Prices

Commodities are a cornerstone of many countries' economies, for commodity exporters as well as importers, see Byrne et al. (2013). As many countries are so dependent on commodities and their prices, much interest of academic research has centered on the determinants of commodity prices in general, and the possibilities for countries to affect prices in particular.

While most of the empirical studies focusing on the commodity price determinants show a worldwide or U.S. regional scope, the commodity consumption shifted from Europe and the USA towards Asia, mainly China, within the last decades, see also Section 3.1 for a more in-depth view. As this demand shift and the impact of emerging economies on commodity prices has gained substantial attention in academic research, we specifically include, where available, empirical studies analyzing Chinese variables within each section. Hereby, we aim to provide an overview of the most important commodity price determinants and forecasting factors. First, we focus on monetary policy, indicated by interest rates and monetary aggregates, a key determinant affecting economies and the financial markets, making it a relevant determinant for commodities as well, as we outline in Section 2.1.1. The same holds for exchange rates, where especially those of small, developing and commodity producing countries are found to be indicative for commodity price fluctuations, see Section 2.1.2.

We introduce and outline in Section 2.1.3 several macroeconomic indicators as key determinants for commodity prices, as they potentially determine the overall demand for commodities. There are various measures to capture the economies' status, starting with the industrial production, over the overall economic activity, representing the entire economy. While the aforementioned measures are lagging economic indicators, commodity purchases usually occur at the very beginning of the supply chain. Therefore, shipping indices, often considered leading economic indicators, are potentially very helpful in explaining commodity prices.

To represent the impact of financial market participants on commodities, futures prices and positions are analyzed, as well as the time-series properties of the respective data, within the studies described in Section 2.1.4. Since the oil price is regarded as an input variable for the production process of metals, rather than as a commodity itself, we include studies analyzing the oil price in Section 2.1.5. Additionally, we review studies considering and modeling the physical supply and demand of commodities within this section.

2.1.1 Monetary Policy

Many central banks aim to ensure price stability[1] or in case of the FED, a dual mandate, which consists of price stability, paired with maximum, stable employment, see The Federal Reserve Bank of St. Louis (2022). Hereby, central banks adjust their policy with the goal to lower or raise the current inflation level. Over many decades, the short-term interest rates were the main tool of central banks in that respect. Hereby, interest rates are assumed to be inversely related to the inflation rate. A high inflation rate lowers the expected future value of money, while rising interest rates raises it. Central banks aim to use this inverse relation between the interest and inflation rate to steer the economy. For commodity markets, inflation is supposed to move in the same directions as commodity prices do. In case of a rising inflation rate, investors would potentially move out of bonds and allocate their capital to other, more inflation resilient asset classes like commodities, see Calvo (2008).

This causality is analyzed by Frankel and Hardouvelis (1985), who states the announcement of higher monetary growth will lead to a higher inflation rate, where investors will allocate more capital on commodities, out of bond and stock markets, which rises

[1]While price stability is achieved through a constant inflation rate, the FED, as well as it's European counterpart, the ECB, do not consider themselves to be inflation-rate targeting banks, see Meyer (2001).

commodity prices. However, inflation may be related to commodity prices via further channels. It is generally regarded a measure on the current state of the economy, where a high inflation indicates a strong and expanding economy, which leads to demand, and ultimately commodity price increases. Second, in a situation of high inflation, prices for all goods and services are supposed to rise, hence also commodity prices will do. Therefore, many studies use commodity prices in real terms, that is, the actual prices deflated by the inflation rate. However, when the aim is to predict true prices, as observable on exchanges, nominal prices need to be forecasted. The effect of inflation on prices may therefore be represented by including the consumer price index (CPI) as determinant for the nominal commodity price. The CPI acts as a measure of inflation, since it represents the change in prices of a certain consumer goods' basket. Wang et al. (2020) therefore include the log change of the CPI as inflation measure, detecting a positive and significant influence in the prediction of precious metal prices. Theoretically, the inflation rate is one of the variables influencing all commodity prices simultaneously. Dinh et al. (2022) validate this assumption, as they identify the inflation rate as a driver of the correlation of precious metal prices.

Hence, commodity prices should co-move with inflation and be inversely related to interest rates. Empirically, the inverse relation between commodity prices and interest rates is supported by the findings of Guzmán and Silva (2018), Pierdzioch et al. (2016) and Baffes and Savescu (2014), among others. This means, an increase in the real interest rate leads to a decline in commodity prices and vice versa. Frankel and Rose (2010) analyze potential channels through which the interest rate additionally affects commodity prices. First, a higher interest rate increases the cost of capital for holding a commodity, ultimately leading to higher storage costs. Hence, the demand generated through storage build-up should decline. Second, the higher interest rate sparks the incentives of commodity producers to increase the supply, as they aim to allocate the money in bonds, profiting from higher interest rates, see Frankel (2014). Overall, both effects should lead to an increased supply and lower demand, which ultimately lowers prices.

In his early work, Frankel (1986) applies the overshooting model of Dornbusch (1976), initially developed for exchange rates, on commodity markets. According to this theory, commodity prices should overreact, in the inverse direction, to interest rate changes, a phenomenon called overshooting. While Frankel (1986) analyzes the overshooting effect only for agricultural commodity prices, the empirical supplement to his study, see Frankel (2008), also includes oil and mineral commodities. Hereby, the inverse relation of interest rates and commodity prices can only be verified on specific, historical data sets, where on more recent data there even is a positive relation between commodity prices and interest rates. Frankel (2008) attributes these changes to further, commodity price determining covariates, which are not included in his model.

The theoretical motivation for the overshooting behavior of prices is as follows. In a model with three points in time, t_0, t_1 and t_2, money supply is reduced in t_0, let's say by one percent. After a given (long enough) period of time, let's assume in t_2 in our case, all prices will have declined by one percent. However, regular prices are sticky in the short run. Therefore, when money supply is reduced, interest rates need to be raised to match the money demand and prevent arbitrage conditions. As the regular goods prices are fixed, so is the inflation rate in the short run, meaning a raise in the nominal interest rate is an equivalent raise in the real interest rate. In this example, we now have two factors. One, at the end of the scenario, in t_2, all prices should have declined by one percent. Two, following the theory of Hotelling (1931), commodity prices must increase over time by an amount equal to the interest rate, to ensure arbitrage free markets. Following these two conditions, commodity prices must overshoot the one percent interest rate drop in t_0, in other words fall more than one percent, only to increase by the interest rate over time (in the two periods between t_0 and t_2) and match the one percent reduction in t_2.

However, as Frankel and Hardouvelis (1985) and Frankel and Rose (2010) state, markets actually react to changes in monetary policy, where interest rates are only an indication or a measure of the central banks current, conventional monetary policy. This may, at least partly, explain why empirically, Hammoudeh et al. (2015), Lombardi et al. (2012) and Nicola et al. (2016) are unable to confirm the inverse relation of interest rates and commodity price, indicating the evidence in the literature is mixed. Anzuini et al. (2013) detect a significant positive effect of the federal funds rate on an overall commodity price index, while for metals the effect is of the same direction, but statistically insignificant. However, the toolbox of monetary policy consists of a broader variety of tools, where interest rate adjustments are regarded as conventional monetary policy and other actions, like asset purchases or forward guidance, are regarded as unconventional monetary policy measures.

Generally, lower interest rates reduce the cost of capital for firms, therefore central banks use a reduction of rates to support the economy. For example, in response to the big financial crisis starting in 2007, the central banking system of the United States of America, the Federal Reserve System, started to continuously lower the interest rate to provide stimulus for the economy in times of crisis. However, interest rates are constrained, as they naturally bear a so-called zero lower bound (ZLB).

When in 2009 the federal funds rate, the main policy rate of the FED, reached this zero lower bound, the economy was still in a crisis, which required further expansionary policy measures. Thereby, the FED used unconventional monetary policy tools like large-scale asset purchase programs (LSAP) to maintain its support for the economy. The effect of those unconventional monetary policy actions on bonds, the economy, stock markets and exchange rate has been extensively studies within the literature, see Keating et al. (2019), Eksi and Tas (2017) and Peersman et al. (2021), among many others. Additionally to the LSAP, the FED also implemented forward guidance, where the FED does not actually implement other actions, but rather ensures market participants to continue a certain policy for a specified period in time. Swanson (2021) states these FED communications influence markets by influencing their participants' expectations on future policy actions and hence markets today. Further, Frankel and Rose (2010) state the long-term inflation expectation may be regarded as monetary policy variable as well. Hereby, commodities may act as an inflation hedge, where an increase in the expected inflation will therefore raise the demand for - and prices of - commodities. However, the question arises how to measure these unconventional monetary policy actions.

The first variable to be considered is the balance sheet size of the FED, since through asset purchases the balance sheet size increases. Therefore, this variable may be used to approximate the effects of LSAPs' on markets. However, Wright (2012) argues the balance sheet size suffers from a timing problem, where the expectation and later the information of asset purchases should impact markets more than the actual purchases themselves. In contrast, Neuhierl and Weber (2019) argue monetary policy impacts markets on a broader basis, not only at the time of the FOMC meetings, where the actions are announced. However, this timing constraint is more relevant in an event-study application, while for time series analyses on lower frequency data the results should be affected to a lesser extent.

The second possibility to represent unconventional monetary policy in econometric models is via shadow rates. Among the most prominent ones is the shadow interest rate created by Wu and Xia (2016), which is based on forward rates that are constructed via Nelson-Siegel-Svensson yield curve estimates. The shadow rate is equal to the short-term rate, the FFR in this case, as long as the short-term rate is above its zero lower bound, but able to represent the unconventional monetary policy actions, once nominal interest rates are below zero. The authors highlight the capabilities of the model in a FAVAR setup, where they show similar correlations of the shadow rate and other macroeconomic determinants, before and after the FFR hit its ZLB.

Hammoudeh et al. (2015) empirically analyze the relation of monetary policy and commodity prices, where they detect a positive, statistically significant reaction of metal prices to a positive shock of the federal funds rate, which is in contrast to theory. They attribute the positive response of commodity prices on interest rate changes via the timing, since interest rates are usually hiked during periods of a strong economy and a resulting strong demand. Therefore, while interest rate hikes may dampen the growth in commodity prices, the strong demand continues to move prices up further. However, a second part of the analysis, performed on a data subset starting in the third quarter of 2008 and performed on sectoral commodity price indices uses the growth rate of the central bank assets as measure of unconventional monetary policy (MP). Hereby, they detect a statistically significant, positive response of the metal price sub-index to a shock on the growth rate of the central bank assets, but with a lag.

Apergis et al. (2020) analyze the impact of conventional and unconventional monetary policy from the U.S. and Euro area on commodity prices. They use the federal funds rate as conventional measure, while they represent the unconventional monetary policy via the shadow rate of Krippner (2015) in the U.S. and via the rate of Wu and Xia (2016) in the Euro area. Their analysis is performed on daily data for individual commodities, such as oil and natural gas, the precious metals gold, silver and platinum, as well as the industrial metals aluminum, copper and nickel. Hereby, they detect the expected inverse relationship of interest rates and metal prices, but of larger magnitude for unconventional MP on all commodity prices, compared to the effect of conventional MP.

Siami-Namini (2021) analyzes the impact of short-term and long-term interest rates, as well as unconventional monetary policy, which she represents through the M2, on commodity prices in an SVAR and SVECM model. In her study, the effect of a shock to the short-term interest rate, representing a contractionary monetary policy, is negative, but statistically not significant. In line with this finding, a positive shock to the M2, which represents an expansionary monetary policy, leads to a positive response of the overall commodity index, but is again not significant. In contrast, an expansionary monetary policy formulated through long-term rates has a positive effect of prices. However, none of the above mentioned findings in the study of Siami-Namini (2021) are statistically significant.

Given the importance of monetary policy for the commodity price formation, as well as the changes in the policy in response to the financial crisis in '07 - '09, we aim to further analyze the effects of monetary policy, specifically on the prices of metals, in the empirical part of this thesis. Further, within the study of Hammoudeh et al. (2015), the causality between monetary policy and commodity prices changed, from a concurrent relation in times of conventional policy, to an inverse relation in the period of unconventional policy. Hereby, we differentiate the effects in periods of conventional and unconventional policy, while we analyze the effects of unconventional monetary policy via multiple measures, specifically also an inflation expectation index.

2.1.2 Exchange Rates

Commodities are, in most cases, produced, manufactured and consumed in different locations and economies across the world, which is why the exchange rates between currencies of those countries should theoretically play a major role for the commodity price determination. Generally, commodities are mostly traded in standardizes contracts at large exchanges, such as the Chicago Mercantile Exchange (CME) and the London Metal Exchange (LME), where prices are quoted in U.S. Dollars.[2]

One of the most prominent studies analyzing the influence of exchange rates on commodity prices is Chen et al. (2010), which detects significant predictive abilities of the exchange rates from commodity-exporting countries on commodity prices, caused by the development state of markets. That is, commodity producing countries are often comparably small economies, which are heavily dependent on the commodity prices.

For example, in Chile about 50 percent of the countries' exports were generated through copper in the period from 2003 to 2017, which is why Pincheira-Brown and Hardy (2019) state Chile's exchange rate is heavily affected by the price of copper. The same holds for South Africa, where a large share of the countries' export is based on platinum group metals, which links the South African Rand to those platinum group metals' prices in the study of Ciner (2017). In theory, expectations on the future development of metal prices should hence be influencing the exchange rate of the exporting countries' currency. Following Chen et al. (2010), exchange rates are hypothesized to adjust to a change in the expectations of future prices of commodities more quickly, as their markets are more developed and commodity markets are lagging in this respect. Therefore, the current exchange rates possibly already contain information on the expected future development of commodity prices and hence predictive abilities for them.

Based on this idea, Gargano and Timmermann (2014) consider the Australian Dollar to U.S. Dollar exchange rate in their study and detect significant predictive abilities of it on a metal price index. Likewise, Ciner (2017) analyzes the out-of-sample forecasting power in the South African Rand for platinum group metals, whereas Pincheira-Brown and Hardy (2019) detect a significant effect of the Chilean Peso exchange rate on the London Metal Exchange Index and five industrial metals of the LME individually. In contrast, Groen and Pesenti (2011) find exchange rates do not show strong predictability against different benchmark forecasts.

However, Lombardi et al. (2012) argue commodity prices will be raised to ensure purchasing power, in case the U.S. Dollar looses value, while the negative effect of exchange rates to metal prices is statistically significant in their study. The same relation should hold when the spending of revenues from commodity exporting countries is analyzed. As commodities are mostly traded in U.S. Dollars, rising commodity prices will lead to a larger amount of U.S. Dollars transferred to the exporting countries. When they spend these U.S. Dollars internationally, they sell the currency, which results in a devaluation. Overall, this further testifies a channel of the inverse relation of commodity prices and exchange rates.

The same, inverse relation between the U.S. Dollar and commodity prices is empirically

[2]In recent times, the Shanghai Futures Exchange (SHFE) gained increasing impact on commodity markets, where the commodities are traded in Yuan (CNY).

found by various other studies, see Akram (2009), Hammoudeh et al. (2015), Liberda (2017) and Sari et al. (2010), among others. Moreover, the studies of Baffes and Savescu (2014), Chen et al. (2014) and Guzmán and Silva (2018) consider the U.S. Dollar index, which represents the exchange rate of the U.S. Dollar against a bucket of six leading currencies, as more general exchange rate measure in their studies.

2.1.3 Economic Activity

Metals are oftentimes inputs for various industrial production processes, with applications ranging from microchips and jewelry to the automotive and construction industry, see Section 3.1. Hence, industrial production may on the one hand be determined by, but also determining on, metal prices. Issler et al. (2014) aim to analyze this relation of metal prices and industrial production, starting by theoretically motivating it. Hereby, the linkage of the variables is based on two basic assumptions. First, the commodities analyzed need to be consumed in the industry that is represented in the industrial production variable. Second, as they perform their empirical analysis on metals, they assume the commodities' short-run supply to be inelastic. That is, new mining projects require long lead times, making supply through mining inelastic. The same holds for inventories, which they argue cannot change in quantity in the short run. As the commodities are inputs in the production process, every firm will aim to schedule production in a way as to minimize costs, being a rationale operator. Hereby, when they increase production, they will raise the demand for metals, which will ultimately increase prices[3]. Therefore, they conclude metal prices should theoretically move in sync with industrial production.

A second, very important aspect of the industrial production variable is the regional scope it monitors. Traditionally, many studies use U.S. based data, motivated by the historical importance of the U.S. economy for commodity markets and the availability of data since 1919, see Gargano and Timmermann (2014) and Issler et al. (2014), for example. However, since the early 2000's, the rising demand for commodities through emerging economies is hypothesized to increasingly influence commodity prices. Hereby, China is the most prominent example, where nowadays a large share of commodities are produced and consumed, see also Section 3.1 and Section 3.2. The growing influence of the emerging economies' industrial production on commodity prices is also represented in the more recent part of the literature, see Guzmán and Silva (2018) for example.

While the theoretical link of commodity prices to the industrial production is certainly strong, the overall economic activity is also considered a potentially influential demand variable as well. As the scope of the overall economic activity is broader, capturing also up- and downward movements in other sectors, further commodity price influencing channels are represented in this variable. Kilian and Zhou (2018) therefore raise the fundamental

[3]The timing relationship of the links is not part of their theoretical model

question: How are fluctuations in global real activity linked to real commodity price fluctuations? As mentioned, the demand for commodities is hypothesized to be stimulated by the overall stance of the economy. They argue commodity price analyses should generally be performed on monthly data, as the monthly data increases the degrees of freedom and imposes less methodological restrictions. However, the gross domestic product (GDP), which would be the appropriate measure for the stance of the economy, is usually reported only in quarterly frequency. They review several measures of real activity, but conclude their exclusion, due to various reasons. First, the historical data availability of some variables and second, in case of the world GDP, which is reported on monthly frequency by the OECD, due to data quality. They argue the world GDP includes U.S. and Chinese GDP data, which should be the most important constituents, but which are unavailable at monthly frequency. Hence, they conclude the indicator must be built on some sort of interpolation. However, in an earlier study, Kilian (2009) constructed his own economic activity index, which he now identifies as superior to other measures. This is rooted in the global scope of the index on the one hand side, hereby representing the entire world and its demand for commodities, as well as the data availability at monthly frequency on the other hand side, while the index is constructed on data of various shipping rates. In the same spirit, Vansteenkiste (2009) extended the industrial production index of the OECD countries by the industrial production of Russia, India, China, Brazil, Indonesia and South Africa.

For the GDP variable, there are numerous studies analyzing its relation to commodity prices. The empirical evidence is mixed, as Gargano and Timmermann (2014) detect no predictive abilities for the U.S. GDP on the metals sub-index on annual frequency, whereas Lutzenberger et al. (2017) do find weak influences of the world GDP on commodity prices. Klotz et al. (2014) focus their empirical study on China and it's impact on prices, using the Chinese GDP and an industrial production variable of the country, where they detect a significant, positive response of industrial metals to a GDP shock.

While also the economic activity index of Kilian (2009) is constructed on freight rates, shipping indices generally represent the current price for the shipment of goods, usually bulk dry goods, on exchanges. Buyers of these goods, such as commodities, will use those contracts to hedge against rising freight rates.

Exemplary, an upward swing in the Chinese economy leads to a production increase, which requires companies to buy more commodities and eventually also buy more freight rates contracts, given the consumed commodities are imported. The increased sales volume and revenue from these products will ultimately raise macroeconomic variables like the industrial production or the GDP. However, those measures are related to the firm's output and therefore lagging. Hence, the timing perspective of shipping indices is a very interesting property for their relation to other macroeconomic and commodity variables.

Hereby, the Baltic Dry Index (BDI) is the most prominent shipping index, measuring the price for the shipment of dry bulk goods, where a raise in the price of the index indicates a larger demand for shipping.

Bakshi et al. (2011) economically test the predictive abilities of the BDI on stock markets and three commodity indices, identifying the 3-month change in the BDI as significant predictor. Additionally, Guzmán and Silva (2018) validate the predictive abilities of the index for copper prices, as they state the BDI is a superior predictor on monthly data frequency, compared to the world industrial production. For the impact of other economic activity measures, Dinh et al. (2022) focus on the overall impact of emerging economies and hereby detect numerous significant effects of macroeconomic variables, from G7 and BRICS countries, on the daily volatility of - and correlation between - precious metal prices. Moreover, Le Pen and Sévi (2017) reinvestigate the excess co-movement of commodity prices and hereby highlight the importance to consider variables from developed and emerging economies in a commodity price analysis.

2.1.4 Financial Markets

Gold is regarded a so-called safe haven asset within the financial industry, see Batten et al. (2010) among others. In the early 2000s, a broader set of commodities, or their futures contracts in particular, gained attention by many financial investors. Hereby, commodity markets were segmented from other financial markets, where especially precious metals and energy commodities, see Belousova and Dorfleitner (2012) provided a diversification effect within the portfolios. Hence, investors use commodity markets to diversify their portfolios, which led to a drastic raise in commodity index investment, increasing the volume from around \$15 billion in 2003 to over \$200 billion in 2008, according to the U.S. Commodity Futures Trading Commission (CFTC), see Tang and Xiong (2012). This process, called financialization, has ever since attracted attention in- and outside the commodity markets research. Since in this period many commodity prices experienced a large upward swing simultaneously, a large strand of the commodity literature has focused on the matter, analyzing whether and how the impact of index investments changed the behavior of commodity price formation.

In this thesis, we analyze spot prices of commodities, which is why a differentiation between two channels is needed. The first channel analyzes whether or not the elevated demand for commodity futures contracts, created by the financial investors, raises the commodity futures prices. The second channel analyzes whether commodity futures prices are a valid forecast for the future commodity spot prices. Only if both channels were found to be valid, elevated futures prices, caused by speculation, would be able to elevate commodity spot prices.

For the first channel, Hamilton and Wu (2015) reviewed and replicated previous studies on the topic, as the claim speculators would elevate prices experienced substantial support outside academia. Therefore, they test how the lagged return of futures prices (t-1), as well as the lagged log of index traders' notional exposure, influences commodity prices. Overall, neither of the two covariates influences the prices of the twelve commodities in the analysis significantly. In this respect, they add to the mixed evidence within the commodity literature whether speculators are inflating prices and and influencing markets.

The second channel, the predictive content of futures prices on future commodity spot prices, is extensively studied in Chinn and Coibion (2014). In their study, they regress the basis of a futures contract, which is the difference between the current spot and the current futures price with maturity in T, on the difference of the spot price at maturity T and the current spot price. If the corresponding β-coefficient appears to be significant, futures prices would bear predictive content for the future spot price. However, among all base metals and maturities, they detect no predictive ability of futures prices for spot prices. Their findings are in sharp contrast to practical applications, where Groen (2014) states the futures prices are regarded the main predictor of future spot prices by many market participants, especially central banks.

However, since the financialization of commodity markets connected those more closely with other financial markets, the current situation on stock markets might influence commodity markets. Buncic and Moretto (2015) therefore use the S&P 500 as predictor variable for copper prices in their study. Similarly, Cifuentes et al. (2020) detect a significant effect of the NASDAQ Emerging Markets Index on the risk premium of copper futures contracts, across all analyzed maturities, ranging from three to 60 months. In the same spirit, Tang and Xiong (2012) state the correlation between commodity prices and the MSCI Emerging Markets Index increased over time, indicating the growing impact of emerging economies.

In addition to all previously mentioned attributes, further financial measures have been created, which are hypothesized to predict future price movements within markets. As asset-specific financial variable, Fama and French (1992) propose the value factor, a measure for the relation of an assets' current price on exchanges, compared to its true value, which they represent by the book value. Hereby the value factor gauges whether a stock is under- or overvalued at the market, which is supposed to bear predictive abilities for future price movements. Asness et al. (2013) transfer this idea, as well as the momentum factor, to commodity markets and hereby increase the portfolio performance when the selection is based on the value or momentum factor, respectively. The momentum factor hereby represents a measure of the current market dynamics and trend behavior of prices. Lutzenberger et al. (2017) include the value and momentum factor as predictor for the spot prices of 30 metals, where they detect high predictive abilities for both variables.

Since, in theory the prices of futures contracts should include information about the future spot prices, Boons and Prado (2019) calculate a momentum factor on futures prices, called basis-momentum, which positively predicts the spot price of the underlying commodity. Their measure hereby represents the difference of the momentum factor of the first and second futures contract available. The factor is able to forecast returns of portfolios from a broader set of commodities, specifically the energy and soft commodities, industrial materials such as cotton, rubber and timber, as well as metals.

Further, according to the theory of storage, commodity futures prices contain the convenience yield, a theoretical measure for the benefit of holding an inventory of the respective commodity. Fernandez (2020) analyzes the predictive content of the convenience yield for future mineral spot prices, using 3-month futures prices for aluminum, copper, nickel, lead, and zinc from the London Metal Exchange. Her results show a strong out-of-sample predictive ability of the convenience yield, at one to 12-months horizons. Bernard et al. (2008) conclude the same for aluminum, although their measure of the convenience yield is different. Further, a positive relation of spot prices and convenience yields is also detected by Casassus and Collin-Dufresne (2005).

Another, quite large strand in the commodity forecasting literature, focuses on the individual time-series of commodity prices. Buncic and Moretto (2015), for example, include the time-series data of the copper price in their framework, while Gargano and Timmermann (2014) find the strongest out-of-sample prediction results for a simple AR(1) model. Likewise, Wang et al. (2020) compare forecasts generated with help of technical indicators, such as momentum factors and moving averages for example, which are extracted or calculated from the prices' time-series, to traditional economic forecasts. Hereby, they highlight the superior forecast abilities of technical indicators.

2.1.5 Metal-Specific Supply and Demand

The literature strand on the prices of oil is certainly among the largest within the commodity literature. However, in this thesis we only give a brief summary on a narrow subsection of the oil price literature, as this thesis aims to identify the constitution of metal markets. Since the production of metals is very intense in energy consumption, see Vansteenkiste (2009) for example, oil is regarded as an input factor for the production and hence a supply variable, rather than a commodity itself. Therefore, higher energy prices, approximated by the price of oil, are hypothesized to drive metal prices up, as also analyzed by Akram (2009), albeit their findings are not statistically significant in this respect. In contrast, Sari et al. (2010) detect a positive, statistically significant response of gold, silver and platinum spot prices to a shock in oil prices. However, the oil price may also be regarded as an indicator for the stance of the global economy and hence may be interpreted as economic activity indicator as well.

Ultimately, many of the above mentioned determinants aim to represent measures for the demand for commodities. This is rooted in the assumption of a good's price being the result of a supply-demand equilibrium, which is why the commodity-specific physical supply and demand partly explain fluctuations of individual commodity prices, especially at medium- and long-term horizons, according to Guzmán and Silva (2018). The same is found by Ahumada and Cornejo (2014), who focus on supply fluctuations. The global supply concentration of raw materials, measured by the Herfindahl-Hirschman Index (HHI), is further considered as criticality indicator in the study of Arendt et al. (2020). As risk in general should be included in prices, the changes in criticality might influence commodity prices. Focusing on the demand side of markets, Stuermer (2018) claims the demand to be the main determinant of commodity prices, especially in the long run.

2.2 Overview of Empirical Studies on Metal Prices

An overview over the large set of empirical studies concerning the topic of modeling and forecasting metal prices highlights the heterogeneity in the field, see Table 2.1. On the one hand side, some studies are commodity-specific analyses, considering very detailed and refined data sets to account for the specific characteristics of the individual commodity markets, see Buncic and Moretto (2015) for the case of copper and Ciner (2017) for precious metals, for example. On the other hand side, studies like Akram (2009), Frankel (2014) and Keating et al. (2019) focus on commodity price indices and their relations to the economy. The second big difference of the commodity price studies is in the time span and frequency of the data considered. While Stuermer (2018) for example analyzes data from 1840 to 2014 on annual basis, Hamilton and Wu (2015) measure the effects of speculation based on only six years of data, while this data is in daily frequency. Further, there methodologies applied are rather heterogeneous, ranging from classic econometric models like linear- and vector autoregression models, all the way to advanced and complex machine learning algorithms. Additionally, the empirical studies also vary widely on the selection of price influencing factors.[4]

[4]Hereby, within Table 2.1, the variable *Emerging Markets* relates to numerous influences from emerging markets on commodity prices, e.g. stock market indices, interest rates, and economic activity measures, while the variable *Uncertainty* summarizes multiple variables that are related to financial market or commodity market uncertainty, such as economic uncertainty indices, volatility indices of stock markets, risk premiums and so forth.

Table 2.1: Overview of Empirical Studies Modeling and Forecasting Metal Prices and Markets

	Commodity-Specific	Forecasting	Methodology	Startdate	Enddate	Frequency	Nominal/real	Short-term IR	Long-term IR	Term spread	Shadow rates	Monetary Aggregates	Exchange rates	Industrial Production	Economic Activity	CPI	Inflation Expectation	Shipping Indices	Emerging Markets	Oil Price	Financial Market	Trading Positions	Commodity Index	Price timeseries	Futures Prices	Other commodity prices	Supply/ Demand	Inventories	Uncertainty
Ahumada and Cornejo (2014)	x		TSCS	01.01.1960	31.12.2010	a	r	x				x	x	x	x	x					x					x	x	x	
Akram (2009)			SVAR	01.01.1989	31.12.2007	q	r	x					x	x		x				x			x						
Antonakakis and Kizys (2015)	x		VAR	06.01.1987	22.07.2014	w	n						x																
Anzuini et al. (2013)			VAR	01.01.1970	31.12.2008	m	n	x				x		x		x							x						
Apergis et al. (2020)	x		EGARCH-X	01.01.1990	31.12.2016	d	n	x			x																		
Baffes and Savescu (2014)	x		Reduced-form price det	01.01.1991	31.12.2012	q	n	x	x				x	x														x	
Bakas and Triantafyllou (2018)	x		VAR	01.01.1985	31.12.2016	d	n			x			x	x						x									x
Bakshi et al. (2011)		x	Lin Reg	01.05.1985	31.10.2010	m	n											x											
Bernard et al. (2008)	x	x	GARCH/ Jump diffusion	01.01.1989	31.12.2003	d	n																	x					
Buncic and Moretto (2015)	x	x	DMA/DMS	01.06.1996	31.06.2014	m	n			x			x	x				x		x	x			x	x	x	x	x	
Byrne et al. (2013)	x		FAVAR	01.01.1900	31.12.2008	a	r	x							x	x				x									x
Cabrales et al. (2014)	x		SVAR	01.01.1980	30.09.2010	q	r	x				x			x	x													
Chen et al. (2010)	x		GC Reg	01.01.1994	31.03.2003	q	n						x										x						
Chen (2016)	x	x	Pred Reg	01.08.1983	31.10.2013	m	r	x					x		x						x								
Chinn and Coibion (2014)	x	x	Lin Reg	01.07.1997	01.07.2012	m	n																	x	x				
Cifuentes et al. (2020)	x	x	Lin Reg	01.10.2010	30.06.2018	w	n	x		x									x			x						x	x
Ciner (2017)	x	x	Lin Reg	07.10.1996	29.07.2016	x	n						x																
Daskalaki et al. (2014)	x		Cross-section/ PCA	01.01.1989	31.12.2010	m/q	n	x				x	x	x	x	x							x						
Dinh et al. (2022)	x	x	DCC-GARCH MIDAS	02.03.1998	31.08.2018	d/m	n	x				x	x	x		x			x		x								
Fernandez (2015)	x		Lin Reg	01.01.1900	31.12.2010	a	r			x			x		x						x						x		
Fernandez (2020)	x	x	Lin Reg	01.01.1983	31.12.2007	m	n	x					x												x				
Frankel (2008)	x		Lin Reg	01.01.1950	31.12.2005	m/a	r	x	x				x			x													
Frankel (2014)	x		Lin Reg	01.01.1950	31.12.2005	m/a	r	x	x				x		x	x								x	x			x	x

	Frankel and Rose (2010)	Gargano and Timmermann (2014)	Groen and Pesenti (2011)	Guzmán and Silva (2018)	Hamilton and Wu (2015)	Hammoudeh et al. (2015)	He et al. (2015)	He et al. (2017)	Henderson et al. (2014)	Toan Luu Duc Huynh (2020)	Idilbi-Bayaa and Qadan (2021)	Issler et al. (2014)	Jerrett and Cuddington (2008)	Keating et al. (2019)	Kilian (2009)	Klotz et al. (2014)	Kriechbaumer et al. (2014)	Kristoufek and Vosvrda (2014)	Sanchez Lasheras et al. (2015)	Lee et al. (2006)	Le Pen and Sévi (2017)	Liberda (2017)	Liu et al. (2017)	Lombardi et al. (2012)	Lutzenberger (2014)
Uncertainty	×			×					×	×	×	×													
Inventories	×		×	×																		×			
Supply/ Demand															×										
Other commodity prices																							×		
Futures Prices	×		×	×																					
Price timeseries	×	×					×	×									×	×	×	×					
Commodity Index		×		×												×									×
Trading Positions		×		×	×				×												×				
Financial Market				×				×	×		×	×									×	×	×		×
Oil Price			×	×				×														×		×	
Emerging Markets									×			×				×					×				
Shipping Indices			×	×					×												×				
Inflation Expectation																									
CPI	×	×							×					×							×	×		×	×
Economic Activity	×	×				×								×	×										×
Industrial Production		×	×	×							×	×									×	×		×	×
Exchange rates	×	×	×	×		×		×	×		×	×									×	×		×	×
Monetary Aggregates		×	×	×		×								×							×				×
Shadow rates																									
Term spread		×	×			×					×														×
Long-term IR	×	×	×									×													×
Short-term IR	×	×	×	×		×						×		×							×	×		×	×
Nominal/real	r	n	r	r	n	r	n	n	n	n	n	r	r	r	r	r	n	n	n	r	n	n	n	r	n
Frequency	a	m	m	m	d/w	q	d	d	d	d	m	m/q/a	a	q	m	m	m	d	d	a	m	d/m	d	q	m
Enddate	31.12.2008	31.12.2010	28.02.2009	30.11.2015	03.01.2012	30.09.2008	31.03.2014	28.10.2016	14.01.2014	03.10.2019	31.12.2009	31.12.2012	31.12.2006	31.12.2015	01.12.2007	01.12.2012	01.04.2012	22.07.2013	16.01.2014	01.01.1990	01.11.2013	31.12.2016	01.12.2015	30.09.2008	30.06.2010
Startdate	01.01.1960	01.01.1947	01.03.1973	01.05.1996	11.04.2006	01.01.1957	03.01.1989	04.01.1993	01.01.2003	03.01.1990	01.01.1986	01.01.1900	01.01.1850	01.01.1967	01.01.1973	01.01.1998	01.01.1960	01.01.2000	02.01.2002	01.01.1870	01.02.1993	01.01.1997	03.01.2008	01.01.1976	01.01.1972
Methodology	Lin Reg	Lin/Ridge/ Subset Reg	PLS Regression	VAR	Lin Reg	SVAR	CMFM	MEMD	Lin Reg	NN Granger	Lin Reg	VECM & Fcst Comb	BP Filter	SVAR	SVAR	GC with GIRF	Wavelet ARIMA	Efficiency Index	NN & ARIMA	LM & Lin Reg	PCA & Lin Reg	MIDAS Reg	Decision Tree	FAVAR	Lin Reg
Forecasting		×	×				×	×		×	×	×							×	×			×		×
Commodity-Specific	×			×	×	×	×	×		×	×	×	×		×		×	×	×	×	×	×	×	×	

	Commodity-Specific	Forecasting	Methodology	Startdate	Enddate	Frequency	Nominal/real	Short-term IR	Long-term IR	Term spread	Shadow rates	Monetary Aggregates	Exchange rates	Industrial Production	Economic Activity	CPI	Inflation Expectation	Shipping Indices	Emerging Markets	Oil Price	Financial Market	Trading Positions	Commodity Index	Price timeseries	Futures Prices	Other commodity prices	Supply/ Demand	Inventories	Uncertainty
Lutzenberger et al. (2017)			Two-way sorted Pf	01.01.1990	31.12.2013	a	n	x					x	x	x	x					x		x				x	x	
Ornelas and Mauad (2019)		x	Pred Reg	01.02.2003	31.12.2014	d	n						x								x		x			x			
Pierdzioch et al. (2016)	x	x	Lin Reg	01.01.1977	31.12.2014	q	r	x		x		x	x		x					x	x								
Pincheira-Brown and Hardy (2019)	x	x	Lin Reg	01.10.1999	30.06.2017	m/q	n						x																
Pindyck and Rotemberg (1990)	x		Lin Reg	01.04.1960	01.11.1985	m	n	x				x	x	x		x					x								
Prokopczuk et al. (2019)	x	x	Lin Reg	01.01.1990	31.12.2005	m	n			x		x	x	x															x
Qadan (2019)	x		Lin Reg	01.01.1990	31.07.2018	d	n																						x
Robinson (2019)	x		SVAR	31.12.1990	31.12.2017	a	n	x					x		x					x									
Rossen (2015)	x		Boom/Slump	01.01.1910	31.12.2011	m	r																	x					
Sari et al. (2010)	x		VAR	04.01.1999	19.10.2007	d	n						x							x									
Scrimgeour (2015)	x		Event Study & VAR	01.01.1994	01.03.2008	d	n	x					x																
Shah et al. (2021)	x		DY Spillover	01.01.1987	00.01.1900	m	n														x								x
Siami-Namini (2021)			SVECM	01.01.1992	30.06.2017	m	n	x	x			x	x	x		x				x			x						
Stuermer (2018)	x		VAR	31.12.1840	31.12.2014	a	r								x														
Tang and Xiong (2012)	x		Corr Anal & Lin Reg	02.01.1998	15.07.2011	d	n	x	x				x						x	x	x								
Tapia et al. (2020)	x		Nonlinear dynamic test	01.01.1900	31.12.2015	a	r																	x					
Vansteenkiste (2009)	x		Common Factor & Lin Reg	01.01.1957	31.03.2008	q	r	x					x	x						x	x								
Wang et al. (2019)	x	x	ANN	06.09.1968	07.11.2018	d	n																	x					
Wang et al. (2020)		x	Pred Reg & Fcst Comb	01.01.1982	31.12.2017	m	n	x	x				x	x	x	x					x			x					

This table provides an overview on the empirical studies modeling and forecasting metal prices. It displays per study whether the analysis is commodity-specific or on index-level, whether it is a forecasting or price describing approach, the methodology used, the underlying time span and frequency of data analyzed, whether prices are expressed in real or nominal terms, as well as the influential variables considered.

2.3 Detailed Discussion of Selected Empirical Studies on Metal Prices

This section highlights four studies on the determination and prediction of metal prices, which are closely related to this thesis, starting with the article *How important are common factors in driving non-fuel commodity prices? A dynamic factor analysis* by Vansteenkiste (2009), which aims to identify the real drivers of commodity prices, while simultaneously highlighting the heterogeneity in the commodity market literature. Second, the study *Commodity Prices, Commodity Currencies, and Global Economic Developments* by Groen and Pesenti (2011), which highlights the importance of commodity price predictions and aims to enhance these predictions by the inclusion of a large set of predictor variables, at least within one of the models analyzed. Third, we present the study *Using common features to understand the behavior of metal-commodity prices and forecast them at different horizons* by Issler et al. (2014), which analyzes the relation of industrial metal prices to a world industrial production index, as well as to the U.S. industrial production index. In a second part, the authors aim to forecast these metals' prices using different models and forecast combination techniques. Finally we analyze the findings of the study *Forecasting commodity price indexes using macroeconomic and financial predictors* by Gargano and Timmermann (2014), who aim to forecast commodity spot price indices. Hereby, they consider a broad set of potential predictor variables, as well as a variety of forecasting models, while they additionally highlight the changes in the price determination over time.

How important are common factors in driving non-fuel commodity prices? A dynamic factor analysis - by Vansteenkiste (2009)

This study is among the first to highlight the heterogeneity in the literature on the determinants of commodity prices, where the author emphasizes the importance of commodity prices, as they are affecting economic activity on a global level. On the one hand, the economies of commodity exporters, mostly comparably poor, developing countries, are oftentimes heavily dependent on commodity prices, while on the other hand, commodity importers fear the inflationary pressure that rising commodity prices bear.

First, she starts her reasoning on the anomalies of the commodity price boom in the early 2000s based on the common view within the literature, where these anomalies are hypothesized to be caused by an increased demand, which in turn is caused by the rapid growth of developing countries. Second, the above mentioned period was experiencing rising oil prices, which could, due to the production process of metals, pass through to their prices. Third, commodity prices are inversely linked to the value of the U.S. Dollar.

In times of the '07 financial crisis, the U.S. Dollar was substantially loosing in value, compared to a broad set of other currencies, hence potentially also spiking commodity prices. Fourth, the role of interest rates and money supply. She refers to Calvo (2008), who argues lower interest rates expand money supply, which generally elevates prices, with commodities among the most flexible ones moving first and most in magnitude. This is in line with the argument of Frankel (2008), while she further argues speculation could be an additional issue. Given the broad set of possible reasons for the price boom, she states the heterogeneity in literature on that matter and the lack of proof as to what really is determining commodity prices. She argues via the unavailability of data as reason for this research gap.

To evaluate the truly influential factors on commodity prices, she subsequently applies a linear state-space model, which models each commodity price by an autoregressive and a common factor component. Hereby, she differentiates the common factor per commodity group and uses the methodology on 32 individual commodity prices. These include food, agricultural raw materials like cotton, and the LME industrial metals, where all data is aggregated to quarterly frequency from 1957 to 2008. Hereby, she regards oil as an input cost factor for the analyzed commodities, rather than a commodity itself, which is why it is excluded as individual commodity specifically.

She analyzes bi-variate correlations and detects large values for seemingly unrelated commodities, for example tin with palm oil (51%), where she argues such observations could be the cause for the excess co-movement literature. The correlation of the individual metal prices with the common factor is high, mostly between 40% and 50%, whereas the comparably small correlation (19%) of aluminum marks an exception for the metals.

Her estimated common factor is subsequently being checked for its determinants via a regression analysis. Potential candidate variables are the U.S. Dollar exchange rate, the U.K. Brent spot price, U.S. short-term real interest rate, fertilizer prices, the Dow Jones stock market index and the industrial production of the OECD countries, extended by the industrial production of Russia, India, China, Brazil, Indonesia and South Africa. Hereby, the common factor is mainly driven by the oil price, the exchange rate, the interest rate and phosphate rock (a fertilizer), as well as the industrial production for a sub-sample analysis with data from 1990 to 2008.

Overall, she shows the common factor is, in combination with some commodity-specific factors, able to explain large shares of the price movements within non-energy commodity markets. Hence, she concludes most of the price movement is determined by macroeconomic conditions, rather than being caused by herding or irrational behavior of speculators on capital markets.

Commodity Prices, Commodity Currencies, and Global Economic Developments - by Groen and Pesenti (2011)

The study highlights the importance of commodity price predictions, as it was written in 2009, a period where commodity prices inhibited large upward movements. In the period starting from 2003, commodity prices rallied upwards almost non-stop, until mid 2008, when markets seemed to collapse. Hence, this study is written in a time when policymakers and scientists alike ask themselves, what is to come next for commodity prices. The authors aim to forecast commodity prices, while they base their study on the idea of Chen et al. (2010), but extend it further. Chen et al. (2010) use commodity-currencies, exchange rates of countries with an overall comparably small economy, which produce a large share of a specific commodity, to predict its future price. In contrast, Groen and Pesenti (2011) use various commodity indices and aim to forecast their prices, once only using past information of the commodity-currencies, and in the other two cases build in model upon a large set of potentially influential covariates, which all relate to current economic conditions.

Within commodity markets, microeconomic factors still play an important role, where for metals the worldbank states price increases in industrial metals were rooted in large demand increases, in conjunction with an inelastic supply side of markets, see World Bank (2009). However, they argue these forces may be drivers of long-term price movements, but are unable to forecast short-term fluctuations in prices. As for the speculation hypothesis, where futures prices are thought of influencing the future commodity spot prices, the authors argue speculators on futures markets can only influence spot markets when two conditions hold. First, the supply side of markets anticipates higher prices at a later point in time, which motivates them to curb production momentarily. At the same time, the demand for commodities must be inelastic to the price increases. Given those two conditions, commodity spot prices would rise in the future and make the speculation profitable. However, these are exactly the market mechanisms that would be explainable by fundamentals, where the two theories are therefore basically identical in their result.

Methodologically, they apply a predictive regression, for their first model only based on commodity currencies, as well as an autoregressive and a random-walk benchmark. Subsequently, they apply a factor-augmented regression as their second model, which use principal components of a broader data pool for the prediction. However, the principal component analysis only selects covariates that explain most of the variance between the covariates, which does not necessarily mean this component is the best predictor for the prices. Therefore, they subsequently apply a partial least squares regression as their third model, where the covariance between the factor and the dependent variable is maximized in the model fit. Since more than one factor could potentially be included in such a model, the optimal number of factors to forecast the commodity prices has to be determined, which is done via the BICM criterion, which is similar to the BIC criterion and penalizes the inclusion of an additional estimated factor.

The authors perform an expanding window approach and the model selection, the partial least squared calculation, for each out-of-sample forecast separately, before they evaluate their forecasts by the standard test of Clark and West (2007).Within their results section, they analyze and compare the predictive abilities of their three models, for a set of ten commodity price indices, as well as over five different time horizons, ranging from one-month to ten-months ahead. Generally, their results are inconclusive, as it is not clear which horizon or which index can be forecasted best, while additionally no model outperforms the others in all constellations.

Overall, they are unable to support the findings of Chen et al. (2010), as their predictions based on the commodity currencies performed relatively poor. However, almost the same holds for their other attempts. While their second model is based on principal components of the macroeconomic data and performs equally poor, the third model is based on a partial least squares factor-augmented model, where results seem to be better, but are still unable to outperform a random-walk forecast in most of the cases. Overall, the key message of the study is to take commodity price forecasts with great caution, especially when monetary policy adjustments are formulated based on such forecast exercises.

Using common features to understand the behavior of metal-commodity prices and forecast them at different horizons - by Issler et al. (2014)

The study is among the few to perform forecast exercises explicitly on metal prices, while simultaneously aiming to understand why the variables considered influence prices. Overall, the contribution of the paper is twofold. In the first part, the authors analyze and theoretically motivate short-run fluctuations in metal prices. As many previous studies detected, see Arezki et al. (2014) and Cuddington and Nülle (2014), among others, metal prices are oftentimes in a persistent negative trend, with short boom periods. The authors relate those cyclical fluctuations in metal prices to the fluctuations in industrial production.

First, the authors theoretically motivate the relation between the two variables, see also Section 2.1.3. Hereby, commodity prices should theoretically move in a common cycle with the industrial production. On monthly frequency, they use LME prices for aluminum, copper, nickel, lead, tin and zinc in the period from 1957 to 2012. The considered industrial production index on monthly frequency is calculated by J.P. Morgan and includes Chinese and Indian data. They further consider various other, potentially influencing factors on metal prices, including measures of the U.S. exchange rates, a volatility index and the returns of various U.S. government bonds, for example.

To start, the authors perform a cointegration analysis and detect 10 out of 15 commodity pairs to be cointegrated at monthly frequency. Subsequently, they check the cointegration of each commodity with the global industrial production, where they detect no evidence of cointegration, based on data from 1992 - 2012. However, when analyzing the common feature in prices, using a GMM approach, they find common cycles with the industrial production for all metals, except lead. They further perform the same tests for U.S. data, for comparability reasons on the same timespan, but identify those of the global industrial production to be stronger, compared to the results for the U.S. data. Based on annual data, they find evidence for common cycles for all metal pairs, except for tin-zinc, where overall the data showed much more synchronization at annual frequency.

In the second part of the study, the authors proceed with the forecasts, or their combinations, respectively. In the empirical application, they start by splitting their data sample in three sub-samples, starting with the estimation sample, where the individual forecast models are calibrated and the forecasts performed. The second part of the data is used to determine the weight that is attributed to each of the forecasts in their combination, referred to as the training sample, while the last part of data is used for the actual out-of-sample predictions and the respective valuation of the forecasts.

Hereby, they perform monthly, short-term forecasts and annual, long-term forecasts. On monthly data, their base model is a seven variable VAR model with two lags, in level, with the prices of six commodities and one measure of industrial production. Further, they use forecast combination techniques to enhance the performance of their forecasts. Hereby, the combination of individual forecasts yields in superior results only if the individual forecasts of the combined models differ from one another in a reasonable way. Therefore, the authors combine various AR, VAR and VECM models, each using distinct predictors, but leave it unclear which individual models are used in detail. Subsequently, they perform the bias-corrected average forecast as a forecast combination approach.

The authors further proceed with different combination strategies, for example with weights based on the inverse of the MSPE in the training data set, or an equally weighted combination of only the best five models. For the analysis of those forecast combinations, they observe heterogeneous results. There is no clear indication which of combination strategies performs best, but the results rather differ based on the metal analyzed and the time steps ahead to be predicted. Finally, they disentangle which model individually performs best as forecaster. Hereby, they detect the restricted VECM, using the U.S. industrial production is far superior than any other model, on monthly frequency. While the study relates the metal price movements to industrial production indices, the factors influencing the individual forecasts remain unclear.

Forecasting commodity price indexes using macroeconomic and financial predictors - by Gargano and Timmermann (2014)

The study analyzes the in- and out-of-sample predictability of commodity spot price indices, while differentiating between segmented and aggregated indices, between varying forecast horizons, between simple and more advanced forecasting models, as well as between the predictability in recession and expansion periods of the economy.

To start, the authors use a simple linear regression model to forecast different commodity research bureau indices in- and out-of-sample. These indices are calculated as unweighted mean of the underlying, individual commodity prices, using end-of month closing prices in U.S. Dollar for the sample period of January 1947 to December 2010. For this thesis we focus on the results for their metals index, including the prices of copper scrap, lead scrap, steel scrap, tin, and zinc. Hereby, they consider an overall set of 16 predictor variables, where seven of those originate from the stock market prediction literature, as also used and provided by Welch and Goyal (2008). These include the dividend price ratio, measured as the log return of the 12-month moving sum of dividends and the S&P 500 index, the 3-month treasury bill rate, the long-term rate of U.S. bonds, as well as the term spread, which is the difference between the long-term rate and the treasury-bill rate. Further, the default return spread as the difference between long-term corporate bond and long-term government bond, the investment to capital ratio, which relates the amount of aggregate investments to aggregate capital for the whole economy, and the log growth of the consumer price index as a measure of inflation.

Additionally, they consider the S&P Goldman Sachs Commodity Index, as this index is long in futures contracts for a broad set of commodities, as well as open interest data on the futures markets for industrial and metal commodities, to capture the effects of financial derivatives on commodity markets. Moreover, to measure the current state of the economy, they include the industrial production growth, the money stock growth and the annual GDP growth, as well as the unemployment rate. As commodities are further linked to microeconomic variables, they approximate the demand, especially from emerging economies, using Kilian's real economic activity index. Finally, they use two commodity currencies, the U.S. Dollar to the Australian Dollar exchange rate, as well as the U.S. Dollar to the Indian Rupee rate, as they are two of the largest producers of the industrial and agricultural commodities. They proceed with an in-sample analysis, but since in-sample forecasting results generally contain little information on the true predictive abilities of variables, we focus on the results they generated in their out-of-sample experiment.

Hereby, they forecast the metals index one step ahead, either one month, one quarter or one year, via a univariate, linear regression model, where they analyze the forecast performance via the Mean Squared Prediction Error. As standard in the forecasting literature on commodity prices, the significance of the predictive abilities of their models is determined via the Clark-West test of Clark and West (2007). They perform their forecasts in a rolling window setup, using a window length of 20 years and forecast prices from January 1971 to December 2010. However, since not all input variables are available for the entire time-period, they exclude some of the variables for certain sub-periods. In their setup, the metals commodity index is significantly predictable by the long-term interest rate, the default return spread, the Australian exchange rate, as well as by historical price data, which they represent by an AR(1) model, which overall performs best.

Further, they analyze whether the forecastability of commodity returns changes over time. Therefore, they split their data sample in sub-sample one ranging from 1971 to 1990 and sub-sample two ranging from 1991 to 2010. The results show a stronger predictability in sub-sample one, again with the AR(1) model as the best predictor, followed by the long-term interest rate and other models. For sub-sample two, the AR(1) model again performs best, followed by the two commodity currency models.

Additionally, they apply ridge regressions and subset combinations. Ridge regression are multivariate regression models, which penalize multicollinearity via a penalty term, which is subject to a predefined parameter λ. The higher the lambda value, the higher the penalty term and the more variables are excluded from the model. They obtain the best results in the metal price forecast by setting $\lambda = 200$, where the error ratio of the forecast is significantly better than the one of the benchmark model. However, the multivariate model performs worse compared to the AR(1) model.

The second extension of the study is the application of subset regressions, where the forecast is archived via an average of all models considering a specific number of variables. Hereby, for the metal price index, the models with 4 or 5 variables perform equally good and best, while still performing worse than the AR(1). A time dependent analysis of the forecast errors reveals the forecast model for the metal prices only outperforms the BMK model after around 2004, where it underperformed in the period from 1975 to 2003.

Lastly, they divide their data sample in crisis and non-crisis periods via the monthly unemployment ratio, proposed as crisis indicator by Stock and Watson (2010). In studies analyzing stock market predictability, the predictability is larger in recession periods, whereas the authors detect the same holds for metal commodities. Their univariate forecasts perform significantly better in recession periods, at least for metals and the one-month ahead forecasts.

Overall, the study shows the forecastability varies greatly between different forecast horizons, as do the influential variables. Commodity currencies show the strongest predictive abilities at monthly and annual frequency, while industrial production only has predictive power at annual frequency, with overall strongest results for the quarterly horizon.

Most commodities are better predictable in recessions, with only little to no predictability in expansion periods. However, the simple AR(1) model oftentimes outperforms their more sophisticated forecasts.

Summary of the Previous Empirical Studies on Metal Prices

Overall, there is a vast amount of potentially influential variables on metal prices, originating from macroeconomic, financial and microeconomic backgrounds. Further, the studies on metal price determinants and predictions vary by the models used, the metals or commodity-indices analyzed, as well as the underlying data frequency and sample, as already Vansteenkiste (2009) states. Especially the usage of commodity price indices, in contrast to individual commodity or metal prices, neglects the heterogeneity in markets. While Gargano and Timmermann (2014) use sub-indices to partly disentangle the effects between different commodity groups, their methodological approach of subset and ridge regressions does not allow for an analysis of the variables of predictive power, at least in the multivariate case. The same holds for the study of Issler et al. (2014), where the variables of predictive power are not analyzed in more detail. Therefore, the question arises which of the attributes of the numerous potential predictors is influential on metal prices and how these selected attributes differ between the metals and metal groups. Further, potential differences between price determinants and predictors should be addressed, while additionally the question arises whether the metal markets and their characteristics changed over time, as indicated by Gargano and Timmermann (2014).

2.4 Co-Movement of Commodity Prices and Linkages of Commodity Markets

Studies which analyze the behavior and relation of multiple commodity prices detect these move jointly, even for seemingly unrelated commodities, which partly attributes to a common factor, explaining the simultaneous price fluctuations of several commodities, see Pindyck and Rotemberg (1990). Delle Chiaie et al. (2022) detect the global economic activity is determining a common factor, which in turn simultaneously co-moves commodity prices, whereas general macroeconomic fundamentals are hypothesized to be the common factors' main determinants in the study of Vansteenkiste (2009).

In the study of Byrne et al. (2013), the common factor is negatively related to the interest rate, as well as a risk measure, while the relation remains valid under supply and demand shocks. Overall, commodity prices are influenced by macroeconomic determinants via various channels. While changes in the interest rate can set incentives to buy more commodities as of now, hereby directly influencing markets, these changes may also influence the expectations of markets participants on the future market environment, i.e. through the storage of commodities, as already Pindyck and Rotemberg (1990) point out.

However, commodity prices move in closer synchronization as what would be explainable by the common impact of macroeconomic conditions, probably rooted in further dependencies between the commodities. Hereby, they are, in addition to the macroeconomic circumstances, potentially related via their production and consumption relations. For the consumption dimension, commodities can, on the one hand side, act as substitutes, such as copper and aluminum for example, which are exchangeable within certain electricity applications, leading to effects of the copper demand on aluminum prices, according to Baffes et al. (2020). On the other hand side, especially metals may be used simultaneously, in alloys for example, to enhance the materials strength or robustness through the specific, individual properties of each alloying element. Hereby, in practice the substitution and co-consumption relations occur simultaneously, depending on the metal pair and application considered.

Further, metals might be related via their co-production, where usually the rock material extracted in mines contains several ores at once, which represents another channel of connection, as pointed out by Campbell (1985), where over 50% of the lead production originate from mixed Lead-Zinc ores, according to Nassar et al. (2015) and Shammugam et al. (2019). Please refer to Section 3.2 for a more detailed analysis.

Additionally, through the increasing investments in commodity indices since around 2004, the co-movement in commodity prices was elevated significantly. Tang and Xiong (2012) empirically validate this phenomenon, as they point out the co-movement is stronger for commodities that are included in the same index. Basak and Pavlova (2016) develop a theoretical model that shows why the prices of indexed futures are correlated stronger than those of non-indexed futures. In contrast to the empirically observed, increased co-movement in the time-series, the study of Hamilton and Wu (2015) is unable to show direct effects of the trading positions on prices. However, Büyüksahin and Robe (2014) show linkages of the equity and commodity markets via hedge fund investors. Since their trading activity is less constrained than the one of regular traders, they could increase cross-market linkages. In this regard, the behavior of investors on financial, and especially commodity markets may further contribute to the co-movement of prices, in addition to the common macroeconomic conditions. Overall, the prices and markets of industrial metals may be, in addition to metal-specific determinants, related through the three channels outlined in this section.

3 Data

For the analysis of commodity markets, we consider a wide range of metal commodities, which necessarily include the three precious metals silver (Ag), gold (Au) and platinum (Pt), as well as the six industrial metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn). In addition, we consider fifteen further minor metals, namely: bismuth (Bi), cadmium (Cd), cobalt (Co), chromium (Cr), gallium (Ga), germanium (Ge), indium (In), lithium (Li), magnesium (Mg), molybdenum (Mo), manganese (Mn), antimony (Sb), titanium (Ti), vanadium (V), and tungsten (W). Hereby, the selection of minor metals is primarily based on the availability of historical monthly price series.

For the determinants and forecasting factors of these prices, we rely on a wide range of attributes, where the selection of these attributes is based on the variables previously considered in literature on the subject, see Section 2.1. These attributes include microeconomic variables, commodity-specific financial variables, financial market as well as macroeconomic determinants. In the following, we first present the industrial applications of each commodity in Section 3.1, followed by the co-mining of the industrial metals described in Section 3.2. Subsequently, we provide an overview of the commodity price determinants and data sources in Section 3.3, before outlining the data adjustment procedures in Section 3.4. Additionally, we analyze the properties and descriptive statistics of the different variables in Section 3.5, before we outline possible channels of relation between the markets of the industrial metals in Section 3.6.

3.1 Metal Applications

While precious metals are mainly used for jewelry, their physical properties qualify them for a variety of industrial applications as well.

Silver has the highest known electrical and thermal conductivity of any metal and is found in many naturally occurring minerals. Because of its electrical conductivity, combined with its corrosion resistance, silver contacts and switches are used in many electrical products, while the metal's reflective effect makes it an ideal coating for glass in applications such as mirrors, where nowadays it is also used in the manufacturing of solar panels, see Geoscience Australia (2022). Similarly, gold is, for the share of it that is consumed within the technology sector, mainly used for electronics. While the share of gold that is consumed in the technology sector is comparably small, other demand sectors include the role of gold as central bank reserve, as well as a store of value and alternative asset class. However, the jewelry industry still accounts for around 50% of annual gold demand, making it by far the largest sector, according to The World Gold Council (2022). According to European Commission, Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (2020), platinum, which is the most important of the platinum group metals, is primarily used for its catalytic properties, which makes it an ideal component of emission control systems in cars, as well as in the petroleum industry. Other applications of platinum include electronics, glass manufacturing, jewelry, as well as specialty dental and medical alloys. It should be noted that there are no effective substitutes for platinum, other than the other platinum group metals.

For the industrial metals, their applications span across a broad variety of products and sectors. Aluminum, as the most abundant metallic element in the earth's crust, is hereby consumed in a variety of technologies. Over one fourth of the aluminum consumption is in the automotive and transportation sector, while the second quarter is used in the construction industry. The remaining shares distribute on the sectors packaging and foil, electrical engineering and consumer goods. As for many industrial metals, the regional distribution of their consumption changed drastically over the last 50 years. While in 1972 the U.S. were the largest aluminum consumer, accounting for 36% of the commodities' worldwide demand, China played a neglectable role, consuming only about 3%, see Carmine Nappi (2013). In 2020, however, almost 60% of the primary aluminum demand was generated in China, with additionally over ten percent originate from further Asian countries, see Wood Mackenzie (2022). Further, copper is mainly used for wires, accounting for over 60% of the commodities' consumption, as well as for tubes, flat rolled products, rods and bars. These semi-products are subsequently end-used in equipment, the construction industry, infrastructure, transportation and other industrial applications. As for aluminum, the regional consumption of copper shifted towards Asia massively. While in 1960 almost 60% of the copper consumption was inherited in Europe, in 2020 China alone accounted for 74% of the worldwide consumption, see The International Copper Study Group (2022).

Nickel, the fifth most common element on earth, is in it's first use mainly needed for stainless steel, accounting for almost 70% of the commodities' consumption, for batteries and non-ferrous alloys. These first-use products are subsequently used in engineering, as metal goods and in transportation, according to the Nickel Institute (2022). Lead is, for the largest part, which accounts for around 80% of the consumption, end-used in batteries. The remaining 20% of lead distribute over a wider range of products and sectors, such as construction, pigments, and ammunition, see Leder (2020). According to the International Tin Association (2020), almost 50% of tin's first-use application is in solders, followed by chemicals and tinplate, accounting for 18% and 12% respectively. Zinc is mainly used as a protection layer on steel products, with around 50% of the commodity used for galvanizing and another 17% in zinc-alloys. Further, another 17% of the metals annual consumption attributes to brass and bronze products, see the International Lead and Zinc Study Group (2020).

For the minor metals, the applications and characteristics are widespread. While bismuth shows a very low melting point of only 271°C, and is primarily used as substitute for lead and in the pharmaceuticals industry, see Critical Raw Materials Alliance (2022a), tungsten shows at 3.422°C the highest melting point, making it an ideal component of alloys used in high-temperature environments, such as the aerospace industry, see Critical Raw Materials Alliance (2022c). Further, many of the minor metals are used as steel additives and within batteries. 71% of the worldwide lithium consumption is attributed to (lithium-ion) batteries, according to U.S. Geological Survey (2022), while also cadmium's largest field of application is in (nickel-cadmium) batteries, see The Royal Society of Chemistry (2022b). Further, cobalt is used for cathodes in both types of the previously mentioned batteries, according to Hitzman et al. (2017). The latter is also used to enhance the corrosion resistance of steel via galvanizing processes, while chromium and vanadium are mainly used as components of stainless steel, simultaneously hardening it and preventing it from rusting, see S&P Global Commodity Insights (2022), The Royal Society of Chemistry (2022c), and Critical Raw Materials Alliance (2022d). Depending on the application, also molybdenum and manganese may be added to the steel, according to The Royal Society of Chemistry (2022h) and The Royal Society of Chemistry (2022g), or these high-grade steels may be substituted by titanium, see Critical Raw Materials Alliance (2022b). For high-strength, very lightweight applications, alloys of magnesium, mainly with aluminum, are used, according to The Royal Society of Chemistry (2022f).

However, there are also other types of applications for minor metals, outside the batteries and steel sector, as indium is mainly used for flat panel displays, according to European Commission, Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (2020), while gallium is mainly used in solar cells and light emitting diodes (LED), see The Royal Society of Chemistry (2022d). Further, germanium is mainly used for optical applications, such as camera lenses, according to The Royal Society of Chemistry (2022e), while antimony is mainly used in semiconductors, see The Royal Society of Chemistry (2022a).

3.2 Co-Mining of Industrial Metals

To represent the co-production relation between metals in general, and industrial metals in particular, there is a broad spectrum of determinants to possibly be considered. First, the regional or geological distribution of mixed ores, or rock material that contains multiple ores simultaneously. Second, the actual production per metal and mining project, which is reported and available via the S&P Global Market Intelligence (S&P) (2019). Third, the per country aggregation of production per metal, where the respective data is available via the annual U.S. Geological Survey Minerals Yearbooks, see U.S. Geological Survey (2019).

However, the problem with the first perspective is in the specific characteristics of ores within each mining project. That is, while at certain mining projects numerous ores might be extractable from the ground, they oftentimes differ in their concentration, as well as in their reach. Some ores are buried lower in the ground than others, where this aspect is oftentimes neglectable from a geological perspective, but not from the revenue calculations of mining operators. Therefore, we neglect this perspective from further analysis.

For the second perspective, we analyze the reported mining operations from the year 2016, which mark the last year data is available across all metals within the *S&P Global Market Intelligence database*.[1] The database reports, per metal, the production volume per mine, as well as the respective mine's share of the world production, in annual frequency.

Overall bauxite, corresponding to the industrial metal aluminum, marks a special role within the group. The largest ten mining projects, such as *Darling Range*, *Weipa*, *Boddington*, and *MRN*, which account for over 30 percent of the world production alone, are located in Australia and Brazil. Hereby, these mines, as well as most other bauxite mines, only extract bauxite and no other commodity at the same time, indicating the independence of aluminum from a production perspective.

In contrast, copper is mainly mined in countries like Chile, Peru or Mexico within Latin America, as well as in the United States of America. Hereby, it is co-mined with multiple other metals, such as silver, gold or molybdenum, but only to a lesser extent with other industrial metals. However, within five of the largest twenty mines that produce copper, other industrial metals are co-mined. The *Antamina* mine in Peru, as well as the *Mount Isa Copper*, mine copper with lead and zinc, the *KGHM Polska Miedz* in Poland with nickel and lead, as well as the *Norilsk* and *Polar Division* in Russia with nickel.

While aluminum and copper were mostly standalone from their production relation,

[1]While more recent data may be available from the S&P Capital IQ Pro on request, it is unavailable for this thesis. Further, the database generally does not report figures for tin, independent of the reported year.

lead, nickel and zinc are integrated to a way larger extend. Hereby, lead is co-mined with zinc in 245 of the 249 reported lead mines, where in only two of those nickel is co-mined and within 88 of those copper. However, while the relation to zinc is really strong, where seven of the ten largest lead mines are among the top fifteen zinc producers as well, see *Kazzinc Consolidated*, *Mount Isa Zinc* and *Red Dog* for example, only the *KGHM Polska Miedz* in Poland produces significant amounts of lead and copper simultaneously, as it ranks number seventeen of the lead producers, as well as number nine for copper.

Nickel holds a comparably strong co-mining relation with copper, as almost half of the reported mining projects co-mine the two commodities, while, on the other hand, only the *Polar Division* mine in Russia is ranked among the top producers for both commodities. Further, the co-production to other metals is almost neglectable, where none of the reported mines co-produces nickel with lead or aluminum, and only two mines co-mine it with zinc.

In turn, zinc is, obviously, closely related to lead, where 267 of the 294 reported mines for zinc co-produce the two commodities. Hereby, the largest 20 zinc mines already account for one-third of the global production of the commodity, while the same mines approximately also account for one-third of the global lead production. Further 117 zinc mines also extract copper, only three co-produce nickel, whereas none of them simultaneously extracts bauxite.

While this perspective definitely benefits from the in-depth analysis of each metals' mining, it suffers from unavailability of tin data, as well as the incompleteness of data. That is, the aggregated, mine-specific production volumes only sum up to 60 to 100 percent of the world production. In addition, this perspective suffers from partly neglecting political influences. When a commodity producing country, like Russia, decides to turn down exports, or other countries decide to lower import from one country, this will affect multiple commodities simultaneously, independent of the exact mining project. For example, a reduced export from Russia would affect the *Uchaly* (Copper, Zinc) mine, as well as *Norilsk* (Nickel, Copper) and *Dalpolimetall* (Lead, Zinc) simultaneously, although perspective two would regard them as independent. Therefore, we proceed to the third of the above mentioned perspectives, where the co-production is represented by the aggregated primary production per country.

Hereby, the top producing countries of the industrial metals are displayed in Table 3.1. The role of China is especially noteworthy in this case, where it is the top producer for four of the metals and among the top five producers for all metals. However, China's mining operations are only rarely listed among the top producers in the *S&P Global Market Intelligence database*, indicating the production within China spreads across numerous smaller mines, while in turn, this still results in a dominant market position.

Table 3.1: Largest Mining Nations of Industrial Metals

	Producer 1	%	Producer 2	%	Producer 3	%	Producer 4	%	Producer 5	%
Al	China	55.38	India	5.76	Russia	5.76	Canada	4.51	UAE	4.11
Cu	Chile	28.38	Peru	12.06	China	8.24	Congo	6.32	USA	6.18
Ni	Indonesia	32.68	Nickel	12.38	Russia	10.69	N. Caledonia	7.97	Canada	6.39
Pb	China	42.37	Australia	10.78	Peru	6.53	USA	5.81	Mexico	5.49
Sn	China	28.55	Indonesia	26.18	Burma	14.19	Peru	6.72	Bolivia	5.74
Zn	China	33.15	Peru	11.02	Australia	10.47	USA	5.93	India	5.67

This table presents the five largest production countries (in regard to the primary production) for the industrial metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn), as well as the corresponding share of the world production in percent, based on data of the year 2019 obtained from the annual U.S. Geological Survey Minerals Yearbooks, see U.S. Geological Survey (2019).

3.3 Determinants of Metal Prices

As the aim of this thesis is to analyze metal markets, the prices mark the most central element in the analysis. We hereby rely on spot market prices from the London Metals Exchange for the industrial metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn). For the precious metal prices silver (Ag), gold (Au), and platinum (Pt), we rely on the global benchmark prices, which are provided by the LBMA and administered by the ICE benchmark administration for gold and silver, while platinum prices are administered by the LME.

Within Table 3.2, we display, per metal, the unit per spot market contract, the start date and frequency of the data series, as well as the data source and the database ticker. For the minor metals bismuth (Bi), cadmium (Cd), cobalt (Co), gallium (Ga), germanium (Ge), indium (In), magnesium (Mg), manganese (Mn), molybdenum (Mo), antimony (Sb), titanium (Ti), vanadium (V), and tungsten (W), we consider the NorthWest Europe (NWE) prices, as provided by Thomson Reuters, where the seller of the commodity is responsible for the Cost, Insurance and Freight (CIF) of the commodities until a port in North-Western Europe. For chromium (Cr) and lithium (Li), we again rely on Thomson Reuters NWE spot price data, which has been backwards extended by historical metalbulletin data, as this data dates back further.

Table 3.2: Data Sources - Metal Spot Prices

	Name	Unit	Database Ticker	Source	Start	Freq
Ag	LBMA Silver Price	$/t oz		ICE Benchmark Administration (2022b)	02/1968	d
Au	LBMA Gold Price	$/t oz		ICE Benchmark Administration (2022a)	02/1968	d
Pt	LBMA Platinum Price	$/.9995 fine oz		London Metal Exchange (2022)	04/1990	d
Al	LME-Aluminium 99.7% Cash	$/t	[MAL0]	Thomson Reuters Eikon (2022j)	01/1957	d
Cu	LME-Copper Grade A Cash	$/t	[MCU0]	Thomson Reuters Eikon (2022k)	01/1957	d
Ni	LME-Nickel Cash	$/t	[MNI0]	Thomson Reuters Eikon (2022m)	07/1993	d
Pb	LME-Lead Cash	$/t	[MPB0]	Thomson Reuters Eikon (2022l)	07/1993	d
Sn	LME-Tin 99.85% Cash	$/t	[MSN0]	Thomson Reuters Eikon (2022o)	01/1957	d
Zn	LME-SHG Zinc 99.995% Cash	$/t	[MZN0]	Thomson Reuters Eikon (2022n)	01/1957	d
Bi	Bismuth CIF NWE	$/lb	[BIS-LON]	Thomson Reuters Eikon (2022b)	11/1994	d
Cd	Cadmium 99.99% CIF NWE	$/lb	[CAD-99.99-LON]	Thomson Reuters Eikon (2022c)	10/1994	d
Co	Cobalt Cathode 99.8% CIF NWE	$/lb	[COB-CATT-LON]	Thomson Reuters Eikon (2022e)	10/1993	d
Cr*	Chromium =99.2%, Coarse Particle	$/t	[SOTHCRM]	Thomson Reuters Eikon (2022d)	01/1990	d
Ga	Gallium Ingots CIF NWE	$/kg	[GAL-ING-LON]	Thomson Reuters Eikon (2022f)	03/2002	d
Ge	Germanium 50ohm CIF NWE	$/kg	[GERM-DIOX-LON]	Thomson Reuters Eikon (2022g)	06/1995	m
In	Indium CIF NWE	$/t	[IND-ING-LON]	Thomson Reuters Eikon (2022h)	10/1993	d
Li*	Lithium Metal =99%, Battery Grade	$/t	[SMINLTM]	Thomson Reuters Eikon (2022i)	01/1997	d
Mg	Magnesium 99.9% China CIF NWE	$/t	[MGN-CHINA]	Thomson Reuters Eikon (2022p)	10/1995	d
Mn	Manganese Electro CIF NWE	$/t	[MGN-LON]	Thomson Reuters Eikon (2022q)	10/1993	d
Mo	Molybdenum Mo3 CIF NWE	$/lb	[MLY-OXIDE-LON]	Thomson Reuters Eikon (2022r)	10/1993	m
Sb	Antimony 99.65% CIF NWE	$/t	[ANT-LON]	Thomson Reuters Eikon (2022a)	10/1993	d
Ti	Titanium Sponge CIF NWE	$/kg	[TIT-SPONGE-LON]	Thomson Reuters Eikon (2022s)	10/1993	d
V	Vanadium Fe 80 CIF NWE	$/kg	[VAN-FERRO-LON]	Thomson Reuters Eikon (2022u)	10/1993	d
W	Tungsten Ferro CIF NWE	$/kg	[TUN-FERRO-LON]	Thomson Reuters Eikon (2022t)	10/1993	d

This table displays per metal the name of the price series (Name), as well as the corresponding unit of notation (Unit), the database ticker (Ticker), the source of the data (Source), as well as the start date (Start) and the frequency (Freq) of the series. For chromium (Cr) and lithium (Li), indicated by a *, the Thomson Reuters spot price data is historically extended by metalbulletin data.

As potential price determinants, we include metal-specific supply and demand variables in our data set. For the supply variable ($\mathbf{supply_i}$) per metal $i = 1, \ldots, N$, we use the worldwide primary production, as provided by U.S. Geological Survey (2019). We further include the Herfindahl-Hirschman-Index (HHI), representing the production concentration of the supply side, as a risk measure. It is defined as the aggregated and squared production share of a metal for each producing country:

$$HHI_{i,t} = 10000 \cdot \sum_{r=1}^{R} \left(\frac{prod_{i,t,r}}{\sum_{r=1}^{R} prod_{i,t,r}} \right)^2, \tag{3.1}$$

with $prod_{i,t} = \sum_{r=1}^{R} prod_{i,t,r}$ representing the production for metal i at time $t = 1, \ldots, T$, for all production countries $r = 1, \ldots, R$, whereby the production data is the per country breakdown of our ($\mathbf{supply_i}$) variable, as provided in the annual U.S. Geological Survey Minerals Yearbooks, see U.S. Geological Survey (2019) for example.

Further, we approximate a metal's demand by its global apparent consumption, which we obtain by adjusting the U.S. apparent consumption, drawn from U.S. Geological Survey (2020), by a conversion ratio of the U.S. GDP to the World GDP for the industrial sector:[2]

$$demand_{i,t} = \frac{GDP_t^{World}}{GDP_t^{U.S.}} \cdot \left(prod_{i,t} + imports_{i,t} - exports_{i,t} + \Delta stocks_{i,t}\right). \tag{3.2}$$

Further, we obtain, in addition to the forward-filled supply and demand values, as described in Section 3.4, true monthly supply and demand data from a bespoke report of the World Bureau of Metal Statistics (WBMS), see World Bureau of Metal Statistics (2021), for the industrial metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn).

As metal-specific, financial variables, we consider the value and momentum factor, as proposed by Asness et al. (2013). The value factor is hereby constructed in analogy to the value factor for stocks, see Fama and French (1992), and represents the relation of the current market price of a metal to its true value, where in the stock market literature the book value of a company is oftentimes regarded as true value. Since for commodities no book value is defined, a historical average of spot prices is used to represent this missing, true value. Therefore, the value factor of commodity i at time t is defined as the log of the average spot price from 4.5 to 5.5 years ago, $\overline{price}_{i,t}$, divided by the most recent spot price:

$$VAL_{i,t} = \ln\left(\frac{\overline{price}_{i,t}}{price_{i,t}}\right). \tag{3.3}$$

[2]Since the data for the U.S. GDP of the industrial sector is only available from 1997 onward, we extended the series backwards for the years 1995 and 1996 with the conversion ratio of 1997. While this procedure considers forward looking data, it is not as problematic in this analysis, as the respective data points are not within the out-of-sample window of the prediction part of this thesis.

The momentum factor of commodity i at time t is measured as the cumulative raw return[3] of the past 12 months for each metal, while neglecting the most recent month's return $return_{i,t-1}$:

$$MOM_{i,t} = \prod_{\tilde{t}=2}^{12}(1 + return_{i,t-\tilde{t}}) - 1. \tag{3.4}$$

It is constructed to represent current market dynamics and measures, as its name indicates, the momentum of the price series. Since we use our data set, at least partly, for a forecast exercise of future metal spot prices, we include futures prices as a determinant, see Table 3.3. That is, we include the price of the first-running futures contract as predictor for the future spot prices.

Moreover, we represent the benefit of physically holding a metal via the convenience yield, which we define as:

$$CY_{i,t} = SIR_t - \frac{1}{T_1 - t} \ln\left(\frac{FUT_{i,t}}{price_{i,t}}\right), \tag{3.5}$$

with SIR_t denoting the 3-Month U.S. Treasury Rate and $FUT_{i,t}$ the three-month futures contract, which is, according to Table 3.3, the first-running contract $FUT1_{i,t}$ for the industrial metals, while it represents the second running futures contract $FUT2_{i,t}$ for silver and gold.[4] Further, we consider the basis-momentum factor of Boons and Prado (2019), representing a risk component that originates from speculators and financial market participants, defined as the difference between the momentum of the first- and second-running futures contracts, $FUT1_{i,s}$ and $FUT2_{i,s}$:

$$BM_{i,t} = \prod_{\tilde{t}=2}^{12}(1 + return_{FUT1_{i,t-\tilde{t}}}) - \prod_{\tilde{t}=2}^{12}(1 + return_{FUT2_{i,t-\tilde{t}}}). \tag{3.6}$$

[3]In accordance to the calculations performed in the initial paper of Asness et al. (2013), we use regular first differences of the monthly metal price as return series in this case.

[4]As the time span of data availability of the second futures contract of platinum is very limited, we base the convenience yield calculations on the first running, one-month contract, in this case, where we consider the 1-month LIBOR as interest rate.

Table 3.3: Data Sources - Metal Futures Prices

		Name	Unit	Contract Spec.	Ticker	Source	Start	Freq
Ag	$FUT1$	CMX-SILVER - SETT. PRICE - 1 Months	$/t oz	5000t oz	[SIc1]	Thomson Reuters Eikon (2021c)	01/1973	d
	$FUT2$	CMX-SILVER - SETT. PRICE - 3 Months	$/t oz	5000t oz	[SIc3]	Thomson Reuters Eikon (2021d)	01/1973	d
Au	$FUT1$	CMX-GOLD - SETT. PRICE - 1 Months	$/t oz	100t oz	[GCc1]	Thomson Reuters Eikon (2021a)	11/1979	d
	$FUT2$	CMX-GOLD - SETT. PRICE - 3 Months	$/t oz	100t oz	[GCc3]	Thomson Reuters Eikon (2021b)	11/1979	d
Pt	$FUT1$	NYM-PLATINUM - SETT. PRICE - 1 Months	$/t oz	50t oz	[PLc1]	Thomson Reuters Eikon (2021q)	01/1973	d
	$FUT2$	NYM-PLATINUM - SETT. PRICE - 5 Months	$/t oz	50t oz	[PLc3]	Thomson Reuters Eikon (2021r)	12/2004	d
Al	$FUT1$	LME-Aluminium 99.7% 3 Months	$/t	25t	[MAL3]	Thomson Reuters Eikon (2021f)	01/1980	d
	$FUT2$	LME-Aluminium 99.7% 15 Months	$/t	25t	[MAL15]	Thomson Reuters Eikon (2021e)	07/1993	d
Cu	$FUT1$	LME-Copper, Grade A 3 Months	$/t	25t	[MCU3]	Thomson Reuters Eikon (2021h)	07/1993	d
	$FUT2$	LME-Copper, Grade A 15 Months	$/t	25t	[MCU15]	Thomson Reuters Eikon (2021g)	04/1991	d
Ni	$FUT1$	LME-Nickel 3 Months	$/t	6t	[MNI3]	Thomson Reuters Eikon (2021l)	04/1979	d
	$FUT2$	LME-Nickel 15 Months	$/t	6t	[MNI15]	Thomson Reuters Eikon (2021k)	07/1993	d
Pb	$FUT1$	LME-Lead 3 Months	$/t	25t	[MPB3]	Thomson Reuters Eikon (2021j)	07/1993	d
	$FUT2$	LME-Lead 15 Months	$/t	25t	[MPB15]	Thomson Reuters Eikon (2021i)	07/1993	d
Sn	$FUT1$	LME-Tin 99.85% 3 Months	$/t	5t	[MSN3]	Thomson Reuters Eikon (2021p)	06/1989	d
	$FUT2$	LME-Tin 99.85% 15 Months	$/t	5t	[MSN15]	Thomson Reuters Eikon (2021o)	07/1993	d
Zn	$FUT1$	LME-SHG Zinc 99.995% 3 Months	$/t	25t	[MZN3]	Thomson Reuters Eikon (2021n)	11/1988	d
	$FUT2$	LME-SHG Zinc 99.995% 15 Months	$/t	25t	[MZN15]	Thomson Reuters Eikon (2021m)	07/1993	d

This table displays per metal and futures contract the corresponding name (Name), the unit of price notation (Unit), the quantity specification per contract (Contract Spec.), the database ticker (Ticker), the source of the data (Source), as well as the start date (Start) and the frequency (Freq) of the series.

We now turn our attention to the macroeconomic and financial market determinants of metal prices, which we consider in the empirical application of our models. The covariates, their description as well as the start date of the data series and corresponding source are displayed within Table 3.4. For interest rates, we include the 3-Month U.S. Treasury Rate ($SIR_{U.S.}$) as short-term interest rate, drawn from Organization for Economic Co-operation and Development (OECD) (2022), as well as the 10-Year U.S. Treasury Rate ($LIR_{U.S.}$) as long-term interest rate, drawn from Board of Governors of the Federal Reserve System (US) (2022d). Motivated by the rapid growth of the Chinese economy and its importance for the worldwide commodity supply and demand, we add the Chinese 3-Month Interbank interest rate (SIR_{China}), drawn from State Administration of Foreign Exchange, China

(2022b), and, in analogy to the interest rates of the U.S., the 10-Year Government bond as long term rate (LIR_{China}), drawn from State Administration of Foreign Exchange, China (2022a). Further, we include the term spread ($T10Y3M$), drawn from Federal Reserve Bank of St. Louis (2022a), which is calculated as the difference from the 10-Year minus the 3-Month U.S Government Bond and widely regarded as reverse crisis indicator. In regular markets, long-term interest rates are expected to be higher than short-term rates, leading to a positive term spread. When the yield curve flattens or even moves into an inverted shape, indicated by a small or negative term spread, this is widely regarded as a sign of an economy drifting into a recession. Hereby, markets expect falling short-term interest rates, which should cause commodity prices to rise, due to their inverse relationship, see Idilbi-Bayaa and Qadan (2021).

Further, we include the federal funds rate (FFR), which is the daily median of the transactions at which banks borrow money from the Federal Reserve, drawn from Board of Governors of the Federal Reserve System (US) (2022b). The federal funds rate is the main monetary policy tool of the FED, at least during times of conventional monetary policy actions. In contrast, the WuXia rate ($WuXia$), drawn from Federal Reserve Bank of Atlanta (2022), is a shadow rate, which is equal to the policy rate when it is above a 0.25 percent threshold. Once the policy rate is continuously lowered and reaches its natural zero lower bound, the shadow rate model uses data from yield curve estimates to estimate what the interest rate would be like, without the zero lower bound constraint, enabling shadow rates to replicate the effects of unconventional monetary policy actions. The shadow rate model is hereby constructed via three factors, which each constitute of a VAR(1) process, and is based on data of one-month forward rates, spanning from a quarter year to ten years ahead, which in turn are based on Nelson-Siegel-Svensson yield curve parameters, provided by Gürkaynak et al. (2006). Hereby, the WuXia rate exhibits similar correlations to macroeconomic determinants from 2009 on, when the federal funds rate hit the ZLB, as the federal funds rate did in the period before 2009. While shadow rate models usually are only calculated for periods where nominal interest rates are at the ZLB, the WuXia rate is one of the few that provides a longer history of data, making it applicable for a wide range of econometric models.

We further include additional variables that we hypothesize to represent the unconventional monetary policy actions. First, the total assets of the FED, which is the balance sheet size ($WALCL$), drawn from Board of Governors of the Federal Reserve System (US) (2022a). As the federal funds rate was continuously lowered in response to the global financial crisis, and reached its zero lower bound at the end of 2008, the FED continued to provide stimulus for the economy. Therefore, it bought large amounts of securities from private banks, hence expanding the monetary base and hereby influencing the long-term interest rates. As these so bought assets are included in the balance sheet, the balance sheet size can be regarded as econometric measure for quantitative easing. With an increasing amount of circulation money in the economy, prices should generally be rising. Hence, we include the overall monetary base (MB), drawn from Board of Governors of the Federal Reserve System (US) (2022e), which measures the balances and currency in circulation of the U.S. economy, as well as the broad monetary aggregate M4 ($M4$), drawn from Center for Financial Stability (CFS) (2022), which specifically represents the assets included in the asset purchases, see Keating et al. (2019).

As commodities are quoted in U.S. Dollar on exchanges, we include the U.S. Dollar index (FX), drawn from ICE Futures U.S. (2022), which measures the value of the U.S. Dollar relative to a basket of six foreign currencies, namely the Euro, the Japanese Yen, the British Pound, the Canadian Dollar, the Swedish Krona and the Swiss Franc. We further include a measure of the U.S. industrial production ($IP_{U.S.}$), drawn from Board of Governors of the Federal Reserve System (US) (2022c), which measures the output of the manufacturing, mining, electric and gas utilities sectors, which account for a large share in the variation of the U.S. output. Additionally, we also include the same measure, based on the equivalent worldwide sectors (IP_{World}), drawn from The World Bank (2022), as well as the corresponding Chinese variable, the Chinese Industrial Production (IP_{China}), drawn from National Bureau of Statistics of China (2022), in our analysis. Subsequently, to gauge the stance of the U.S. economy, we include the U.S. Gross Domestic Product (GDP), drawn from Organization for Economic Co-operation and Development (2022b). Hereby, the appropriate measure of true economic activity is an ever ongoing debate within the field of economics, where Kilian (2009) proposes his own economic activity indicator ($EAKilian$), which is based on various shipping rates. As metal markets are globalized, with different locations of mining, manufacturing, trading and consumption, transportation is a key aspect, while shipping rates are additionally considered a leading indicator of the world economy and hence a potential forecasting factor. Therefore, we include the largest shipping index, the Baltic Dry Index (BDI), drawn from The Baltic Exchange (2022), which represents a measure of the current, global freight rates.

In general, when the inflation is rising, financial market investors are hypothesized to move out of conventional assets, towards more inflation resilient asset classes, typically including commodities, see Calvo (2008). Therefore, commodity prices are hypothesized to be concurrently related to the inflation, which we represent via the U.S. Consumer Price Index (CPI), drawn from Organization for Economic Co-operation and Development (2022a). However, during the low interest rate period after the worldwide financial crisis in the late 2000s, the FED used, in addition to the large scale asset purchase programs, forward guidance as further unconventional monetary policy tool. Hereby, the FED communicates its expectations on the futures monetary policy actions, which ultimately influences the long-term interest and inflation rates, as an announcement of no further central bank actions over a certain period raises the market expectations to refinance at the current, low interest rates in the future. Since the main objective of central banks are stable prices, such communications reveal the central banks' expectations on the future inflation, which will likely also influence the market expectation on the future inflation. This is why we include an inflation expectation index ($T5YIFR$), drawn from Federal Reserve Bank of St. Louis (2022b), which displays the markets expectations and reactions to this unconventional monetary policy instrument, to measure the effect of forward guidance from an econometrics point of view.

It might be counter-intuitive to include the price of oil as determinant in our analysis, rather than analyzing this commodity individually as well, but the oil price marks a special case. That is, the production process of many metals, especially aluminum and nickel for example, is very energy intense. In this respect, the oil price is regarded as a proxy for the input costs of the production, rather than a commodity itself. Further, the oil price also acts as a macroeconomic indicator, where a high oil price usually indicates a strong economy. Hence, we include a WTI crude oil price (OIL), drawn from International Monetary Fund (2022), in our analysis.

To include a measure of overall metal prices, which acts like a market model, we consider a sub-index of the Rogers International Commodity Index, the total return RICI metals index ($RICIM$), drawn from Rogers (2022). It represents the price level of the six LME industrial metals aluminum, copper, nickel, lead, tin and zinc, as well as the four precious metals gold, silver, platinum and palladium. In contrast, to represent a broader picture across commodity markets, we also include the Bloomberg commodity index ($BCOM$), drawn from Bloomberg Index Services Limited (2022). To account for the effects of financial markets on commodity prices, we further include the Morgan Stanley Capital International world index ($MSCIW$), drawn from MSCI (2022), which is a global stock index consisting of approximately 1600 stocks and regarded one of the largest indices worldwide. Further, to emphasize the focus on the U.S. economy, we include the Standard and Poor's 500 (SPX), drawn from Standard & Poor's (2022), which represents the stock prices of the 500 largest U.S. companies.

Table 3.4: Data Sources - General Metal Price Determinants

Covariate	Description	Source	Start	Freq.
$SIR_{U.S.}$	U.S. 3-Month Short-term interest rates	Organization for Economic Co-operation and Development (OECD) (2022)	06/1964	m
SIR_{China}	China (Mainland) Interbank lending weighted average interest rate, 3-Month	State Administration of Foreign Exchange, China (2022b)	01/1996	m
$LIR_{U.S.}$	U.S. 10-Year Constant Maturity Market Yield, Quoted on an Investment Basis	Board of Governors of the Federal Reserve System (US) (2022d)	04/1953	m
LIR_{China}	China (Mainland) 10-Year Government Benchmarks, Bid, CNY	State Administration of Foreign Exchange, China (2022a)	06/2002	m
$T10Y3M$	U.S. 10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity	Federal Reserve Bank of St. Louis (2022a)	01/1982	m
FFR	Effective Federal Funds Rate	Board of Governors of the Federal Reserve System (US) (2022b)	01/1955	m
$WuXia$	Wu-Xia Shadow Federal Funds Rate	Federal Reserve Bank of Atlanta (2022)	01/1990	m
MB	Monetary Base; Total, Millions of Dollars, Monthly, Not Seasonally Adjusted	Board of Governors of the Federal Reserve System (US) (2022e)	01/1959	m
$WALCL$	Assets: Total Assets: Total Assets (Less Eliminations from Consolidation): Wednesday Level	Board of Governors of the Federal Reserve System (US) (2022a)	12/2002	w
$M4$	Divisia M4 - Including Treasuries - U.S.	Center for Financial Stability (CFS) (2022)	01/1990	m
$T5YIFR$	5-Year Forward Inflation Expectation Rate, Percent, Daily, Not Seasonally Adjusted	Federal Reserve Bank of St. Louis (2022b)	01/2003	d
FX	U.S. Dollar Index	ICE Futures U.S. (2022)	12/1970	d
$IP_{U.S.}$	U.S. Industrial Production	Board of Governors of the Federal Reserve System (US) (2022c)	01/1919	m
IP_{World}	World Industrial Production	The World Bank (2022)	01/1991	m
IP_{China}	China (Mainland) Production, Overall, Industrial production	National Bureau of Statistics of China (2022)	01/1990	m
GDP	Gross Domestic Product, normalized for the United States	Organization for Economic Co-operation and Development (2022b)	01/1959	m
$EAKilian$	Index of Global Real Economic Activity	Federal Reserve Bank of Dallas (2022)	01/1968	m
BDI	Baltic Dry Index London	The Baltic Exchange (2022)	07/1999	m
CPI	Consumer Price Index: Total, All Items for the United States	Organization for Economic Co-operation and Development (2022a)	01/1960	m
OIL	Global price of WTI Crude	International Monetary Fund (2022)	01/1990	d
$BCOM$	The Bloomberg Commodity Index	Bloomberg Index Services Limited (2022)	01/1991	d
$RICIM$	RICI Metals Total Return Index	Rogers (2022)	12/1987	d
$MSCIW$	MSCI World Index	MSCI (2022)	01/1980	d
SPX	Standard & Poor's 500 Index	Standard & Poor's (2022)	02/1970	d

This table displays the name of the co-variate (Covariate), the description of the series (Description), as well as the corresponding data source (Source), the start date of the series (Start) and the frequency (Freq) for the general metal price determinants.

3.4 Data Preparation

The data used in this thesis is consolidated from various data sources and providers, while it differs in its properties and frequencies. To ensure the validity of our empirical analyses, we consider only stationary time-series in our models, and therefore check and adjust our initial data series in the following ways. First, we apply the Augmented Dickey Fuller (ADF) test, based on the ten percent significance level, to each variable. In case non-stationarity is found, we calculate one of following three returns, while we proceed with the original, unadjusted variable names.

Log differences:

$$\mathsf{v}_t = ln\left(\mathsf{v}_t\right) - ln\left(\mathsf{v}_{t-1}\right), \tag{3.7}$$

first differences:

$$\mathsf{v}_t = \frac{\mathsf{v}_t}{\mathsf{v}_{t-1}} - 1, \tag{3.8}$$

or differences:

$$\mathsf{v}_t = \mathsf{v}_t - \mathsf{v}_{t-1}. \tag{3.9}$$

The supply, HHI and demand series are only available at annual frequency. To consider those microeconomic determinants within models which require higher frequency data, we apply the following forward-filling procedure: First, the annual return of each variable is taken, according to Equation 3.8. We then shift these returns forward by one year and decompose them into monthly values by filling each point in time forward by one-twelfth of the annual change, as shown in Table 3.5 for the exemplary calculations for silver (Ag).

For the commodity prices, we obtained the initial series as described in Table 3.2. Hereby, except for germanium (Ge) and molybdenum (Mo), all series are at daily frequency, which we aggregated to monthly frequency by taking the monthly average price. Subsequently, the individual series are checked for stationarity using the ADF-test and log differences, according to Equation 3.7, are calculated in case the initial series were non-stationary, while for the value and momentum factor we calculate differences, according to Equation 3.9, in case of non-stationarity. Subsequently, we repeat the procedure until stationarity is ensured across all variables. All futures prices are available at daily frequency, see Table 3.3, while we convert them to monthly frequency again by taking the monthly average prices and calculate log-differences according to Equation 3.7, in case the monthly series are found to be non-stationary. Since the basis momentum and convenience yield are rates already, we calculate differences according to Equation 3.8 in case of non-stationarity. Again, we recursively apply the procedure until stationarity is ensured for all variables.

Table 3.5: Conversion and Forward Filling of Annual Microeconomic Variables

Year	Month	Production
1995		14896
1996		15003
1997		16139
...		
1995		
1996		$(15003 - 14896)/14896 = 0.00718$
1997		$(16139 - 15003)/15003 = 0.07572$
...		
1995	1	
1995	2	
...	...	
1995	12	
1996	1	$(1/12) \cdot 0.00718 = 0.00060$
1996	2	0.00060
...	...	
1996	12	0.00060
1997	1	$(1/12) \cdot 0.07572 = 0.00631$
1997	2	0.00631
...	...	
1997	12	0.00631
...		

This table displays the forward-filling procedure applied to the annual supply and demand data in order to obtain monthly data series.

We proceed in the same way for the macroeconomic attributes. Daily figures are aggregated to monthly data by taking the monthly average, while for the financial- and commodity-indices, shipping indices, industrial production measures, the GDP, as well as the monetary aggregates, we calculate log-returns according to Equation 3.7 in case of non-stationarity of the aggregated variables. In contrast, for all interest rate variables, the term spread, as well as the inflation expectation index and the consumer price index, we compute regular returns, according to Equation 3.8.

To enhance the estimation quality of our models, we perform a seasonality adjustment for the data used in the models described in Section 4.2 and Section 4.4. We therefore take, per co-variate v, the actual value v_t and divide it by the average of the variable, calculated per respective month. Exemplary, for v_1, which represents the value of variable v in January 1995 in our sample, we calculate the average of the corresponding data of v from January 1996, January 1997 until January 2019, which marks the end of our sample. Subsequently, we divide the January 1995 value by this average to obtain the seasonally adjusted variable. Formally, this adjustment process is performed as follows, where $\lfloor\rfloor$ denotes the floor function:

$$l = t - \left(\left\lfloor \frac{t}{12} \right\rfloor \cdot 12\right) \forall t = 1, ..., T. \tag{3.10}$$

Using l as defined above and setting $n = \lfloor \frac{T}{12} \rfloor$, we derive:

$$\mathsf{v}_t^{seas} = \begin{cases} \dfrac{\mathsf{v}_t}{\frac{1}{\mathsf{n}} \cdot \sum_{k=1}^{\mathsf{n}} \mathsf{v}_{12k}}, & for\ l = 0 \\ \dfrac{\mathsf{v}_t}{\frac{1}{\mathsf{n}} \cdot \sum_{k=0}^{\mathsf{n}-1} \mathsf{v}_{12k+l}}, & else. \end{cases} \tag{3.11}$$

The seasonally adjusted data v_t^{seas} is subsequently used in the empirical application within Section 5.1. Further, we calculate the mean and standard deviation of the seasonally adjusted data as follows:

$$\mu^{seas} = \frac{1}{\mathsf{n}} \cdot \sum_{t=1}^{\mathsf{n}} \mathsf{v}_t^{seas}, \tag{3.12}$$

$$\sigma^{seas} = \frac{1}{\mathsf{n}} \cdot \sum_{t=1}^{\mathsf{n}} (\mathsf{v}_t^{seas} - \mu^{seas})^2. \tag{3.13}$$

Using the seasonally adjusted data, as well as the corresponding mean and standard deviation, we obtain the final, seasonally adjusted and standardized data via:

$$\mathsf{v}_t^{stand} = \frac{\mathsf{v}_t^{seas} - \mu^{seas}}{\sigma^{seas}}, \tag{3.14}$$

which we subsequently use in the application of the global vector autoregressions on the industrial metal markets, as described in Section 5.3.

3.5 Descriptive Statistics

In the following, we give a brief overview on the characteristics of the adjusted data series for each of the 24 metals considered in the analysis, as displayed in Table 3.6.[5] Hereby, futures prices ($FUT1$ and $FUT2$), as well as the corresponding convenience yield (CY) and basis-momentum factor (BM), are only available for the precious and industrial metals. The momentum factor (MOM) is stationary across all commodities in level, which is rather intuitive, given the factor is a rate of accumulated returns, whereas the same holds for the convenience yield (CY) and the basis-momentum factor (BM).

[5] The corresponding descriptive statistics of the unadjusted, level data are displayed within Table B.1 of Appendix B.

Table 3.6: Descriptive Statistics of the Adjusted, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Silver (Ag)	*supply*	-0.01	-0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	-1.16	1.76	300	-5.53**	106.00***
	HHI	-0.06	-0.04	-0.01	0.01	0.02	0.03	0.09	0.18	0.05	1.64	4.17	300	-6.31**	351.84***
	demand	-0.03	-0.02	-0.00	0.00	0.00	0.01	0.02	0.02	0.01	-0.46	0.57	300	-4.53**	14.64***
	price	-0.22	-0.09	-0.03	-0.00	0.00	0.04	0.11	0.19	0.06	-0.09	1.19	300	-19.68**	18.11***
	VAL	-1.44	-1.15	-0.74	-0.18	-0.26	0.12	0.60	0.74	0.54	-0.21	-0.87	300	-1.81.	11.67***
	MOM	-0.37	-0.26	-0.10	0.00	0.07	0.18	0.61	1.28	0.27	1.44	2.73	300	-5.20**	196.84***
	FUT1	-0.22	-0.09	-0.03	0.00	0.00	0.04	0.11	0.19	0.06	-0.11	1.25	300	-18.28**	20.14***
	FUT2	-0.22	-0.09	-0.03	0.00	0.00	0.04	0.11	0.19	0.06	-0.11	1.25	300	-18.44**	20.14***
	CY	-7.50	-2.41	-0.38	0.98	1.27	2.76	5.97	12.69	2.54	0.53	1.19	300	-8.98**	31.75***
	BM	-0.01	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.01	0.00	0.39	2.47	300	-20.74**	83.87***
Gold (Au)	*supply*	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.01	0.01	0.00	-0.17	-0.45	300	-3.83**	3.98
	HHI	-0.15	-0.11	-0.05	-0.04	-0.04	-0.02	0.00	0.01	0.04	-1.16	1.23	300	-2.80**	86.19***
	demand	-0.02	-0.02	-0.00	0.00	-0.00	0.00	0.01	0.02	0.01	-0.71	0.77	300	-5.55**	32.62***
	price	-0.12	-0.05	-0.02	0.00	0.00	0.03	0.07	0.16	0.04	0.34	1.56	300	-18.16**	36.20***
	VAL	-1.06	-0.98	-0.76	-0.11	-0.25	0.16	0.35	0.40	0.46	-0.34	-1.33	300	-2.59**	27.89***
	MOM	-0.27	-0.15	-0.04	0.04	0.06	0.15	0.33	0.57	0.15	0.54	0.06	300	-3.58**	14.63***
	FUT1	-0.12	-0.05	-0.02	0.00	0.00	0.03	0.06	0.16	0.04	0.32	1.41	300	-17.98**	29.97***
	FUT2	-0.12	-0.05	-0.02	0.00	0.00	0.03	0.06	0.16	0.04	0.33	1.41	300	-18.11**	30.30***
	CY	-2.56	-1.38	-0.03	0.87	1.05	2.37	3.45	5.33	1.55	0.05	-0.70	300	-6.36**	6.25*
	BM	-0.01	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.01	0.00	0.50	1.34	300	-8.95**	34.95***
Platinum (Pt)	*supply*	-0.02	-0.01	-0.00	0.00	0.00	0.01	0.01	0.02	0.01	-0.74	2.47	300	-8.60**	103.64***
	HHI	-0.22	-0.10	-0.05	-0.00	-0.01	0.02	0.11	0.19	0.07	-0.07	1.75	300	-8.75**	38.53***
	demand	-0.12	-0.04	-0.02	0.00	-0.00	0.01	0.03	0.03	0.03	-2.26	6.82	300	-6.05**	836.79***
	price	-0.29	-0.08	-0.03	0.01	0.00	0.03	0.08	0.23	0.05	-0.77	5.37	300	-14.50**	390.11***
	VAL	-0.21	-0.08	-0.03	-0.00	0.00	0.03	0.08	0.32	0.06	0.89	5.09	290	-11.79**	351.34***
	MOM	-0.52	-0.27	-0.08	0.03	0.05	0.18	0.44	0.66	0.22	0.36	0.34	300	-3.36**	7.92*
	FUT1	-0.34	-0.08	-0.02	0.00	0.00	0.03	0.08	0.18	0.05	-1.19	7.90	300	-18.38**	850.93***
	FUT2	-0.50	-0.07	-0.03	0.00	0.00	0.03	0.08	0.32	0.07	-1.97	19.56	180	-12.02**	2985.88***
	CY	-166.25	-10.91	-1.13	0.02	-0.26	1.60	15.68	41.86	15.89	-6.45	65.23	181	-10.12**	33344.45***
	BM	-0.44	-0.14	-0.00	-0.00	-0.00	0.00	0.10	0.55	0.08	1.01	20.29	169	-11.74**	2927.68***
Aluminum (Al)	*supply*	-0.01	-0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	-2.02	6.17	300	-5.55**	679.88***
	$supply_M$	-0.11	-0.06	-0.02	0.00	0.00	0.02	0.07	0.16	0.04	0.32	1.46	300	-27.76**	31.70***
	HHI	-0.12	-0.05	-0.01	0.05	0.05	0.11	0.20	0.21	0.08	0.15	-0.55	300	-5.60**	4.91.
	demand	-0.02	-0.02	-0.00	0.00	0.00	0.01	0.01	0.01	0.01	-0.82	-0.00	300	-2.23*	33.62***
	$demand_M$	-0.11	-0.07	-0.03	-0.00	0.00	0.03	0.08	0.19	0.05	0.45	0.68	300	-24.54**	15.89***
	price	-0.21	-0.07	-0.03	0.00	-0.00	0.03	0.07	0.14	0.05	-0.43	1.73	300	-23.37**	46.66***
	VAL	-0.77	-0.66	-0.19	-0.05	-0.06	0.12	0.37	0.48	0.27	-0.65	0.40	300	-1.90.	23.12***
	MOM	-0.55	-0.22	-0.11	0.02	0.03	0.16	0.40	0.72	0.20	0.39	1.15	300	-4.54**	24.14***
	FUT1	-0.21	-0.07	-0.03	0.00	-0.00	0.03	0.07	0.14	0.04	-0.49	2.15	300	-16.64**	69.79***
	FUT2	-0.21	-0.05	-0.02	0.00	0.00	0.02	0.05	0.13	0.04	-0.69	4.06	300	-12.54**	229.85***
	CY	-10.64	-9.47	-4.43	-2.49	-2.10	0.08	5.36	16.50	4.42	0.87	2.19	300	-15.06**	97.80***
	BM	-0.13	-0.07	-0.02	0.00	0.00	0.03	0.08	0.23	0.05	0.31	2.20	300	-4.11**	65.31***

Descriptive Statistics of the Adjusted, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Copper (Cu)	*supply*	-0.00	-0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.45	-0.40	300	-5.69**	12.13***
	$supply_M$	-0.18	-0.08	-0.02	0.00	0.00	0.03	0.08	0.12	0.05	-0.32	0.56	300	-23.84**	9.05**
	HHI	-0.06	-0.06	-0.03	0.00	0.00	0.04	0.10	0.12	0.05	0.69	-0.09	300	-7.81**	23.91***
	demand	-0.19	-0.09	-0.04	0.00	0.00	0.04	0.10	0.23	0.06	0.22	0.41	300	-24.60**	4.51
	$demand_M$	-0.02	-0.02	-0.00	0.00	-0.00	0.00	0.01	0.01	0.01	-1.25	2.36	300	-5.83**	147.74***
	price	-0.35	-0.09	-0.03	0.00	0.00	0.04	0.08	0.23	0.06	-0.65	5.33	300	-16.32**	376.24***
	VAL	-0.25	-0.09	-0.04	-0.00	0.00	0.03	0.10	0.41	0.07	0.96	6.66	300	-14.19**	600.52***
	MOM	-0.60	-0.31	-0.11	0.01	0.08	0.22	0.68	1.28	0.31	1.14	2.00	300	-3.99**	114.98***
	$FUT1$	-0.36	-0.08	-0.03	0.00	0.00	0.03	0.08	0.23	0.06	-0.73	6.04	300	-11.78**	482.66***
	$FUT2$	-0.33	-0.07	-0.02	0.00	0.00	0.03	0.08	0.23	0.05	-0.76	6.49	300	-12.21**	555.38***
	CY	-4.52	-3.42	-1.11	0.54	3.73	6.32	21.45	38.85	8.09	1.85	3.17	300	-3.45**	296.74***
	BM	-0.25	-0.10	-0.02	-0.00	0.00	0.02	0.15	0.30	0.07	0.79	4.18	300	-3.61**	249.61***
Nickel (Ni)	*supply*	-0.02	-0.02	-0.00	0.00	0.00	0.01	0.02	0.02	0.01	-0.36	0.40	300	-5.79**	8.48**
	$supply_M$	-0.26	-0.12	-0.02	0.00	0.00	0.04	0.13	0.25	0.07	-0.33	2.01	300	-17.73**	55.70***
	HHI	-0.27	-0.18	-0.05	-0.01	-0.01	0.05	0.22	0.26	0.11	0.14	0.80	300	-5.80**	8.98**
	demand	-0.02	-0.02	-0.00	0.00	0.00	0.01	0.01	0.02	0.01	-0.55	-0.35	300	-6.03**	16.66***
	$demand_M$	-0.31	-0.14	-0.06	0.01	0.00	0.06	0.15	0.26	0.09	-0.22	0.50	300	-22.91**	5.59.
	price	-0.38	-0.12	-0.05	-0.01	0.00	0.06	0.14	0.24	0.08	-0.22	1.17	300	-12.62**	19.53***
	VAL	-0.27	-0.14	-0.06	-0.01	-0.00	0.06	0.16	0.42	0.09	0.49	1.03	251	-9.61**	21.14***
	MOM	-0.66	-0.39	-0.17	0.00	0.10	0.31	0.94	1.75	0.43	1.21	1.81	300	-2.69**	114.16***
	$FUT1$	-0.37	-0.12	-0.05	-0.00	0.00	0.06	0.13	0.20	0.08	-0.25	1.01	300	-15.29**	15.88***
	$FUT2$	-0.34	-0.11	-0.05	-0.00	0.00	0.05	0.12	0.17	0.07	-0.23	1.07	300	-13.03**	16.96***
	CY	-6.07	-1.97	-1.31	-0.47	2.33	1.95	18.16	48.41	7.37	2.92	9.67	300	-4.01**	1595.18***
	BM	-0.34	-0.11	-0.01	-0.00	0.02	0.03	0.24	0.54	0.11	1.72	5.70	300	-3.80**	554.04***
Lead (Pb)	*supply*	-0.01	-0.00	-0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.22	-0.74	300	-5.78**	9.26***
	$supply_M$	-0.27	-0.09	-0.02	0.00	0.00	0.03	0.10	0.35	0.06	0.42	7.03	300	-23.41**	626.72***
	HHI	-0.10	-0.06	0.00	0.05	0.05	0.07	0.17	0.23	0.07	0.39	0.89	300	-8.62**	17.51***
	demand	-0.01	-0.01	-0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.05	-1.02	300	-4.80**	13.13***
	$demand_M$	-0.20	-0.08	-0.03	0.00	0.00	0.03	0.09	0.19	0.05	0.15	1.49	300	-24.75**	28.93***
	price	-0.29	-0.10	-0.03	0.01	0.00	0.04	0.11	0.23	0.07	-0.60	2.66	300	-13.88**	106.45***
	VAL	-0.24	-0.11	-0.05	-0.00	0.00	0.04	0.13	0.34	0.08	0.83	2.48	251	-10.69**	93.14***
	MOM	-0.63	-0.24	-0.10	0.01	0.10	0.23	0.72	1.60	0.34	1.49	3.49	300	-3.04**	263.26***
	$FUT1$	-0.30	-0.10	-0.03	0.01	0.00	0.04	0.11	0.23	0.06	-0.67	3.30	300	-13.56**	158.57***
	$FUT2$	-0.30	-0.08	-0.02	0.01	0.00	0.03	0.09	0.25	0.06	-0.61	4.76	300	-13.41**	301.82***
	CY	-10.67	-7.04	-3.71	-1.29	0.75	2.86	17.47	29.42	7.11	1.51	2.22	300	-5.00**	175.61***
	BM	-0.30	-0.08	-0.02	0.00	0.01	0.02	0.15	0.36	0.08	1.02	5.57	300	-4.08**	439.83***

Descriptive Statistics of the Adjusted, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Tin (Sn)	*supply*	-0.03	-0.02	-0.00	0.00	0.00	0.01	0.01	0.01	0.01	-1.40	2.01	300	-7.43**	148.50***
	$supply_M$	-0.32	-0.12	-0.03	0.00	0.00	0.04	0.11	0.22	0.08	-0.61	2.49	300	-21.92**	96.14***
	HHI	-0.20	-0.13	-0.02	0.03	0.01	0.06	0.10	0.14	0.08	-0.89	0.13	300	-5.89**	39.82***
	demand	-0.02	-0.02	-0.00	0.00	0.00	0.00	0.01	0.02	0.01	-0.40	0.82	300	-6.69**	16.41***
	$demand_M$	-0.31	-0.14	-0.04	0.00	0.00	0.04	0.14	0.36	0.09	0.15	2.36	300	-26.39**	70.79***
	price	-0.24	-0.09	-0.03	0.00	0.00	0.03	0.10	0.16	0.06	-0.14	1.40	300	-18.31**	25.48***
	VAL	-0.16	-0.11	-0.04	0.00	-0.00	0.03	0.10	0.29	0.06	0.50	1.66	300	-15.10**	46.94***
	MOM	-0.51	-0.29	-0.09	0.03	0.08	0.19	0.67	1.01	0.28	0.93	0.57	300	-3.68**	47.31***
	$FUT1$	-0.24	-0.09	-0.03	0.00	0.00	0.03	0.10	0.16	0.06	-0.20	1.57	300	-14.24**	32.81***
	$FUT2$	-0.23	-0.08	-0.02	0.00	0.00	0.03	0.10	0.15	0.05	-0.36	2.03	300	-13.20**	57.99***
	CY	-1.97	-1.45	-0.11	1.98	2.63	4.08	9.71	22.42	3.64	1.51	3.42	300	-4.47**	260.21***
	BM	-0.13	-0.06	-0.01	-0.00	0.00	0.01	0.07	0.28	0.05	1.65	8.75	300	-3.79**	1093.16***
Zinc (Zn)	*supply*	-0.01	-0.01	-0.00	0.00	0.00	0.00	0.01	0.01	0.00	-0.24	0.79	300	-6.28**	10.68***
	$supply_M$	-0.20	-0.07	-0.02	0.00	0.00	0.03	0.07	0.19	0.05	0.27	2.89	300	-21.70**	107.80***
	HHI	-0.11	-0.07	0.00	0.04	0.03	0.06	0.13	0.18	0.06	0.09	0.36	300	-7.58**	2.02
	demand	-0.02	-0.01	-0.00	0.00	-0.00	0.00	0.01	0.01	0.01	-0.55	-0.60	300	-5.05**	19.63***
	$demand_M$	-0.33	-0.08	-0.03	0.00	0.00	0.04	0.09	0.24	0.06	-0.61	4.29	300	-23.67**	248.27***
	price	-0.29	-0.10	-0.03	0.00	0.00	0.04	0.09	0.23	0.06	-0.50	2.23	300	-19.74**	74.66***
	VAL	-1.69	-1.32	-0.33	-0.07	-0.14	0.14	0.52	0.65	0.49	-1.12	1.29	300	-2.17*	83.52***
	MOM	-0.55	-0.37	-0.12	0.02	0.09	0.21	0.74	1.78	0.36	1.86	5.19	300	-4.09**	509.68***
	$FUT1$	-0.28	-0.10	-0.03	0.00	0.00	0.04	0.09	0.22	0.06	-0.38	1.89	300	-13.79**	51.87***
	$FUT2$	-0.26	-0.08	-0.02	0.00	0.00	0.03	0.08	0.16	0.05	-0.49	2.32	300	-13.37**	79.28***
	CY	-8.83	-7.86	-4.84	-2.10	-1.02	0.49	8.84	55.34	6.64	3.61	22.63	300	-7.48**	7053.07***
	BM	-0.14	-0.08	-0.02	0.01	0.02	0.03	0.12	0.45	0.07	2.68	11.17	300	-3.55**	1918.73***
Bismuth (Bi)	*supply*	-0.02	-0.01	-0.00	0.00	0.00	0.01	0.02	0.04	0.01	0.85	1.28	300	-4.81**	56.60***
	HHI	-0.09	-0.07	-0.01	0.01	0.05	0.09	0.28	0.39	0.11	1.54	2.16	300	-3.61**	176.90***
	demand	-0.05	-0.05	-0.02	0.00	-0.00	0.01	0.03	0.04	0.02	-0.45	-0.40	300	-4.76**	12.13***
	price	-0.31	-0.10	-0.03	0.00	-0.00	0.02	0.11	0.26	0.07	0.16	3.69	300	-10.57**	171.48***
	VAL	-0.27	-0.11	-0.02	0.00	0.01	0.04	0.13	0.33	0.08	0.12	2.98	235	-7.65**	87.52***
	MOM	-0.62	-0.44	-0.16	0.01	0.06	0.17	0.46	3.15	0.46	3.84	20.34	289	-2.37*	5692.07***
Cadmium (Cd)	*supply*	-0.01	-0.01	-0.00	0.00	0.00	0.00	0.01	0.01	0.01	-0.16	-0.55	300	-9.51**	5.06.
	HHI	-0.05	-0.03	-0.01	0.03	0.04	0.06	0.12	0.28	0.07	1.75	4.23	300	-5.52**	376.79***
	demand	-0.13	-0.09	-0.01	-0.00	-0.01	0.01	0.03	0.04	0.04	-2.26	5.60	300	-5.56**	647.38***
	price	-0.77	-0.21	-0.05	0.00	-0.00	0.02	0.23	0.55	0.13	0.14	6.62	300	-12.12**	548.79***
	VAL	-2.57	-2.04	-1.04	-0.18	-0.12	0.86	1.68	2.49	1.22	0.04	-0.83	237	-1.82.	6.87*
	MOM	-0.78	-0.55	-0.31	-0.03	0.14	0.45	1.36	2.99	0.65	1.66	3.54	290	-3.05**	284.61***
Cobalt (Co)	*supply*	-0.02	-0.01	0.00	0.01	0.01	0.01	0.02	0.02	0.01	-0.38	0.30	300	-6.22**	8.34**
	HHI	-0.33	-0.17	-0.02	0.02	0.04	0.11	0.24	0.25	0.13	-0.47	0.42	300	-8.24**	13.25***
	demand	-0.03	-0.02	-0.00	0.00	-0.00	0.01	0.01	0.03	0.01	-0.24	0.51	300	-8.01**	6.13*
	price	-0.77	-0.16	-0.06	0.00	-0.00	0.06	0.17	0.72	0.13	0.08	8.57	300	-17.61**	918.38***
	VAL	-0.63	-0.20	-0.07	-0.00	-0.00	0.07	0.18	0.85	0.14	0.85	7.35	248	-13.50**	588.10***
	MOM	-0.75	-0.48	-0.23	-0.03	0.10	0.23	1.26	2.21	0.52	1.39	2.00	300	-3.60**	146.60***

Descriptive Statistics of the Adjusted, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Chromium (Cr)	*supply*	-0.02	-0.02	0.00	0.00	0.00	0.01	0.02	0.02	0.01	-0.56	-0.07	300	-6.01**	15.74***
	HHI	-0.17	-0.13	-0.04	0.03	0.00	0.05	0.13	0.14	0.08	-0.27	-0.81	300	-6.27**	11.85***
	demand	-0.14	-0.08	-0.00	0.00	-0.01	0.01	0.04	0.05	0.04	-2.14	5.65	300	-6.61**	628.01***
	price	-0.17	-0.06	-0.02	0.00	0.00	0.01	0.08	0.26	0.05	0.83	5.28	300	-12.41**	382.93***
	VAL	-0.23	-0.09	-0.02	0.00	0.00	0.03	0.08	0.18	0.05	-0.36	2.50	293	-9.42**	82.63***
	MOM	-0.42	-0.29	-0.10	0.04	0.05	0.21	0.38	0.67	0.21	0.08	-0.46	300	-2.89**	2.97
Gallium (Ga)	*supply*	-0.07	-0.01	-0.00	0.00	0.00	0.01	0.02	0.03	0.02	-2.12	7.31	300	-4.13**	892.67***
	HHI	-0.21	-0.14	0.00	0.00	0.05	0.09	0.33	0.44	0.14	0.95	1.20	300	-2.76**	63.12***
	demand	-0.05	-0.04	-0.01	0.01	-0.00	0.01	0.02	0.03	0.02	-1.00	0.36	300	-3.90**	51.62***
	price	-0.30	-0.11	-0.03	0.00	-0.00	0.01	0.11	0.23	0.06	0.20	3.52	213	-9.19**	111.38***
	VAL	-0.22	-0.14	-0.03	0.00	0.01	0.06	0.14	0.38	0.08	0.43	2.69	147	-6.14**	48.85***
	MOM	-0.59	-0.42	-0.20	-0.03	0.04	0.18	0.88	1.40	0.39	1.31	1.89	201	-2.15*	87.41***
Germanium (Ge)	*supply*	-0.03	-0.02	-0.01	0.00	0.00	0.01	0.02	0.04	0.02	0.30	0.46	300	-4.68**	7.14*
	HHI	-0.19	-0.15	-0.02	0.00	-0.01	0.03	0.06	0.20	0.07	-0.09	1.78	300	-5.61**	40.01***
	demand	-0.03	-0.02	-0.00	-0.00	0.00	0.00	0.02	0.04	0.01	1.02	3.06	300	-4.36**	169.06***
	price	-0.27	-0.08	0.00	0.00	0.00	0.00	0.09	0.32	0.06	0.25	6.88	294	-13.73**	582.91***
	VAL	-0.29	-0.10	-0.03	-0.00	-0.00	0.02	0.10	0.25	0.07	-0.11	3.39	228	-11.12**	109.63***
	MOM	-0.49	-0.40	-0.21	-0.02	0.06	0.27	0.71	1.35	0.35	1.04	1.08	282	-2.62**	64.54***
Indium (In)	*supply*	-0.06	-0.02	-0.00	0.00	0.00	0.01	0.03	0.04	0.02	-1.24	4.86	300	-8.30**	372.13***
	HHI	-1.11	-0.19	-0.06	-0.00	-0.03	0.04	0.27	0.44	0.26	-2.67	10.26	300	-8.16**	1672.29***
	demand	-0.02	-0.01	-0.00	0.00	0.00	0.01	0.02	0.03	0.01	0.14	0.26	300	-4.71**	1.83
	price	-0.35	-0.13	-0.04	-0.00	0.00	0.03	0.16	0.50	0.09	1.18	4.64	300	-10.61**	338.74***
	VAL	-0.33	-0.15	-0.05	0.00	0.01	0.06	0.20	0.36	0.11	0.08	1.22	248	-7.39**	15.64***
	MOM	-0.68	-0.53	-0.28	-0.07	0.22	0.32	2.46	4.37	0.91	2.43	5.94	300	-1.96*	736.29***
Lithium(Li)	*supply*	-0.02	-0.02	-0.00	0.01	0.01	0.01	0.02	0.05	0.01	0.77	1.71	300	-6.17**	66.20***
	HHI	-0.35	-0.33	-0.07	0.06	0.03	0.15	0.31	0.32	0.17	-0.47	-0.37	300	-7.12**	12.76***
	demand	-0.09	-0.07	-0.01	0.00	-0.00	0.01	0.03	0.04	0.03	-1.73	3.79	300	-4.32**	329.20***
	price	-0.16	-0.04	0.00	0.00	0.01	0.00	0.07	0.32	0.05	3.24	18.41	275	-9.54**	4364.69***
	VAL	-0.33	-0.09	-0.01	0.00	-0.00	0.02	0.07	0.16	0.06	-2.44	11.51	209	-7.99**	1361.06***
	MOM	-0.36	-0.22	-0.04	0.00	0.11	0.16	0.79	1.60	0.32	2.10	4.98	263	-2.21*	465.08***
Magnesium(Mg)	*supply*	-0.01	-0.01	0.00	0.00	0.00	0.01	0.02	0.02	0.01	0.17	-0.17	300	-7.00**	1.81
	HHI	-0.17	-0.16	-0.01	0.03	0.04	0.06	0.25	0.27	0.11	0.36	-0.13	300	-4.87**	6.69*
	demand	-0.05	-0.03	-0.00	-0.00	-0.00	0.01	0.02	0.02	0.01	-1.75	4.25	300	-5.51**	378.91***
	price	-0.24	-0.08	-0.02	0.00	-0.00	0.01	0.07	0.19	0.05	-0.21	6.54	290	-11.26**	518.96***
	VAL	-1.22	-0.78	-0.36	0.03	-0.04	0.30	0.58	0.82	0.44	-0.47	-0.45	225	-1.83.	10.18***
	MOM	-0.55	-0.29	-0.11	-0.02	0.02	0.11	0.45	1.29	0.27	2.16	7.30	278	-2.66**	833.45***
Manganese (Mn)	*supply*	-0.16	-0.01	-0.00	0.00	-0.00	0.01	0.02	0.02	0.03	-4.19	17.06	300	-6.85**	4515.85***
	HHI	-0.19	-0.17	-0.06	0.04	0.02	0.09	0.16	0.21	0.11	-0.25	-0.84	300	-6.24**	11.94***
	demand	-0.07	-0.03	-0.01	0.00	-0.00	0.01	0.03	0.04	0.02	-1.21	3.01	300	-6.40**	186.46***
	price	-0.34	-0.09	-0.02	0.00	0.00	0.02	0.11	0.43	0.07	1.00	9.61	300	-11.15**	1204.40***
	VAL	-0.44	-0.12	-0.02	-0.00	0.00	0.04	0.11	0.39	0.08	-0.55	6.45	248	-8.54**	442.40***
	MOM	-0.46	-0.31	-0.13	-0.04	0.07	0.18	0.75	2.70	0.39	3.16	14.41	300	-2.87**	3094.88***

Descriptive Statistics of the Adjusted, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Molybdenum (Mo)	*supply*	-0.01	-0.01	-0.00	0.00	0.00	0.01	0.02	0.02	0.01	0.35	-0.52	300	-7.04**	9.50***
	HHI	-0.14	-0.13	-0.03	0.00	0.01	0.06	0.11	0.12	0.07	-0.31	-0.32	300	-5.85**	6.08*
	demand	-0.11	-0.06	-0.01	0.00	-0.00	0.02	0.04	0.04	0.03	-1.51	3.19	300	-5.52**	241.21***
	price	-0.65	-0.18	-0.04	0.00	0.00	0.03	0.18	0.83	0.14	1.07	10.39	300	-15.34**	1406.65***
	VAL	-0.85	-0.17	-0.05	0.00	0.00	0.05	0.18	0.75	0.14	-0.42	10.98	248	-12.32**	1253.08***
	MOM	-0.75	-0.53	-0.16	0.00	0.20	0.31	1.62	4.82	0.74	2.85	11.02	300	-3.83**	1924.13***
Anitmony (Sb)	*supply*	-0.03	-0.03	-0.00	0.00	0.00	0.01	0.02	0.02	0.01	-0.67	0.03	300	-6.81**	22.46***
	HHI	-0.26	-0.15	-0.02	-0.01	-0.01	0.02	0.12	0.17	0.08	-0.70	1.97	300	-5.07**	73.01***
	demand	-0.04	-0.02	-0.01	0.00	-0.00	0.00	0.02	0.03	0.01	-0.27	0.23	300	-6.85**	4.31
	price	-0.29	-0.11	-0.04	0.00	0.00	0.03	0.11	0.35	0.07	0.39	4.09	300	-10.62**	216.71***
	VAL	-0.33	-0.12	-0.03	-0.00	-0.00	0.04	0.12	0.20	0.07	-0.56	2.58	248	-8.29**	81.74***
	MOM	-0.43	-0.34	-0.18	-0.03	0.10	0.26	0.94	2.61	0.44	2.15	6.67	300	-5.29**	787.24***
Titanium (Ti)	*supply*	-0.01	-0.01	-0.00	0.00	0.00	0.00	0.02	0.02	0.01	0.77	1.06	300	-6.90**	43.69***
	HHI	-0.14	-0.12	-0.07	0.00	-0.01	0.03	0.09	0.27	0.09	1.04	2.23	300	-6.19**	116.24***
	demand	-0.05	-0.04	-0.00	0.01	0.00	0.01	0.02	0.03	0.02	-1.05	0.38	300	-4.39**	56.93***
	price	-0.41	-0.07	0.00	0.00	0.00	0.00	0.07	0.82	0.08	5.12	56.81	300	-11.16**	41652.92***
	VAL	-0.81	-0.08	-0.01	0.00	0.00	0.03	0.11	0.41	0.09	-3.78	37.79	248	-9.03**	15347.46***
	MOM	-0.67	-0.24	-0.09	-0.02	0.12	0.07	0.52	4.48	0.71	4.64	22.58	300	-2.83**	7449.68***
Vanadium (V)	*supply*	-0.01	-0.01	-0.00	0.00	0.00	0.01	0.01	0.01	0.01	-0.15	0.19	300	-6.41**	1.58
	HHI	-0.21	-0.12	-0.03	0.01	0.00	0.05	0.10	0.18	0.08	-0.55	0.93	300	-7.04**	25.94***
	demand	-0.48	-0.16	-0.01	0.01	-0.02	0.02	0.04	0.07	0.10	-3.63	13.22	300	-5.84**	2843.45***
	price	-0.57	-0.17	-0.05	-0.00	0.00	0.04	0.21	0.74	0.13	0.49	6.36	300	-11.19**	517.62***
	VAL	-0.73	-0.20	-0.06	0.01	0.00	0.06	0.21	0.58	0.14	-0.34	4.77	248	-9.45**	239.89***
	MOM	-0.77	-0.60	-0.19	0.04	0.22	0.56	1.48	3.99	0.69	2.03	6.68	300	-3.13**	763.82***
Tungsten (W)	*supply*	-0.05	-0.01	-0.00	0.00	0.00	0.01	0.03	0.03	0.01	-1.40	4.83	300	-5.90**	389.61***
	HHI	-0.24	-0.22	-0.04	0.01	0.01	0.06	0.19	0.34	0.12	0.37	1.45	300	-6.65**	33.13***
	demand	-0.02	-0.02	-0.00	0.00	0.00	0.01	0.02	0.03	0.01	0.23	-0.19	300	-5.55**	3.10
	price	-0.34	-0.07	-0.02	0.00	0.01	0.03	0.11	0.34	0.07	0.55	7.83	300	-11.25**	781.49***
	VAL	-0.33	-0.10	-0.02	0.00	0.00	0.04	0.10	0.39	0.08	-0.06	7.17	248	-8.81**	531.37***
	MOM	-0.55	-0.29	-0.09	0.04	0.13	0.21	0.74	2.54	0.41	2.67	10.50	300	-2.57**	1734.57***

This table displays the descriptive statistics minimum (Min), five-percent quantile (Q5), twenty-five percent quantile (Q25), median (Med), mean (Mean), seventy-five quantile (Q75), ninety-five percent quantile (Q95), maximum (Max), the standard deviation (SD), skewness (Skew), and excess kurtosis (Kurt), as well as the number of observations available for each adjusted series and the results of the test statistics of the Augmented Dickey-Fuller test (ADF) and the Jarque-Bera test (JB), with the corresponding significance levels (0.1% (***), 1% (**), 5% (*) and 10% (.)).

Precious Metals: The value factor is only stationary for silver and gold, whereas their prices all show an excess kurtosis. Silver and platinum prices are left skewed, which is in line with the findings of Dinh et al. (2022) and Gargano and Timmermann (2014), while the price of gold shows a positive skewness, as also found by Batten et al. (2016) and Buncic and Moretto (2015). However, non of the precious metals' price series is normally distributed, which is in line with the results of Idilbi-Bayaa and Qadan (2021). While for silver and gold both futures contracts individually show very similar characteristics, with a positive, excess kurtosis, the second futures contract of platinum differs, probably rooted in the shorter time span of data availability and the different maturity (3-month vs. 5-month). In general, for gold and silver all data is available for the entire sample period, while the availability of the value factor, the second futures contract and the basis momentum factor is limited for platinum.

For silver, the supply is increasing over time, almost doubling in the period of the analysis, as does the demand, see Figure C.1. However, the demand peaks in 2010, before entering a phase of a downward trend. The price increases steadily from around $5 to almost $42, with a maximum in the spring of 2011, before decreasing again to around $15-$20, see again Figure C.1. The basis-momentum is more volatile in the first half of the sample, with two comparably large peaks, while it's level drops significantly in and after the financial crisis, starting in 2007. The convenience yield shows a more volatile behavior, compared to the one of gold, while the basis-momentum factor exhibits a huge excess kurtosis.

For gold, the HHI exhibits an artificial peak in 2016, which is rooted in a change of reporting standards.[6] About $\frac{1}{4}$-th of the production of gold is now summarized in *Other countries*, leading to the HHI increase, whereas the production only increased mildly. While the demand is relatively constant over time, with only little fluctuation, the price is steadily increasing and exhibits its maximum in 2011, well after the financial crisis.

In contrast, the demand for platinum is slightly decreasing over time, reaching its minimum in 2010, while the supply is increasing until 2006, with a slight decrease afterwards, see Figure C.3. However, the commodities' decreasing HHI is noteworthy, as this variable is increasing for most of the other commodities. While the price of the commodity is rising sixfold over the period of the analysis, from below $500 to over $2000 per fine oz, it peaks around 2008, with a deep, but very short, plunge afterwards.

Industrial Metals: Within this group, the HHI is only stationary for nickel, while the value factor (VAL) is stationary for aluminum and zinc. Further, we obtain, in addition to the forward-filled supply and demand values, as described in Section 3.4, true monthly supply and demand data from a bespoke report of the World Bureau of Metal Statistics (WBMS), see World Bureau of Metal Statistics (2021). Within Table 3.6 and Table B.1, these are indicated as monthly supply ($supply_M$) and monthly demand ($demand_M$). Hereby, the monthly demand for copper, the HHI of zinc and the both futures prices of nickel are normally distributed, according to the results of the Jarque-Bera test, see Table 3.6.

All prices of the industrial metals are left skewed and show an excess kurtosis, which is in line with the findings of Fernandez (2020), except for lead, where Fernandez (2020) observes right skewed data. Overall, the price series show very similar descriptive statistics, with all prices having a mean and median of almost zero, while also the standard devia-

[6]We correct for this artificial jump in the return series, where we insert the historical mean instead of the actual datapoint for the corrupted datapoint.

tions vary only from 5% for aluminum to 8% for nickel. Further, the set of the industrial metals share the most homogeneous data set, where data is available for the entire period for each attribute of the six metals. While the basis-momentum was relatively volatile before the financial crisis and calm afterwards for all industrials, the momentum factor is the only one showing substantial mean and median differences.

For aluminum, the demand slightly increases over time, while the monthly demand ($demand_M$) is increasing almost simultaneously to the supply and HHI. The price series shows the obvious increase prior to, followed by the deep plunge within, the financial crisis, see Figure C.4. Additionally, the price remains comparably volatile after the financial crisis. For copper, the supply is ever increasing over time, while the HHI reaches its maximum in 2004, decreasing significantly afterwards until 2015. In 2016, we observe a sharp increase, which is again caused by the reporting standards for the country-specific production data, the same as for gold, which is why we apply the identical correction to the return series data. However, the price pattern is different compared to aluminum, increasing from the start of the millennium until the mid 2008, followed by a rapid decrease and another price peak at the end of 2010. The following decline in level is noticeable, as for most of the other metals, but not as large in magnitude. The basis momentum shows an interesting pattern, where it is comparably volatile until the financial crisis in '07 and relatively calm afterwards. Overall, all variables of the commodity show a relatively large excess kurtosis, ranging from 1.6 to 6.7.

For nickel, the demand pattern is very similar to the supply pattern, increasing over time, although not as smoothly as for the other metals. In contrast, the HHI shows no real trend, but is relatively volatile, while the price series has an extreme, but very short peak in 2007, reaching a maximum thirteen-times as high as the minimum value. Afterwards, the price has a few upwards phases, but is generally decreasing. The basis momentum shows a very similar pattern to the corresponding variable for copper, being very volatile before the crisis and calm afterwards. The demand for lead is very similar to nickel, while also supply and HHI are increasing over time, although the monthly supply ($supply_M$) is comparably volatile. The price again shows the regular pattern, with a very narrow peak in 2007, which reaches nine times the value of the minimum. However, the price remained on a plateau afterwards, at around the four times the level from the end of the millennium.

For tin, the supply and demand are comparably volatile, both with a strong upwards trend. However, the two attributes show a synchronous drop during the financial crisis. The shape of the HHI is especially noteworthy, increasing from the start of the analysis period in 1995, with a peak in 2007, and a downward trend afterwards, while the price pattern for tin is also different to the other commodities, with a short peak at the end of 2007, but an even larger increase afterwards, until an overall peak in 2011, followed by a plateau. In contrast, the basis momentum factor shows similar characteristics to the other metals, but the calm period of the co-variate started later. The supply and HHI attributes of zinc follow similar patterns as the ones for lead do, whereas the demand shows a similar pattern to the aluminum demand. The price variable is similar to the other metals, strongly increasing before the short peak in '07, followed by a drop and a new plateau at twice the price level afterwards, compared to pre-crisis values, while it is increasing again towards the end of the sample period.

Minor Metals: For this metal group, the value factor is stationary for cadmium, gallium, and magnesium only. Regarding the microeconomic attributes, only the indium, antimony and tungsten demand, as well as the magnesium and vanadium supply, are normally distributed, according to the results of the Jarque-Bera test. For none of the metals in this group historical data is available over the entire sample period across all covariates. Similar to the price variables of the metals in the other categories, the series show neglectable mean-median differences. However, all price series show an excess kurtosis, ranging from 3.52 for gallium to 56.81 for titanium, indicating the fat-tails of the price distributions, as also found by Dinh et al. (2022) for precious metals and Lutzenberger et al. (2017) for minor metals, which is partly attributable to very tight markets in the period around '05, see Bloomberg (2006), for example. Regarding the skewness, all price series, except magnesium, are right skewed, which is in contrast to the series of the precious and industrial metals, but for most metals in line with the findings of Rossen (2015).

For bismuth, the supply is increasing over time, with a sharp increase in 2004, rooted in a production increase in China, which is also noticeable in the simultaneously increasing HHI. The metals' price shows, compared to the other metals, a prolonged double-peak in 2007, followed by a plateau with comparably volatile prices and two further peaks, at the end of 2010 and the end of 2014, respectively, see Figure C.10. The cadmium demand marks a special case, as it is very volatile, but without a trend, while the corresponding supply is volatile and mildly increasing over time. The HHI is also increasing over time, with a jump in 2008, again originating from a production increase in China, while the commodities' price shows the typical pattern of a short and very pronounced peak in 2007, followed by a reduction to the pre-crisis level afterwards.

For cobalt, the demand increases over time, probably because of the enlarged consumption for renewable energy technologies, see Section 3.1, while at the same time the supply increases relatively steadily, with a jump in 2010. However, the increased production originates from multiple countries, as the HHI is not corresponding in that peak, although the trend is similar. The price shows the regular pattern prior and during the financial crisis, while there is a period of a strong upwards trend starting at the end of 2015 again, caused by a drop in production from the Democratic Republic of Congo, while simultaneously a Canadian company purchased a large quantity of the commodity, further tensioning the market, according to Sethuraman and Soren (2017). For chromium, as for most commodities, the supply and HHI are increasing over time, while also the demand increases, but not as pronounced. The corresponding price slightly decreases over time, with two large peaks, one in 2007 and one in 2018.

The gallium demand is very small in level, as also the case for indium, but is rather volatile, with two large peaks. The metal's supply is closely synchronized with the HHI, at a low level during the beginning of the sample period, while there is a sharp increase in both variables from 2009 onward, whereas the price series has a delayed start with a peak in late 2010 to early 2011. For germanium, supply is volatile, with a strong upward trend, while the HHI shows a slightly negative trend with a large plateau from 2004 to 2008. This is artificial, as data availability for the metal's production are very limited in this period, where only the three largest producers, the United States of America, Russia and China reported figures, which is why we again correct for the two corrupted data points, as was the case for gold and copper. However, the price characteristics are very different from those of the other metals, showing lower fluctuations compared to the other prices and a downward trend since the beginning of the sample, see Figure C.15. Although price peaks around 2007 and 2010 are present, they are not as pronounced in magnitude, while the second one is also comparably long lasting.

Indium demand increases steadily over time, with a slight downward movement from 2006 to 2013 and a subsequent increase, consistent with supply and the HHI, while the latter two variables show a synchronous upward jump in 2000 and 2005. The price of the metal has a different pattern, with a short decreasing period, followed by a price boom maxing out in 2003/2004, which is relatively long lasting, with a plateau that contains two further price peaks afterwards. However, the financial crisis is not visible as clearly as for other prices, see Figure C.16. The magnesium demand shows a slightly decreasing, fluctuating trend, while supply and HHI increase steadily over time. The price follows the classic pattern with a decline in the first part of the sample, followed by a small peak in '03-'04, before rising sharply in 2007 and remaining at a high level thereafter.

Manganese production shows a steady upwards trend, while the corresponding HHI shows a similar pattern, but with an artificial decline in 2016, again due to reporting standards, while the price shows a very short double peak during the financial crisis and a subsequent plateau. We again correct for the corrupted data point in HHI timeseries in 2016, as we did for gold, copper and germanium. For molybdenum, supply has been steadily increasing over time, with a plateau since 2014, while the HHI, in contrast, shows a U-shape, declining until 2003/2004 and increasing thereafter. The metal's price shows a double peak, where both peaks of the series are earlier than for the other metals, with the second one prolonging much further and a slightly elevated plateau after the peaks.

Demand for antimony is constant over the period of the analysis, while the corresponding supply fluctuates with no substantial trend. The HHI is almost constant at the beginning, but declines from 2009 onward, due to the drop in production in China, which is compensated for by several countries, such as Russia and Tajikistan. The price increases over time, with little to no peaks during the financial crisis, but a sharp price increase around 2011, which was caused by production interruptions in China, see U.S. Geological Survey (2019), followed by a subsequent decline. For titanium, demand increases slightly over time, but is also relatively volatile, while the metal's supply is steadily increasing, with a jump in 2017, whereas the HHI is declining over time. The corresponding price has the typical, quite high, peak during the crisis, followed by a slight plateau afterwards.

Vanadium demand is trending upwards, similar to the supply and HHI of the metal, while the price, in contrast, has a W-shaped pattern with three peaks. Here, the first peak is in 2005, followed by a smaller peak in 2008 and another major peak in 2019. For tungsten, supply is in a continuous upwards trend, with a large peak in 2005 and 2006, while the HHI is very closely related to supply. However, the price is different from most other commodities, where it starts to increase significantly in 2005 and maintains this trend, with some minor corrections, until 2012, followed by a larger correction, whereas it remains on a high plateau afterwards, see Figure C.24.

Table 3.7: Descriptive Statistics of the Adjusted, General Metal Price Determinants

	Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
$SIR_{U.S.}$	0.11	0.13	0.44	2.04	2.69	5.31	6.05	6.73	2.24	0.33	-1.51	300	-1.92*	33.95***
SIR_{China}	0.01	0.02	0.03	0.04	0.05	0.05	0.12	0.13	0.03	1.70	2.48	288	-2.39*	212.52***
$LIR_{U.S.}$	1.50	1.76	2.54	3.97	3.96	5.11	6.53	7.78	1.56	0.24	-1.04	300	-2.25*	16.40***
LIR_{China}	-0.17	-0.06	-0.03	-0.00	0.00	0.03	0.08	0.18	0.05	0.29	1.92	211	-13.45**	35.37***
$T10Y3M$	-4.29	-0.66	-0.13	-0.02	0.03	0.11	0.70	8.00	0.98	3.72	33.93	300	-18.80**	15082.48***
FFR	0.07	0.09	0.18	1.75	2.50	5.20	5.85	6.54	2.25	0.37	-1.50	300	-1.94*	34.97***
$WuXia$	-2.99	-1.97	-0.19	1.65	2.05	5.02	5.85	6.65	2.69	0.00	-1.27	300	-2.08*	20.16***
MB	-0.09	-0.02	-0.00	0.00	0.01	0.01	0.04	0.24	0.03	4.09	31.12	300	-8.74**	12942.09***
$WALCL$	-0.09	-0.01	-0.00	0.00	0.01	0.01	0.03	0.54	0.04	9.28	106.55	205	-8.05**	99915.09***
$M4$	-0.01	-0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.00	-0.15	3.65	300	-9.39**	167.66***
$T5YIFR$	-0.73	-0.07	-0.03	0.00	0.00	0.03	0.09	0.64	0.09	-0.47	34.44	204	-17.70**	10089.48***
FX	-0.05	-0.03	-0.01	0.00	0.00	0.01	0.03	0.06	0.02	-0.12	0.25	300	-12.61**	1.50
$IP_{U.S.}$	-0.05	-0.03	-0.01	-0.00	0.00	0.01	0.03	0.05	0.02	0.12	0.51	300	-28.18**	3.97
IP_{World}	-0.10	-0.07	-0.03	-0.00	0.00	0.03	0.09	0.12	0.05	0.23	-0.22	300	-25.52**	3.25
IP_{China}	-0.14	-0.03	-0.01	-0.00	-0.00	0.01	0.03	0.15	0.03	-0.19	12.96	272	-27.76**	1905.20***
GDP	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	-1.81	5.74	300	-2.16*	575.65***
$EAKilian$	-162.97	-84.08	-43.54	-8.34	4.07	40.38	127.66	188.20	66.62	0.66	0.09	300	-2.42*	21.88***
BDI	-1.33	-0.34	-0.11	0.01	0.00	0.12	0.33	0.67	0.23	-1.13	5.46	246	-13.39**	357.92***
CPI	-1.92	-0.34	0.00	0.19	0.18	0.40	0.68	1.22	0.34	-0.90	4.81	300	-8.79**	329.70***

Descriptive Statistics of the Adjusted, General Metal Price Determinants

	Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
OIL	-0.34	-0.14	-0.05	0.02	0.00	0.06	0.12	0.22	0.08	-0.75	1.51	300	-13.16**	56.63***
BCOM	-0.22	-0.06	-0.01	0.01	0.01	0.03	0.05	0.11	0.04	-1.38	5.85	300	-13.31**	523.00***
RICIM	-0.22	-0.06	-0.02	0.01	0.00	0.03	0.06	0.13	0.04	-0.69	3.63	300	-12.26**	188.52***
MSCIW	-0.25	-0.06	-0.01	0.01	0.00	0.03	0.05	0.12	0.04	-1.49	7.54	300	-12.95**	821.65***
SPX	-0.19	-0.07	-0.02	0.01	0.01	0.03	0.07	0.10	0.04	-0.89	1.74	300	-16.02**	77.45***

This table displays the descriptive statistics minimum (Min), the five-percent quantile (Q5), the twenty-five percent quantile (Q25), the median (Med), the mean (Mean), the seventy-five quantile (Q75), the ninety-five percent quantile (Q95), the maximum (Max), as well as the standard deviation (SD), the skewness (Skew) and the excess kurtosis (Kurt), as well as the number of observations available for each adjusted series and the results of the test statistics of the Augmented Dickey-Fuller test (ADF) and the Jarque-Bera test (JB), with the corresponding significance levels (0.1% (***), 1% (**), 5% (*) and 10% (.)).

General Determinants: Turning our attention to the characteristics of the general metal price determinants, as displayed in Table 3.7 for the return data and Table B.2 for the level data, we observe the Chinese short-term interest rate, the U.S. long-term interest rate, as well as the federal funds rate and the shadow federal funds rate of WuXia are stationary in level. Additionally, the economic activity index of Kilian and the U.S. consumer price index are stationary in level as well, while, again based on level data, the U.S. GDP variable follows a normal distribution. For the return data, the U.S. Dollar index, the U.S. as well as the world industrial production are normally distributed, which is in contrast to the findings of Lutzenberger et al. (2017), but in line with Bakas and Triantafyllou (2018). All interest rates show a positive skewness, except the shadow rate with a skewness close to zero. This is in line with theory, as regular interest rates are constrained at the zero lower bound, while the shadow rates are constructed specifically to bypass this constraint. The short- and long-term rates of China, as well as the term spread, show an excess kurtosis. Moreover, all three U.S. short-term interest rates, the 3-month interest rate, the federal funds rate, and the WuXia shadow interest rate have comparatively large mean-median differences, further underlining the non-normality of their distributions, while they are also more volatile, compared to the long-term rates.

For the monetary aggregates, the monetary base and the balance sheet size of the FED show a large positive skewness, as well as a huge excess kurtosis. This can be easily explained by the plots within Figure D.1, where both variables show a strong upwards trend, indicated also by a positive mean in the return data, as seen in Table 3.7. Further, the large scale asset purchasing programs of the FED caused a level shift in both variables at the time of the purchases, explaining the large excess kurtosis. The inflation expectation index shows a large positive skewness as well, as also observable by a mean above the median.

The U.S. Dollar index is, from a descriptive statistics point of view, similar to the interest rates, but with a substantially smaller skewness and excess kurtosis, making it one of the few variables following a normal distribution. While the U.S. industrial production and the world industrial production show, at least for the descriptive statistics, similar patterns, the Chinese variable again differs substantially.

Regarding the readability of differences, the fluctuations in the U.S. gross domestic product index are smaller than one percent, making them invisible in classic descriptive statistics, whereas a comparison between the Baltic dry index and the economic activity index of Kilian is difficult as well, since the economic activity index is among the few variables that are stationary in level. However, the Baltic dry index is among the most volatile variables in the analysis, which is in line with the findings of Buncic and Moretto (2015).

The oil price, as well as all of the commodity- and financial market indices are left skewed, in concordance with an excess kurtosis, while Al-Yahyaee et al. (2019) detect a skewness close to zero, based on weekly data. Additionally, the oil price is more volatile than the commodity indices, which is in accordance with Pierdzioch et al. (2016). While the RICI metals index follows, in level, a similar pattern as the industrial metals do, the Bloomberg commodity index' shape is in close proximity to the oil price, rooted in the respective components of the index, where around 30% originate from the energy sector.

3.6 Connection Channels of Industrial Metal Markets

As outlined in Section 2.4, commodity prices tend to move synchronously. Therefore, Section 4.4 outlines our application of the global vector autoregressive model of Pesaran et al. (2004) to commodity markets. Initially, the model is constructed to represent multiple economies individually, while accounting for the interdependencies and influences among each other. Therefore, the economies are connected by so-called weight matrices, which in turn contain the trade weights between the countries, representing their relationships. However, for the industrial metals markets, to which we apply the model, we represent their relationships through several weight matrices based on the relationship channels outlined in Section 2.4, based on the setup proposed in Schischke et al. (2021). First, we represent the co-production of metals through information on their supply concentration, see also Section 3.2:

$$w_{i,\tilde{\imath}} = \sum_{r=1}^{R} prod_{r,i} \cdot prod_{r,\tilde{\imath}} . \forall i, \tilde{\imath} = 1, \ldots, N, \; i \neq \tilde{\imath}. \tag{3.15}$$

Hereby, $w_{i,\tilde{\imath}}$ denotes the relation between metal i and $\tilde{\imath}$, whereas $prod_{r,i}$ represents the per-country share of the annual world production, for country $r = 1, \ldots, R$ and metal i, respectively. The production data is the averaged, primary production over the period from 2010 to 2019, and again obtained from U.S. Geological Survey (2019).[7]

Table 3.8: Information Matrix on the Co-Production of Industrial Metals

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.05	0.04	0.24	0.17	0.19
Cu	0.05	1.00	0.02	0.06	0.05	0.06
Ni	0.04	0.02	1.00	0.04	0.06	0.03
Pb	0.24	0.06	0.04	1.00	0.16	0.19
Sn	0.17	0.05	0.06	0.16	1.00	0.13
Zn	0.19	0.06	0.03	0.19	0.13	1.00

This table shows the information matrix on the co-production of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn).

Second, we relate the metals through the industry sectors in which they are consumed, approximating the economy by the sectors: *Automotive/Transportation*, *Chemistry/Pharmaceutics*, *Electrics*, *Construction*, and *Mechanical Engineering*. In total, these sectors account for up to 90% of industrial metal demand, where the respective consumption data for the industry sectors is obtained from Brandtzæg (2018) and Leder (2020), while we assume the consumption to be time-invariant.

For each of the six industrial metals, we display the corresponding information of the consumption in Table 3.9 to Table 3.14. However, not all applications can be allocated to the five industry sectors. For this reason, aluminum consumption in the *Foil*, *Packaging*, *Consumer Goods*, and *Other* sector is neglected from further calculations, where we assume the consumption in these sectors is zero. Overall, aluminum in mainly used in the transportation sector due to its high strength and low weight, while it is additionally consumed in the construction sector, with the consumption data of aluminum being provided by Brandtzæg (2018) and displayed in Table 3.9.

For the demand for copper, displayed in Table 3.10, we are unable to assign the consumption for *Trade* and *Other* to the five industry sectors, and hence exclude them from further calculations. As already the case for aluminum, copper is not consumed in the *Chemistry/Pharmaceutics* sector, whereas the main application, consuming over 50% of the commodity, is in *Cables and Electrics*, which we allocate to the *Electrics* sector.

The main application of nickel, displayed in Table 3.11, is as a component of stainless steel, see also Section 3.1. As stainless steel is end-used in a wide range of applications, we equally allocate the consumption for stainless steel to the sectors *Automotive/Transportation*, *Construction*, and *Mechanical Engineering*, see Table 3.15. However, we are unable to relate the consumption for *Nickel alloys*, *Platings*, *Steel refiner*,

[7]While the construction of the supply-sided information matrix based on the extracted amounts per metal and individual mining project would be desirable, as outlined within Section 3.2, the data unavailability for tin mining operations requires the application of the country-specific production data.

Table 3.9: Consumption per Application - Aluminum

Industry	%
Automotive/Transportation	26.00
Construction Industry	24.00
Mechanical and Plant Engineering	11.00
Electrical Engineering	11.00
Foil	8.00
Packaging	8.00
Consumer Goods	6.00
Other	6.00

This table displays the proportion of aluminum (Al) consumption per application.

Table 3.10: Consumption per Application - Copper

Industry	%
Cables and Electrics	57.00
Construction Industry	15.00
Automotive	9.00
Mechanical Engineering	8.00
Trade	5.00
Other	6.00

This table displays the proportion of copper (Cu) consumption per application.

Table 3.11: Consumption per Application - Nickel

Industry	%
Stainless steel	57.00
Nickel Alloys	13.00
Platings	11.00
Steel Refiner	9.00
Foundries	6.00
Other	9.00

This table displays the proportion of nickel (Ni) consumption per application.

Table 3.12: Consumption per Application - Lead

Industry	%
Electrical Engineering (Lead-acid Batteries)	74.00
Construction (Roof, Facade)	6.00
Plant Construction (Radiation Prot., Anodes)	6.00
Chemistry (Pigments)	5.00
Other (Alloys, Cable Sheath, Glass)	9.00

This table displays the proportion of lead (Pb) consumption per application.

Table 3.13: Consumption per Application - Tin

Industry	%
Electronics Industry (Solder)	52.00
Chemical Industry (PVC Stabilizer)	15.00
Packaging (Tinplate)	16.00
Brass Bronze	6.00
Float Glass	2.00
Other	9.00

This table displays the proportion of tin (Sn) consumption per application.

Table 3.14: Consumption per Application - Zinc

Industry	%
Automotive Engineering (Galvanizing)	50.00
Construction (Zinc, Brass Products)	23.00
Chemistry / Pharmaceutics	6.00
Other (Zinc Casting Alloys)	21.00

This table displays the proportion of zinc (Zn) consumption per application.

Foundries, and *Other* to specific industry sectors, which is why we again exclude these consumption shares from further calculations.

As with copper, the main use of lead, displayed in Table 3.12, is within the *Electrics* sector, where almost three quarters of the metal are used for lead-acid batteries. It is additionally consumed in almost all remaining sectors, while the corresponding data is again obtained from Leder (2020).

In addition, tin is mainly used for solder, see Table 3.13, which in turn means more than 50% of the metal's consumption can be allocated to the *Electrics* sector, while the consumption for *Brass Bronze*, *Float Glass*, *Packaging (Tinplate)*, and *Other* cannot be allocated to any of the five industry sectors displayed in Table 3.15.

As shown in Table 3.14, zinc in mainly used for galvanizing processes within the *Automotive/Transportation* sector, while it is additionally also consumed in the *Construction* and the *Chemistry/Pharmaceutics* sector, but to a lesser extent.

We map the metal-specific consumption data of Table 3.9 to Table 3.14 to the five industry sectors considered in our analysis, as shown in Table 3.15.

Table 3.15: Matching of Metal Applications with Industry Sectors

	Automotive/ Transportation	Chemistry/ Pharmaceutics	Electrics	Construction	Mechanical Engineering
Al	Automotive/ Transportation		Electrical Engineering	Construction Industry	Mechanical and Plant Engineering
Cu	Automotive		Cables and Electrics	Construction Industry	Mechanical Engineering
Ni	Stainless Steel		Electrical Engineering	Stainless Steel	Stainless Steel
Pb		Chemistry	Electrical Engineering & Other	Construction	Plant Construction
Sn		Chemical Industry	Electronics Industry		
Zn	Automotive Engineering	Chemistry/ Pharmaceutics		Construction	

This table displays the mapping of the applications of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn) to the five industry sectors *Automotive/Transportation*, *Chemistry/Pharmaceutics*, *Electrics*, *Construction*, and *Mechanical Engineering*.

This results in a measure of metal consumption per sector, as displayed in Table 3.16.

Table 3.16: Consumption of Metals per Industry Sector

Industry	Al	Cu	Ni	Pb	Sn	Zn
Automotive/Transportation	0.36	0.10	0.32	0.00	0.00	0.63
Chemistry/Pharmaceutics	0.00	0.00	0.00	0.05	0.22	0.08
Electrics	0.15	0.64	0.05	0.83	0.78	0.00
Construction	0.33	0.17	0.32	0.06	0.00	0.29
Mechanical Engineering	0.15	0.09	0.32	0.06	0.00	0.00

This table displays the consumption of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn) in the industry sectors *Automotive/Transportation*, *Chemistry/Pharmaceutics*, *Electrics*, *Construction*, and *Mechanical Engineering*.

Using the consumption data from Table 3.16, we are able to construct a demand-side information matrix, as displayed in Table 3.17, via:

$$\omega_{i,\tilde{\iota}} = \sum_h ind_{h,i} \cdot ind_{h,\tilde{\iota}}. \text{ for } i, \tilde{\iota} = 1, \ldots, N,\ i \neq \tilde{\iota}. \quad (3.16)$$

Hereby, $\omega_{i,\tilde{\iota}}$ represents the relationship between metal i and metal $\tilde{\iota}$, whereas $ind_{h,i}$ shows the share of metal i consumed in industry sector $h = \{$Automotive/ Transportation, Chemistry/Pharmaceutics, Electrics, Construction, Mechanical Engineering$\}$.

Table 3.17: Information Matrix on Co-Consumption of Industrial Metals

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.20	0.27	0.15	0.12	0.33
Cu	0.20	1.00	0.15	0.55	0.50	0.11
Ni	0.28	0.15	1.00	0.08	0.04	0.29
Pb	0.16	0.55	0.08	1.00	0.66	0.02
Sn	0.12	0.50	0.04	0.66	1.00	0.02
Zn	0.33	0.11	0.29	0.02	0.02	1.00

This table displays the information matrix on the co-consumption of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn), approximated over the five industry sectors Automotive/Transportation, Chemistry/Pharmaceutics, Electrics, Construction and Mechanical Engineering.

Third, to represent the degree of co-movement that results from common trading behavior on commodity exchanges, we relate the averaged futures trading volumes from two of the biggest commodity exchanges, the London Metal Exchange and Shanghai Futures Exchange, in the period from 2010 to 2019 (see Table 3.18), via their respective Pearson correlation coefficient.

Table 3.18: Information Matrix on Co-Trading of Industrial Metals

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.07	0.85	0.87	0.72	0.25
Cu	0.07	1.00	-0.05	0.13	-0.05	-0.51
Ni	0.85	-0.05	1.00	0.64	0.75	0.41
Pb	0.87	0.13	0.64	1.00	0.54	-0.01
Sn	0.72	-0.05	0.75	0.54	1.00	0.10
Zn	0.25	-0.51	0.41	-0.01	0.10	1.00

This table displays the Pearson correlation between the aggregated first futures trading volumes of the industrial metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn), from the London Metal Exchange (LME) and Shanghai Futures Exchange (SHFE), calculated over the period of 2010 to 2019.

The GVAR model, as outlined in Section 4.4, requires the weight matrices linking the individual models to have row sums of one, so we scale the information matrices displayed in Table 3.8, Table 3.17, and Table 3.18 accordingly. The final weight matrices are displayed in Table 3.19, Table 3.20 and Table 3.21, which represent the common supply (**S**), demand (**D**) and trading (**T**) channel. Further, all three of the above listed channels are active simultaneously, which is why we construct a fourth, common weight matrix (**C**), as displayed in Table 3.22, by equally weighing the supply, demand and trading matrices.

Table 3.19: Weight Matrix Supply

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.08	0.06	0.34	0.25	0.27
Cu	0.21	0.00	0.10	0.26	0.19	0.24
Ni	0.19	0.12	0.00	0.21	0.32	0.16
Pb	0.34	0.09	0.06	0.00	0.23	0.28
Sn	0.30	0.08	0.11	0.28	0.00	0.23
Zn	0.32	0.10	0.05	0.32	0.22	0.00

This table displays the supply weight matrix (**S**) for the metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn).

Table 3.20: Weight Matrix Demand

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.19	0.26	0.14	0.11	0.30
Cu	0.14	0.00	0.10	0.36	0.33	0.08
Ni	0.33	0.18	0.00	0.10	0.05	0.35
Pb	0.11	0.37	0.05	0.00	0.45	0.01
Sn	0.09	0.37	0.03	0.49	0.00	0.01
Zn	0.42	0.15	0.38	0.03	0.03	0.00

This table displays the demand weight matrix (**D**) for the metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn).

Table 3.21: Weight Matrix Trading

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.02	0.31	0.31	0.26	0.09
Cu	0.08	0.00	0.06	0.16	0.07	0.63
Ni	0.32	0.02	0.00	0.24	0.28	0.15
Pb	0.40	0.06	0.29	0.00	0.25	0.01
Sn	0.33	0.02	0.35	0.25	0.00	0.05
Zn	0.20	0.39	0.32	0.01	0.08	0.00

This table displays the trading weight matrix (**T**) for the metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn).

Table 3.22: Weight Matrix Common

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.10	0.21	0.26	0.21	0.22
Cu	0.14	0.00	0.09	0.26	0.20	0.32
Ni	0.28	0.11	0.00	0.18	0.22	0.22
Pb	0.28	0.17	0.13	0.00	0.31	0.10
Sn	0.24	0.16	0.16	0.34	0.00	0.10
Zn	0.31	0.21	0.25	0.12	0.11	0.00

This table displays the common weight matrix (**C**) for the metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn).

4 Methodology

In this chapter, we start with the introduction of linear regression models, used to model and forecast metal prices in this thesis, followed by the introduction of various goodness of fit measures, as well as a test for the predictive accuracy of linear models. Subsequently, we change the perspective of the analysis slightly and explain a vector autoregressive (VAR) model, used to model the metal's dependencies with economic conditions. Hereby, we consider a metal index as a general measure of metal markets. As we hypothesize a change in the relation between metals and macroeconomic conditions, in particular interest rates, in the empirical section of this thesis, we further introduce the F-test framework of Zeileis et al. (2002), which is based on multiple iterations of the F-test introduced by Chow (1960) and constructed to detect the point in time of structural breaks in the relations of linear models. Further, we explain three types of Impulse Response Functions (IRF), the regular, orthogonalizied and generalized impulse response functions, used to analyze and visualize the relations between the variables in VAR models. Subsequently, we introduce a novel framework to jointly model multiple metal markets. The framework is based on the global vector autoregressive model (GVAR), introduced by Pesaran et al. (2004) to model the worldwide economy. We transpose the idea to metal markets, to be able to consider metal-specific attributes, such as metal-specific supply and demand, while simultaneously accounting for the interrelations between the individual metal markets.

4.1 Linear Regression

The following section is based on the setup proposed in Papenfuß et al. (2021). Initially, we model the price $\mathsf{y}_{i,t}$ of metal $i = 1, \ldots, N$ at time $t = 1, \ldots, T$ by the $k = 1, \ldots, K_i$ metal-specific covariates $\mathsf{x}_{i,1}, \ldots, \mathsf{x}_{i,K_i}$, via an OLS based, multivariate linear regression model, defined as:

$$\mathsf{y}_{i,t} = \beta_{i,0} + \beta_{i,1}\mathsf{x}_{i,1,t} + \ldots + \beta_{i,K_i}\mathsf{x}_{i,K_i,t} + \varepsilon_{i,t}, \tag{4.1}$$

where $\beta_{i,0}$ denotes the intercept, $\beta_{i,1}, \ldots, \beta_{i,K_i}$ are the coefficients corresponding to the K_i metal-specific covariates and $\varepsilon_{i,t}$ is the error term.

Besides the identification of metal price determinants, we additionally aim to forecast metal prices. Therefore, we again model the influence of the K_i metal-specific covariates

$\mathsf{x}_{i,1}, \ldots, \mathsf{x}_{i,K_i}$ via a multivariate regression model, but on a leading price series. Hereby, the covariates at time t are hypothesized to forecast the prices at time $t+1$:

$$\mathsf{y}_{i,t+1} = \beta_{i,0} + \beta_{i,1}\mathsf{x}_{i,1,t} + \ldots + \beta_{i,K_i}\mathsf{x}_{i,K_i,t} + \varepsilon_{i,t}, \tag{4.2}$$

where the $\beta_{i,k}$ coefficients and the error-term $\varepsilon_{i,t}$ are defined as above.

To enhance the estimation quality of the $\beta_{i,k}$ parameters, a sparse selection of covariates is essential, given a limited number of observations, which is why we apply a two-stage model selection procedure, individually for the price determinants as well as the forecasting factors. As the regression models described in Equation 4.1 and Equation 4.2 model the linear relation between the covariates and the price variable, we exclude all covariates with a Pearson correlation coefficient smaller than 15%, measured in absolute terms, in the first stage of our model selection. The second step of our model selection is performed on the regression Equation 4.1 and Equation 4.2. In contrast to the standard forward (backward) model selection procedures, where covariates are iteratively added (excluded) from the model, we apply our model selection on the complete enumeration of the possible covariates combinations. This ensures the ideal set of metal-specific covariates is selected, while we exclude parameter combinations suffering from multicollinearity, indicated by a variance inflation factor (VIF) above four, for one or more variables. Hereby, the Bayesian information criterion (BIC), used to determine a models goodness of fit to the price data, is defined as:

$$BIC_i = K_i \ln(T) - 2\ln(\hat{L}_i), \tag{4.3}$$

where T denotes the number of historical data points used in the model estimation of Equation 4.1 or Equation 4.2 and $\hat{L}_i$ represents the corresponding likelihood function. The first part of Equation 4.3 penalizes the number of covariates K_i included in the model, to ensure sound estimates for the coefficients. Hereby, the number of covariates K_i is weighted by the number of observation points T the model is estimated on, while the second part of the equation measures the model's goodness of fit. A larger BIC_i, in absolute values, indicates a better model. Overall, this leads to the desired, sparse selection of influential covariates.

In addition to the BIC_i criterion described above, we introduce further goodness of fit measures. As the predictive abilities of a model should be analyzed on a data set that is assumed to be unknown at the time of the model estimation, we first split our data set in an in-sample and out-of sample part. Subsequently, various goodness of fit measures can be used to analyze how well the model forecasted the (unknown) actual data points. When analyzing the predictors and their influence on metal prices, we split our data set with observations $t = 1, \ldots, T$ into an in-sample set with observations $t = 1, \ldots, \mathsf{Q}$ and the out-of-sample set, which is assumed to be unknown, with observations $t = \mathsf{Q}+1, \ldots, \mathsf{Q}+\mathsf{P} =$

$\mathsf{Q}+1,\ldots,T$, where in the empirical section we apply $\mathsf{Q}/(\mathsf{Q}+\mathsf{P}) = 3/4$.

Subsequently, the model selection for Equation 4.2 is performed on the initial in-sample window. Knowing the best input variables for each metal, we can forecast the returns one-step ahead by a rolling window procedure. In particular, for each time in the out-of-sample set $\tau = 1,\ldots,\mathsf{P}-1$, which corresponds to $t = \mathsf{Q}+1,\ldots,\mathsf{Q}+\mathsf{P}-1$, we estimate the parameters of the linear regression model in Equation 4.2 via OLS, using the covariates $\mathsf{x}_{i,1},\ldots,\mathsf{x}_{i,K_i}$ specified by the model selection, with observations in the set $\tau,\ldots,Q+\tau-2$. Given the estimators of the parameters $\hat{\beta}_{i,0,t},\hat{\beta}_{i,1,t},\ldots,\hat{\beta}_{i,K_i,t}$, we predict the return $\hat{\mathsf{y}}_{i,\tau}$ of metal $i = 1,\ldots,N$ in period τ, using the values of the covariates $\mathsf{x}_{i,1,Q+\tau-1},\ldots,\mathsf{x}_{i,K_i,Q+\tau-1}$.

To assess the accuracy of our resulting models and predictions, we rely on multiple goodness of fit measures. First, as standard in the regression literature, we use the adjusted coefficient of determination $\mathcal{R}^2_{i,adj}$. The *regular* $\mathcal{R}^2_i$ is defined as:

$$\mathcal{R}^2_i = \frac{SSE_i}{SST_i} = \frac{\sum(\hat{\mathsf{y}}_{i,t}-\bar{\mathsf{y}}_i)^2}{\sum(\mathsf{y}_{i,t}-\bar{\mathsf{y}}_i)^2}, \tag{4.4}$$

where SSE_i denotes the explained sum of squares and SST_i the total sum of squares of the model. The $\mathcal{R}^2_i$ therefore measures the proportion of data variation that is captured by the model. Naturally, the values of $\mathcal{R}^2_i$ are constrained, as the model could in the best (worst) case explain all (none) of the data variation. Hence, $\mathcal{R}^2_i \in [0,1]$. However, the coefficient is naturally increasing with the number of parameters included in the model, as the inclusion of additional covariates contributes to the SSE_i via each variables' noise, boosting the $\mathcal{R}^2_i$ value. Therefore, we use the adjusted coefficient of determination $\mathcal{R}^2_{i,adj}$, which, similar to the BIC described in Equation 4.3, penalizes the number of covariates included in the model:

$$\mathcal{R}^2_{i,adj} = 1-(1-\mathcal{R}^2_i)\frac{\mathsf{Q}-1}{\mathsf{Q}-K_i}, \tag{4.5}$$

with Q as the length of the in-sample window, indicating the number of data points the model is fitted on and K_i representing the number of covariates. This allows for a more accurate comparison of models with a differing number of covariates. However, even if Equation 4.5 is calculated based on Equation 4.2, the goodness of fit is an in-sample measure, which could occur spuriously and does not necessarily indicate true forecastability of prices. Hence, we introduce further goodness of fit measures, which are calculated only on our out-of sample predictions. The Mean Absolute Prediction Error (MAPE) and Mean Squared Prediction Error (MSPE) measure the mean absolute and squared deviation of our forecast from the observed data and are defined as:

$$MAPE_i = \mathsf{P}^{-1} \sum_{t=\mathsf{Q}}^{T-1} |\mathsf{y}_{i,t+1} - \hat{\mathsf{y}}_{i,t+1}|, \tag{4.6}$$

$$MSPE_i = \mathsf{P}^{-1} \sum_{t=\mathsf{Q}}^{T-1} (\mathsf{y}_{i,t+1} - \hat{\mathsf{y}}_{i,t+1})^2, \tag{4.7}$$

where small $MAPE_i$ and $MSPE_i$ values indicate a good forecast of the underlying data.

As the forecastability of data is potentially influenced by many circumstances and sometimes data characteristics, such as cyclical market behavior, predictive performance is generally measured in comparison to some benchmark model by the above mentioned goodness of fit measures. Therefore, we introduce two possible benchmark models. First, the no-change benchmark, which assumes today's price is equal to yesterdays price. As our data, at least the prices variables, are expressed in log-returns, this is equivalent to a random walk (rw) benchmark:

$$\mathsf{y}^{rw}_{i,t+1} = \varepsilon_{i,t+1}, \tag{4.8}$$

with $\mathbb{E}\left[\mathsf{y}^{rw}_{i,t+1}\right] = \mathbb{E}\left[\varepsilon_{i,t+1}\right] = 0$. Further, we use the historical mean of returns as our second benchmark model, which is a random walk with drift (rwd):

$$\mathsf{y}^{rwd}_{i,t+1} = \beta_{i,0} + \varepsilon_{i,t+1}. \tag{4.9}$$

Hereby, $\mathbb{E}\left[\mathsf{y}^{rwd}_{i,t+1}\right] = \mathbb{E}\left[\beta_{i,0} + \varepsilon_{i,t+1}\right] = \mathbb{E}\left[\beta_{i,0}\right] = \beta_{i,0}$ holds. Equal to our forecasting model, we estimate the benchmark models of Equation 4.8 and Equation 4.9 by OLS, using the observations $\mathsf{y}_\tau, \ldots, \mathsf{y}_{Q+\tau-1}$ for $\tau = 1, \ldots, \mathsf{P}-1$, so on the same data that our forecasting model is fitted on, for our benchmark predictions $\hat{\mathsf{y}}^{BMK}_{i,t+1}$.

In line with various studies in the literature, see Groen and Pesenti (2011), Issler et al. (2014) and Fernandez (2020) for example, we subsequently apply the Clark and West (2007) test to determine the significance of the outperformance of our forecasts. Hereby, we benefit from the fact that our benchmark models of Equation 4.8 and Equation 4.9 are nested to our forecast model, displayed in Equation 4.2. That means, the benchmark models are subset versions of the forecasting model, with fewer (no) covariates and estimated parameters. However, the additional parameters, which are estimated in our forecast model, denoted as model 2, generate additional noise in the forecast. Clark and West (2007) show this additional noise is only present in finite samples and hence propose to correct the $MSPE_{i,2}$ of the non-nested forecast model 2 by the adjustment term $adj_{i,2}$. The adjusted $MSPE_{i,2,adj}$ of model 2 is defined as:

$$\begin{aligned} MSPE_{i,2,adj} &= MSPE_{i,2} - adj_{i,2} \\ &= \mathsf{P}^{-1}\sum_{t=\mathsf{Q}}^{T-1}(\mathsf{y}_{i,t+1} - \hat{\mathsf{y}}_{i,2,t+1})^2 - \mathsf{P}^{-1}\sum_{t=\mathsf{Q}}^{T-1}(\hat{\mathsf{y}}_{i,1,t+1} - \hat{\mathsf{y}}_{i,2,t+1})^2, \end{aligned} \tag{4.10}$$

with $\hat{\mathsf{y}}_{i,1,t+1}$ denoting the forecast of the (nested) benchmark model 1 and $\hat{\mathsf{y}}_{i,2,t+1}$ the forecast of our model 2, while $\mathsf{y}_{i,t+1}$ represents the true observation of the underlying data. The null of the test assumes equal forecasts of the nested benchmark and the tested model, given the adjusted $MSPE_{i,2,adj}$ of Equation 4.10 for the forecast model. That is, $MSPE_{i,1} - MSPE_{i,2,adj} = 0$, which we test via regressing the difference between $MSPE_{i,1}$ and $MSPE_{i,2,adj}$ on a constant, and using a standard t-statistic for the resulting coefficient to determine the significance of our findings. According to Clark and West (2007), the application of 1.645 (1.282) as critical value represents the 95% (90%) quantile.[1]

4.2 Vector Autoregression

The following section is based on Koop et al. (1996), Pesaran and Shin (1998) and Schischke et al. (2023). While in Section 4.1 we propose the methodology to identify individual metal price determinants and forecasting factors, this section aims to provide the necessary tools for an analysis of the metals' interrelation with the general economy.

The linear regression model of Equation 4.1 assumes all covariates are influential on the metal prices, but does not account for the reverse direction, i.e. the influence of a metal price on it's supply and demand, or other, macroeconomic variables. Therefore, we excluded models with interrelated price determinants, as the estimators of their beta coefficients are biased, leading to possible misinterpretations of the variables' relations. To overcome these limitations, we now propose the application of a vector autoregression, where we assume the variables of vector $\mathbf{y}_t = (\mathbf{y}_{1,t}, \ldots, \mathbf{y}_{\mathcal{K},t})'$ are interrelated and their current values are determined by their historical observations, hence these follow an autoregressive process. We hereby assume metal prices are not only influenced by, but also influencing on, macroeconomic variables. The resulting VAR(P) model, with P lags, is estimated via OLS:

$$\mathbf{y}_t = \mathbf{\Phi}_1\mathbf{y}_{t-1} + \ldots + \mathbf{\Phi}_P\mathbf{y}_{t-P} + \boldsymbol{v}_t, \tag{4.11}$$

where $\mathbf{\Phi}_p$ are the coefficient matrices of lags $p = 1, \ldots, P$ and $\mathbf{y}_t$ is the data vector, consisting of $\mathcal{K}$ variables. We assume the errors $\boldsymbol{v}_t$ follow a multivariate normal distribution with $\mathbb{E}[\boldsymbol{v}_t] = 0$ and covariance matrix $\mathbb{E}[\boldsymbol{v}_t\boldsymbol{v}_t'] = \mathbf{V}$, where $\mathbb{E}[\boldsymbol{v}_t\boldsymbol{v}_s'] = 0$ for $s \neq t$.

[1] As these proposed values correspond to those of a normal distribution, we apply the values for a normal distribution in case of the remaining significance levels, at the 99% (2.326) and 99.9% (3.090) level respectively.

In general, a VAR(P) process is regarded stable if the following condition holds:

$$det(\mathbf{I}_{\mathcal{K}} - \mathbb{H}z) \neq 0, \ \ \forall |z| \leq 1, \tag{4.12}$$

with $\mathbf{I}_{\mathcal{K}}$ being the $\mathcal{K} \times \mathcal{K}$ dimensional unit matrix and

$$\mathbb{H} = \begin{bmatrix} \mathbf{\Phi}_1 & \mathbf{\Phi}_2 & \dots & \mathbf{\Phi}_P \\ \mathbf{I}_{\mathcal{K}} & 0 & \dots & 0 \\ 0 & \mathbf{I}_{\mathcal{K}} & & \\ 0 & \dots & \mathbf{I}_{\mathcal{K}} & 0 \end{bmatrix},$$

hence:

$$det(\mathbf{I}_{\mathcal{K}} - \mathbb{H}z) = det(\mathbf{I}_{\mathcal{K}} - \mathbf{\Phi}_1 z - \mathbf{\Phi}_2 z - \dots - \mathbf{\Phi}_P z) \neq 0, \ \ \forall |z| \leq 1. \tag{4.13}$$

If the roots of 4.13 fall outside the unit circle, the underlying process of Equation 4.11 is covariance stationary and yields in a stable VAR estimation.

Impulse Response Functions, analysis tools which we will introduce later in this section, are constructed for moving average (MA) processes. Under the assumption of model stability, the AR(P) process of data vector $\mathbf{y}_t$ can be represented as an infinite moving average process MA(∞) of the error terms $\boldsymbol{\upsilon}_t$:[2]

$$\mathbf{y}_t = \sum_{\mathsf{p}=0}^{\infty} \mathbf{B}_{\mathsf{p}} \boldsymbol{\upsilon}_{t-\mathsf{p}}, \tag{4.14}$$

with coefficient matrices:

$$\begin{aligned} &\mathbf{B}_{\mathsf{p}} = 0, \forall \mathsf{p} < 0 \\ &\mathbf{B}_0 = \mathbf{I}_{\mathcal{K}} \\ &\mathbf{B}_{\mathsf{p}} = \mathbf{\Phi}_1 \mathbf{B}_{\mathsf{p}-1} + \mathbf{\Phi}_2 \mathbf{B}_{\mathsf{p}-2} + \dots + \mathbf{\Phi}_P \mathbf{B}_{\mathsf{p}-P}, \forall \mathsf{p} = 1, \dots, . \end{aligned} \tag{4.15}$$

Similar to an autocorrelation analysis performed on the error terms of linear regression models, such stability analysis in a VAR(P) models assures the reliability of the results obtained from the subsequent impulse response function analysis.

Structural Change Framework

To analyze whether the relation between the variables of a regression equation changed over time, we apply the F-test from the structural change framework of Zeileis et al. (2002). Hereby, we analyze the single shift alternative, that is, testing the null of *no structural change* against the specified alternative, which assumes *one structural change*

[2] We here present the simplest form of VAR models, without a mean component and exogenous variables. That is, we will use this representation later for the analysis of the model, where the further components do not influence the results and hence only complicate the readability.

at point $\mathsf{t}_0 \in [\mathcal{K}, T-\mathcal{K}]$, based on the test of Chow (1960):

$$\beta_{\mathsf{j},\mathsf{t}} = \begin{cases} \beta_{ss1,\mathsf{j}}, \ (1 \leq t \leq \mathsf{t}_0) \\ \beta_{ss2,\mathsf{j}}, \ (\mathsf{t}_0 < t \leq T) \end{cases} . \tag{4.16}$$

We apply the structural change test on each of the regression equations $\mathsf{j} = 1, \ldots, \mathcal{K}$ of Equation 4.11 separately. Hereby, we split our data in the two sub-samples $ss1$ and $ss2$, with $\mathbf{y}_{ss1} = \mathbf{y}_1, \ldots, \mathbf{y}_{\mathsf{t}_0}$ and $\mathbf{y}_{ss2} = \mathbf{y}_{\mathsf{t}_0+1}, \ldots, \mathbf{y}_T$. Depending on the choice of the time t_0 at which the structural break is tested, we subsequently estimate the regression equation j for each sub-sample separately and compare the corresponding error terms $\hat{e}_\mathsf{j} = (\hat{\varepsilon}_{ss1,\mathsf{j}}, \hat{\varepsilon}_{ss2,\mathsf{j}})'$ to the error terms $\hat{\varepsilon}_\mathsf{j}$ of the regular, restricted model, estimated on the entire sample period $\mathbf{y} = \mathbf{y}_1, \ldots, \mathbf{y}_T$:

$$F_{\mathsf{j},\mathsf{t}_0} = \frac{\hat{\varepsilon}_\mathsf{j}'\hat{\varepsilon}_\mathsf{j} - \hat{e}_\mathsf{j}'\hat{e}_\mathsf{j}}{\hat{e}_\mathsf{j}'\hat{e}_\mathsf{j}/(T-2\mathcal{K})}. \tag{4.17}$$

Hereby, under the assumption of normality, $F_{\mathsf{j},\mathsf{t}_0}/\mathcal{K}$ follows an F-distribution with $\mathcal{K}$ and $T-2\mathcal{K}$ degrees of freedom, under the null of no structural change, where large values of $F_{\mathsf{j},\mathsf{t}_0}$ indicate a structural change is present in the data. To identify the point in time at which the structural break occurs, we apply the Chow methodology described above numerous times, in the interval of potential breakpoints $t \in [\underline{\mathsf{t}}, \bar{\mathsf{t}}]$, for $\mathcal{K} < \underline{\mathsf{t}} \leq t \leq \bar{\mathsf{t}} < T - \mathcal{K}$. In our case, we define $\underline{\mathsf{t}} = 0.15$ and $\bar{\mathsf{t}} = 0.85$, following Andrews (1993). As we compute the Chow test numerous times, we obtain a new time-series of test statistics, and rely on the sup$F$ statistic of Andrews (1993), where the null hypothesis of no structural break is rejected in case the maximum of the F statistics is crossing the threshold value:

$$supF_\mathsf{j} = \underset{\underline{\mathsf{t}} \leq t \leq \bar{\mathsf{t}}}{sup} F_{\mathsf{j},\mathsf{t}}. \tag{4.18}$$

We base our results on the 5% significance level, where the p-values are obtained from the study of Hansen (1997).

4.3 Impulse Response Analysis

While VAR models benefit from the ability to model interactions between multiple variables, the estimated coefficients lack in regard to interpretability. That is, the coefficients indicate the effect of a change in one variable to another variable, however, the assumption of a VAR model is an interrelation of all variables within the system, which is not represented in that parameter. To overcome this, the seminal paper of Sims (1980) introduced impulse response functions as a tool for the dynamic analysis of VAR models.

The following section provides an introduction into regular impulse response functions, those using orthogonalized shocks to represent contemporaneous effects between certain variables (OIRF) and a generalization of IRFs, which is invariant of the variable ordering, the generalized impulse response function (GIRF). Please note the following section only holds for linear, stable models. For nonlinear models, the history independence assumption used in the calculation of impulse response functions does not hold.

4.3.1 Impulse Response Function

Since the main objective in the estimation of the VAR model of Equation 4.11 is in the analysis of the underlying relations within the data, we rely on impulse response functions (IRF) for the graphical representation of those. In a regression analysis, the beta coefficient represents the implications of it's corresponding covariate, once it is increased by one, on the depended variable. In the same spirit, the regular IRFs shock each variable within the vector $\mathbf{y}$ of the VAR model by $\boldsymbol{\delta}$ and measure the resulting implications, given the available information $\boldsymbol{\Omega}_{t-1}$. Hereby, the change in the system can be regarded as the difference between the system with and without shock at time $t+n$:

$$\mathbf{IR}_{\mathbf{y}}(n, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) = \mathbb{E}\left[\mathbf{y}_{t+n} | \boldsymbol{\upsilon}_t = \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}\right] - \mathbb{E}\left[\mathbf{y}_{t+n} | \boldsymbol{\Omega}_{t-1}\right]. \tag{4.19}$$

That is, how does the expected value of $\mathbf{y}$ at time $t+n$, conditional on the available information set $\boldsymbol{\Omega}_{t-1}$, change, when the error term $\boldsymbol{\upsilon}_t$ is shocked by $\boldsymbol{\delta}$. Using the MA(∞) representation of our VAR model from Equation 4.14, we write:

$$\begin{aligned} \mathbf{IR}_{\mathbf{y}}(n, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) &= \mathbb{E}\left[\sum_{\mathsf{p}=0}^{\infty} \mathbf{B}_{\mathsf{p}} \boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\upsilon}_t = \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}\right] - \mathbb{E}\left[\sum_{i=0}^{\infty} \mathbf{B}_{\mathsf{p}} \boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\Omega}_{t-1}\right] \\ &= \sum_{i=0}^{\infty} \mathbf{B}_{\mathsf{p}} \mathbb{E}\left[\boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\upsilon}_t = \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}\right] - \sum_{\mathsf{p}=0}^{\infty} \mathbf{B}_{\mathsf{p}} \mathbb{E}\left[\boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\Omega}_{t-1}\right]. \end{aligned} \tag{4.20}$$

By assumption, we know $\mathbb{E}\left[\boldsymbol{\upsilon}_t\right] = 0$ and hence:

$$\mathbf{IR}_{\mathbf{y}}(n, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) = \sum_{\mathsf{p}=0}^{\infty} \mathbf{B}_{\mathsf{p}} \mathbb{E}[\boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\upsilon}_t = \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}]. \tag{4.21}$$

Since the error terms are, by assumption *iid*, especially for $\mathsf{p} \neq n$, $\boldsymbol{\upsilon}_{t+n-\mathsf{p}}$ is independent of $\boldsymbol{\upsilon}_t$:

$$\mathbb{E}\left[\boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\upsilon}_t = \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}\right] = 0. \tag{4.22}$$

In case of $\mathsf{p} = n$, it holds:

$$\mathbb{E}\left[\boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\upsilon}_t = \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}\right] = \mathbb{E}\left[\boldsymbol{\upsilon}_t | \boldsymbol{\upsilon}_t = \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}\right] = \boldsymbol{\delta}. \tag{4.23}$$

Using Equation 4.22 and Equation 4.23 in Equation 4.21, the impulse response function of the system is:

$$\mathbf{IR}_{\mathbf{y}}(n, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) = \mathbf{B}_n \boldsymbol{\delta},\ n = 0, 1, 2, \ldots, . \tag{4.24}$$

In analogy to the analysis of conventional regression models, we set $\boldsymbol{\delta} = 1$. For the linear model described here, the IRF is history independent, i.e. the response of a variable is not conditional on its historical representation, other than the historical observations determining the parameter matrix $\mathbf{B}_n$.

4.3.2 Orthogonalized Impulse Response Function

In case of the traditional IRFs, contemporaneous effects between variables are not displayed by this type of response function. Additionally, the shock size of $\boldsymbol{\delta} = 1$ is unrelated to the historical data, i.e. level data would be shocked by the same magnitude as return data. To overcome these limitations, Sims (1980) also introduced the orthogonalized impulse response functions. Hereby, we shock one variable within the system by one standard deviation and measure its effects, by construction also the contemporaneous effects, on all variables within the system. Therefore, we first obtain the $\mathcal{K} \times \mathcal{K}$ lower triangular matrix $\mathbf{E}$ of the covariance matrix of errors $\mathbf{V}$, via a Cholesky decomposition:

$$\mathbf{E}\mathbf{E}' = \mathbf{V}. \tag{4.25}$$

With the basic matrix calculus of $\mathbf{E}\mathbf{E}^{-1} = \mathbf{I}_{\mathcal{K}}$ and $\mathbf{B}\mathbf{I}_{\mathcal{K}} = \mathbf{B}$, we can rewrite Equation 4.14 as:

$$\begin{aligned} \mathbf{y}_t &= \sum_{\mathsf{p}=0}^{\infty} (\mathbf{B}_{\mathsf{p}}\mathbf{E})(\mathbf{E}^{-1}\boldsymbol{\upsilon}_{t-\mathsf{p}}) \\ &= \sum_{\mathsf{p}=0}^{\infty} (\mathbf{B}_{\mathsf{p}}\mathbf{E})\boldsymbol{\zeta}_{t-\mathsf{p}}, \end{aligned} \tag{4.26}$$

where $\boldsymbol{\zeta}_t = \mathbf{E}^{-1}\boldsymbol{\upsilon}_t$ are orthogonalized via $\mathbb{E}\left[\boldsymbol{\zeta}_t \boldsymbol{\zeta}_t'\right] = \mathbf{I}_{\mathcal{K}}$. The orthogonalized impulse response function of a one standard deviation shock to the j-th variable is:

$$\mathbf{OIR}_{\mathbf{y}}(n, \mathfrak{s}_{\mathsf{j}}, \boldsymbol{\Omega}_{t-1}) = \mathbf{B}_n \mathbf{E} \mathfrak{s}_{\mathsf{j}}, n = 0, 1, 2, \ldots, . \tag{4.27}$$

where $\mathfrak{s}$ is the $(\mathcal{K} \times 1)$ selection vector, with $\mathfrak{s}_{\mathsf{j}} = 1$ for the j-th element and 0 else. Hereby, contemporaneous effects are replicated by the OIRF, as $\mathbf{OIR}_{\mathbf{y}}(0) = \mathbf{I}_{\mathcal{K}}\mathbf{E}\mathfrak{s}_{\mathsf{j}}$. However, as $\mathbf{E}$ is a lower triangular matrix, the first variable $\mathbf{y}_1$ of the data matrix $\mathbf{y}$ has a contemporaneous effect on all other variables, while the last variable $\mathbf{y}_{\mathcal{K}}$ does not have any contemporaneous effects. Hence, the variable ordering becomes a crucial and sometimes debatable component of the modeling process. In the empirical application of OIRFs, we follow the identification scheme similar to Bernanke and Kuttner (2005), where the data vector of the underlying VAR model is sorted by the principle slow to respond to fast to respond. Hereby, the slowest variable, the one that is not affected by any of the other variables, is placed first in the data vector, while the fastest variable, reacting immediately to changes in all other variables, is placed last. Generally, exchange rates and commodity prices are regarded fast, whereas measures like CPI or industrial production are considered slow.

4.3.3 Generalized Impule Response Function

To overcome the problem of variable ordering, while still benefiting from the contemporaneous effects of shocks and the shock size related to the variables' characteristics, generalized impulse response functions may be used. Hereby, we shock the j-th variable of $\mathbf{y}$ by the shock size $\boldsymbol{\delta}$ and measure the resulting responses within the system. Therefore, we again start with Equation 4.19 and the MA(∞) representation of the VAR model in Equation 4.14. The generalized impulse response function is the difference in the system with and without shock. It is defined as:

$$\mathbf{GIR}_{\mathbf{y}}(n, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) = \mathbb{E}\left[\sum_{\mathsf{p}=0}^{\infty} \mathbf{B}_{\mathsf{p}} \boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\upsilon}_{\mathsf{j},t} = \delta_{\mathsf{j}}, \boldsymbol{\Omega}_{t-1}\right] - \mathbb{E}\left[\sum_{\mathsf{p}=0}^{\infty} \mathbf{B}_{\mathsf{p}} \boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\Omega}_{t-1}\right]. \quad (4.28)$$

Similar to Equation 4.21, under linearity of the model this simplifies to:

$$\mathbf{GIR}_{\mathbf{y}}(n, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) = \sum_{\mathsf{p}=0}^{\infty} \mathbf{B}_{\mathsf{p}} \mathbb{E}\left[\boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\upsilon}_{\mathsf{j},t} = \delta_{\mathsf{j}}, \boldsymbol{\Omega}_{t-1}\right]. \quad (4.29)$$

By assumption, the error terms are *iid*, especially for $\mathsf{p} \neq n$, $\boldsymbol{\upsilon}_{t+n-\mathsf{p}}$ is independent of $\boldsymbol{\upsilon}_{\mathsf{j},t}$:

$$\mathbb{E}\left[\boldsymbol{\upsilon}_{t+n-\mathsf{p}} | \boldsymbol{\upsilon}_{\mathsf{j},t} = \delta_{\mathsf{j}}, \boldsymbol{\Omega}_{t-1}\right] = 0. \quad (4.30)$$

For $\mathsf{p} = n$:

$$\mathbb{E}\left[\boldsymbol{\upsilon}_{t} | \boldsymbol{\upsilon}_{\mathsf{j},t} = \delta_{\mathsf{j}}, \boldsymbol{\Omega}_{t-1}\right] = \frac{\mathbb{E}\left[\boldsymbol{\upsilon}_{t} \boldsymbol{\upsilon}_{\mathsf{j},t}\right]}{\mathbb{E}\left[\boldsymbol{\upsilon}_{\mathsf{j}z}^2\right]} \cdot \delta_{\mathsf{j}}, \quad (4.31)$$

where $\mathbb{E}\left[\boldsymbol{\upsilon}_{t} \boldsymbol{\upsilon}_{\mathsf{j},t}\right]$ is the covariance between the error term and the errors of the j-th equation, which is the j-th column of the $\mathbf{V}$ matrix, $\mathbf{V}\mathfrak{s}_{\mathsf{j}} = (\sigma_{1\mathsf{j}}, \sigma_{2\mathsf{j}}, \ldots, \sigma_{\mathcal{K}\mathsf{j}})'$. Further, $\mathbb{E}\left[\boldsymbol{\upsilon}_{\mathsf{j},t}^2\right] = \sigma_{\mathsf{jj}}$. Hence,

$$\mathbb{E}\left[\boldsymbol{\upsilon}_{t} | \boldsymbol{\upsilon}_{\mathsf{j},t} = \delta_{\mathsf{j}}, \boldsymbol{\Omega}_{t-1}\right] = \mathbf{V}\mathfrak{s}_{\mathsf{j}} \sigma_{\mathsf{jj}}^{-1} \delta_{\mathsf{j}}. \quad (4.32)$$

Therefore, we can write:

$$\mathbf{GIR}_{\mathbf{y}}(n, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) = \frac{\mathbf{B}_n \mathbf{V} \mathfrak{s}_{\mathsf{j}}}{\sqrt{\sigma_{\mathsf{jj}}}} \cdot \frac{\delta_{\mathsf{j}}}{\sqrt{\sigma_{\mathsf{jj}}}}. \tag{4.33}$$

Shocking the system by one standard deviation of the j-th variable, i.e. $\delta_{\mathsf{j}} = \sqrt{\sigma_{\mathsf{jj}}}$ and zero else, the resulting response is:

$$\mathbf{GIR}_{\mathbf{y}}(n, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) = \frac{1}{\sqrt{\sigma_{\mathsf{jj}}}} \cdot \mathbf{B}_n \mathbf{V} \mathfrak{s}_{\mathsf{j}}, n = 0, 1, 2, \ldots, . \tag{4.34}$$

4.3.4 Bootstrapping

To evaluate the significance of the findings generated via the impulse responses, we calculate confidence intervals of the responses via the bootstrap procedure proposed by Dées et al. (2007). These confidence intervals provide a measure of accuracy for the responses, without assumptions on the distribution of the initial, underlying data. In this thesis, we use 68% confidence bounds, which we base on 500 bootstrap replications, as outlined in the following.

In general, within a bootstrapping exercise, we re-estimate the model under evaluation several times, on a subset of data. In our case, since we use time-series data, we are unable to draw our subset of data from the initial data set, as this would ignore the time dependence structure. However, since we assume the error terms of the (G)VAR models to follow a multivariate normal distribution, the error terms are time independent. We therefore draw 500 times from the error terms a set of 250 errors each, with replacement. Given these errors, we use the most recent data point of the actual data series, as well as the coefficient matrices estimated within the initial model, to generate the 500 bootstrap data samples that each contains 250 data points.[3]

Given this new time-series, we re-estimate the (G)VAR model, and subsequently calculate the OIRFs and GIRFs, 500 times. Finally, we sort the resulting responses in ascending order, per time period, and draw the $(0.32/2) \cdot 500 = 80$-th, as well as the $(1 - 0.32/2) \cdot 500 = 420$-th value, which represents the confidence bounds of our IRF at the 68%-level.

[3]In the application of the bootstrapping for the GIRFs of the GVAR model, we additionally use the coefficient matrices and the weight matrix to also derive the bootstrap time series of the external, starred variables.

4.4 Global Vector Autoregression

The VAR(P) model described in the previous section is applied to a metal index in the empirical part of this thesis, rather than on individual metal level. As metals are still production goods in real economies, we hypothesize their supply and demand still influence their prices. Since an analysis of microeconomic determinants is not feasible on index level, such an analysis requires metal-specific models. To combine the benefits of microeconomic influences with the ability to model interrelated variables, even between individual metals, we introduce a framework for metal markets, based on Schischke et al. (2021), which in turn is based on a global vector autoregression, initially introduced by Pesaran et al. (2004).

Therefore, we individually model the market of each metal $i = 1, \ldots, N$ of the analysis via a vector autoregressive (VAR(P)) model, which consists of a supply ($\mathbf{supply}_i$), demand ($\mathbf{demand}_i$) and price ($\mathbf{price}_i$) variable. These variables are represented by the vector $\mathbf{x}_{i,t} = (supply_{i,t}, demand_{i,t}, price_{i,t})'$, for all time periods $t = 1, \ldots, T$, where the VAR model is of the form:

$$\begin{aligned}\mathbf{x}_{i,t} = {} & \mathbf{\Phi}_{i,1}\mathbf{x}_{i,t-1} + \mathbf{\Phi}_{i,2}\mathbf{x}_{i,t-2} + \cdots + \mathbf{\Phi}_{i,9}\mathbf{x}_{i,t-9} \\ & + \mathbf{\Psi}_{i,0}\mathbf{e}_t + \mathbf{\Psi}_{i,1}\mathbf{e}_{t-1} + \cdots + \mathbf{\Psi}_{i,9}\mathbf{e}_{t-9} \\ & + \boldsymbol{\varepsilon}_{i,t}.\end{aligned} \tag{4.35}$$

Hereby, the coefficients matrices $\mathbf{\Phi}_{i,1}, \mathbf{\Phi}_{i,2}, \ldots, \mathbf{\Phi}_{i,9}$ are of dimension $K_i \times K_i$, where the number of variables within each market, represented by the length of $\mathbf{x}_{i,t}$, is $K_i = 3$. We set the maximum lag length $P = 9$, which is applied for specific data characteristics.[4] Since metal markets are related to current economic conditions, we additionally include a vector $\mathbf{e}_t$ of K_{exog} macroeconomic determinants in our model. Hereby, these variables influence metal markets via the coefficient matrices $\mathbf{\Psi}_{i,0}$, $\mathbf{\Psi}_{i,1}, \ldots, \mathbf{\Psi}_{i,9}$, which are of dimension $K_i \times K_{exog}$. We further assume the error terms of the model, $\boldsymbol{\varepsilon}_{i,t}$, to be serially uncorrelated, as well as independently and identically distributed. Hence, they have mean zero and a variance-covariance matrix $\mathbf{V}_{ii}$, which means they follow a multivariate normal distribution $\boldsymbol{\varepsilon}_{i,t} \sim iid(0, \mathbf{V}_{ii})$.

In addition to macroeconomic circumstances, which we include in our model as exogenous variables, metal markets are potentially related via further channels, which are their co-production, co-consumption and co-trading activities on exchanges, as outlined

[4]Within the empirical application of the model, we test the autocorrelation of the residuals via the Durbin-Watson test, their heteroscedasticity via the ARCH-LM test and the parameter stability via the OLS-CUSUM test. In case either of the tests indicates autocorrelation, heteroscedasticity or parameter instability, we increase the lag length by one. Ultimately, this leads to a final lag length of nine, which is why we explain the resulting model in this section with nine lags.

in Section 2.4 and Section 3.6. While metal-specific, individual VAR models are unable to replicate the entire complexity of markets, we could model all metal markets simultaneously within one large VAR model. However, the estimation of the parameters included in the model quickly gets infeasible, given their rapidly increasing number. Formally, such a model includes K_i parameters, for each metal i and lag p, while additionally, the inclusion of K_{exog} macroeconomic variables requires the estimation of $(P_{exog} + 1)$ parameters per macroeconomic variable on top. While for six metals, three macroeconomic determinants and one lag this would result in only 24 parameters per equation, the same model for six metals, three macroeconomic variables and the nine lags applied in the empirical part of this thesis would already require 192 estimated parameters per equation.

Given the low data frequency of microeconomic variables, this quickly results in major issues within the parameter estimation and becomes impracticable. Since the above mentioned situation, a large set of potentially influential variables in conjunction with low frequency of data, is a very common bottleneck in econometrics, Pesaran et al. (2004) developed the global vector autoregressive model. The idea of the model is the combination - or aggregation - of several, individual models, into one large, central model. While initially the model was designed to connect several individual economies, we transfer the idea to metal markets. Hereby, the model benefits from the predefined relations between the individual models, which reduces the number of estimated parameters. Initially, we therefore model each industrial metal market via the classical, microeconomic supply, demand and price, as well as the macroeconomic variables. The methodology of the GVAR is hereby based on Pesaran et al. (2004), Dées et al. (2007), and Dées et al. (2007).

Therefore, the metal-specific VARs from Equation 4.35 are enlarged by the $K_i^* \times 1$ vector $\mathbf{x}_{i,t}^* = (supply_{i,t}^*, demand_{i,t}^*, price_{i,t}^*)'$ of external variables, which are specific to metal i:

$$\begin{aligned}\mathbf{x}_{i,t} &= \mathbf{\Phi}_{i,1}\mathbf{x}_{i,t-1} + \mathbf{\Phi}_{i,2}\mathbf{x}_{i,t-2} + \cdots + \mathbf{\Phi}_{i,9}\mathbf{x}_{i,t-9} \\ &\quad + \mathbf{\Lambda}_{i,0}\mathbf{x}_{i,t}^* + \mathbf{\Lambda}_{i,1}\mathbf{x}_{i,t-1}^* + \cdots + \mathbf{\Lambda}_{i,9}\mathbf{x}_{i,t-9}^* \\ &\quad + \mathbf{\Psi}_{i,0}\mathbf{e}_t + \mathbf{\Psi}_{i,1}\mathbf{e}_{t-1} + \cdots + \mathbf{\Psi}_{i,9}\mathbf{e}_{t-9} \\ &\quad + \boldsymbol{\varepsilon}_{i,t}.\end{aligned} \tag{4.36}$$

Hereby, $\mathbf{\Lambda}_{i,0}, \mathbf{\Lambda}_{i,1}, \ldots, \mathbf{\Lambda}_{i,9}$ represent the $K_i \times K_i^*$ matrices of coefficients, corresponding to the external, metal-specific variables with lag p. For our model, we determine $K_i^* = K_i$

and define the external variables as:

$$
\begin{aligned}
supply^*_{i,t} &= \sum_{\tilde{\imath}=1}^{N} w_{i,\tilde{\imath}} supply_{\tilde{\imath},t}, \\
demand^*_{i,t} &= \sum_{\tilde{\imath}=1}^{N} w_{i,\tilde{\imath}} demand_{\tilde{\imath},t}, \\
price^*_{i,t} &= \sum_{\tilde{\imath}=1}^{N} w_{i,\tilde{\imath}} price_{\tilde{\imath},t}.
\end{aligned}
$$

Hereby, $w_{i,\tilde{\imath}}$ represents the degree of relation, or weight in the GVAR terminology, between metal i and metal $\tilde{\imath}$. With the conditions $w_{i,i} = 0$ and $\sum_{\tilde{\imath}=1}^{N} w_{i,\tilde{\imath}} = 1$, for $i = 1, \ldots, N$, the weights are representable in a weight matrix $(w_{i,\tilde{\imath}})_{i,\tilde{\imath}=1,\ldots,N}$. We construct the weight matrices as outlined in Section 3.6, hereby representing the metal relations described in Section 2.4, in contrast to the model's initial application by Pesaran et al. (2004), who used trade weights, the import and export relations of countries, to replicate their interrelations.

To implement the GVAR model, we define the vector $\mathbf{z}_{i,t} = (\mathbf{x}'_{i,t}, \mathbf{x}^{*\prime}_{i,t})'$, which is of dimension $(K_i + K^*_i) \times 1$ and subsequently rewrite Equation 4.35 for $i = 1, \ldots, N$:

$$
\begin{aligned}
\mathbf{A}_{i,0}\mathbf{z}_{i,t} &= \mathbf{A}_{i,1}\mathbf{z}_{i,t-1} + \mathbf{A}_{i,2}\mathbf{z}_{i,t-2} + \cdots + \mathbf{A}_{i,9}\mathbf{z}_{i,t-9} \\
&\quad + \mathbf{\Psi}_{i,0}\mathbf{e}_t + \mathbf{\Psi}_{i,1}\mathbf{e}_{t-1} + \cdots + \mathbf{\Psi}_{i,9}\mathbf{e}_{t-9} \\
&\quad + \boldsymbol{\varepsilon}_{i,t}.
\end{aligned} \tag{4.37}
$$

Hereby, $\mathbf{A}_{i,0} = (\mathbf{I}_{K_i}, -\mathbf{\Lambda}_{i,0})$, while $\mathbf{I}_{K_i}$ denotes a unit matrix of dimension $K_i \times K_i$, and $\mathbf{A}_{i,1} = (\mathbf{\Phi}_{i,1}, \mathbf{\Lambda}_{i,1})$, $\mathbf{A}_{i,2} = (\mathbf{\Phi}_{i,2}, \mathbf{\Lambda}_{i,2}), \ldots, \mathbf{A}_{i,9} = (\mathbf{\Phi}_{i,9}, \mathbf{\Lambda}_{i,9})$ are $K_i \times (K_i + K^*_i)$ dimensional matrices. Further, the matrices $\mathbf{A}_{i,0}$ to $\mathbf{A}_{i,9}$ are required to have full row rank for all metals. Additionally, $\mathbf{x}_t = (\mathbf{x}'_{1,t}, \ldots, \mathbf{x}'_{N,t})'$ represents a global vector, which is of dimension $K \times 1$, with $K = \sum_{i=1}^{N} K_i$, and contains all metal-specific variables.

Using the above mentioned weights $w_{i,\tilde{\imath}}$ of the respective weight matrix, we define link matrices $\mathbf{Z}_i$, such that $\mathbf{z}_{i,t} = \mathbf{Z}_i\mathbf{x}_t$, where we can rewrite Equation 4.37 as:

$$
\begin{aligned}
\mathbf{A}_{i,0}\mathbf{Z}_i\mathbf{x}_t &= \mathbf{A}_{i,1}\mathbf{Z}_i\mathbf{x}_{t-1} + \mathbf{A}_{i,2}\mathbf{Z}_i\mathbf{x}_{t-2} + \cdots + \mathbf{A}_{i,9}\mathbf{Z}_i\mathbf{x}_{t-9} \\
&\quad + \mathbf{\Psi}_{i,0}\mathbf{e}_t + \mathbf{\Psi}_{i,1}\mathbf{e}_{t-1} + \cdots + \mathbf{\Psi}_{i,9}\mathbf{e}_{t-9} \\
&\quad + \boldsymbol{\varepsilon}_{i,t}.
\end{aligned} \tag{4.38}
$$

Aggregating these equations for all metals, we get:

$$\begin{aligned}\mathbf{G}_0\mathbf{x}_t &= \mathbf{G}_1\mathbf{x}_{t-1} + \mathbf{G}_2\mathbf{x}_{t-2} + \cdots + \mathbf{G}_9\mathbf{x}_{t-9} \\ &\quad + \boldsymbol{\Psi}_0\mathbf{e}_t + \boldsymbol{\Psi}_1\mathbf{e}_{t-1} + \cdots + \boldsymbol{\Psi}_9\mathbf{e}_{t-9} \\ &\quad + \boldsymbol{\varepsilon}_t.\end{aligned} \tag{4.39}$$

Hereby, the matrices $\mathbf{G}_0$ to $\mathbf{G}_9$, corresponding to the metal-specific variables, are of dimension $K \times K$, and defined as $\mathbf{G}_0 = ((\mathbf{A}_{1,0}\mathbf{Z}_1)', \ldots, (\mathbf{A}_{N,0}\mathbf{Z}_N)')'$, $\mathbf{G}_1 = ((\mathbf{A}_{1,1}\mathbf{Z}_1)', \ldots, (\mathbf{A}_{N,1}\mathbf{Z}_N)')', \ldots, \mathbf{G}_9 = ((\mathbf{A}_{1,9}\mathbf{Z}_1)', \ldots, (\mathbf{A}_{N,9}\mathbf{Z}_N)')'$, while the matrices corresponding to the exogenous, macroeconomic variables
$\boldsymbol{\Psi}_0 = (\boldsymbol{\Psi}'_{1,0}, \ldots, \boldsymbol{\Psi}'_{N,0})'$, $\boldsymbol{\Psi}_1 = (\boldsymbol{\Psi}'_{1,1}, \ldots, \boldsymbol{\Psi}'_{N,1})', \ldots, \boldsymbol{\Psi}_9 = (\boldsymbol{\Psi}'_{1,9}, \ldots, \boldsymbol{\Psi}'_{N,9})'$ are all of dimension $K \times K_{exog}$. Further, the error term is of dimension $k \times 1$ and defined as $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}'_{1,t}, \ldots, \boldsymbol{\varepsilon}'_{N,t})'$.

When non-singularity of the matrix $\mathbf{G}_0$ is ensured, we can multiply Equation 4.39 with the inverse of $\mathbf{G}_0$, $\mathbf{G}_0^{-1}$, which represents the GVAR model in its final form:

$$\begin{aligned}\mathbf{x}_t &= \mathbf{H}_1\mathbf{x}_{t-1} + \mathbf{H}_2\mathbf{x}_{t-2} + \ldots + \mathbf{H}_9\mathbf{x}_{t-9} \\ &\quad + \boldsymbol{\Upsilon}_0\mathbf{e}_t + \boldsymbol{\Upsilon}_1\mathbf{e}_{t-1} + \cdots + \boldsymbol{\Upsilon}_9\mathbf{e}_{t-9} \\ &\quad + \boldsymbol{\upsilon}_t.\end{aligned} \tag{4.40}$$

Hereby, the matrices included in the model are defined as
$\mathbf{H}_1 = \mathbf{G}_0^{-1}\mathbf{G}_1$, $\mathbf{H}_2 = \mathbf{G}_0^{-1}\mathbf{G}_2, \ldots, \mathbf{H}_9 = \mathbf{G}_0^{-1}\mathbf{G}_9$ and
$\boldsymbol{\Upsilon}_0 = \mathbf{G}_0^{-1}\boldsymbol{\Psi}_0$, $\boldsymbol{\Upsilon}_1 = \mathbf{G}_0^{-1}\boldsymbol{\Psi}_1, \ldots, \boldsymbol{\Upsilon}_9 = \mathbf{G}_0^{-1}\boldsymbol{\Psi}_9$, where $\boldsymbol{\upsilon}_t = \mathbf{G}_0^{-1}\boldsymbol{\varepsilon}_t$.

The final model therefore includes metal-specific information, as well as cross-metal relations, while simultaneously accounting for the impact of macroeconomic determinants. For the analysis of the relations modeled within the GVAR, we propose the application of impulse response functions. Since the orthogonalized impulse response functions described in Section 4.3.2 require an ordering of variables, which is implausible in this application, we base the analysis of our model, following Pesaran et al. (2004) and Dées et al. (2007), on the generalized impulse response functions, similar to those described in Section 4.3.3, hereby benefiting from their invariance property of the variable ordering.

When we shock the element j of vector $\mathbf{x}_t$, which is equal to the k_i-th variable of metal i, the generalized impulse response is:

$$\begin{aligned}\mathbf{GIR}_{\mathbf{x}}(n, \sqrt{\sigma_{ii,k_ik_i}}, \boldsymbol{\Omega}_{t-1}) &= \mathbb{E}\left[\mathbf{x}_{t+n} | \, \varepsilon_{i,k_i,t} = \sqrt{\sigma_{ii,k_ik_i}}, \boldsymbol{\Omega}_{t-1}\right] - \mathbb{E}\left[\mathbf{x}_{t+n} | \boldsymbol{\Omega}_{t-1}\right], \\ n &= 0, 1, 2, \ldots, .\end{aligned} \tag{4.41}$$

Hereby, $\boldsymbol{\Omega}_{t-1}$ represents all available information at time $t-1$. Under the assumption the error terms of the model, $\boldsymbol{\varepsilon}_t$, follow a multivariate normal distribution, the generalized impulse response function of the GVAR model is defined as:

$$\begin{aligned} GIR_{\mathbf{x}}(n,\, \sqrt{\sigma_{ii,k_ik_i}},\, \boldsymbol{\Omega}_{t-1}) &= \frac{1}{\sqrt{\sigma_{ii,k_ik_i}}}\mathbf{B}_n\mathbf{G}_0^{-1}\mathbf{V}\mathfrak{s}_j, \\ n &= \, 0,1,2,\ldots,. \end{aligned} \tag{4.42}$$

with the coefficient matrices:

$$\begin{aligned} \mathbf{B}_n &= 0, \forall\; n < 0 \\ \mathbf{B}_0 &= \mathbf{I}_K, \\ \mathbf{B}_n &= \mathbf{H}_1\mathbf{B}_{n-1} + \mathbf{H}_2\mathbf{B}_{n-2} + \ldots + \mathbf{H}_9\mathbf{B}_{n-9}, \forall\; n = 1,2\ldots,. \end{aligned} \tag{4.43}$$

Hereby, the variance-covariance matrix $\mathbf{V}$ of the error terms $\boldsymbol{\varepsilon}_t$ is of dimension $K \times K$, and σ_{ii,k_ik_i} is its ii, k_ik_i-th element. As we shock one variable at a time, we define a selection vector $\mathfrak{s}_j$, which we set equal to one for the shocked variable j and zero else. Since the generalized impulse response function is defined for all K variables, it is able to represent the effects within and across the individual metal markets.

5 Results

In the following section, we present the results of the empirical application of the models described within Chapter 4. Hereby, all of the models are applied on metal markets on monthly data frequency, in the period from 1995 to 2019.
First, we model the relation of metal markets to the U.S. economy in general, and the U.S. monetary policy in particular, via a vector autoregression within Section 5.1. We hereby identify a structural break in the relation of the economic system in general, and the role of monetary policy in particular, within the financial crisis, which is why we perform a sub-sample analysis to disentangle the differing effects between the variables in the respective time periods.
Second, within Section 5.2, we perform a metal-specific linear regression analysis, to identify the individual price determinants and predictors. As the constitution of metal markets substantially changed over the course of the last 25 years, as also indicated by the structural break test of the vector autoregression within Section 5.1, we also perform the identical sub-sample analysis for the metal price determinants and predictors.
Third, as the results within Section 5.2, as well as the literature review within Section 2.4, suggest, commodity prices show a substantial degree of co-movement, we apply global vector autoregressions on the industrial metal markets. Hereby, we individually model each metal's market, while simultaneously linking the individual markets via information on their co-production, co-consumption and co-trading, also outlined within Section 3.6.

5.1 Metal Prices and Monetary Policy

To analyze the relations between metal markets and monetary policy, we focus on the impact of the American central bank, the federal reserve system, on metal prices. Therefore, we model the U.S. economy via a VAR(P) model, as outlined within Section 4.2, and subsequently analyze the effects of various shocks to metal markets, via orthogonalized impulse response functions, based on the setup of Schischke et al. (2023). The vector of endogenous variables, $\mathbf{y}_t$, hereby consists of macroeconomic variables, monetary policy proxies as well as a metal price index in monthly frequency, capturing the period from 1995 to 2019. The macroeconomic factors are the U.S. industrial production, measuring the U.S. real output for all facilities including manufacturing, mining, electric, and gas utilities, and the consumer price index, representing all items for the U.S..

We measure the conventional monetary policy via the federal funds rate, and add an inverse recession indicator, represented by the term spread between the short- and long-term interest rate, which is in our case the 10-Year Treasury Constant Maturity minus 3-Month Treasury Constant Maturity. Further, we include the RICI metals index, which constitutes of the industrial metals aluminum, copper, nickel, lead, tin and zinc, as well as the precious metals gold, palladium, platinum and silver. Since most of the metals are traded in U.S. Dollar, we also include the U.S. Dollar index as exchange rate. To ensure stationarity across all variables, we follow the adjustment process of variables as outlined in Section 3.4, where we also seasonally adjust the data, but proceed with the original variable names. As highlighted within Section 4.2, the variable ordering, oftentimes referred to as identification scheme of the VAR model, within the vector $\mathbf{y}_t$, can become a crucial component of the modeling process. We hereby use a recursive Cholesky identification scheme, in line with Bernanke and Kuttner (2005), which is based on the principle slow to respond to fast to respond, where the vector of endogenous variables is $\mathbf{y}_t = (IP_{U.S.}, CPI, FFR, T10Y3M, RICIM, FX)'$. Hereby, we assume the policy variables immediately react to the industrial production and the CPI, while we assume monetary policy only has a lagged and no contemporaneous effect on these variables. However, monetary policy does have a contemporaneous effect on the metals index and the exchange rate. In turn, the metal price index affects all variables, except the exchange rate, only with a lag, while, in addition to the monetary policy variables, it immediately responds to the macroeconomic conditions. Lastly, the U.S. Dollar index causes a lagged reaction within all variables of the economy. Assuming this presented identification scheme, we analyze the effects of monetary policy and other shocks to metal prices via orthogonalized impulse response functions, based on the 68% significance level obtained by bootstrapping, see Section 4.3.2 and Section 4.3.4.[1]

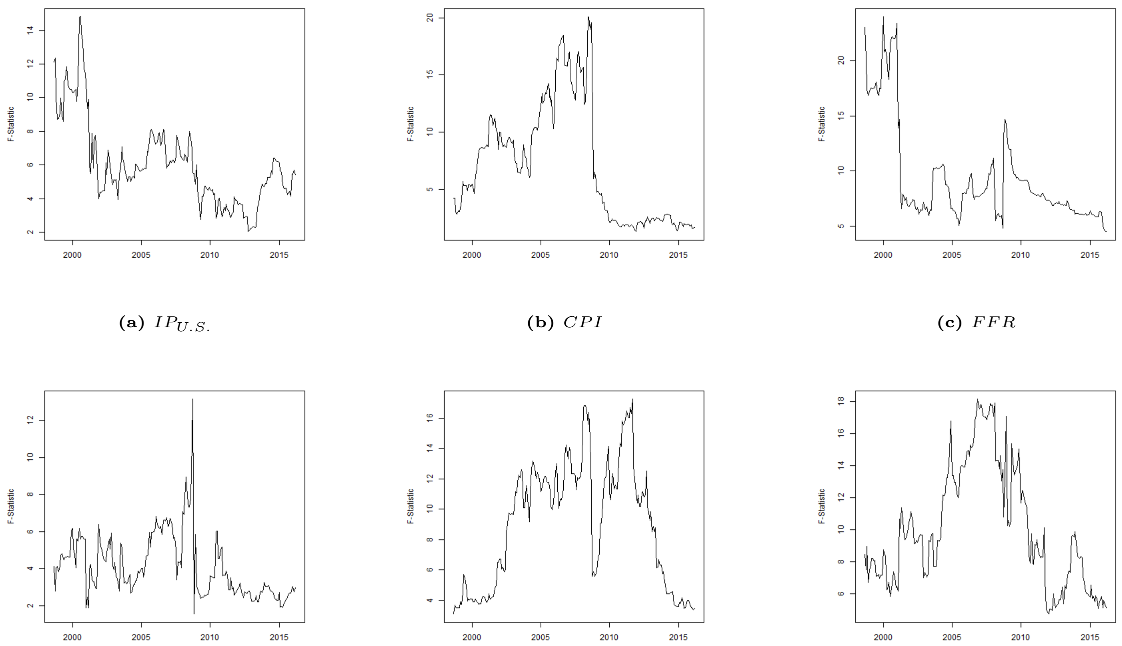
As outlined within Section 2.1.1, the FED lowered their policy rate to near zero in Q4 of the year 2008 and implemented unconventional monetary policy actions, such as forward guidance and asset purchases, in the following period. Therefore, we aim to analyze whether this zero-interest rate policy led to significant changes in the relation between monetary policy and metal prices. To start, we apply the structural break test of Zeileis et al. (2002), as described within Section 4.2, on each of the regression equations of the VAR model.

Since we repeat the Chow-Test numerous times, for each data point within the range of 0.15 to 0.85 percent of the analysis' time span, we obtain a time-series of F-statistic values

[1]Due to the symmetry of responses within impulse response functions, we only consider a positive shock to the variables, reflecting a contrarian monetary policy shock for the interest rates, while for our unconventional monetary policy proxies this represents an expansionary policy shock.

for each variable within the VAR system, which are displayed in Figure 5.1. For our main variable, the RICI metals index, we see two peaks within the F-statistics, which correspond to April 2008 and and September 2011, and are of almost equal values. Further, also the F-statistics of the CPI, the FFR, as well as the term-spread show a peak during the period of the financial crisis.[2] To disentangle monetary policy effects on metal prices between different monetary policy regimes, we split our initial, total-sample, in sub-sample one, covering the period from 1995 until the end of 2008, as well as sub-sample two, spanning from 2009 to 2019.

Figure 5.1: Structural Break Test Results



(a) $IP_{U.S.}$ (b) CPI (c) FFR

(d) $T10Y3M$ (e) $RICIM$ (f) FX

This figure displays the time-series of the test statistics of the structural break test, applied on each individual linear regression within the vector autoregression model, covering the total-sample period.

The first sub-sample covers the period until the FFR hit the ZLB and hence represents the period of conventional monetary policy in our analysis, while the second sub-sample covers the period that includes unconventional monetary policy actions. Subsequently, we compare the impulse response functions of the VAR models in the first and second sub-sample, where our main focus is on the relation between monetary policy shocks and metal prices.

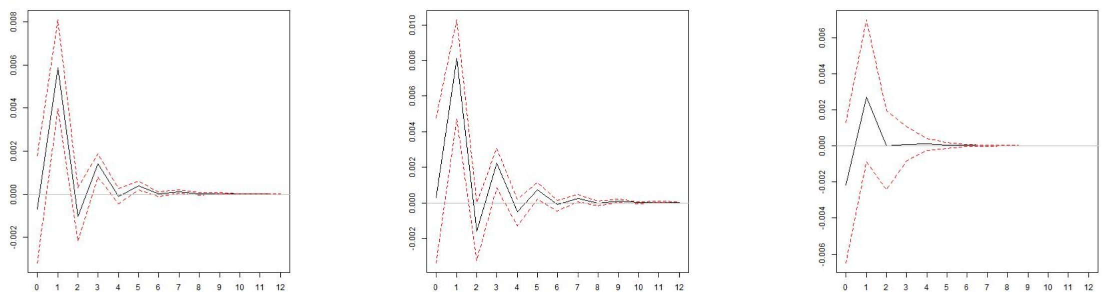
For the second sub-sample, we therefore estimate and analyze an enlarged VAR model to account for the effect of unconventional monetary policy, where we consider different proxies of unconventional policy. These include the balance sheet size of the FED, which

[2] However, none of the above mentioned structural breaks during the financial crisis is statistically significant at the 5%-level, as can be seen within Table A.1 of Appendix A.

is supposed to capture the asset purchases/ quantitative easing practices of the FED, as well as the inflation expectation index, which is supposed to capture the overall effects of monetary policy on markets. As the practice of forward guidance only consists of a verbal communication of the central banks' future actions, there exists no numerical variable that would directly replicate forward guidance, such as the federal funds rate for conventional policy. However, through forward guidance the FED aims to influence the markets' expectations on the future economic conditions, which, in turn, is represented in the inflation expectation index. Moreover, we repeat the model estimation again and replace the federal funds rate in all (sub-) samples, as well as the measure of unconventional monetary policy in the second sub-sample, by the shadow rate of Wu and Xia (2016), as this rate is a composite measure of conventional and unconventional monetary policy.[3]

As our initial structural break test indicates the economic system changed during the financial crisis, we further investigate whether and how this break affects the impact of the economic conditions on metal prices. In line with Akram (2009), Byrne et al. (2020) and Lombardi et al. (2012), a positive shock to the economic activity, the U.S. industrial production in our case, leads to increasing commodity prices in the total-sample, as well as in sub-sample one, while the effect is insignificant for sub-sample two, see Figure 5.2. This finding is in line with theory, as the consumption of metals in general, and industrial metals in particular, massively shifted towards Asia over the course of the last fifty years, see also Section 3.1, which reduces the impact of the U.S. industrial sector on metal prices.

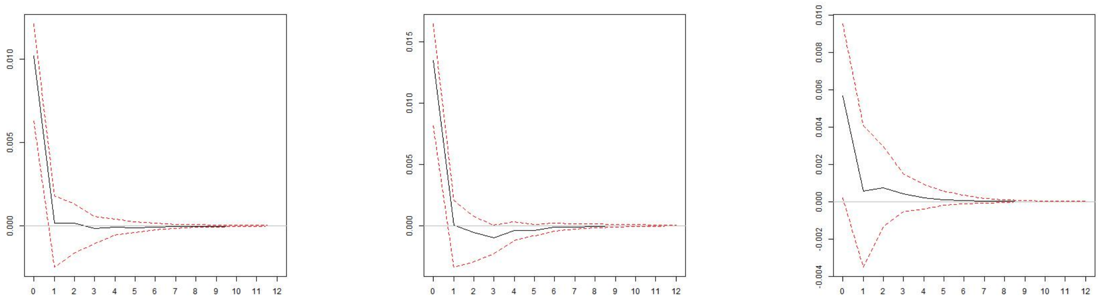
Figure 5.2: Response of Metals Index - U.S. Industrial Production Shock



(a) 1995 - 2019 **(b)** 1995 - 2008 **(c)** 2009 - 2019

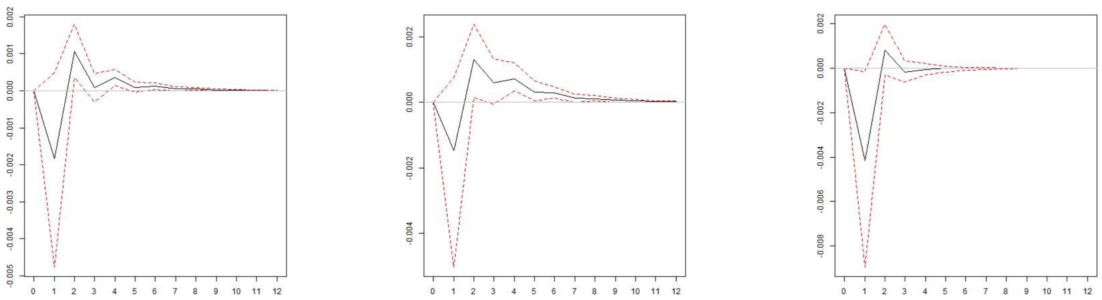
[3]For the enlarged VAR models, we use the identification schemes
$\mathbf{y}_t = (IP_{U.S.}, CPI, FFR, T10Y3M, WALCL, RICIM, FX)'$
and $\mathbf{y}_t = (IP_{U.S.}, CPI, FFR, T10Y3M, T5YIFR, RICIM, FX)'$, assuming metal prices react contemporaneously to the unconventional monetary policy variable. In case of the model containing the shadow rate ($WuXia$), the shadow rate replaces the conventional and unconventional monetary policy variable in the VAR, leading to the identification scheme $\mathbf{y}_t = (IP_{U.S.}, CPI, WuXia, T10Y3M, RICIM, FX)'$.

Figure 5.3: Response of Metals Index - U.S. Consumer Price Index Shock



(a) 1995 - 2019 **(b)** 1995 - 2008 **(c)** 2009 - 2019

Figure 5.4: Response of Metals Index - U.S. Dollar Index Shock



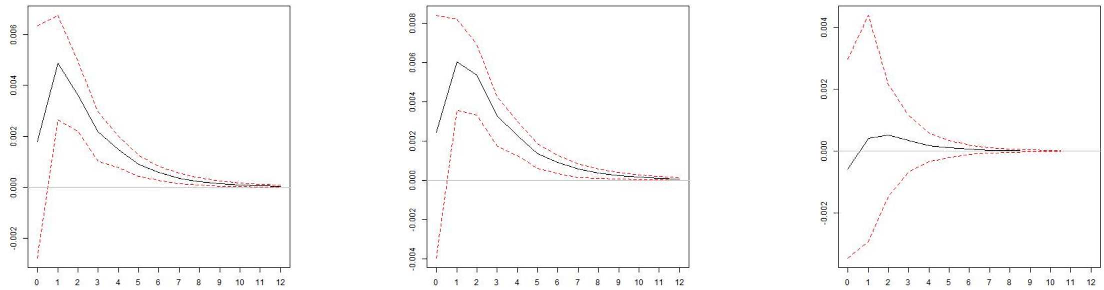
(a) 1995 - 2019 **(b)** 1995 - 2008 **(c)** 2009 - 2019

Moreover, the effect of the inflation rate on metal prices remains almost unchanged over the different models, while it is slightly larger in magnitude for the sub-sample one, see Figure 5.3. The positive response of metal prices to a shock in the inflation rate is in line with the theory, as a high inflation rate is one channel through which monetary policy can influence commodity prices, see Anzuini et al. (2013). Additionally, the inflation rate also represents a measure for the current stance of the economy. When the economy is strong, inflation is usually high, as is the demand for commodities, hence the two variables should move in sync.

In addition, since commodities are traded worldwide, a raise in the U.S. Dollar exchange rate should be accompanied by lower metal prices, due to the law of one price, as outlined within Section 2.1.2. Our sub-sample analysis underlines this relation, as an increase in the U.S. Dollar index, indicating a strong dollar, leads to decreasing metal prices in the second sub-sample, see Figure 5.4, while for the total-sample and sub-sample one the effect is smaller and statistically not significant.

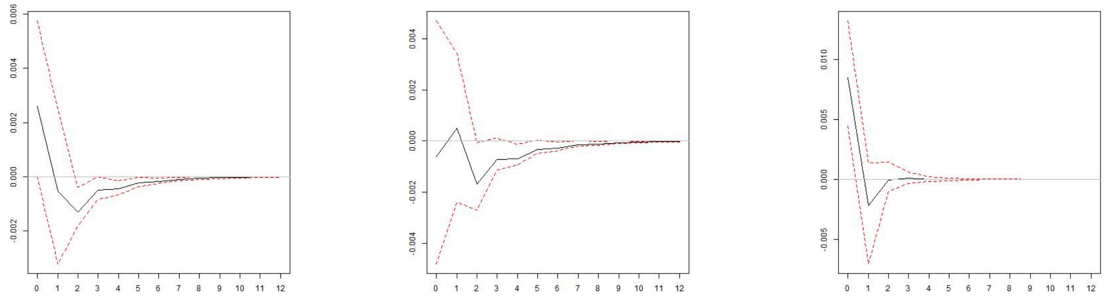
In the following, we analyze whether the effect of interest rates on metal prices changed. Hereby, the analysis of monetary policy implications on metal markets reveals a contrarian monetary policy, represented by a positive shock to the interest rate, leads to increasing metal prices in the total-sample, covering the period from 1995 to 2019, as well as in sub-sample one, spanning from 1995 to 2008, see Figure 5.5a and Figure 5.5b. Byrne et al. (2020) partly detect an inverse relation of interest rates and a sectoral factor of metal prices, while Lombardi et al. (2012), Siami-Namini (2021) and Zhu et al. (2015) do not find any statistically significant effect of interest rate changes on commodity prices. As is the case in our analysis in the total-sample and sub-sample one, Hammoudeh et al. (2015) and Österholm and Zettelmeyer (2008) display a significant positive response of commodity prices to interest rate shocks, which is against the theoretical direction of relation. However, also Frankel (2008) shows in the empirical analysis of agricultural and mineral commodity prices a positive relation between interest rates and prices, when data in the period from 1980 to 2005 is considered. Hammoudeh et al. (2015) argue the positive response of prices may be caused by the timing of interest rate changes, which usually occur during times of a strong economy and therefore strong demand. Subsequently, while lowering the interest rate might mitigate the rise in commodity prices, the continuously strong demand continues to drive commodity prices upwards, a link that is also found by Baffes and Savescu (2014) for longer term interest rates, indicating the empirical evidence in the literature is heterogeneous.

Figure 5.5: Response of Metals Index - Federal Funds Rate Shock



(a) 1995 - 2019 **(b)** 1995 - 2008 **(c)** 2009 - 2019

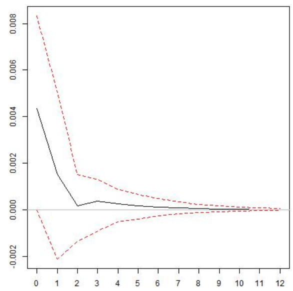
Figure 5.6: Response of Metals Index - Term Spread Shock



(a) 1995 - 2019 **(b)** 1995 - 2008 **(c)** 2009 - 2019

While our analysis reveals a positive response of the metals price index to shocks in the interest rate, which is more pronounced in the first sub-sample, the effect is rather

Figure 5.7: Response of Metals Index - Balance Sheet Size Shock



(a) 2009 - 2019

small and especially insignificant in the second sub-sample, see Figure 5.5c, covering the period of unconventional monetary policy. This indicates interest rates have, as expected, a stronger impact prior to the zero-interest rate policy.

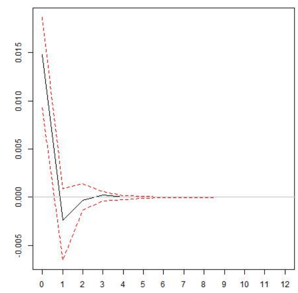
Due to the zero-interest rate environment, central banks implemented unconventional monetary policy actions, like quantitative easing, which may be approximated via the balance sheet size of the FED. Therefore, we include this variable as an additional monetary policy measure in our enlarged model for the second sub-sample, starting in 2009. In line with theory and the empirical finding of Hammoudeh et al. (2015), we hereby observe a significant, positive reaction of metal prices to an expansionary monetary policy, reflected by a positive shock in the balance sheet size, see Figure 5.7. However, our results are very close to being statistically insignificant in this case. While these results are in line with the basic theory, they are of opposite direction to the impact of monetary policy in the total-sample, as well as in sub-sample one. We further analyze this change of relation between monetary policy and metal prices at the end of this chapter.

Additionally, a positive shock to our inverse recession indicator, the term spread, leads to a significant, positive response of the metal index, in the total-sample as well as in the second sub-sample. Our finding is in line with the theory, as a potential crisis should lead to lower demand expectations and ultimately to decreasing prices in metals, and vice versa.

Subsequently, we analyze the effect of the U.S. inflation expectation index as further unconventional monetary policy proxy, which we hypothesize to represent the effect of the entire monetary policy on markets, as does the shadow rate of Wu and Xia (2016). Therefore, we first replace the balance sheet size of the FED in our extended model of sub-sample two by the U.S. inflation expectation index. Theoretically, the FED influences market expectations on future levels of inflation by communicating further monetary policy actions, which is represented by the inflation expectation index. In line with the results for the balance sheet size of the FED, an increase in the inflation expectation leads to an immediate increase in metal prices, see Figure 5.8. The shadow rate of Wu and

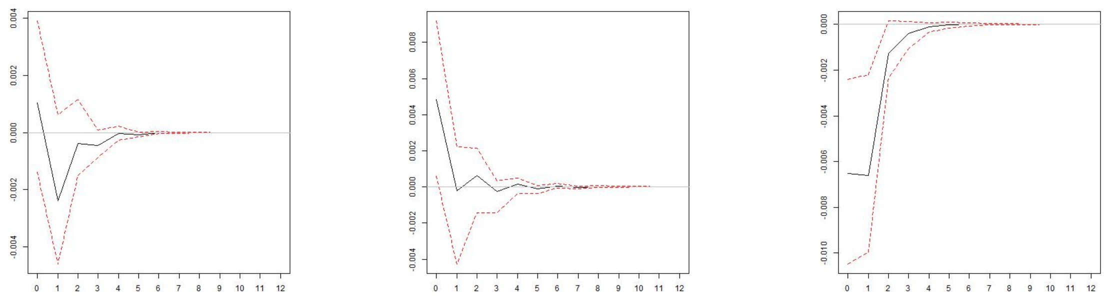
Xia (2016), representing an interest rate based composite measure for monetary policy, is almost equal the federal funds rate until the Q32008[4], while it represents the entire monetary policy, including conventional as well as unconventional actions of the FED, in the following period. Consequently, we replace the interest rate, reflecting the conventional monetary policy, as well as the balance sheet size, reflecting the unconventional monetary policy measure in our enlarged model, by the shadow rate of Wu and Xia (2016) in all our models and sub-periods. In line with the basic theory, a positive shock to the shadow rate, reflecting a contrarian monetary policy, has an immediate and persistent inverse effect on metal prices in the second sub-sample, see Figure 5.9c. In contrast, the response of metal prices to a contrarian monetary policy shock is positive in the total-sample and sub-sample one, while the results in the total-sample are statistically insignificant.

Figure 5.8: Response of Metals Index - U.S. Inflation Expectation Index Shock



(a) 2009 - 2019

Figure 5.9: Response of Metals Index - Shadow Rate Shock



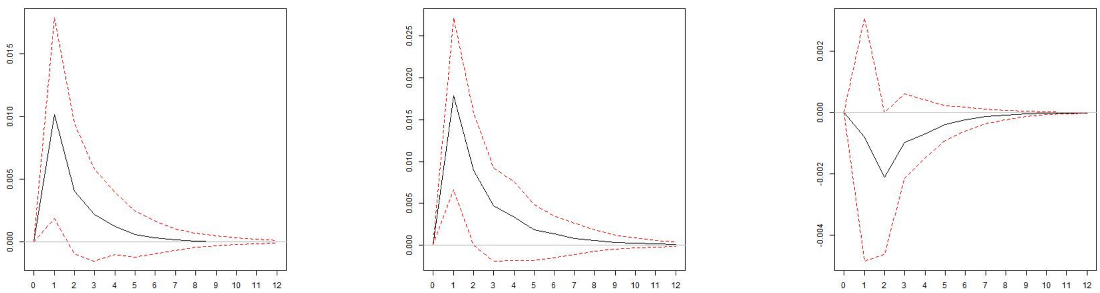
(a) 1995 - 2019 **(b)** 1995 - 2008 **(c)** 2009 - 2019

[4]The differences between the two variables originate from the variable frequency, where the monthly federal funds rate is the average of daily values, see Board of Governors of the Federal Reserve System (US) (2022b), whereas the WuXia rate is based on end-of-month values.

Overall, our analysis indicates conventional monetary policy affects metal prices only in the pre-crisis period, whereas monetary policy in general affects metal prices through unconventional policy actions in the second sub-sample as well. While the effects of the conventional policy in the first sub-sample are in line with the empirical findings of Hammoudeh et al. (2015) and Frankel (2008), they are against the initial theory of an inverse relation between commodity prices and interest rates. However, in the second sub-sample the effects are more pronounced, as well as in line with the theory, since the direction of relation between metal prices and monetary policy changed. That is, an expansionary policy, represented via an increase in the balance sheet size or an increase in the inflation expectation index, results in increasing metal prices. Further, a contractionary policy, represented via an increase in the shadow rate, decreases prices. While the change of channels, through which monetary policy acts, is reasonable, given the zero lower bound of interest rates, the change in the direction of relation is non-intuitive. Hence, we analyze these changes in more detail in the following.

Therefore, we start to investigate the reverse causality, the impact of metal prices on interest rates. Hereby, we observe a positive, lagged and persistent response of the federal funds and shadow rate in the total-sample, as well as in sub-sample one.

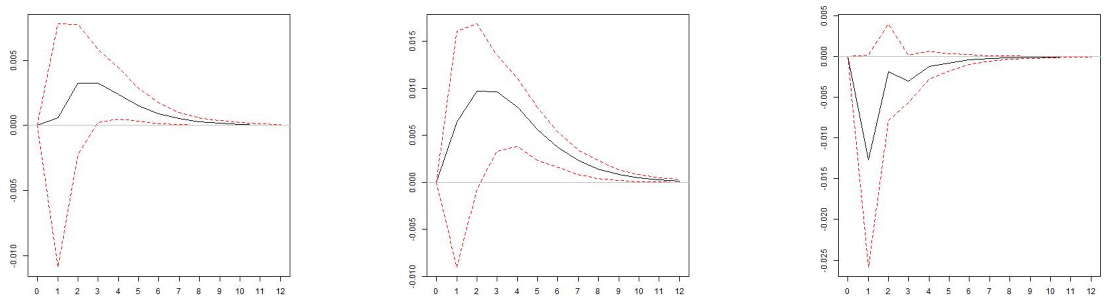
Figure 5.10: Response of Federal Funds Rate - Metals Index Shock



(a) 1995 - 2019 **(b)** 1995 - 2008 **(c)** 2009 - 2019

This indicates the federal funds rate, of which the shadow rate model constitutes in the first sub-sample, reacts, at least partly, in response to metal price developments. However, this effect vanishes in the second sub-sample for both variables. This indicates the monetary policy is no longer adjusted in response to metal prices, a change in policy that is surprising. However, central banks mainly fear the inflationary pressure arising from high energy commodity prices. Hence, we hypothesize these central banks monitor these prices, see also Frankel (2014), whereas metals are of less interest to them. A correlation analysis hereby reveals a correlation of the RICI metals index to the oil price of about 46.3% in the first sub-sample, while the value decreases to only 37.4% in the second sample. This finding is in contrast to the results of Tang and Xiong (2012), where they detect an increasing correlation of various commodities, including copper,

Figure 5.11: Response of Shadow Rate - Metals Index Shock



(a) 1995 - 2019 **(b)** 1995 - 2008 **(c)** 2009 - 2019

to oil. However, their data sample ends in December 2011, where they already detect a decreasing correlation between oil and copper in 2010 and 2011. Therefore, we hypothesize the effects of metal prices on monetary policy are smaller in the second sub-sample, due to the reduced correlation to the main policy monitored commodity price, the oil price.

When monetary policy in adjusted in response to rising commodity prices, the two variables obviously bear a concurrent relation, as can be seen within Figure 5.5b and Figure 5.10b. However, within the second sub-sample, as hypothesized above, monetary policy is only determining on, but not determined by, metal prices. Hence, the theoretical channels for the inverse relation, as outlined in Frankel and Rose (2010), become dominant again. This is consistent across all effects and measures of monetary policy in the second sub-sample, see Figure 5.7, Figure 5.8 and Figure 5.9c.

5.2 Metal Price Forecasts, Predictors and Determinants

Within this section, based on the setup proposed in Papenfuß et al. (2021), we proceed by individually modeling and forecasting metal prices in a rolling window approach for the three precious metals silver, gold, and platinum, the six industrial metals aluminum, copper, nickel, lead, tin, and zinc, as well as the fifteen minor metals bismuth, cadmium, cobalt, chromium, gallium, germanium, indium, lithium, magnesium, molybdenum, manganese, antimony, titanium, vanadium, and tungsten. To start, as shown within Section 4.1, we split our data set in an in-sample and out-of sample part, where the in-sample window covers 75% of the available data points, which span across the period 1995 to 2019. For the prediction of prices, we model each metals' price series via a linear regression model and hereby apply the model selection process as outlined within Section 4.1, to obtain the metal-specific price predictors. Since we lag all predictor variables by one month, the linear regression model is equivalent to a forecast. Further, our results are generally based on Newey-West estimators, to obtain robust standard errors.

We compare our models' forecasts against a random walk, as well as a random walk with drift benchmark, where we determine the significance of our forecast improvements via the standard test of Clark and West (2007), which is based on the MSPE metric. In addition, we also compare our forecasts against the AR benchmark, which represents the metals' last month's return as a predictor for the current return. Hereby, the forecast performance in comparison to the AR benchmark is not checked for statistical significance, as the Clark-West test requires the benchmark model to be a nested version of the analyzed model, which is not the case for this benchmark. Further, we also analyze our findings in comparison to the three benchmarks using the MAPE measure, in addition to the above mentioned MSPE ratio. Moreover, we model each metal's price series via the same linear regression model and variable selection process, but on the contemporaneous series of the covariates, to obtain the metal-specific price determinants.

Commodity markets changed their structure substantially over the last twenty-five years, as indicated by the structural break test of the previous section, see Figure 5.1, and stated within previous studies, e.g. by Buncic and Moretto (2015), who show copper's most relevant predictors changed drastically after 2008. These changes are related to multiple conditions. First, the financialization of commodity markets, starting around the year 2004, which should link commodity prices closer to prices of other commodities and financial markets in general. Second, the monetary policy changed significantly over the last two decades, from the conventional, interest rate based policy, which was in practice until Q42008, to the unconventional monetary policy actions in response to the financial crisis. However, since the end of the last decade, interest rate were rising again, which should theoretically also elevate the impact of interest rates on commodity markets again. Third, the growing influence of emerging markets, especially China, where nowadays a large share of the commodity production and consumption is taking place.

To account for these changes in the markets, we perform the above described analysis three times, for the total-sample covering the period 1995 to 2019, the sub-sample one with data from 1995 until 2008, as well as the second sub-sample spanning from 2009 to 2019. However, as both sub-samples are too short to generate enough out-of sample forecasts for a valid analysis of the forecast performance, we rely on the interpretation of the estimated β-coefficients in both sub-samples. Since we also perform the model estimation twice per commodity and sub-sample, once for the determinants and once for the leading price series, the sub-sample analysis enables us to reveal the changes in the commodity-specific predictors as well.

5.2.1 Total-Sample - Analysis of the Timeperiod 1995 to 2019

To start, we analyze the overall forecast performance of our models, as well as the individual predictor variables. Hereby, we are able to outperform the random walk and random-walk with drift benchmark models in all of the six cases for the three precious metals, while only the forecast improvement for platinum is statistically significant, based on the ten percent level and compared against the RWD benchmark, see Table 5.1.[5]

Further, we outperform the two above mentioned benchmark models in ten of the twelve cases for the six industrial metals, while the forecast improvements are statistically significant in six cases, for both benchmarks and the metals nickel, tin and zinc, based on the five percent level, see Table 5.1.[6] The significance of the forecast improvement is hereby evaluated in comparison to the RW and RWD benchmark models, as the test of Clark and West (2007) requires the benchmark to be a nested version of the tested model, which is not the case for our AR benchmark. Hereby, nickel, tin and zinc are among the smaller markets of the industrial metals, see London Metal Exchange (2019). Turning our attention to the fifteen minor metals, we are able to significantly outperform the RW and RWD benchmark in 14 of the 30 cases, while we are able to reduce the forecast error substantially, by more than five percent, in 22 of the 30 cases. The significant forecast improvements within this group hereby correspond to the metals bismuth, chromium, gallium, indium, antimony, vanadium and tungsten. However, for germanium and titanium, our model is identical to the benchmark model, as none of the potential predictors is selected by our model selection approach.

[5]The plots of the metal-specific price forecasts can be found within Figure E.1 of Appendix E.1.

[6]As we obtained monthly supply and demand data for the industrial metals from a bespoke report of the World Bureau of Metal Statistics (WBMS), see World Bureau of Metal Statistics (2021), we repeat the model estimation considering these attributes, see Table E.3 and Table E.4, but obtain almost identical results in both cases.

When relying on our second goodness-of-fit measure, the Mean Absolute Prediction Error (MAPE), the forecast improvements are smaller and partly even vanish completely. As for the results of the MSPE metric, the performance of the RW and the RWD benchmark models is comparable, whereas the AR benchmark performs substantially worse, similar to the results of the MSPE metric. These differences between the results for the MAPE and MSPE metrics highlight the ability of our model to replicate more of the markets' volatility, compared to the benchmark models.

Table 5.1: Prediction Error Ratios for the Out-Of-Sample Forecasts

	$MSPE$			$MAPE$		
	rw	rwd	$AR(1)$	rw	rwd	$AR(1)$
Ag	0.95	0.91	0.63	0.99	0.97	0.79
Au	0.89	0.89	0.69	0.99	0.96	0.79
Pt	0.89	0.85.	0.64	0.98	0.96	0.76
Al	0.92	0.92	0.59	1.05	1.05	0.78
Cu	0.88	0.88	0.72	1.09	1.06	0.85
Ni	0.80**	0.80**	0.73	0.94	0.94	0.83
Pb	1.11	1.10	0.80	1.07	1.05	0.86
Sn	0.81*	0.76**	0.75	1.01	0.97	0.89
Zn	0.69***	0.69***	0.67	0.85	0.85	0.77
Bi	0.55**	0.55**	0.60	1.05	1.03	0.78
Cd	0.99	0.99	0.78	1.10	1.09	0.90
Co	0.99	0.99	0.61	1.08	1.09	0.77
Cr	0.81*	0.81*	0.59	1.07	1.05	0.77
Ga	0.66*	0.58*	0.76	1.00	0.93	0.92
Ge						
In	0.74**	0.72***	0.65	0.96	0.93	0.74
Li	0.77	0.86	0.96	1.30	1.13	1.07
Mg	0.89	0.89	0.57	1.07	1.06	0.80
Mn	0.89	0.88	0.63	1.07	1.03	0.82
Mo	0.95	0.95	0.63	1.21	1.18	0.83
Sb	0.52***	0.48***	0.69	1.07	1.01	0.89
Ti						
V	0.79**	0.80**	0.79	1.01	1.01	0.92
W	0.79*	0.75**	0.66	1.06	0.99	0.81

This table displays the metal-specific out-of-sample forecast error ratios, which are the models' forecast error divided by the benchmark forecast error, for the mean squared prediciton error (MSPE) and the mean absolute prediction error (MAPE) measures and the three benchmark models: random walk (rw), random walk with drift (rwd), and $AR(1)$. For the rw and the rwd benchmark, the significance of the forecast improvements is tested via the test of Clark and West (2007), which is not applicable for the $AR(1)$ benchmark model.

Turning our attention to the price predictors, we reveal the value factor as the most influential factor, in line with the findings of Asness et al. (2013), which is included in eleven models and, except for zinc, in all models where the resulting forecast improvement is statistically significant, see Table 5.2. Hereby, we exclude the variables of the shaded columns from this analysis, due to the shortened data availability and hence potential biases in the parameter estimation.[7]

However, the value factor shows a negative sign, which is against the theory of mean reverting prices and the empirical findings of Asness et al. (2013). As the value factor is the ratio of historical, *true* prices, divided by the most recent price, a large value factor represents a currently cheap metal. When the value factor rises, this indicates the metal is currently undervalued even more, which should theoretically cause future prices to rise. We attribute these differences to the time-series character of our analysis, see Section 6.2 for further details.

The monetary aggregates MB and M4, which both are included in five models, each show a negative sign. Hereby, the M4's predictive content is especially noteworthy for the industrial metals, which is against the hypothesized direction, as it represents a measure of unconventional monetary policy, where an increase in the variable represents a loose policy and should hence lead to an increase in commodity prices, see Keating et al. (2019). However, it is not included within the prediction model for aluminum, while the metal generally differs in the selected covariates, compared to the other industrial metals.

Moreover, the Bloomberg commodity index and the MSCI world index are each included in four models, always with a positive sign. This represents the co-movement in commodity prices, as well as the integration of metals with financial markets, where a rise in either one causes rising commodity prices as well, which is in line with the findings of Basak and Pavlova (2016). Additionally, the futures prices, as well as the convenience yield, are each included within three models. However, only for zinc, where the prediction model simultaneously includes the convenience yield and the first running futures price, the forecast is significantly outperforming the benchmark forecast. Further, the U.S. Dollar index, our exchange rate measure, is only included in three models, where none of those is outperforming the random walk and random walk with drift BMKs significantly. This is in contrast to theory, where exchange rates are hypothesized to predict commodity prices, due to their speed of including new information. The remaining covariates are included in two or less models, which is why we neglect them from further analysis and interpretation. However, when generally analyzing the results within Table 5.2, we see the sign of the β-coefficients is equal across all metals, with the exception of the supply variable, indicating the stability of the relations modeled within the prediction analysis.

When we turn our attention to the variable categories, we see comparably little influence of interest rates on prices, where only two of the six measures representing different interest rates enter the forecast models, while the β-coefficient of the Chinese short-term interest rate for copper is of the hypothesized, negative sign, representing the inverse relation of interest rates on prices, as hypothesized by Frankel (1986). However, the β-

[7] Due to the short time-series for the second futures contract of platinum, we exclude the corresponding basis-momentum factor from all models and sub-periods.

coefficient for the federal funds rate in the model of magnesium is slightly positive. In contrast, the monetary aggregates are included more often, especially in the models of the metals where the forecasts are able to outperform the BMK, with thirteen inclusions overall. However, they are always included with a negative sign, which is against the theory and the empirical findings of Ahumada and Cornejo (2014). Further, our measures of industrial production, representing a proxy of overall commodity demand, are selected in none of the models, independent of the regional scope these variables cover, while also the measures of economic activity are included in only three models overall.

In contrast, the commodity and financial market variables and indices are included thirteen times overall, all with a positive sign. This is in line with theory, as the oil price is a proxy for input costs in the commodity supply and therefore an increase in its price should be accompanied by rising metal prices as well, which is empirically also found by Sari et al. (2010) for precious metals, as well as Vansteenkiste (2009) for food, agricultural raw materials and industrial metals, while in our case, this relation only holds for the minor metals, at least in the prediction dimension.[8] The same holds for the commodity indices Bloomberg commodity index and RICI metals index, where through the co-movement of commodity prices, an index increase transfers to other commodity markets as well, which is represented by a positive sign of the β-coefficients in our model. Additionally, this causality holds also for financial market variables, where a raise in the MSCI world index or the S&P 500 translates to metal prices as well, where through financialization effects metal markets seem to be connected closer to financial market conditions. While the metal-specific supply and demand variables are only included within three models, the predictors representing the individual price components are, with the inclusion within 20 models, the most influential category by far. In contrast to the common believe of futures prices being an appropriate predictor for future spot prices, see Groen and Pesenti (2011) for example, there is generally little empirical support for the assumption, as already found by Fama and French (1987), which also holds in our case, where the futures price is only a predictor in one of the significant models.

We now change the perspective slightly and evaluate the metal price determinants, as displayed within Table 5.3, where we regress the determinants timely on the metal prices, without a lag. Hereby, we again observe two metals, germanium and titanium, where the model selection yields in no selected variable. Further, we still exclude, as for the prediction, the shaded areas from the analysis. In addition, we further exclude the first running futures contract, as it is almost identical to the actual price, as can be seen from the unrestricted version of this model, displayed within Table E.2 of Appendix E.1. Further, we also exclude the value factor, as this variable includes the actual price of the metal itself, see Equation 3.3, which would potentially yield to misleading interpretation.

[8]For the price determinants, see also Table 5.3, we show the hypothesized relation for three of the industrial metals.

Additionally, we exclude the RICI metals index for the industrial and precious metals, as these are the constituents of the index and hence obviously this variable should be highly correlated to the actual prices. However, we include the Bloomberg commodity index, which also includes silver, aluminum, copper, nickel, and zinc, but with a substantially smaller weight. For the case of gold, which is also included in the Bloomberg commodity index, with a comparably large share, the index is selected neither as determinant nor predictor for the metal, which is rather surprising. However, it still is included in six models, the one of platinum, three of the industrial metals, as well as two minor metals, always with a positive sign, which is in line with the co-movement relation described above.

For the included covariates, the CPI shows, when included, always a positive coefficient, indicating a rising inflation leads to rising commodity prices, which is in line with the theory, see Frankel and Rose (2010) for example. This is the case for all precious metals, tin, as well as five minor metals. Further, the exchange rate is included in seven models, two of which are precious and four industrial metals, always with a negative sign. This is, again, in line with theory, as a strong dollar should lead to falling commodity prices and vice versa, see Akram (2009), for example. Additionally, the MSCI world index is included in seven models, for all industrial metals, as well as the platinum model, with a positive sign. This is also in line with theory, where through the financialization rising stock market prices should translate into rising commodity prices. Further, the selection of the MSCI world in contrast to the S&P 500 index indicates the global scope of modern metal markets.

For the monetary aggregates, the monetary base is included in seven models, where the sign is always negative, which is in contrast to the literature, but in line with the relation observed within the prediction part of this thesis. The economic activity index of Kilian (2009) is included in six models, within five of those with a positive sign. However, it is a determinant for none of the industrial metals, which is surprising, as the index should have the largest impact on those commodities, given the volume they are shipped, while, on the other hand, it is included for magnesium, which is the third most commonly used metal, in terms of structural components, after steel and aluminum, see International Magnesium Association (2022).

The convenience yield is a determinant for the three precious metals, as well as aluminum and copper. Hereby, for gold and silver the relation is negative, while for the other metals the relation is positive. The negative sign for gold and silver, which is against theory, probably originates in the large storage of those metals within financial institutions and reserves, which makes a shortage of physical availability for the respective metals rather unlikely. The convenience yield for the two precious metals is calculated on the second running futures contract, in contrast to the first running contract for the industrial metals, which is on average above the corresponding spot price, possibly explaining the differences in the sign of the coefficient. For the remaining determinants, the oil price and the basis momentum factor are included in three of the industrial metals' models each, always with a positive sign, which is in line with theory for both variables. Further, the GDP index is also included in three models, also with a positive sign, which is also in line with theory for this variable.

We now again change the perspective slightly and analyze the differences between the metal-specific predictors and determinants, as displayed in Table 5.3 and Table 5.2. Hereby, we detect a substantially larger impact of the MSCI world index, the Bloomberg commodity index, as well as the oil price in the determination models, compared to the predictor analyses. This is in line with theory, where financial market conditions should have synchronous effects on commodity markets in general, via the closer connection of commodity indices to other financial markets, and also individual metal prices, mainly those included within the indices. Moreover, we reveal the exchange rate as one of the most important determinants for metal prices, while at least for the precious and industrial metals, the covariate is irrelevant in the prediction. This is in contrast to previous findings within the literature, where exchange rates are hypothesized to be strong predictors of commodity prices, see Chen et al. (2010) and partly Gargano and Timmermann (2014). However, the differences most likely originate from the scope our exchange rate variable covers, where the U.S. Dollar index is a rather general, broad measure, while studies like Chen et al. (2010), Ciner (2017), Gargano and Timmermann (2014) and Pincheira-Brown and Hardy (2019) focus on the Dollar exchange rates of small, commodity exporting economies, like Chile and South Africa, for example.

Moreover, the economic activity index of Kilian (2009) is only a determinant and not of predictive ability for metal prices, which is in line with theory. While freight rates, of which the economic activity index is constructed, are theoretically leading indicators of the economy, they should be timely in regard to commodity prices. When companies buy commodities, they would theoretically hedge the shipping costs via freight indices at the time of the commodity purchase. While the metals are subsequently consumed within the economy, higher freight rates should be indicative of future economic activity and growth, while the relation to commodities should be, as found within this thesis, timely.

Overall, the $Adj.R^2$ values are substantially larger in the price determination models for all industrial and precious metals, in comparison to the prediction models. This increase of the models' abilities to describe a larger share of the current metal price even holds without autoregressive price influencing variables.[9] For the minor metal markets, the relation is the other way round, where changes in the covariates are priced with a

[9] These findings are based on our restricted metal price determinants models, where for the unrestricted version, including the first running futures prices, the $Adj.R^2$ range between 93% and 99%.

lag, which we attribute to the market efficiency and speed of markets. For minor metals, the spot markets are most likely less developed, in comparison to the LME and precious metal markets. Hence, changes in economic conditions are priced with a lag, which enables the prediction of these prices based on current economic and financial covariates. Additionally, the minor metals seem to bear a larger idiosyncratic component within each price series, which makes the value factor so influential in the price prediction. Hereby, it is included in nine of the fourteen prediction models, especially in all models where the forecast is significantly outperforming the benchmark. Moreover, we see, especially in the price determination models, a clustering between the metal groups. With the exception of aluminum, the industrial metals show very homogeneous determinants, which are heavily linked to other financial market variables and the exchange rate. The same holds for the precious metals, although the inflation index seems to be a more important determinant for this commodity class, while the minor metals are very heterogeneous in the selected covariates within the price determination.

Table 5.2: Linear Regression Results for the Metal Price Predictors - Total-Sample

	supply	hhi	demand	VAL	MOM	FUT1	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	T10Y3M	FFR	WuXia	MB	WALCL	M4	T5YIFR	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	EAKilian	BDI	CPI	OIL	BCOM	RICIM	MSCIW	SPX	$Adj.R^2$
Ag							-0.01 (0.02)																								0.31 (0.01)		0.08
Au							-0.01 (0.00)																						0.17 (0.11)				0.12
Pt					-0.04 (0.04)	0.26 (0.02)																							0.41 (0.01)				0.19
Al		-0.11 (0.01)																						13.27 (0.00)					0.28 (0.00)				0.20
Cu						0.30 (0.00)				-0.80 (0.01)						-0.36 (0.03)		-2.44 (0.01)															0.25
Ni				-0.29 (0.00)														-3.04 (0.02)															0.14
Pb								0.19 (0.03)								-0.42 (0.11)				-0.71 (0.04)													0.12
Sn				-0.29 (0.00)														-1.90 (0.05)															0.13
Zn						0.26 (0.00)	-0.00 (0.10)	0.14 (0.10)										-2.61 (0.01)															0.20
Bi				-0.43 (0.00)																										0.35 (0.00)			0.33
Cd																-0.95 (0.04)											0.07 (0.03)						0.13
Co																				-1.48 (0.01)												0.62 (0.08)	0.08
Cr				-0.38 (0.00)														-1.25 (0.01)										0.10 (0.01)					0.39
Ga				-0.34 (0.00)																													0.14
Ge																																	
In	-1.36 (0.00)			-0.31 (0.00)																											0.51 (0.00)		0.32
Li	0.77 (0.08)			-0.46 (0.00)																													0.27
Mg														0.01 (0.00)													0.03 (0.01)				0.39 (0.00)		0.17
Mn				-0.36 (0.00)																										0.24 (0.10)			0.28
Mo																-1.29 (0.00)				-1.66 (0.00)													0.17
Sb				-0.28 (0.00)																								0.17 (0.00)					0.21
Ti																																	
V				-0.24 (0.02)												-0.68 (0.01)													0.83 (0.01)				0.22
W				-0.39 (0.00)																											0.31 (0.02)		0.25

This table displays the averaged β-coefficients and corresponding p-values of the metal price predictors in the total-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table 5.3: Linear Regression Results for the Metal Price Determinants - Total-Sample

	$supply$	hhi	$demand$	VAL	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
Ag							-0.01 (0.00)													-1.16 (0.00)							0.03 (0.01)						0.19
Au							-0.00 (0.08)													-0.78 (0.00)							0.01 (0.04)						0.22
Pt							+0.00 (0.00)									-0.20 (0.18)											0.03 (0.01)		0.28 (0.16)		0.35 (0.00)		0.36
Al							+0.00 (0.00)													-0.43 (0.03)								0.10 (0.09)	0.29 (0.01)		0.33 (0.00)		0.42
Cu										-0.76 (0.00)						-0.43 (0.00)												0.19 (0.00)	0.29 (0.07)		0.50 (0.00)		0.45
Ni								0.19 (0.00)																				0.19 (0.00)			0.88 (0.00)		0.33
Pb							+0.00 (0.02)	0.18 (0.03)								-0.39 (0.08)				-0.91 (0.00)											0.41 (0.00)		0.28
Sn																				-0.60 (0.03)							0.02 (0.1)		0.32 (0.05)		0.50 (0.00)		0.31
Zn								0.24 (0.00)												-0.80 (0.00)											0.62 (0.00)		0.32
Bi																								14.92 (0.00)									0.05
Cd			-0.59 (0.05)										0.03 (0.05)			-1.21 (0.02)																	0.16
Co																														0.58 (0.12)			0.02
Cr																		-1.01 (0.1)							+0.00 (0.00)		0.03 (0.00)						0.26
Ga											0.04 (0.00)									-0.60 (0.03)					-0.00 (0.05)								0.19
Ge																																	
In									-0.01 (0.06)															17.79 (0.00)									0.09
Li			0.37 (0.00)													-0.37 (0.00)													0.34 (0.01)				0.14
Mg																								8.46 (0.03)	+0.00 (0.04)		0.03 (0.00)						0.17
Mn																-0.51 (0.02)									+0.00 (0.08)					0.37 (0.00)			0.18
Mo																-1.02 (0.03)																	0.07
Sb																											0.03 (0.00)		0.38 (0.01)				0.08
Ti																																	
V																									+0.00 (0.04)		0.09 (0.00)						0.12
W		0.21 (0.00)																							+0.00 (0.00)		0.04 (0.00)						0.17

This table displays the averaged β-coefficients and corresponding p-values of the metal price determinants in the total-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

5.2.2 Sub-Sample One - Analysis of the Timeperiod 1995 to 2008

We extend our initial analysis of the predictors and determinants of metal prices by two sub-sample analyses, where for sub-sample one we only consider data in the period from 1995 to 2008. We hereby exclude the identical variables as in the prediction and determinant models of the total-sample, due to short data availability, while we additionally exclude gallium, since its price series only starts in the year 2002. In comparison to the total-sample, we assume a few differences in sub-sample one.

First, through the financialization of commodity markets, starting around the year 2004, the price changes on commodity markets should be connected closer to other commodity and financial market conditions in recent times. Hence, we hypothesize a smaller impact of commodity and financial market variables on commodity prices in the first sub-sample, due to the larger idiosyncratic component within prices. Second, as the monetary policy consisted of conventional policy actions prior to Q42008, we hypothesize a larger influence of interest rates on prices. Third, as the commodity production and consumption gradually shifts towards Asia, we hypothesize a larger impact of U.S. variables on prices in the first sub-sample, compared to the total- and especially the sub-sample two.

To start, for the prediction of prices, we observe an even more pronounced effect of the value factor, which is included in fourteen models as a predictor, in comparison to eleven models in the total-sample, see Table 5.4 in comparison to Table 5.2, which is in line with the first of the above mentioned hypothesis. Further, this finding indicates the commodity markets were less developed during those times, where the new financial and economic conditions were priced with a lag in metal markets, especially those of minor metals. Additionally, the commodity indices and oil prices are included within eight models in the total-sample, while they are only predictors for four metals in the first sub-sample, again underlining our first hypothesis, the reduced co-movement between commodities in sub-sample one. For the interest rates, we do see a larger impact in the first sub-sample, within seven models in comparison to two models in the total-sample, which again supports our hypothesized differences between the samples. However, the signs of estimated coefficients are mixed, e.g. always positive for the federal funds rate, which is in line with the empirical findings of Frankel (2008) and our analysis within Section 5.1, but in contrast to the standard theory, where commodity prices should be related inversely to interest rates. Finally, with the exception of aluminum, cobalt, gallium, molybdenum, and vanadium, the $Adj.R^2$ is larger for all metals in the first sub-sample, indicating a stronger predictability of prices during this period.

Turning our attention to the price determinants, we see a substantially larger interrelation of metal prices and the determinants in the total-sample, where 46 determinants are included in the models in sub-sample one, in contrast to 66 variables in the total-sample, see Table 5.5 in comparison to Table 5.3. Again in line with our second hypothesis, the effect of interest rates on metal prices is more pronounced in the first sub-sample, also as determinant. Further, the financial market and commodity indices do have a smaller impact in the first sub-sample, supporting our first hypothesis of an enlarged integration of commodity markets over time. Moreover, exchange rates have a substantially smaller impact on sub-sample one. While the impact of the convenience yield remains unchanged between the two samples, the inflation rate has a smaller impact in the first sample, and especially no impact on any of the precious and industrial metals, which is rather counter intuitive. Additionally, the changes in the influence of the economic activity index of Kilian (2009) are noteworthy, as it is a determinant of only one metal in the first sub-sample, while it influences six metals in the total-sample, a change that we attribute to less developed markets for shipping rates. However, we are unable to verify the reduced impact of emerging markets on commodity prices, which is against our third hypothesis. Overall, the determinants analysis indicates a substantially larger idiosyncratic component in metal prices and therefore less integration of prices with economic and financial market conditions, which is in line with our first hypothesis.

Table 5.4: Linear Regression Results for the Metal Price Predictors - Sub-Sample One

	$supply$	hhi	$demand$	VAL	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
Ag			-1.85 (0.01)				-0.01 (0.00)																										0.11
Au							-0.01 (0.00)																						0.26 (0.02)				0.17
Pt						0.24 (0.07)																		50.68 (0.04)					0.56 (0.00)				0.27
Al																								35.39 (0.03)					0.50 (0.00)				0.18
Cu						0.35 (0.00)												-4.97 (0.00)						49.84 (0.07)									0.29
Ni				-0.38 (0.00)																													0.17
Pb				-0.30 (0.00)										0.18 (0.00)																			0.15
Sn				-0.38 (0.00)																													0.16
Zn						0.3 (0.00)	-0.00 (0.01)	0.15 (0.04)										-3.43 (0.05)															0.27
Bi				-0.6 (0.00)																													0.39
Cd				-0.36 (0.00)												-1.24 (0.00)									-0.05 (0.00)								0.26
Co																																0.77 (0.01)	0.04
Cr				-0.53 (0.00)														-2.02 (0.00)															0.44
Ga																																	
Ge															0.01 (0.01)																		0.07
In				-0.23 (0.00)											-0.02 (0.00)																0.5 (0.00)		0.41
Li				-0.51 (0.00)																		-0.41 (0.05)											0.30
Mg				-0.36 (0.00)												-0.86 (0.00)																	0.24
Mn				-0.52 (0.00)												-0.99 (0.00)																	0.42
Mo														0.53 (0.00)	-0.02 (0.02)																		0.11
Sb				-0.35 (0.00)	-0.03 (0.01)									0.21 (0.00)																			0.27
Ti				-0.52 (0.00)																													0.26
V				-0.29 (0.03)																									1.53 (0.00)				0.22
W				-0.55 (0.00)										0.22 (0.01)																			0.39

This table displays the β-coefficients and corresponding p-values of the metal price predictors in sub-sample 1, 1995-2008, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table 5.5: Linear Regression Results for the Metal Price Determinants - Sub-Sample One

	$supply$	hhi	$demand$	VAL	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
Ag																				-0.89 (0.00)									0.46 (0.00)				0.17
Au																				-1.02 (0.00)													0.27
Pt							+0.00 (0.00)		-0.14 (0.01)							-0.87 (0.00)													0.51 (0.00)				0.48
Al							+0.00 (0.00)													-0.45 (0.00)									0.47 (0.00)		0.23 (0.00)		0.39
Cu																-0.84 (0.00)													0.67 (0.00)		0.32 (0.00)		0.42
Ni								0.16 (0.00)																					0.73 (0.00)		0.67 (0.00)		0.33
Pb							+0.00 (0.00)	0.18 (0.02)								-0.57 (0.00)				-0.80 (0.00)													0.31
Sn	-1.47 (0.03)							0.18 (0.05)																					0.52 (0.00)		0.33 (0.00)		0.27
Zn					-0.08 (0.00)			0.46 (0.00)						0.18 (0.00)																	0.52 (0.00)		0.40
Bi																								87.86 (0.00)			0.04 (0.01)						0.13
Cd			-0.70 (0.01)										0.03 (0.01)																				0.12
Co																																	
Cr																-0.38 (0.00)								-45.08 (0.00)			0.02 (0.01)						0.21
Ga																																	
Ge																																	
In															-0.02 (0.00)																0.50 (0.00)		0.15
Li																														0.37 (0.03)			0.09
Mg																									0.01 (0.01)		0.04 (0.00)						0.14
Mn																-0.78 (0.00)											0.05 (0.03)						0.18
Mo														0.49 (0.00)	-0.02 (0.01)																		0.12
Sb																								-68.98 (0.00)						0.38 (0.00)			0.09
Ti														0.20 (0.15)																			0.02
V																											0.12 (0.00)						0.09
W														0.19 (0.01)																			0.06

This table displays the β-coefficients and corresponding p-values of the metal price determinants in sub-sample 1, 1995-2008, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

5.2.3 Sub-Sample Two - Analysis of the Timeperiod 2009 to 2019

For the second sub-sample, we again hypothesize a few changes in the markets, compared to the total- and, especially, the first sub-sample. Thereby, our second hypothesis suggests interest rates should have less impact on prices, while we include our proxies for the unconventional monetary policy, the balance sheet size, the U.S. Inflation expectation index, and the Wu-Xia shadow rate as a composite measure for monetary policy. Additionally, the variables that regionally account for either the entire world, or China in particular, should also have gained more impact, according to our third hypothesis, while also the co-movement between the commodity prices, as well as the integration with other financial markets should have increased, as stated previously.

We again start our comparison of the two samples with the prediction models and, especially, with the value factor, which looses even more predictive abilities in the second sub-sample, with its inclusion in only eight models, in comparison to eleven models in the total-sample and fourteen in the first sample, see Table 5.6. We attribute this change to the development and data quality of the minor metal markets, which now relates them closer to macroeconomic and financial market conditions, while simultaneously reducing the idiosyncratic component included within each series. However, the value factor still remains the most important predictor. Additionally, the Baltic dry index, which was excluded in the first sub-sample and the total-sample, due to a shortened data availability, is among the most important predictors in the second sub-sample, but not included as a determinant, highlighting the forward looking characteristics of the index, which is in line with the findings of Bakshi et al. (2011) and Guzmán and Silva (2018). However, this is in contrast to the findings in the total-sample, where the economic activity index of Kilian (2009), which is also based on freight rates, only acts as a determinant, but not as a predictor, while the sign of the corresponding β-coefficient is also against the theory. Moreover, the metal-specific demand variable is a more important predictor in the second sub-sample, where in four of the five cases the sign is negative, which is in contrast to the theoretical relation, where demand increases should cause rising prices.

Further, the 3-Month U.S. interest rate is a significant predictor for four of the six industrial metals, with the negative sign that is imposed by the theory. Within Section 5.1 we discovered very little impact of interest rates in the second sub-sample, the federal funds rate in this case, on the RICI metals index, which we attribute to the implementation of unconventional monetary policy actions, in response to the interest being constrained at the lower zero bound. However, the differences in the findings might be rooted in the different interest rate, where also in this individual regression analysis the federal funds rate has no impact on the prediction or determination of the precious or industrial metals.

Since these metals are the constituents of the RICI metals index, which was analyzed in Section 5.1, we attribute the different findings between the analyses to these differences. Moreover, the shadow rate of Wu and Xia (2016) is included in three models, with the hypothesized negative sign, which is in line with theory and the empirical findings within Section 5.1, as the rate represents conventional and unconventional measures of monetary policy simultaneously.

Although the $Adj.R^2$ is not the appropriate measure to evaluate true forecast performance, we again rely on it in the comparison between the sub-samples and the total-sample, as the only ten years of data in the sub-sample two make an evaluation of the out-of-sample predictions infeasible. Hereby, we detect, on average, a lower $Adj.R^2$, when compared to sub-sample one and the total-sample, again underlining the further state of development within metal markets.

When turning our attention to the price determinants, we observe the CPI remains the most important determinant for the prices, followed by the MSCI world and the U.S. Dollar exchange rate. This is again in line with theory and the development of the markets, where, in contrast to the financialization theory and literature, the Bloomberg commodity index looses in its price determination abilities. However, the effect of the Bloomberg index seems to have loaded onto the MSCI world, as the respective coefficients increased, underlining the elevated integration of commodity and financial markets. Moreover, the convenience yield also looses in descriptive characteristics, as does the monetary base, while for the latter the effect probably loads onto the inflation expectation index and the balance sheet size of the FED, which both have been excluded from the sub-sample one and the total-sample, due to shortened data availability. However, the last two variables seem to be very important for the price determination in the most recent period, indicating the significant effect of unconventional monetary policy actions on metal prices. For the $Adj.R^2$ in the price determination, we see mixed results, where in fourteen cases the measure is lower, and in ten cases larger, compared to the total-sample.

Overall, the analysis performed within this section of the thesis reveals the significant forecast improvements through a metal-specific variable selection. Hereby, especially metals of the minor metal group show predictability, partly also the industrial metals. However, over time the predictability of prices seems to be decreasing, as indicated by the lower $Adj.R^2$ values in the second sub-sample, while the autoregressive component within each price series still seems to be the most important predictor. Moreover, we do find empirical support for our first hypothesis, the closer connection of metal markets to other commodity and financial markets. However, we do not find as much empirical support for our second and third hypothesis, the enlarged impact of interest rates on prices in the first sub-sample and the rising impact of emerging markets in the second sub-sample.

Table 5.6: Linear Regression Results for the Metal Price Predictors - Sub-Sample Two

	$supply$	hhi	$demand$	VAL	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
Ag																														0.53 (0.00)			0.09
Au						0.22 (0.01)	-0.01 (0.01)																			-0.03 (0.01)							0.16
Pt																										-0.04 (0.02)				0.34 (0.00)			0.11
Al			-1.25 (0.00)												-0.02 (0.00)	0.41 (0.00)																	0.20
Cu			-1.04 (0.03)				-0.01 (0.00)		-0.13 (0.00)						-0.02 (0.00)											-0.05 (0.00)							0.32
Ni									-0.11 (0.01)						-0.03 (0.00)														0.56 (0.01)				0.14
Pb					-0.04 (0.05)				-0.09 (0.00)																								0.11
Sn				-0.21 (0.02)																						-0.06 (0.00)							0.11
Zn			-2.76 (0.00)		-0.07 (0.00)				-0.10 (0.00)									-2.29 (0.01)								-0.05 (0.00)							0.27
Bi				-0.28 (0.00)																										0.42 (0.01)			0.17
Cd																																	
Co																														0.66 (0.00)			0.06
Cr			-0.21 (0.02)								0.16 (0.01)																						0.09
Ga				-0.32 (0.00)																										0.70 (0.00)			0.31
Ge	-1.45 (0.00)															0.71 (0.01)																	0.11
In		-0.26 (0.01)		-0.23 (0.00)																											0.57 (0.03)		0.19
Li			0.40 (0.00)	-0.38 (0.00)																													0.22
Mg																			0.17 (0.01)														0.06
Mn												0.36 (0.01)		0.09 (0.01)																			0.10
Mo																						-0.58 (0.00)					0.08 (0.00)						0.08
Sb		0.16 (0.00)		-0.21 (0.01)	0.03 (0.02)																									0.40 (0.00)	0.38 (0.03)		0.33
Ti																								15.45 (0.03)									0.05
V				-0.31 (0.00)										0.12 (0.00)					0.49 (0.00)														0.20
W				-0.20 (0.01)																									0.75 (0.02)				0.15

This table displays the β-coefficients and corresponding p-values of the metal price predictors in sub-sample 2, 2009-2019, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table 5.7: Linear Regression Results for the Metal Price Determinants - Sub-Sample Two

	$supply$	hhi	$demand$	VAL	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
Ag							-0.01 (0.00)													-0.88 (0.01)							0.04 (0.02)						0.27
Au							-0.01 (0.01)				-0.18 (0.00)						-0.36 (0.02)			-0.48 (0.02)							0.02 (0.00)						0.37
Pt																				-0.75 (0.00)							0.03 (0.01)					0.35 (0.01)	0.23
Al																			0.20 (0.01)	-0.68 (0.00)											0.34 (0.01)		0.32
Cu																			0.30 (0.00)										0.53 (0.00)		0.36 (0.04)		0.41
Ni			-1.07 (0.01)				0.02 (0.03)												0.28 (0.01)												0.87 (0.00)		0.32
Pb																				-1.26 (0.00)											0.50 (0.00)		0.27
Sn																				-1.21 (0.00)											0.72 (0.00)		0.36
Zn					-0.07 (0.00)			1.13 (0.00)											0.22 (0.02)	-1.10 (0.00)											0.34 (0.04)		0.43
Bi																	1.34 (0.00)							20.39 (0.02)									0.11
Cd														0.12 (0.03)														0.26 (0.01)					0.06
Co	-2.19 (0.03)												-0.03 (0.05)																				0.09
Cr	-1.02 (0.02)																																0.03
Ga	-0.51 (0.02)													-0.17 (0.00)													0.06 (0.01)						0.24
Ge																													0.56 (0.09)				0.04
In		-0.20 (0.05)															1.67 (0.00)							29.19 (0.01)			0.06 (0.00)						0.23
Li																									-0.00 (0.00)				0.38 (0.05)				0.11
Mg																																	
Mn																																	
Mo																					1.37 (0.05)						0.09 (0.00)						0.09
Sb		0.17 (0.00)																							+0.00 (0.00)	0.04 (0.05)	0.05 (0.00)						0.21
Ti																					0.64 (0.05)												0.04
V																																	
W		0.27 (0.02)																									0.05 (0.01)						0.09

This table displays the β-coefficients and corresponding p-values of the metal price determinants in sub-sample 2, 2009-2019, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

5.3 Linkages Within and Across Industrial Metal Markets

Given the interrelation of the industrial metal prices with each other, represented via similar price determinants for all metals within this group, as displayed within Table 5.3 of Section 5.2, as well as the potential channels of relation across metal markets outlined within Section 2.4, we proceed by jointly modeling the industrial metal markets. Therefore, we apply a global vector autoregressive model, as outlined within Section 4.4 and proposed in Schischke et al. (2021), on the market of the six industrial metals, namely aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn). Hereby, we link the metals via the channels outlined within Section 2.4, which leads to the construction of the supply (**S**), demand (**D**), trading (**T**) and common (**C**) weight matrices described within Section 3.6. The model is based on the metal-specific supply ($\mathbf{supply}_i$), demand ($\mathbf{demand}_i$) and price ($\mathbf{price}_i$) series, as shown within Section 3.3, which are obtained in monthly frequency for the period 1995 to 2019.

Additionally, we include three exogenous factors, to account for common macroeconomic conditions. These are the U.S. Dollar index as exchange rate (FX), the shadow rate of Wu and Xia (2016) as interest rate ($WuXia$), which represents conventional as well as unconventional monetary policy actions, see Section 5.1, as well as the economic activity indicator of Kilian ($EAKilian$). All variables are checked for stationarity according to the procedure outlined within Section 3.4, and adjusted in case non-stationarity is present in the original series. Further, we seasonally adjust and standardize the data to enhance the estimation quality of the parameters within the model. For the analysis of the model, we measure the effect of a one standard deviation shock to each variable on all other variables, within and across the metal markets. Therefore, we apply the generalized impulse response functions, as described in Section 4.4, based on the 68% confidence bounds, which we obtain by the bootstrap procedure described in Section 4.3.4, where the methodology benefits from the ability to display direct and indirect effects on the variables, given an initial shock. As the bootstrapping is performed on the error terms of the initial model, we carefully check for the properties of the errors terms. That is, we test their autocorrelation via the Durbin-Watson test and their heteroskedasticity via the ARCH-LM test. In case either test indicates autocorrelation or heteroskedasticity, based on the 5% significance level, we increase the lag length of the model by one. This results in nine lags within the final model.[10] However, the analysis of a GVAR model via GIRF

[10]Given this setup, the ARCH-LM test still indicates heteroskedasticity in the VAR model for aluminum, when the demand, trading and common weight matrix are used, for nickel when the supply or trading matrix is used, as well as for tin, when the demand matrix is used. Additionally, heteroskedasticity is found in the error terms of the individual VAR models of copper and lead. However, further increasing the lag length was, due to data limitations, not feasible.

functions, suffers from the chance of false negative effects, as outlined by Lütkepohl (1990) and Galesi and Lombardi (2009). Within the following section, we start with the analysis of the individual, metal-specific VAR models, before we proceed to our main results, the GIRF analysis of the GVAR models. Hereby, we compare the four different weight matrices, as well as the metals and determinants that are influencing on - or influenced by - other attributes.

5.3.1 Analysis of Metal-Specific Vector Autoregressions

To simplify the analysis of the GIRF results, we rely on the interpretation of the results within the overview Table 5.8. Hereby, we indicate a significant positive, or negative, response of the column variables to a shock in the row variables by a (+), or (-), respectively, where the results are based on the responses within the first time period of the GIRF analysis and on the 68% confidence bounds.[11]

First, we detect no significant relation of the variables within the individual markets of copper and zinc. For aluminum, nickel, lead, and tin, the supply and demand variables are positively related. The lead market shows further metal-specific relations, as a supply and demand increase each negatively affect prices. While the effect of the supply variable is in line with theory, the demand effect most likely originates from indirect effects displayed within the GIRF analyses. Moreover, a price increase leads to a supply and demand reduction in this market.

Table 5.8: Results of the Metal-Specific Vector Autoregressions

	Al			Cu			Ni			Pb			Sn			Zn		
	supply	**demand**	**price**	**supply**	**demand**	**price**	**supply**	**demand**	**price**	**supply**	**demand**	**price**	**supply**	**demand**	**price**	**supply**	**demand**	**price**
supply	+	+		+			+	+		+	+	-	+	+		+		
demand	+	+			+		+	+		+	+	-	+	+			+	
price			+			+			+	-	-	+			+			+

This table displays the results of GIRF analysis for the individual, metal-specific VAR models, showing the response of the column variables to a one standard deviation shock of the row variables **supply**, **demand** and **price** of the metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn), where significant positive (+) or negative (-) effects are displayed based on the 68%- level.

[11]The actual GIRF plots are displayed within Appendix E.3.1.

5.3.2 Analysis of Global Vector Autoregressions

As for the individual VAR models described in Section 5.3.1, our interpretation again relies on the overview Table 5.9, where a significant response of the column variables, positive or negative, to a shock in the row variables, is indicated by a (+) or (-) respectively.[12] We estimate the GVAR model four times, to allow a comparison between the linkages across metal markets, represented via the four different weight matrices supply (**S**), demand (**D**), trading (**T**) and common (**C**), where the weight matrix is indicated in column W of Table 5.9. The diagonal of Table 5.9 shows significant responses for all cases, irrelevant of the metal, variable or weight matrix, as it displays the response to a shock within the same variable.

Metal-specific vs. global vector autoregressions: Comparing the results of the different GVAR models with those of the individual models of Table 5.8 in Section 5.3.1, we observe, for the case of aluminum, tin, and zinc, all relations detected in the individual models remain valid in the GVAR models. The GVAR model indicates a negative effect of the price on supply in case of copper, while for nickel, the supply and demand relations vanish. Further, the negative effect of a demand increase on prices, which was against theory, vanishes in the lead market as well.

Weight matrix comparison: Overall, our models reveal numerous significant responses, within and across metal markets, despite the risk of false negatives in GIRF analyses of GVAR models. To start, we simply count the number of significant responses, where we observe the largest number of significant results for the model using the supply weight matrix (**S**) with 102 significant responses, followed by the model with the common matrix (**C**) with 99 responses. While the demand matrix (**D**) yields in 97 significant responses, the trading matrix (**T**) shows, with 96, the fewest significant results. As the differences between the weight matrices are very small, they can not be interpreted further. However, this underlines the persistence of the revealed effects within and between the metal markets.

Overall attributes and metal comparison: For the attributes, the metal prices are influencing the other variables most, as they generate 170 significant effects, while the differences between the demand and supply are comparably small, as they yield in 114 and 110 significant responses, respectively. In turn, the demand variables are influenced most, as they show 151 significant responses, while the supply variables show 122 and the price variables 121 responses. Moreover, the supply side of markets is connected the least, with 68 significant supply-on-supply effects, followed by the demand side with 79 demand-on-demand effects. However, the co-movement between the industrial metal prices leads to 109 price-on-price effects, all with a positive sign.

[12] The actual GIRF plots are displayed within Appendix E.3.2.

When turning our attention to the metal perspective, the influence on the individual metals is rather heterogeneous, with the significant responses ranging from 50 for tin, over aluminum, nickel and lead, with 57, 58, and 63 significant responses respectively, to 76 responses for copper, while the zinc market is influenced most, as recognizable via 90 significant responses.

However, the differences between the influence of the individual metals are smaller. Hereby, lead and zinc show, with 76 and 68 significant responses caused, the most effects, followed by tin and nickel, which in turn cause 67 and 66 responses, respectively. Aluminum causes 59 significant responses, while copper produces only 58 significant effects. This is rather counter intuitive, as copper is the largest market in terms of trading volume, measured in U.S. Dollar, see London Metal Exchange (2019), where we would assume its impact on the other metals to be more pronounced.

Metal-clusters and bi-variate relations: When we go into further detail on the analysis of relation between the individual metal markets, we only outline relations that are persistent across two or more weight matrices. Overall, we observe a strong, bi-variate cluster for lead and zinc, which most likely originates from the joint production of the metals, which are predominantly mined from mixed lead-zinc ores, see Section 2.4 and Section 3.2. Hereby, a shock to the supply, demand and price in lead results in an increase of the corresponding variable within the zinc market, while also a lead demand increase causes a supply increase in zinc. Further, in the reverse direction, a supply, demand and price increase in zinc each cause a significant, positive response within the corresponding variable of lead, while additionally a supply increase in zinc leads to a demand increase for lead.

Further, tin and zinc show strong effects on copper, while the reverse causality is smaller, where the relation of the metals is probably rooted in the joint consumption of copper and zinc, which are used in alloys and in brass products, marking the second largest field of application for zinc, see International Lead and Zinc Study Group (2020). Moreover, the main application of zinc is as a protective layer for steel products, a procedure that is widely applied to car bodies as well, where also a substantial amount of copper products, such as cables, are end-used. Due to adverse health effects caused by lead, modern solders are usually lead free and made of tin, which marks with 50% of total consumption by far the largest application of the metal, see International Tin Association (2020). As solder is mainly used in electronics, the components, wires for example, are mostly made from copper, indicating a co-consumption relation between these metals as well. Hereby, a tin supply, demand and price shock each cause a significant, positive response within the corresponding copper variable. For zinc, as was the case for tin, a supply, demand or price increase results in a significant positive response of the corresponding copper variable, again highlighting the co-consumption relationship, which is further underlined by the effect a zinc demand increase causes an elevated copper supply. For the reverse direction, a copper demand increase also elevates the tin demand. For zinc, a copper supply shock results in a zinc demand increase, while also a copper price increase results in a zinc price increase. Additionally, aluminum and copper show a bi-variate relation as well, where an aluminum price increase results in a copper demand decrease and price increase, while in the reverse direction, a copper price increase results in an aluminum demand and price increase.

Moreover, we observe a strong bi-variate cluster for copper and nickel as well, which we attribute to the joint end-use of the metals within engineering products. Hereby, a copper demand increase yields in a nickel supply and demand increase, whereas a price increase results in a nickel supply decrease as well as a price increase. For the reverse direction, a nickel demand and price increase both yield in an increase in the corresponding copper variable. Additionally, the copper demand is affected in a positive (negative) direction via a nickel supply (price) increase. The bi-variate cluster of nickel and tin shows a positive, bi-directional price relation, while nickel supply negatively affects tin supply and demand. Moreover, a tin demand increase yields in a nickel supply decrease, whereas the tin price positively affects the nickel supply.

Moreover, the nickel market has a strong effect on aluminum and zinc, while the reverse causality is smaller. A supply, demand and price increase in nickel each results in a significant response of the corresponding aluminum and zinc variable, which is positive in all cases except the nickel demand on zinc demand. Additionally, a nickel supply increase yields in an aluminum demand increase. In the reverse direction, a zinc demand increase results in a nickel demand decrease. The relation between the metals most likely originates from the joint application within NiZn batteries, which are increasingly used in recent times, starting around the year 2000, see Parker et al. (2017). Additionally, the galvanizing processes to enhance the corrosion resistance of steel products, gradually transforms from pure zinc galvanizing, to zinc-nickel alloy coatings, see Lofti et al. (2018). For the effect of aluminum on nickel, a supply, demand and price increase in aluminum each results in a significant response of the corresponding zinc variable.

Relations between microeconomic attributes: We now change our perspective slightly and analyze the effects of the microeconomic attributes of the industrial metals in more detail. In addition to the clusters and close bi-metal relations outlined above, we detect numerous further effects between the supply and demand variables of the metals. Hereby, the lead supply positively affects the copper supply, whereas its effect on the tin supply is negative. Zinc supply has a negative effect on the aluminum supply, while the copper supply has a positive effect on zinc demand.

For the demand effects across markets, we detect, again in addition to the previously described clusters, a positive effect of copper demand on tin demand, while the effect on lead demand is negative. Moreover, the tin demand has a negative (positive) effect on the lead (zinc) demand.

Relations of microeconomic attributes and prices: In addition to the clusters and close bi-metal relations described above, aluminum demand has a negative effect on the tin price. Moreover, we observe effects of prices on the supply and demand variables across markets. Hereby, the aluminum price has a negative effect on copper demand and lead supply, whereas a copper price increase results in an aluminum demand increase.

Effects between the metal prices: The price variables show the strongest connections across the metals, where each metals' price is related to at least three other prices. Further, the relation between prices is always positive, supporting the findings of the co-movement literature strand, especially those of Basak and Pavlova (2016). In detail, the aluminum price acts on the copper, nickel, tin, and zinc price, while the copper price influences the price of aluminum, nickel and zinc. Additionally, the nickel price affects the aluminum, copper, tin and zinc price, while the lead and tin prices act on all remaining price variables. Moreover, the zinc price acts only on copper, nickel and lead.

Overall, the analysis of the global vector autoregressions highlights, while the effects within each market remain mostly persistent, numerous relations across markets, and especially between the prices of the industrial metals. The strong relation of prices is in line with the literature, see Lombardi et al. (2012), for example. Further, we reveal numerous clusters between metal pairs. We attribute the aluminum and nickel cluster to their joint consumption, within alloys such as Raney nickel catalysts for example, which are frequently used in the chemical and food industry. The relation between nickel and tin is attributed to the substitutability of the two metals, where both are frequently used for coatings of other metals. Moreover, we relate the cluster between nickel and copper to the application of both metals within engineering products, while the nickel zinc cluster most likely originates from the common use within batteries. In addition, we attribute the tin copper relation the application of tin solder on copper wires, while we hypothesize the zinc copper relation to be rooted in the car manufacturing, through the galvanizing of car bodies and large consumption for cables. Lastly, the lead zinc relation is attributed to the strong co-production relation of the metals, as outlined within Section 3.2.

Table 5.9: Results of the Global Vector Autoregressions

			Al			Cu			Ni			Pb			Sn			Zn		
		W	supply	demand	price	supply	demand	price	supply	demand	price	supply	demand	price	supply	demand	price	supply	demand	price
Al	supply	S	+	+					+									+		
		D	+	+									+							
		T	+	+					+											
		C	+	+					+											
	demand	S	+	+			+			+										
		D	+	+													-			
		T	+	+						+							-			
		C	+	+						+							-			
	price	S			+		-	+			+	-			+		+			+
		D			+		-	+			+						+			+
		T			+			+			+	-					+			+
		C			+		-	+			+	-					+			+
Cu	supply	S	-			+													+	
		D				+													+	
		T				+	-								+					
		C				+													+	
	demand	S					+		+	+			-			+				
		D					+			+			-			+		-	+	
		T		+		-	+	+	+	+						+				
		C					+		+	+			-			+				
	price	S		+	+	-		+	-											+
		D			+	-		+	-		+									+
		T			+		+	+				-								
		C		+	+	-		+			+									+
Ni	supply	S	+	+			+		+						-	-		+		
		D			+				+			-								
		T	+	+			+		+			-			-	-		+		
		C	+	+					+						-	-		+		
	demand	S		+			+			+									-	
		D		+			+			+									-	
		T		+			+			+									-	
		C		+			+			+									-	
	price	S					-	+			+									+
		D			+						+						+	+		+
		T			+		-	+			+				+		+			+
		C			+		-	+			+						+			+
Pb	supply	S	-			+			-			+	+	-	-			+		
		D				+				+		+	+	-	-			+		
		T				+						+	+	-				+		
		C				+						+	+	-	-			+		
	demand	S										+	+						+	
		D	+	+								+	+	-				+	+	
		T										+	+					+	+	
		C										+	+					+	+	
	price	S			+			+			+	-		+			+			+
		D			+			+			+	-	-	+						+
		T			+			+				-	-	+						+
		C			+			+			+	-	-	+			+			+
Sn	supply	S				+				+					+	+			-	
		D				+						-			+	+				
		T				+									+	+				
		C				+									+	+				
	demand	S					+		-	+					+	+				
		D					+						-		+	+			+	
		T					+		-			+			+	+			+	
		C					+		-				-		+	+				
	price	S			+			+	+		+			+			+			+
		D		-	+			+			+						+			+
		T			+			+	+		+			+			+			+
		C			+			+	+		+			+			+			+
Zn	supply	S	-									+	+		-			+		
		D				+	-					+	+					+		-
		T										+						+		-
		C	-			+	-					+	+					+		
	demand	S				+	+			-									+	
		D				+	+			-			+			+			+	
		T				+	+		-	-			+						+	
		C				+	+			-			+						+	
	price	S			+			+	-		+			+				-		+
		D						+						+				-		+
		T						+						+				-		+
		C					-	+			+			+				-		+

This table displays the GIRF results for the GVAR models estimated with one of the four different weight matrices supply (**S**), demand (**D**), trading volume (**T**) and common (**C**), which are indicated in column (W). We analyze the response of the column variable to a shock in the row variable **supply** , **demand** and **price** of the metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn), and zinc (Zn). Significant positive (+) or negative (-) responses are displayed based on the 68%-level.

6 Discussion

In the following chapter, we summarize the main findings of the empirical analyses performed within Chapter 5, while we additionally relate, compare and contrast our findings to the theory outlined within Chapter 2, as well as the empirical findings of previous studies on the subject.

6.1 Effects of U.S. Monetary Policy on Metal Prices

The relation of interest rates and commodity prices has been subject of numerous theoretical and empirical studies, starting with the work as early as Hotelling (1931). Theoretically, interest rates should bear an inverse relation to commodity prices that is grounded on several effects and channels. To start, higher interest rates increase the cost of capital for storing a commodity, which leads to a decreasing demand generated through commodity storage. Moreover, higher interest rates spark the incentives of commodity producers to increase the supply in the short run, as the interest rate gains from investing their revenues into bonds increase, see Frankel (2014). Further, Calvo (2008) argues declining interest rates lead to a portfolio shift of investors on exchanges, out of bonds and potentially into commodities, ultimately increasing demand and prices. Overall, the above described effects testify the inverse relation between interest rates and commodity prices. Frankel (1986) even argues commodity prices should overreact to interest rate changes, a phenomenon that is referred to as overshooting.

As there is no worldwide measure of monetary policy, we base our empirical analysis on the variables of the largest economy of the world, the United States of America, where we model the economy via a vector autoregression that consists of the industrial production, an inflation measure, the federal funds rate as conventional monetary policy proxy, the term spread as reverse recession indicator, the RICI metals index and the U.S. Dollar index as exchange rate. Further, we extend the model for our second sub-sample by a measure of unconventional monetary policy, either the balance sheet size of the FED, the inflation expectation index or the shadow rate of Wu and Xia (2016), which substitutes the federal funds rate in this case.

Overall, the responses of our metal price index to a shock in the macroeconomic determinants are mostly in line with the hypothesized sign by theory, where, for example, an increase in the industrial production leads to an increase in metal prices, which is also found by Issler et al. (2014), as well as Akram (2009) and Byrne et al. (2020). However, this effect is statistically insignificant in the second sub-sample, indicating the effect of the U.S. economy on metal prices decreases over time. This is in line with the findings of Klotz et al. (2014), who state the rising importance of rapidly growing economies, such as China, on global commodity markets.

Further, the exchange rate has a negative effect on the metals price index, which is in line with the findings of Lombardi et al. (2012), as well as the results of the metal-specific determinants and predictors within Section 5.2. Turning our attention to the main variables of the analysis, the monetary policy indicators, we do see a positive effect of interest rate hikes on the metals index in the total-sample, as well as in sub-sample one. This is in contrast to theory, where, as outlined above, there should be an inverse relation between the two variables. However, this findings integrates into the mixed empirical evidence in the literature, where also Hammoudeh et al. (2015), Österholm and Zettelmeyer (2008), and Frankel (2008) display, at least partly, this positive relation between interest rates and prices, depending on the time period considered. Hereby, we attribute the synchronous behavior of the variables to the timing of interest rate changes, where interest rate hikes usually occur at periods of substantial economic growth, which concurrently fuels commodity prices. While the interest rate effect might dampen the raise in metal prices, the continuously strong demand probably still pushes metal prices up further. When we analyze the relations of our unconventional monetary policy proxies, we observe the hypothesized relation across all measures, where the response of metal prices to a contractionary monetary policy shock, represented by a positive shock to the shadow rate, is negative, while an expansionary policy shock, indicated by either a positive shock to the balance sheet size or the inflation expectation index, leads to increasing metal prices, which is in line with the findings of Apergis et al. (2014) and Hammoudeh et al. (2015). We attribute this change in the sign of relation to the reduced correlation of metal prices and the oil price, where monetary policy is partly adjusted to. Overall, we state the impact of monetary policy on metal prices remains valid over time, where through the application of unconventional policy actions, the variables that represent the policy and direction of relation changed.

6.2 Metal Price Forecasts, Predictors and Determinants

Metals are very heterogeneous in the development of their markets, their applications and characteristics. Hence, we aim to account for these differences via a metal-specific analysis. Our approach differs from previous literature, where we apply a standard linear regression model, see Zakamulin (2013) on the prediction for stock markets for example, but aim to enhance the individual metals' forecasts via a metal-specific variable selection, combined with a broad set of potential predictor variables. We subsequently compare our prediction results, as standard in the commodity market prediction literature, against a random walk and random walk with drift benchmark, where we determine the significance of our forecast improvements via the standard Clark-West test, see Clark and West (2007).

Overall, the study of Gargano and Timmermann (2014) is probably related closest to this prediction exercise. Since Groen (2014) raised concerns on the study design of Gargano and Timmermann (2014), mainly the inclusion of an AR term of prices as predictor, rather than as a benchmark, we acknowledge these concerns and include a third, AR benchmark in our analysis. However, since the test of Clark-West requires the evaluated model to be a nested version of the benchmark model and we do not interfere the model selection process by fixing certain terms in the prediction model, we are unable to evaluate the significance of our forecast improvements in comparison to the AR benchmark. However, the results within Section 5.2, especially within Table 5.1, showcase the AR benchmark performs worst of the three benchmark models, whereas the random walk model performs best, but the results of the latter are very close to those of the random walk with drift benchmark.

We are able to enhance the prediction compared to the AR benchmark for 22 of the 24 metals[1] and 19 for the RW and RWD benchmarks. Hence, we are unable to support the superior predictive abilities of the AR component, while on the other hand side, the value factor, which also represents an AR component of the price series, is by far the most influential predictor in our study, across all metal groups and sub-periods. Hereby, the value factor is included in the prediction models with a negative sign, which is against the theory and the empirical findings of Asness et al. (2013). We attribute these difference to the time-series character of our study, where we check each co-variate for stationarity, prior to the model estimation. In case of the value factor, we calculate first differences in case non stationarity is found, as outlined in Section 3.4. Within our models, the value factor is included only for metals where the initial variable was found non-stationary and

[1] The commodities germanium and tin are excluded from this analysis, as the model selection procedure yields in no selected co-variate, hence our model is identical to the random walk benchmark.

hence adjusted[2]:

$$\begin{aligned}\Delta VAL_{i,t} &= \ln\left(\frac{\frac{1}{12}\sum_{\tau=55}^{66} Price_{i,t-\tau}}{Price_{i,t}}\right) - \ln\left(\frac{\frac{1}{12}\sum_{\tau=56}^{67} Price_{i,t-\tau}}{Price_{i,t-1}}\right) \\ &= \ln\left(\frac{\sum_{\tau=55}^{66} Price_{i,t-\tau}}{\sum_{\tau=56}^{67} Price_{i,t-\tau}} \cdot \frac{Price_{i,t-1}}{Price_{i,t}}\right).\end{aligned} \tag{6.1}$$

As can be seen in Equation 6.1, the stationary value factor consists of two components, where the first one represents the coefficient between two annual averages, where the respective time periods overall for eleven of the twelve months.[3] Hence, this coefficient should be comparably small, while the second coefficient represents the AR component of the series. The inverse characteristic of this return, in conjunction with the negative sign for the β-coefficients within the regression results, showcase the trend following pattern of metal prices, at least at the one month horizon we analyze within this thesis.[4]

The direct comparison to the results of other commodity prediction studies is difficult, since many other studies use commodity indices as dependent variable in their models. However, within the study of Gargano and Timmermann (2014), the metals index is among the best performing sub-indices, while the predictability is strongest at the quarterly horizon and varies across the horizons. Additionally, the more advanced methodological approaches, such as subset and ridge regressions in the study of Gargano and Timmermann (2014), forecast combinations of Issler et al. (2014) or the PLS approach within the study of Groen and Pesenti (2011) leave it unclear which of the variables considered bears predictive content for the commodity price index.

The study of Fernandez (2020) identifies the convenience yield as an important predictor for industrial metals, and is able to outperform the benchmark forecast in the one-month ahead dimension for aluminum, copper, lead, nickel, and zinc, independent of the calculation method of the convenience yield and other potential predictor variables that are included. In contrast, we are only able to outperform the benchmarks for nickel, tin, and zinc, where only the zinc model includes the convenience yield as predictor variable. In addition, the convenience yield also represents a valid metal spot price predictor in the study of Stepanek et al. (2013). However, our findings are, except for the zinc model, in line with Chinn and Coibion (2014), who detect no predictive ability of futures prices for the future spot prices.

[2]With the exception of gallium for the total-sample and the sub-sample two, as well as cadmium and magnesium in sub-sample one.

[3]Please note we refer to all variables with their initial variable names in our analysis, disregarding whether they were adjusted or not.

[4]Hence, we repeat the model estimation by including the return of the previous period as additional predictor, where the effect of the value factor partly shifts to this co-variate, see Table E.1 However, the results in regard to predictability of prices remain unchanged.

When comparing our findings to Wang et al. (2020), they detect superior predictive abilities of technical indicator, e.g. components of the individual price series, which is in line with our results for the value factor. However, we do not find significant predictive abilities of the momentum factor, which is in contrast to their findings, as well as the findings of Lutzenberger et al. (2017). We attribute these differences to the differing construction of the momentum factor, where Lutzenberger et al. (2017) find predictive abilities for the two to six months momentum, and, in line with our results, no predictive ability for the two to twelve months' factor, which we consider in this study. Further, we detect substantial predictive abilities of monetary aggregates, the M4 as well as the monetary base, where the sign of relation for the two variables is against the theory, as an increase in either variable represents an easier monetary policy, which should theoretically lead to increasing commodity prices, see Keating et al. (2019). Further, this finding is in contrast to the empirical observation of Ahumada and Cornejo (2014), but in line with the results of the first part of this thesis, see Section 5.1.

Moreover, we observe changes in the development state of markets, as well as changes in the market characteristics over time. That is, our prediction results weaken over time, where historically there seem to be larger idiosyncratic price components, paired with a higher degree of autocorrelation in prices, which we capture via the value factor, especially in the minor metals sector, raising the predictive abilities of our models.

We hypothesized, based on previous studies on commodity markets, several changes in the characteristics of metal markets.

First, through their financialization, starting around the year 2004, the index investments into commodities raised significantly, see Tang and Xiong (2012) and Adams and Glück (2015), among others. Hereby, commodity prices are hypothesized to move in a more synchronous way, see Basak and Pavlova (2016), for example. We are able to support this hypothesis, where the commodity indices and the oil price show a smaller impact in our first sub-sample, compared to the overall sample, especially in the prediction dimension. For the price determination, we see a smaller impact of the commodity indices in the second sub-sample. However, the effect price effect of the Bloomberg commodity index seems to have shifted onto the MSCI World, which is in line with the financialization hypothesis, as commodity markets are supposed to be connected closer to financial markets as well, see also Tang and Xiong (2012).

Second, the shift of monetary policy, from a conventional, interest rate based policy prior the financial crisis, to asset purchases and forward guidance afterwards, should be represented in the effects of monetary policy variables on the individual metal prices. Hereby, we detect a larger impact of interest rates in the prediction and determination of prices in the first sub-sample, compared to the overall sample, which is in line with theory, while the interest rates remain a valid predictor in our second sub-sample as well.

As the sub-sample two covers the period from 2009 - 2019, it includes a comparably long period after the crisis, when conventional MP was implemented again, probably causing these effects. However, the sign of the coefficients changed from a positive effect in the first sub-sample, to a negative effect in the second sub-sample, which is now in line with basic theory. We observe the same change in ration within the analysis of Section 5.1, where we attribute the differences to the reduced co-movement of the commodity prices to oil, and hence the dampened effect of metal prices changes on the interest rate policy. Further, we see a large impact of the unconventional MP measures, the balance sheet size and the inflation expectation index, which is in line with our findings within Section 5.1, the findings of Hammoudeh et al. (2015) and the idea of Frankel and Rose (2010), who regard the long-term expected inflation as monetary policy proxy as well.

Our third hypothesis addresses the enlarged impact of emerging economies on metal prices, where we are unable to support this hypothesis empirically, as neither the Chinese interest rates, nor the Chinese industrial production, contribute to the price determination or prediction of the metals substantially.

However, the application of the linear regression model represents only linear relationships between the variables, where other, more advanced models could be used, based on the consolidated data set generated within this thesis, to further enhance the predictions of the commodities. Additionally, as the sub-sample analyses revealed the predictors and price determining factors change over time, the model selection procedure could be performed iteratively for each out-of-sample forecast data point and on longer samples. Moreover, the exchange rate measure used in this thesis, the U.S. Dollar index, is rather general and does not account for the individual, country-specific effects, as proposed by Chen et al. (2010), for example. Therefore, future research could construct a metal-specific exchange rate index, based on the weighted exchange rates of the most important commodity producing countries.

6.3 Linkages Within and Across Industrial Metal Markets

Metals are oftentimes jointly consumed within industrial applications, such as buildings and cars, while, on the other hand, their supply is linked, as they are joint outputs of mining businesses, see Cuddington and Jerrett (2008) and our analysis within Section 3.2. The relevance of these supply links is further examined in studies like Jordan (2017), who highlights:

> "*(...) significant cross-price elasticity estimates (...) should call attention to the fact that metal supply should not be considered in isolation*"

Further, the literature strand on the financialization of commodities, see Tang and Xiong (2012) and Basak and Pavlova (2016), among others, suggests the co-movement between commodity prices increased significantly and is, at least partly, attributable to the trading behavior of index investors on exchanges. Given these hypothesized relations between markets, we model the six industrial metal markets via global vector autoregressions, where we highlight the relations between the individual metal markets and prices. Hereby, we link the individual markets via either information based on the co-production, co-consumption, the co-trading of the metals, as well as via an aggregated, equally weighted matrix of the before mentioned three dimensions. Further, we account for common financial market and macroeconomic conditions via the economic activity index of Kilian, the shadow interest rate of Wu and Xia (2016) and the U.S. Dollar index as exchange rate measure.

A comparison between the different weight matrices reveals only minor differences and hence underlines the persistence of the revealed effects within and between the metal markets. In our analysis, supply and demand factors are almost equally influential on markets, whereas the relevance of demand factors for the determination of commodity prices has historically been subject to numerous empirical studies, see Frankel and Rose (2010), Kilian (2009), and Stuermer (2018), among many others. However, most of these studies use macroeconomic determinants to represent demand proxies, as the inclusion of multiple commodities, as well as the macroeconomic determinants, is infeasible in regular, econometric models like vector autoregressions, see Lombardi et al. (2012). Further, studies like Shammugam et al. (2019) identify strong relations between co-consumed metals, as also found in this thesis.

For the metal-specific relations, we reveal numerous strong clusters between the industrial metals. To start, the lead and zinc cluster, which we attribute to the large share of the metals that is co-mined, see Section 2.4 and Section 3.2. Next, we detect an equally strong cluster for copper and nickel, which we attribute to the joint consumption of the two metals within engineering products, especially within copper-nickel alloys, such as cupronickel, which is mainly consumed within marine applications, see Nickel Institute (2022). The same holds for the cluster between aluminum and nickel, which we relate to the joint consumption, for example within raney nickel, mainly applied as a catalyst. Additionally, we detect comparably strong effects between nickel and zinc, tin and copper, as well as zinc and copper. The first most likely originates from the joint consumption within batteries, while the second relation stems from the growing application of tin based solders. Hereby, tin nowadays replaces lead-based solders in a large share of the applications, due to adverse-health effects of the latter. We attribute the zinc-copper relation again to the joint consumption, this time within brass products, which mark the second largest field of application for zinc, as well as the joint end use within the transportation sector, where car bodies are usually galvanized to enhance corrosion resistance, while the cables within the car are made from copper. In contrast, we are unable to verify the causalities between aluminum and copper supply and demand, as detected by Baffes et al. (2020).

For the relation between the individual variables, we see numerous implications of supply and demand factors, within and across markets. However, we clearly identify the relations between the price variables of the metals to be strongest. This is in line with previous studies on the topic, where Lombardi et al. (2012) for example, among Vansteenkiste (2009) and others, highlight the industrial metals co-move with a metals factor.

While the global vector autoregression model provides several advantages over other econometric models, especially the ability to model the dependencies of a large set of variables on a comparably low-frequency data set, it requires the covariates to be included within each individual vector autoregression to be identical. While for specific metal groups, such as industrial metals for example, the price determinants are comparably homogeneous, as also outlined within Section 5.2, the application of this methodology to further commodity classes and their relation would call for an individual covariate selection per commodity and hence further methodological developments.

7 Conclusion

Metals are of great importance to the global economy. This holds for metal importers, mostly developed nations that require metals in a variety of industrial and technical applications, as well as for metal exporting nations, where sometimes a considerable share of a countries' economic activity is linked to one, or multiple commodities and their respective prices. Through the increasing demand for metals, fueled by rapidly growing economies like India and China, as well as the energy transition of developed nations, which require large amounts of metals, an in-depth analysis of metal prices, their determinants, predictors and interrelations is inevitable. As metals are related to so many economic conditions, there exist numerous perspectives on metal markets, ranging from analyses of geological availability, all the way to intraday trading analyses of commodity futures contracts and options on exchanges.

Within the first part of this thesis, we analyzed the relation of metal markets to monetary policy. While metals are produced and consumed worldwide, there is no covariate that represents the current stance of monetary policy on a global scope. Therefore, we relied on the world's largest economy, the United States of America, and the policy effects of their Federal Reserve on metal markets. As the FED continuously lowered its main policy rate, the federal funds rate, until it reached its zero lower bound at the end of 2008, a time when the U.S. economy was still in a severe crisis, the FED implemented quantitative easing, as well as forward guidance as unconventional monetary policy tools, which were supposed to provide further stimulus to the economy when the federal funds rate was constrained. Within the first part of this thesis, we aimed to analyze the different effects of the entire monetary policy on metal prices. Hereby, we detected monetary policy remained influential on metal prices in the periods of unconventional policy as well, but the channel, as well as the direction of relation changed. In our sample the effects of interest rate changes were in opposite direction to the hypothesized relation, which we attributed to the timing of interest rate changes, as well as the adjustment of interest rates to commodity price developments. For the unconventional monetary policy actions, the response of the metal price index showed the hypothesized direction of relation. This part of the thesis was based on a metal price index, while we showcased within Section 3.1 the differing applications and characteristics of individual metals.

Therefore, within the second part of this thesis, we modeled and subsequently forecasted the price series of twenty four metals individually. These metals were the three precious, six industrial, as well as fifteen minor metals. Overall, we were able to significantly outperform the random-walk and random-walk with drift benchmark forecasts in ten cases, which correspond to the industrial metals nickel, tin and zinc, as well as to seven minor metals. Our results are especially noteworthy for the minor metals sector, which receive comparably little attention within the commodity market literature, but will gain more and more importance in the future, e.g. through their application within renewable energy technologies. Moreover, we analyzed the metal-specific predictors, as well as the price determinants, in the period from 1995 to 2019, as well as in two sub-samples which cover the periods prior and posterior the financial crisis. Hereby, we identified the value factor, which represents an autoregressive component of the individual price series, as most important predictor, while the commodity and financial market variables represent the most important price determinants, especially for the precious and industrial metals. We attribute these findings to the financialization of commodity markets, were we additionally observed changes in the channels of monetary policy on prices, as already outlined in the first part of the thesis. However, while each metal market was found to be individual to a certain degree, we highlighted within Section 2.4 and Section 3.2 possible channels of relations between the individual metals. Additionally, we observed a clustering in the price determinants for the metal groups, especially similar price determinants for the industrial metals.

Hence, we proceeded to jointly model the markets of the industrial metals within the third part of this thesis. We therefore applied global vector autoregressions, which model each metals market individually, under the consideration of common macroeconomic determinants, while simultaneously linking these individual models across multiple metals. Hereby, we linked the markets either via information on the co-production, co-consumption or co-trading of the respective metals, or a fourth relation matrix that is an equally weighted combination of the previous three dimensions. Our analysis hereby highlights several bi-variate clusters, as well as the strong interrelation of the metal prices, as already stated numerous times in the literature. The model was further able to relate the individual supply and demand conditions across markets, where we observed a strong cluster between lead and zinc, which we attributed to the co-mining of both metals. Moreover, we observed strong clusters between aluminum and nickel, copper and nickel, as well as nickel and tin, which we all relate to various co-consumption relations, such as use of copper cables within cars with galvanized bodies.

Overall, this thesis highlights the heterogeneity of metals and their markets in various aspects, from their production, consumption, to the determinants and predictors of their prices. Further, this thesis outlines the widespread relations of metals with numerous, individual determinants and hence the necessity for metal-specific forecasts. Hereby, especially the validity of futures prices as predictors for future metal spot prices is highly questionable. While this thesis shows the individuality of metals on the one hand, it simultaneously highlights the dependencies within metal groups on the other hand side. Therefore, we hope to stimulate further research that accounts for the metal-specific characteristics, while simultaneously representing their interrelations, possibly also with other commodity groups.

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A Structural Break Test Results

Table A.1: Structural Break Test Results

	$IP_{U.S.}$	CPI	FFR	$T10Y3M$	$RICIM$	FX
$F_{statistic}$	14.8022	20.079	23.9343	13.1459	17.2522	18.1598
$F_{p.value}$	0.3741	0.0894	0.025	0.527	0.2035	0.1582
$date_{brkpt}$	2000-08-01	2008-06-01	2000-01-01	2008-10-01	2011-09-01	2006-11-01

This table displays the test statistic ($F_{statistic}$) and the corresponding p-value ($F_{p.value}$) of the structural break test, as well as the date of the breakpoint ($date_{brkpt}$), applied on each individual linear regression model within the vector autoregression model, covering the total-sample period.

B Descriptive Statistics of Level Variables

B.1 Metal-Specific Price Determinants

Table B.1: Summary Statistics of the Level, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Silver (Ag)	*supply*†	1.24	1.25	1.54	1.73	1.79	2.14	2.25	2.30	0.33	0.00	-1.30	300	2.09	21.13***
	HHI†	0.82	0.87	0.90	0.97	1.01	1.04	1.31	1.39	0.15	1.20	0.46	300	0.46	74.64***
	demand†	1.83	1.85	2.14	2.90	2.84	3.36	4.10	4.53	0.80	0.39	-1.00	300	0.49	20.10***
	price	4.12	4.51	5.18	12.87	12.98	17.18	31.57	41.97	8.55	1.04	0.65	300	-1.00	59.36***
	VAL	-1.44	-1.15	-0.74	-0.18	-0.26	0.12	0.60	0.74	0.54	-0.21	-0.87	300	-1.81.	11.67***
	MOM	-0.37	-0.26	-0.10	0.00	0.07	0.18	0.61	1.28	0.27	1.44	2.73	300	-5.20**	196.84***
	*FUT*1	4.09	4.51	5.18	12.89	12.97	17.15	31.55	42.75	8.56	1.05	0.69	300	-0.94	61.08***
	*FUT*2	4.10	4.52	5.19	12.99	13.01	17.22	31.59	42.77	8.57	1.05	0.68	300	-0.90	60.91***
	CY	-7.50	-2.41	-0.38	0.98	1.27	2.76	5.97	12.69	2.54	0.53	1.19	300	-8.98**	31.75***
	BM	-0.01	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.01	0.00	0.39	2.47	300	-20.74**	83.87***
Gold (Au)	*supply*	186.16	189.64	204.04	214.04	222.09	243.14	275.00	275.08	27.09	0.73	-0.77	300	2.89	34.06***
	HHI†	0.57	0.58	0.62	0.72	0.80	0.97	1.26	1.27	0.21	0.87	-0.37	300	-4.27**	39.56***
	demand	75.33	77.18	81.48	85.74	88.30	94.30	108.19	111.20	9.80	0.83	-0.29	300	-0.51	35.50***
	price†	0.26	0.27	0.36	0.67	0.81	1.26	1.63	1.78	0.48	0.30	-1.44	300	1.69	30.42***
	VAL	-1.06	-0.98	-0.76	-0.11	-0.25	0.16	0.35	0.40	0.46	-0.34	-1.33	300	-2.59**	27.89***
	MOM	-0.27	-0.15	-0.04	0.04	0.06	0.15	0.33	0.57	0.15	0.54	0.06	300	-3.58**	14.63***
	*FUT*1†	0.26	0.27	0.36	0.67	0.81	1.26	1.63	1.77	0.48	0.30	-1.44	300	1.43	30.42***
	*FUT*2†	0.26	0.28	0.36	0.67	0.82	1.26	1.63	1.77	0.48	0.30	-1.44	300	1.42	30.42***
	CY	-2.56	-1.38	-0.03	0.87	1.05	2.37	3.45	5.33	1.55	0.05	-0.70	300	-6.36**	6.25*
	BM	-0.01	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.01	0.00	0.50	1.34	300	-8.95**	34.95***
Platinum (Pt)	*supply*	11.56	12.40	13.68	15.84	15.26	16.26	17.63	18.12	1.76	-0.53	-0.74	300	0.66	20.89***
	HHI†	4.33	5.11	5.38	5.70	5.73	6.12	6.45	6.48	0.48	-0.72	0.75	300	0.19	32.95***
	demand	50.59	57.80	70.64	80.03	84.07	91.30	130.49	147.48	22.26	1.21	1.14	300	-0.76	89.45***
	price†	0.34	0.37	0.53	0.90	0.95	1.29	1.72	2.06	0.45	0.40	-0.85	300	-0.27	17.03***
	VAL	-1.18	-0.89	-0.53	-0.19	-0.18	0.10	0.55	0.69	0.45	0.07	-0.80	291	-0.90	8.00*
	MOM	-0.52	-0.27	-0.08	0.03	0.05	0.18	0.44	0.66	0.22	0.36	0.34	300	-3.36**	7.92*
	*FUT*1†	0.34	0.37	0.54	0.90	0.95	1.29	1.73	2.02	0.45	0.40	-0.88	300	-0.30	17.68***
	*FUT*2†	0.80	0.84	0.94	1.21	1.24	1.47	1.79	2.15	0.33	0.56	-0.54	181	-0.43	11.66***
	CY	-166.25	-10.91	-1.13	0.02	-0.26	1.60	15.68	41.86	15.89	-6.45	65.23	181	-10.12**	33344.45***
	BM	-0.44	-0.14	-0.00	-0.00	-0.00	0.00	0.10	0.55	0.08	1.01	20.29	169	-11.74**	2927.68***

Summary Statistics of the Level, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Aluminum (Al)	$supply^{\dagger\dagger}$	1.64	1.73	2.03	3.10	3.22	4.34	5.27	5.30	1.21	0.34	-1.29	300	3.59	26.58***
	$supply_M^{\dagger\dagger}$	1.52	1.70	2.05	3.03	3.25	4.48	5.35	5.55	1.25	0.37	-1.30	300	1.68	27.87***
	$HHI^{\dagger}$	0.75	0.78	0.83	1.26	1.69	2.74	3.40	3.50	0.98	0.66	-1.19	300	2.72	39.48***
	$demand^{\dagger\dagger}$	1.61	1.82	2.06	2.33	2.28	2.47	2.73	2.87	0.29	-0.34	-0.12	300	-0.74	5.96.
	$demand_M^{\dagger\dagger}$	1.56	1.73	2.03	2.95	3.19	4.41	5.20	5.61	1.23	0.42	-1.27	300	1.02	28.88***
	$price^{\dagger}$	1.18	1.32	1.51	1.77	1.84	2.05	2.70	3.07	0.41	0.87	0.14	300	-0.47	38.09***
	VAL	-0.77	-0.66	-0.19	-0.05	-0.06	0.12	0.37	0.48	0.27	-0.65	0.40	300	-1.90.	23.12***
	MOM	-0.55	-0.22	-0.11	0.02	0.03	0.16	0.40	0.72	0.20	0.39	1.15	300	-4.54**	24.14***
	$FUT1^{\dagger}$	1.21	1.35	1.53	1.79	1.86	2.08	2.72	3.12	0.42	0.87	0.14	300	-0.70	38.09***
	$FUT2^{\dagger}$	1.28	1.40	1.56	1.81	1.89	2.12	2.67	3.23	0.41	0.86	0.14	300	-0.04	37.22***
	CY	-10.64	-9.47	-4.43	-2.49	-2.10	0.08	5.36	16.50	4.42	0.87	2.19	300	-15.06**	97.80***
	BM	-0.25	-0.10	-0.02	-0.00	0.00	0.02	0.15	0.30	0.07	0.79	4.18	300	-3.61**	249.61***
Copper (Cu)	$supply^{\dagger\dagger}$	0.83	0.92	1.14	1.30	1.30	1.52	1.70	1.70	0.25	0.08	-0.94	300	4.09	11.36***
	$supply_M^{\dagger\dagger}$	0.75	0.89	1.11	1.28	1.30	1.52	1.74	1.85	0.26	0.16	-0.89	300	0.55	11.10***
	$HHI^{\dagger}$	1.17	1.26	1.35	1.46	1.45	1.55	1.57	1.65	0.12	-0.43	-0.63	300	0.14	14.21***
	$demand^{\dagger\dagger}$	0.76	0.83	0.90	0.95	0.96	0.99	1.08	1.10	0.08	-0.19	0.01	300	-0.54	1.81
	$demand_M^{\dagger\dagger}$	0.91	1.00	1.22	1.46	1.49	1.76	2.03	2.27	0.33	0.18	-1.10	300	0.19	16.73***
	$price^{\dagger}$	1.38	1.51	2.01	4.87	4.70	6.92	8.36	9.88	2.50	0.10	-1.45	300	-0.12	26.78***
	VAL	-1.66	-1.57	-0.57	-0.03	-0.18	0.23	0.49	0.66	0.59	-1.01	0.23	300	-1.49	51.67***
	MOM	-0.60	-0.31	-0.11	0.01	0.08	0.22	0.68	1.28	0.31	1.14	2.00	300	-3.99**	114.98***
	$FUT1^{\dagger}$	1.40	1.54	1.98	4.85	4.69	6.92	8.28	9.87	2.50	0.10	-1.47	300	-0.00	27.51***
	$FUT2^{\dagger}$	1.46	1.61	1.95	4.79	4.59	6.89	8.15	9.71	2.48	0.13	-1.51	300	0.11	29.35***
	CY	-4.52	-3.42	-1.11	0.54	3.73	6.32	21.45	38.85	8.09	1.85	3.17	300	-3.45**	296.74***
	BM	-0.25	-0.10	-0.02	-0.00	0.00	0.02	0.15	0.30	0.07	0.79	4.18	300	-3.61**	249.61***
Nickel (Ni)	$supply^{\dagger}$	86.23	88.29	98.68	120.79	141.28	190.35	217.77	232.64	47.45	0.48	-1.29	300	1.30	32.32***
	$supply_M^{\dagger}$	69.85	83.38	102.02	116.70	134.22	170.35	217.76	240.03	43.15	0.75	-0.65	300	0.15	33.11***
	$HHI^{\dagger}$	0.90	0.95	1.01	1.19	1.18	1.28	1.50	1.66	0.18	0.62	-0.03	300	-1.93.	19.23***
	$demand^{\dagger}$	71.22	74.46	82.04	91.46	97.36	110.33	132.79	137.99	19.69	0.58	-0.94	300	-0.05	27.86***
	$demand_M^{\dagger}$	72.21	76.81	93.78	111.37	120.62	139.94	200.53	231.63	36.54	0.99	0.36	300	-0.19	50.37***
	$price^{\dagger}$	3.88	5.21	7.98	12.19	13.73	17.01	29.56	51.80	7.91	1.70	3.99	300	-0.67	343.50***
	VAL	-2.08	-1.46	-0.52	0.01	-0.13	0.32	0.81	1.08	0.68	-0.74	0.21	252	-1.09	23.46***
	MOM	-0.66	-0.39	-0.17	0.00	0.10	0.31	0.94	1.75	0.43	1.21	1.81	300	-2.69**	114.16***
	$FUT1^{\dagger}$	3.94	5.28	8.01	12.30	13.67	16.99	28.46	48.84	7.68	1.56	3.22	300	-0.80	251.29***
	$FUT2^{\dagger}$	4.16	5.35	7.83	11.89	13.22	16.91	27.50	40.01	6.86	1.16	1.26	300	-0.44	87.12***
	CY	-6.07	-1.97	-1.31	-0.47	2.33	1.95	18.16	48.41	7.37	2.92	9.67	300	-4.01**	1595.18***
	BM	-0.34	-0.11	-0.01	-0.00	0.02	0.03	0.24	0.54	0.11	1.72	5.70	300	-3.80**	554.04***

Summary Statistics of the Level, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Lead (Pb)	$supply^{\dagger}$	235.82	238.80	258.47	309.48	324.40	393.33	438.97	440.65	68.76	0.32	-1.43	300	0.49	30.68***
	$supply^{\dagger}_{M}$	209.27	229.20	252.19	313.18	320.60	388.02	441.09	506.41	74.94	0.36	-1.20	300	-0.09	24.47***
	$HHI^{\dagger}$	1.01	1.13	1.42	2.00	2.03	2.54	2.94	3.31	0.65	0.16	-1.13	300	0.45	17.24***
	$demand^{\dagger}$	520.21	539.68	592.33	672.07	694.88	817.73	881.50	894.66	120.82	0.27	-1.44	300	0.40	29.56***
	$demand^{\dagger\dagger}_{M}$	0.41	0.45	0.54	0.72	0.73	0.93	1.03	1.12	0.20	0.14	-1.39	300	0.46	25.26***
	$price^{\dagger}$	0.41	0.45	0.60	1.57	1.42	2.10	2.58	3.72	0.79	0.20	-1.23	300	-0.17	20.91***
	VAL	-2.13	-1.49	-0.71	-0.10	-0.28	0.20	0.39	0.56	0.60	-0.95	0.33	252	-0.93	39.05***
	MOM	-0.63	-0.24	-0.10	0.01	0.10	0.23	0.72	1.60	0.34	1.49	3.49	300	-3.04**	263.26***
	$FUT1^{\dagger}$	0.43	0.46	0.61	1.56	1.43	2.11	2.57	3.66	0.79	0.19	-1.29	300	-0.14	22.61***
	$FUT2^{\dagger}$	0.46	0.49	0.61	1.43	1.42	2.15	2.53	3.37	0.79	0.15	-1.50	300	-0.06	29.25***
	CY	-10.67	-7.04	-3.71	-1.29	0.75	2.86	17.47	29.42	7.11	1.51	2.22	300	-5.00**	175.61***
	BM	-0.30	-0.08	-0.02	0.00	0.01	0.02	0.15	0.36	0.08	1.02	5.57	300	-4.08**	439.83***
Tin (Sn)	$supply^{\dagger}$	16.76	18.12	20.46	22.16	22.45	24.69	26.53	28.37	3.02	-0.02	-1.00	300	-0.15	12.52***
	$supply^{\dagger}_{M}$	15.39	16.98	19.74	24.65	23.92	27.74	30.06	34.16	4.34	-0.14	-1.13	300	-0.36	16.79***
	$HHI^{\dagger}$	1.78	1.84	1.94	2.28	2.27	2.47	2.84	3.05	0.34	0.43	-0.69	300	-0.07	15.20***
	$demand^{\dagger}$	16.87	17.42	19.01	20.75	20.37	21.69	22.94	23.79	1.93	-0.25	-1.06	300	0.00	17.17***
	$demand^{\dagger}_{M}$	18.04	19.77	22.37	28.42	27.14	30.80	33.47	38.66	4.83	-0.27	-1.08	300	-0.58	18.18***
	$price^{\dagger}$	3.69	4.28	5.70	12.33	12.94	19.74	23.43	32.36	7.31	0.32	-1.26	300	-0.12	24.96***
	VAL	-1.64	-1.30	-0.52	-0.08	-0.23	0.12	0.40	0.64	0.51	-0.92	0.08	300	-1.44	42.40***
	MOM	-0.51	-0.29	-0.09	0.03	0.08	0.19	0.67	1.01	0.28	0.93	0.57	300	-3.68**	47.31***
	$FUT1^{\dagger}$	3.74	4.32	5.73	12.17	12.93	19.68	23.37	32.40	7.30	0.32	-1.25	300	-0.17	24.65***
	$FUT2^{\dagger}$	3.88	4.45	5.73	11.48	12.80	19.63	23.27	32.32	7.25	0.35	-1.24	300	0.03	25.35***
	CY	-1.97	-1.45	-0.11	1.98	2.63	4.08	9.71	22.42	3.64	1.51	3.42	300	-4.47**	260.21***
	BM	-0.13	-0.06	-0.01	-0.00	0.00	0.01	0.07	0.28	0.05	1.65	8.75	300	-3.79**	1093.16***
Zinc (Zn)	$supply^{\dagger\dagger}$	0.52	0.62	0.74	0.93	0.89	1.04	1.14	1.15	0.19	-0.26	-1.21	300	1.31	21.68***
	$supply^{\dagger\dagger}_{M}$	0.56	0.60	0.74	0.91	0.88	1.03	1.15	1.27	0.19	-0.07	-1.26	300	0.11	20.13***
	$HHI^{\dagger}$	0.84	0.95	1.08	1.27	1.33	1.63	1.77	1.92	0.31	0.31	-1.21	300	1.47	23.11***
	$demand^{\dagger}$	380.93	393.21	428.64	462.16	460.65	492.32	520.40	540.79	41.51	-0.11	-0.73	300	-0.36	7.27*
	$demand^{\dagger\dagger}_{M}$	0.58	0.61	0.74	0.92	0.91	1.08	1.20	1.26	0.20	-0.07	-1.26	300	0.18	20.22***
	$price^{\dagger}$	0.75	0.79	1.04	1.77	1.77	2.29	3.27	4.38	0.80	0.71	-0.18	300	-0.26	25.61***
	VAL	-1.69	-1.32	-0.33	-0.07	-0.14	0.14	0.52	0.65	0.49	-1.12	1.29	300	-2.17*	83.52***
	MOM	-0.55	-0.37	-0.12	0.02	0.09	0.21	0.74	1.78	0.36	1.86	5.19	300	-4.09**	509.68***
	$FUT1^{\dagger}$	0.77	0.81	1.07	1.79	1.78	2.30	3.27	4.32	0.79	0.69	-0.23	300	-0.32	24.47***
	$FUT2^{\dagger}$	0.81	0.85	1.10	1.82	1.77	2.32	3.04	3.75	0.72	0.43	-0.90	300	0.01	19.37***
	CY	-8.83	-7.86	-4.84	-2.10	-1.02	0.49	8.84	55.34	6.64	3.61	22.63	300	-7.48**	7053.07***
	BM	-0.14	-0.08	-0.02	0.01	0.02	0.03	0.12	0.45	0.07	2.68	11.17	300	-3.55**	1918.73***
Bismuth (Bi)	$supply^{\dagger}$	0.30	0.32	0.48	1.27	1.03	1.40	1.56	1.76	0.48	-0.47	-1.41	300	0.62	35.90***
	$HHI^{\dagger}$	1.72	1.72	2.13	6.10	5.30	7.41	8.21	8.23	2.48	-0.42	-1.51	300	0.87	37.32***
	$demand^{\dagger}$	0.31	0.49	0.57	0.73	0.74	0.82	1.20	1.28	0.22	0.62	0.41	300	-0.77	21.32***
	$price$	2.75	2.85	3.35	4.38	6.00	8.82	12.72	17.75	3.52	1.18	0.52	300	-0.75	73.00***
	VAL	-1.77	-1.48	-0.59	0.02	-0.08	0.40	0.95	1.39	0.72	-0.37	-0.33	236	0.19	6.46*
	MOM	-0.62	-0.44	-0.16	0.01	0.06	0.17	0.46	3.15	0.46	3.84	20.34	289	-2.37*	5692.07***

Summary Statistics of the Level, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Cadmium (Cd)	*supply*†	1.49	1.54	1.66	1.69	1.75	1.89	2.09	2.11	0.18	0.56	-0.83	300	0.36	24.29***
	HHI†	0.67	0.67	0.74	1.11	1.24	1.66	1.78	1.83	0.45	-0.05	-1.77	300	1.11	39.29***
	demand†	0.28	0.30	0.35	0.40	0.50	0.64	0.94	1.04	0.21	1.19	0.27	300	-0.99	71.72***
	price	0.13	0.18	0.52	0.90	1.15	1.45	2.91	5.98	0.92	2.02	5.69	300	-1.57	608.72***
	VAL	-2.57	-2.04	-1.04	-0.18	-0.12	0.86	1.68	2.49	1.22	0.04	-0.83	237	-1.82.	6.87*
	MOM	-0.78	-0.55	-0.31	-0.03	0.14	0.45	1.36	2.99	0.65	1.66	3.54	290	-3.05**	284.61***
Cobalt(Co)	*supply*†	2.04	2.18	3.74	6.14	6.59	9.23	12.16	12.31	3.22	0.17	-1.28	300	1.01	21.92***
	HHI†	1.42	1.45	1.60	1.97	2.42	2.75	4.79	5.04	1.01	1.16	0.53	300	-0.04	70.79***
	demand†	3.34	3.37	3.83	4.21	4.42	4.95	5.71	6.24	0.77	0.54	-0.64	300	-0.28	19.70***
	price	6.40	8.37	13.60	16.84	19.56	24.91	36.01	52.50	8.80	1.15	1.43	300	-1.02	91.69***
	VAL	-1.82	-1.37	-0.32	0.14	0.07	0.62	1.18	1.35	0.75	-0.50	-0.39	249	-1.46	11.95***
	MOM	-0.75	-0.48	-0.23	-0.03	0.10	0.23	1.26	2.21	0.52	1.39	2.00	300	-3.60**	146.60***
Chromium (Cr)	*supply*††	0.99	1.11	1.61	2.26	2.39	3.01	3.59	3.73	0.85	-0.01	-1.32	300	2.17	21.78***
	HHI†	2.00	2.12	2.21	2.38	2.40	2.50	2.79	2.90	0.22	0.38	-0.39	300	0.97	9.12**
	demand†	77.41	113.95	211.54	223.65	227.95	258.90	308.35	322.49	52.92	-0.75	1.40	300	-0.60	52.62***
	price†	3.45	3.80	5.05	7.55	7.54	9.36	13.18	14.45	2.86	0.54	-0.49	300	-0.13	17.58***
	VAL	-1.34	-0.85	-0.40	-0.05	-0.12	0.21	0.54	0.67	0.44	-0.42	-0.47	294	-0.97	11.35***
	MOM	-0.42	-0.29	-0.10	0.04	0.05	0.21	0.38	0.67	0.21	0.08	-0.46	300	-2.89**	2.97
Gallium (Ga)	*supply*	12.08	12.08	14.92	16.92	21.23	29.25	39.41	40.77	9.02	0.84	-0.74	300	-0.21	42.12***
	HHI†	1.53	1.61	1.74	1.90	4.00	6.75	9.24	9.28	2.98	0.78	-1.16	300	1.70	47.24***
	demand	6.32	6.35	8.16	9.18	11.44	14.06	20.18	20.96	4.62	0.88	-0.66	300	-0.48	44.16***
	price†	0.12	0.14	0.21	0.30	0.35	0.43	0.74	1.07	0.19	1.43	1.97	214	-1.18	107.54***
	VAL	-1.17	-1.03	-0.55	0.46	0.24	0.69	1.74	1.79	0.82	0.03	-0.92	148	-1.69.	5.24.
	MOM	-0.59	-0.42	-0.20	-0.03	0.04	0.18	0.88	1.40	0.39	1.31	1.89	201	-4.72**	87.41***
Germanium (Ge)	*supply*†	3.67	3.75	5.25	8.30	8.31	10.89	13.33	13.75	3.20	0.09	-1.31	300	0.34	21.86***
	HHI†	4.66	5.06	5.27	5.67	6.12	5.89	9.05	9.12	1.34	1.56	0.89	300	-0.70	131.58***
	demand	7.24	9.27	9.64	14.97	15.21	21.07	26.18	26.46	5.79	0.42	-1.15	300	-0.18	25.35***
	price†	0.27	0.30	0.59	0.79	0.83	1.12	1.36	1.42	0.33	0.20	-1.01	295	-0.45	14.51***
	VAL	-1.30	-1.01	-0.55	-0.06	-0.03	0.49	1.01	1.07	0.64	-0.06	-1.18	229	-0.90	13.42***
	MOM	-0.49	-0.40	-0.21	-0.02	0.06	0.27	0.71	1.35	0.35	1.04	1.08	282	-2.62**	64.54***
Indium (In)	*supply*	17.50	20.00	32.67	53.17	46.63	58.42	69.83	77.33	17.53	-0.30	-1.16	300	0.90	21.32***
	HHI†	1.41	1.50	2.46	3.16	2.92	3.39	4.02	4.19	0.84	-0.58	-0.82	300	0.07	25.22***
	demand	16.16	16.91	22.86	49.82	46.77	64.09	75.46	79.44	20.97	-0.24	-1.44	300	0.20	28.80***
	price†	0.07	0.07	0.20	0.33	0.41	0.58	0.88	1.04	0.25	0.49	-0.75	300	-0.68	19.04***
	VAL	-2.47	-2.28	-0.66	0.28	0.02	1.03	1.50	1.74	1.19	-0.67	-0.66	249	-0.26	23.15***
	MOM	-0.68	-0.53	-0.28	-0.07	0.22	0.32	2.46	4.37	0.91	2.43	5.94	300	-1.96*	736.29***
Lithium (Li)	*supply*†	14.79	15.22	17.77	31.74	49.72	51.75	172.65	206.44	50.90	2.07	3.01	300	0.49	327.50***
	HHI†	1.90	1.94	2.61	3.20	3.84	5.26	6.36	7.62	1.59	0.63	-0.68	300	0.37	25.63***
	demand†	0.37	0.46	0.95	1.00	0.97	1.08	1.52	1.54	0.29	-0.09	-0.08	300	-0.59	0.48
	price†	16.45	16.45	18.87	31.35	46.40	65.01	122.29	144.96	36.40	1.22	0.32	276	0.91	69.64***
	VAL	-1.29	-1.17	-0.78	-0.54	-0.48	-0.20	0.16	0.19	0.41	0.18	-0.93	210	-0.59	8.70**
	MOM	-0.36	-0.22	-0.04	0.00	0.11	0.16	0.79	1.60	0.32	2.10	4.98	263	-2.21*	465.08***

Summary Statistics of the Level, Metal-Specific Variables

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Magnesium (Mg)	*supply*†	28.39	30.63	35.68	55.80	56.34	75.86	87.42	93.17	20.52	0.25	-1.30	300	1.81	24.25***
	HHI†	1.67	1.93	2.84	6.98	5.60	7.62	7.89	7.90	2.32	-0.60	-1.35	300	1.69	40.78***
	demand†	37.40	38.70	52.70	59.86	56.72	62.75	66.53	69.51	8.85	-0.90	-0.28	300	-0.41	41.48***
	price†	1.30	1.37	1.77	2.36	2.38	2.75	3.40	5.78	0.77	1.25	3.04	291	-1.41	187.84***
	VAL	-1.22	-0.78	-0.36	0.03	-0.04	0.30	0.58	0.82	0.44	-0.47	-0.45	225	-1.83.	10.18***
	MOM	-0.55	-0.29	-0.11	-0.02	0.02	0.11	0.45	1.29	0.27	2.16	7.30	278	-2.66**	833.45***
Manganese)(Mn)	*supply*††	0.55	0.60	0.91	1.30	1.27	1.57	1.89	1.97	0.42	-0.26	-1.09	300	-0.43	18.23***
	HHI†	1.26	1.33	1.56	1.79	2.28	3.25	3.71	3.81	0.87	0.55	-1.34	300	-0.66	37.57***
	demand†	218.19	229.22	254.00	351.24	335.22	406.56	451.91	478.71	82.95	0.07	-1.53	300	-0.59	29.51***
	price†	0.84	0.90	1.27	1.71	1.92	2.35	3.52	4.85	0.84	0.92	0.46	300	-0.67	44.96***
	VAL	-1.75	-1.30	-0.47	0.09	-0.09	0.36	0.59	0.78	0.57	-0.83	-0.06	249	-1.07	28.63***
	MOM	-0.46	-0.31	-0.13	-0.04	0.07	0.18	0.75	2.70	0.39	3.16	14.41	300	-2.87**	3094.88***
Molybdenum (Mo)	*supply*†	10.07	10.73	11.33	17.71	17.32	23.19	24.72	25.44	5.57	0.07	-1.65	300	2.45	34.28***
	HHI†	2.01	2.02	2.22	2.45	2.44	2.68	2.83	2.89	0.28	-0.11	-1.30	300	-1.30	21.73***
	demand†	3.64	5.24	7.85	9.74	10.75	14.86	17.24	18.80	4.12	0.23	-1.01	300	-0.83	15.40***
	price	2.10	2.30	4.35	9.63	11.78	15.00	32.50	39.00	9.26	1.15	0.35	300	-0.96	67.66***
	VAL	-2.71	-2.46	-0.63	0.35	-0.16	0.69	1.10	1.25	1.18	-0.95	-0.56	249	-0.92	40.71***
	MOM	-0.75	-0.53	-0.16	0.00	0.20	0.31	1.62	4.82	0.74	2.85	11.02	300	-3.83**	1924.13***
Antimony (Sb)	*supply*†	8.91	9.37	11.80	12.92	12.73	14.46	15.41	16.09	2.00	-0.31	-0.81	300	0.13	13.01***
	HHI†	3.68	4.23	6.19	7.07	6.89	7.84	8.22	8.23	1.18	-1.10	0.65	300	-0.01	65.78***
	demand†	9.76	10.26	11.73	13.28	13.22	14.15	16.91	17.51	1.95	0.27	-0.30	300	-0.90	4.77.
	price†	1.07	1.20	2.31	5.34	5.58	8.26	12.76	16.98	3.76	0.73	-0.21	300	-0.16	27.20***
	VAL	-1.52	-1.31	-0.89	-0.54	-0.26	0.41	0.99	1.46	0.79	0.45	-1.05	249	-0.93	19.84***
	MOM	-0.43	-0.34	-0.18	-0.03	0.10	0.26	0.94	2.61	0.44	2.15	6.67	300	-5.29**	787.24***
Titanium (Ti)	*supply*††	0.51	0.52	0.63	0.72	0.75	0.85	1.06	1.07	0.15	0.35	-0.61	300	0.02	10.78***
	HHI†	0.98	1.01	1.12	1.43	1.45	1.59	2.08	2.11	0.35	0.53	-0.76	300	-1.00	21.26***
	demand†	5.88	6.19	8.68	14.24	13.31	16.93	19.93	27.67	5.32	0.50	0.00	300	-0.00	12.50***
	price	4.23	5.75	6.75	7.75	9.84	9.90	24.27	31.50	5.68	2.17	3.74	300	-0.73	410.29***
	VAL	-1.53	-1.32	-0.31	0.08	-0.06	0.35	0.96	1.19	0.63	-0.57	-0.04	249	-1.35	13.50***
	MOM	-0.67	-0.24	-0.09	-0.02	0.12	0.07	0.52	4.48	0.71	4.64	22.58	300	-2.83**	7449.68***
Vanadium (V)	*supply*†	3.02	3.36	3.56	4.87	5.02	5.96	7.14	7.24	1.34	0.17	-1.32	300	1.84	23.23***
	HHI†	3.08	3.17	3.28	3.56	3.62	3.96	4.13	4.45	0.37	0.41	-0.91	300	0.69	18.76***
	demand†	0.48	0.73	1.54	2.09	2.93	4.33	6.69	7.00	1.81	0.76	-0.50	300	-0.87	32.01***
	price	6.20	8.00	15.13	24.99	28.86	32.70	73.66	128.21	21.24	2.11	5.38	300	-1.55	584.41***
	VAL	-2.57	-1.77	-0.83	0.24	-0.14	0.62	0.92	1.07	0.94	-0.76	-0.76	249	-1.20	29.96***
	MOM	-0.77	-0.60	-0.19	0.04	0.22	0.56	1.48	3.99	0.69	2.03	6.68	300	-3.13**	763.82***
Tungsten (W)	*supply*†	2.77	2.89	3.78	5.64	5.48	6.98	7.48	8.47	1.70	-0.17	-1.27	300	0.36	21.61***
	HHI†	5.29	5.79	6.50	6.76	6.79	7.04	8.01	8.27	0.64	0.04	0.54	300	0.63	3.73
	demand†	3.66	3.79	4.58	5.61	6.04	7.38	8.46	10.29	1.77	0.47	-0.80	300	0.32	19.05***
	price	4.40	5.50	6.44	26.57	23.95	35.04	48.88	54.00	15.90	0.15	-1.37	300	-0.12	24.59***
	VAL	-1.86	-1.72	-0.62	-0.23	-0.41	0.02	0.64	0.72	0.71	-0.62	-0.56	249	-0.74	19.21***
	MOM	-0.55	-0.29	-0.09	0.04	0.13	0.21	0.74	2.54	0.41	2.67	10.50	300	-2.57*	1734.57***

This table displays the descriptive statistics minimum (Min), five-percent quantile (Q5), twenty-five percent quantile (Q25), median (Med), mean (Mean), seventy-five quantile (Q75), ninety-five percent quantile (Q95), the maximum (Max), standard deviation (SD), skewness (Skew) and excess kurtosis (Kurt), as well as the number of observations available for each series and the test statistics of the Augmented Dickey-Fuller test (ADF) and the Jarque-Bera test (JB), with the corresponding significance levels (0.1% (***), 1% (**), 5% (*) and 10% (.)). Hereby, the statistics are based on the initial level data and variables indicated by a † have been divided by 1000 prior to the calculation of the descriptives.

B.2 General Metal Price Determinants

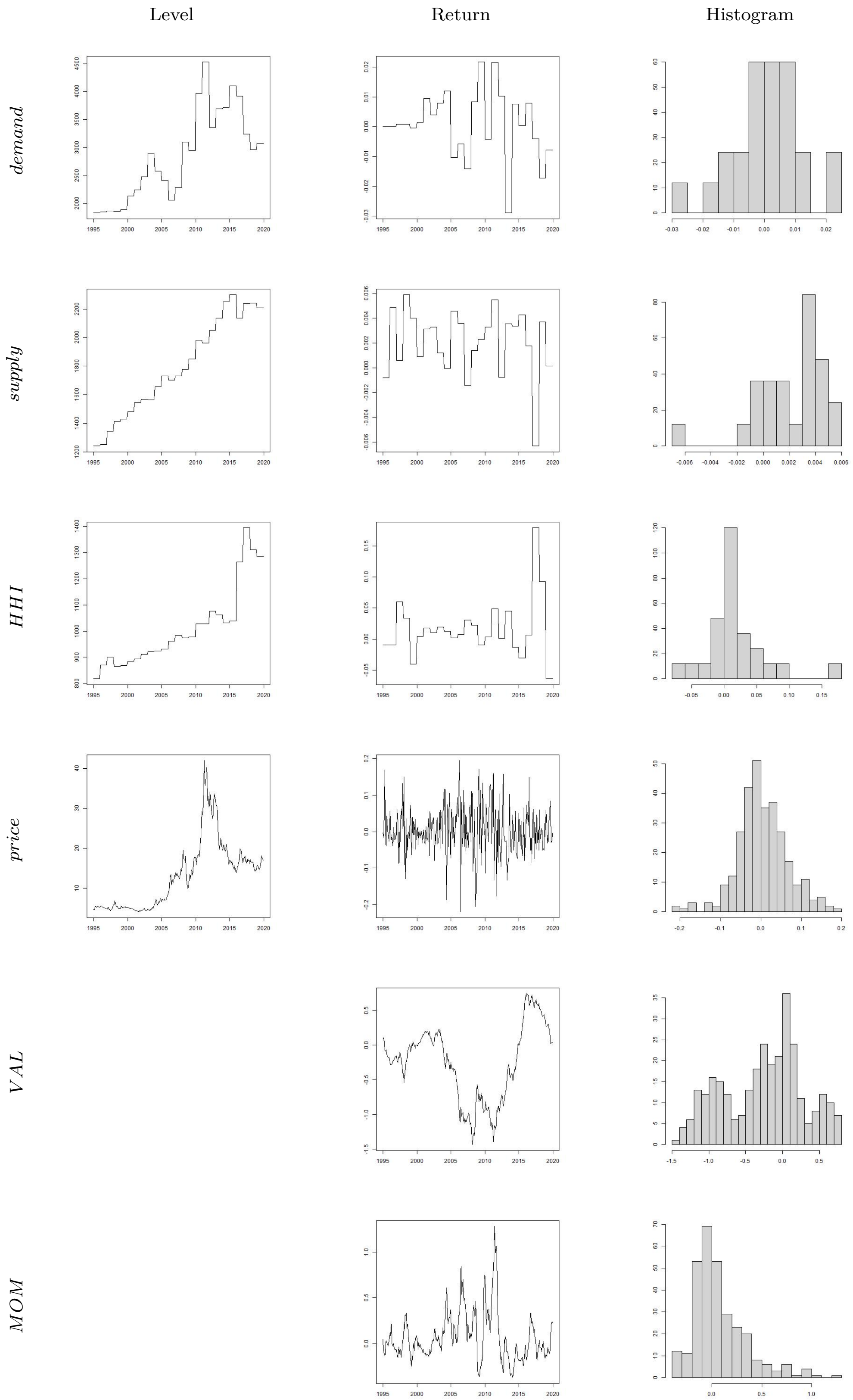
Table B.2: Summary Statistics of the Level, General Metal Price Determinants

	Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
$SIR_{U.S.}$	0.11	0.13	0.44	2.04	2.69	5.31	6.05	6.73	2.24	0.33	-1.51	300	-1.92.	33.95***
SIR_{China}	0.01	0.02	0.03	0.04	0.05	0.05	0.12	0.13	0.03	1.70	2.48	288	-2.39*	212.52***
$LIR_{U.S.}$	1.50	1.76	2.54	3.97	3.96	5.11	6.53	7.78	1.56	0.24	-1.04	300	-2.25*	16.40***
LIR_{China}	0.03	0.03	0.03	0.04	0.04	0.04	0.05	0.05	0.01	0.51	-0.46	211	-0.14	11.01***
$T10Y3M$	-0.77	-0.23	0.68	1.56	1.57	2.49	3.34	3.79	1.12	0.01	-0.95	300	-1.40	11.29***
FFR	0.07	0.09	0.18	1.75	2.50	5.20	5.85	6.54	2.25	0.37	-1.50	300	-1.94.	34.97***
$WuXia$	-2.99	-1.97	-0.19	1.65	2.05	5.02	5.85	6.65	2.69	0.00	-1.27	300	-2.08*	20.16***
$MB^{\dagger\dagger}$	0.42	0.44	0.60	0.83	1.75	3.25	3.93	4.08	1.35	0.56	-1.40	300	2.57	40.18***
$WALCL^{\dagger\dagger}$	0.72	0.75	0.87	2.82	2.62	4.27	4.49	4.51	1.50	-0.04	-1.63	205	2.50	22.75***
$M4^{\dagger}$	0.51	0.54	0.76	1.11	1.05	1.28	1.55	1.67	0.32	-0.10	-1.09	300	11.91	15.35***
$T5YIFR$	0.73	1.68	2.07	2.37	2.29	2.52	2.73	2.88	0.33	-0.93	1.59	204	-0.67	50.90***
FX	72.12	76.06	82.18	89.70	91.20	97.92	113.95	118.97	10.89	0.56	-0.27	300	0.16	16.59***
$IP_{U.S.}$	70.01	73.85	89.01	94.98	93.31	99.80	103.23	106.13	8.34	-0.96	0.35	300	0.79	47.61***
$IP^{\dagger\dagger\dagger\dagger}_{World}$	0.86	0.93	1.07	1.28	1.30	1.52	1.74	1.89	0.26	0.22	-1.11	300	0.42	17.82***
IP_{China}	101.80	105.62	107.90	111.40	111.44	114.88	118.10	123.20	4.32	0.17	-0.86	286	-0.32	10.19***
GDP	97.76	98.50	99.61	99.99	100.07	100.55	101.59	101.83	0.86	-0.14	0.07	300	0.47	1.04
$EAKilian$	-162.97	-84.08	-43.54	-8.34	4.07	40.38	127.66	188.20	66.62	0.66	0.09	300	-2.42*	21.88***
$BDI^{\dagger}$	0.32	0.66	1.01	1.53	2.29	2.76	6.68	11.44	2.05	2.13	4.69	246	-1.54	411.47***
CPI	-1.92	-0.34	0.00	0.19	0.18	0.40	0.68	1.22	0.34	-0.90	4.81	300	-8.79**	329.70***
OIL	11.31	17.20	27.24	49.90	53.20	74.42	102.92	133.93	29.05	0.47	-0.80	300	-0.38	19.05***
$BCOM$	77.84	80.54	95.30	116.80	120.66	143.58	172.64	214.67	31.36	0.57	-0.55	300	-0.45	20.03***
CRB	118.82	140.62	180.70	206.44	234.64	295.22	349.85	462.74	70.50	0.53	-0.64	296	-0.29	18.91***
$LME^{\dagger}$	1.67	2.16	2.76	3.05	3.04	3.31	4.15	4.43	0.55	0.06	0.34	138	-0.82	0.75
$RICIM^{\dagger}$	0.47	0.50	0.58	1.70	1.47	2.16	2.62	3.10	0.80	0.04	-1.52	300	0.57	28.96***
$MSCIW^{\dagger}$	0.61	0.76	1.00	1.23	1.31	1.60	2.11	2.32	0.40	0.51	-0.50	300	2.06	16.13***
$SPX^{\dagger}$	0.46	0.65	1.08	1.29	1.44	1.69	2.76	3.18	0.60	0.97	0.28	300	3.52	48.02***

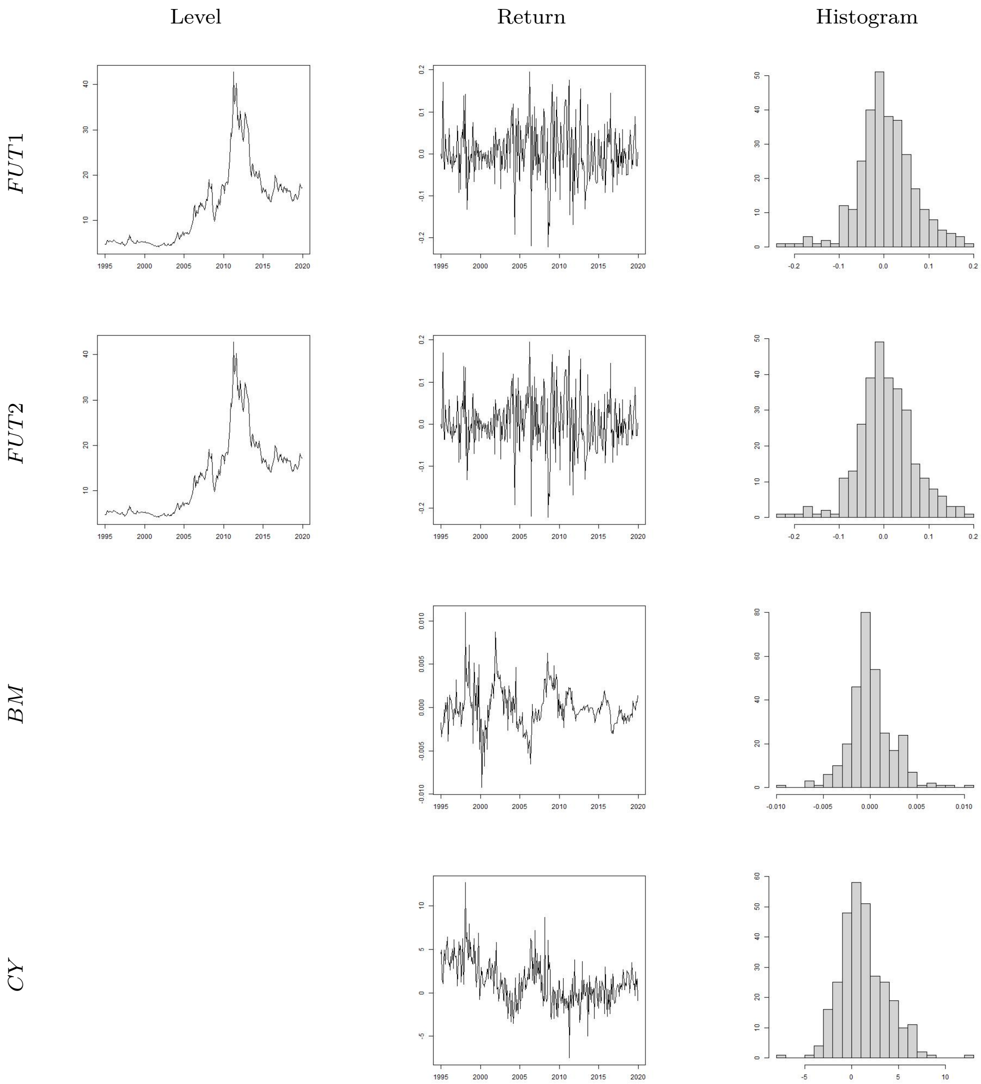
This table displays the descriptive statistics minimum (Min), the five-percent quantile (Q5), the twenty-five percent quantile (Q25), the median (Med), the mean (Mean), the seventy-five quantile (Q75), the ninety-five percent quantile (Q95), the maximum (Max), as well as the standard deviation (SD), the skewness (Skew) and the excess kurtosis (Kurt), as well as the number of observations available for each series and the results of the test statistics of the Augmented Dickey-Fuller test (ADF) and the Jarque-Bera test (JB), with the corresponding significance levels (0.1% (***), 1% (**), 5% (*) and 10% (.)). Hereby, the statistics are based on the inital level data and variables indicated by a † have been divided by 1000 prior to the calculation of the descriptives.

C Plots of Metal-Specific Price Determinants

Figure C.1: Plots of Metal-Specific Covariates - Silver

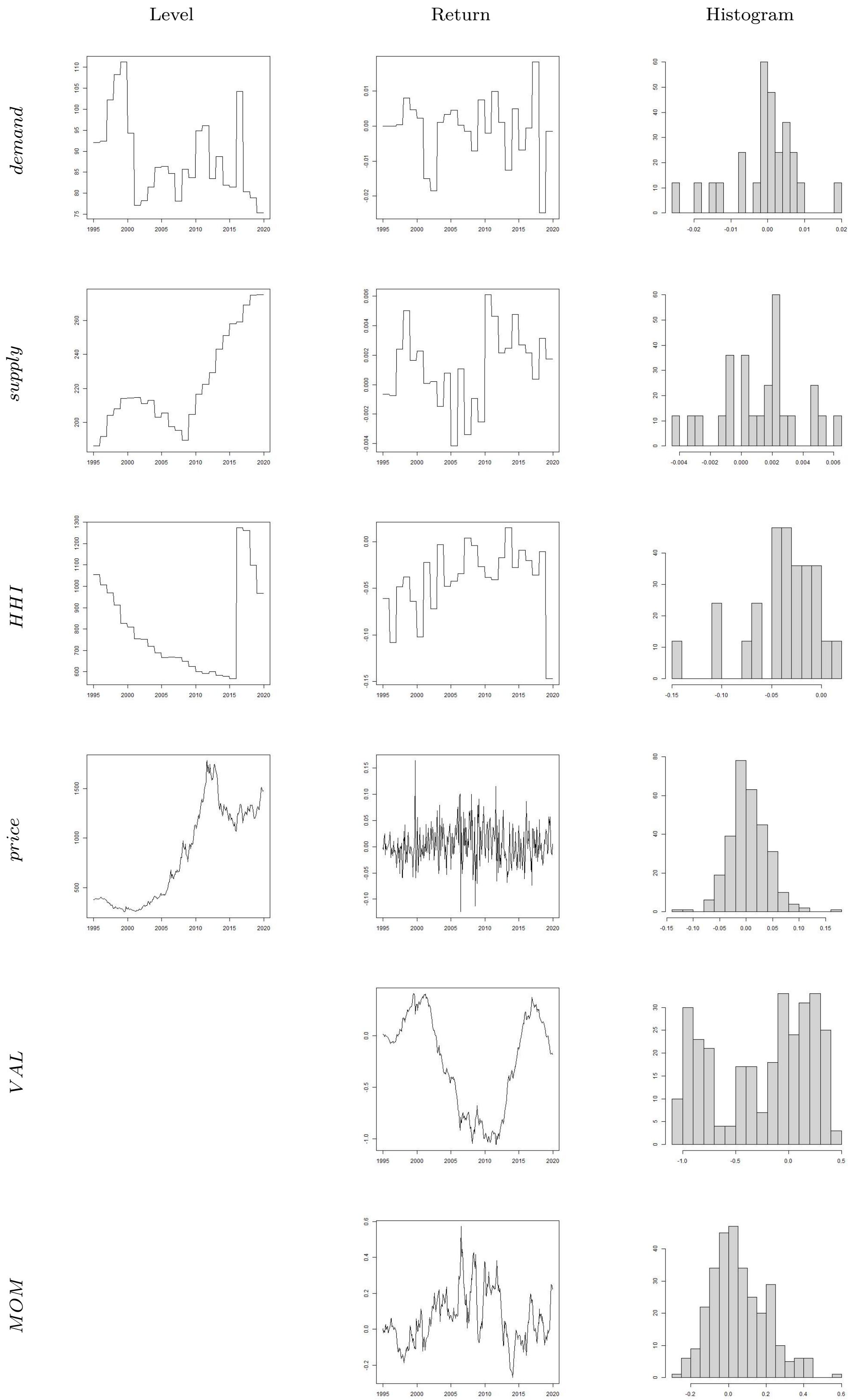


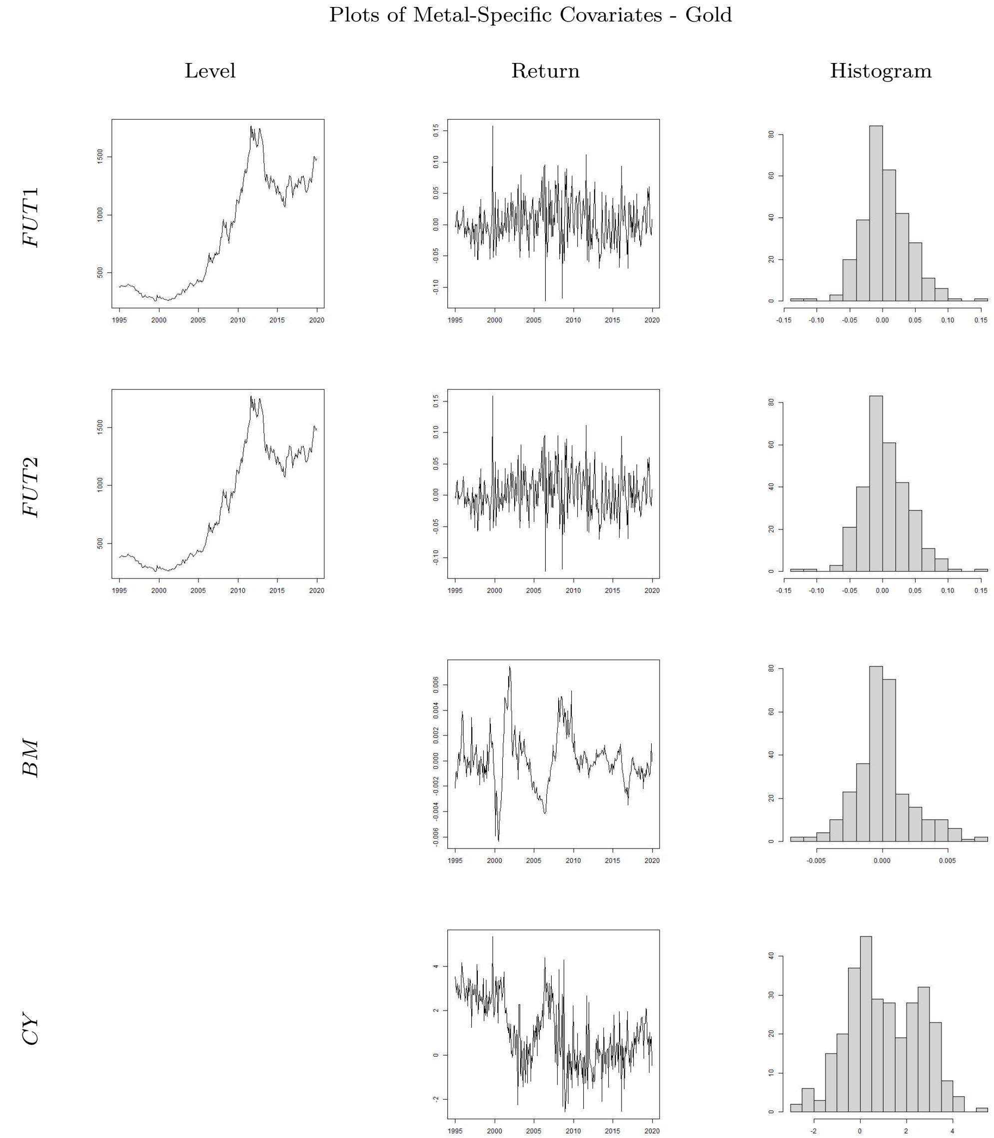
Plots of Metal-Specific Covariates - Silver



This figure displays the time-series of the metal-specific price determinants for silver in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

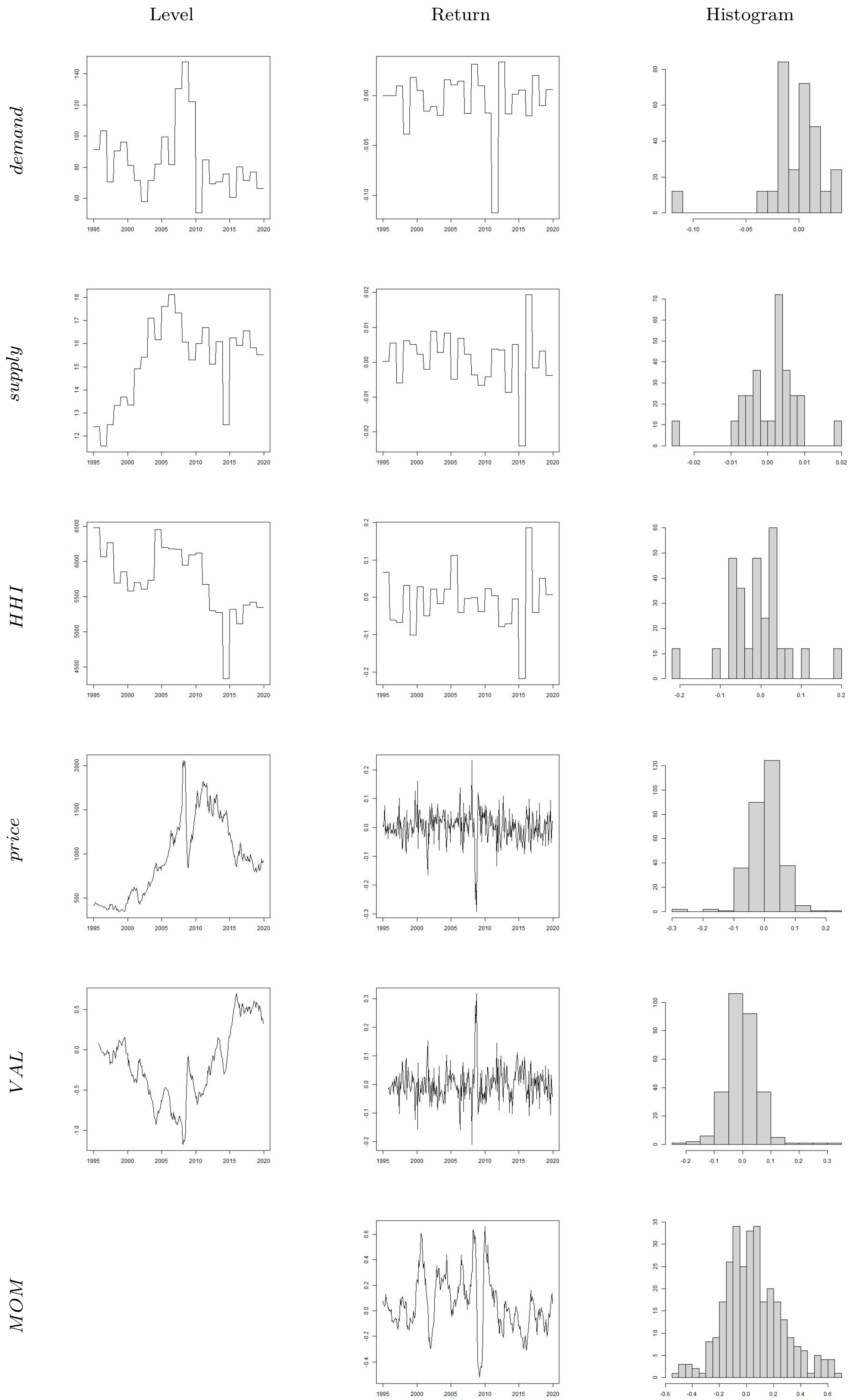
Figure C.2: Plots of Metal-Specific Covariates - Gold



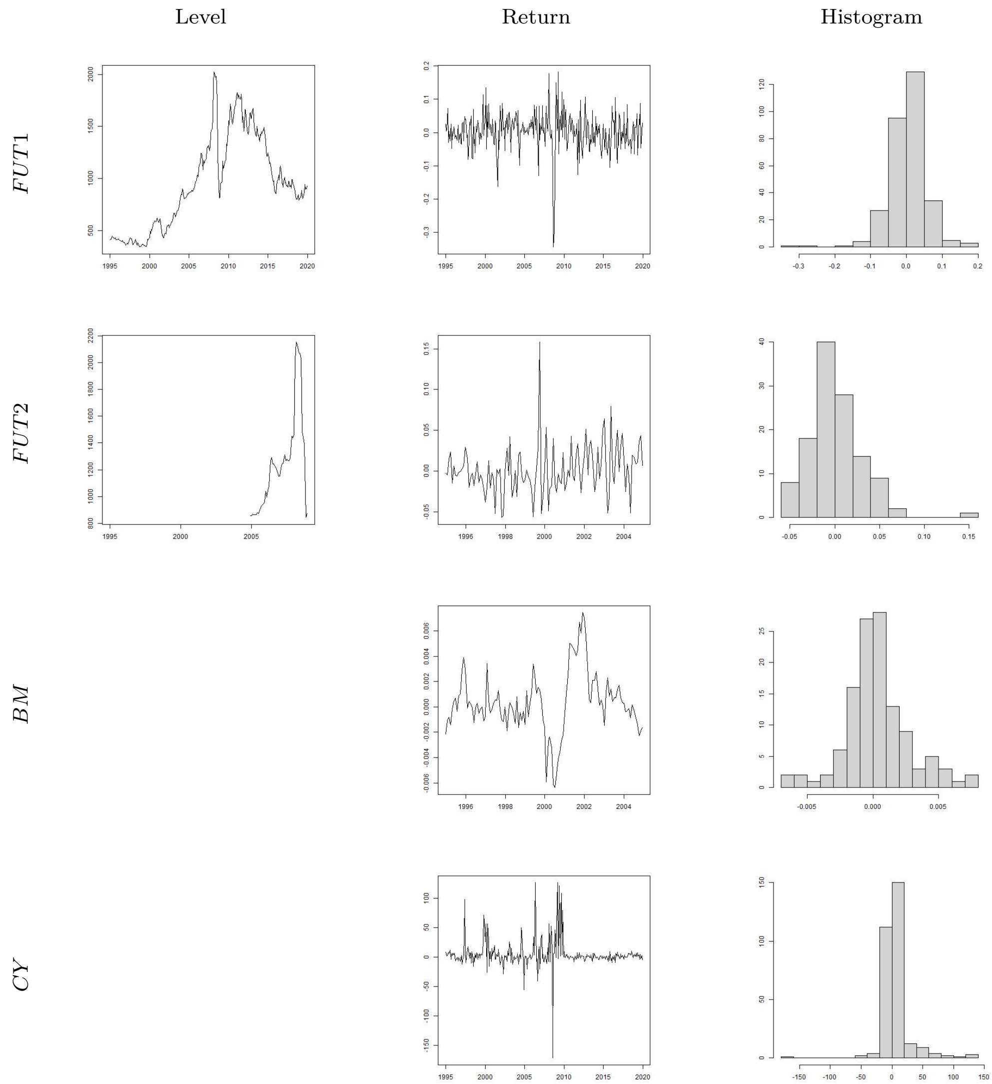


This figure displays the time-series of the metal-specific price determinants for gold in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.3: Plots of Metal-Specific Covariates - Platinum

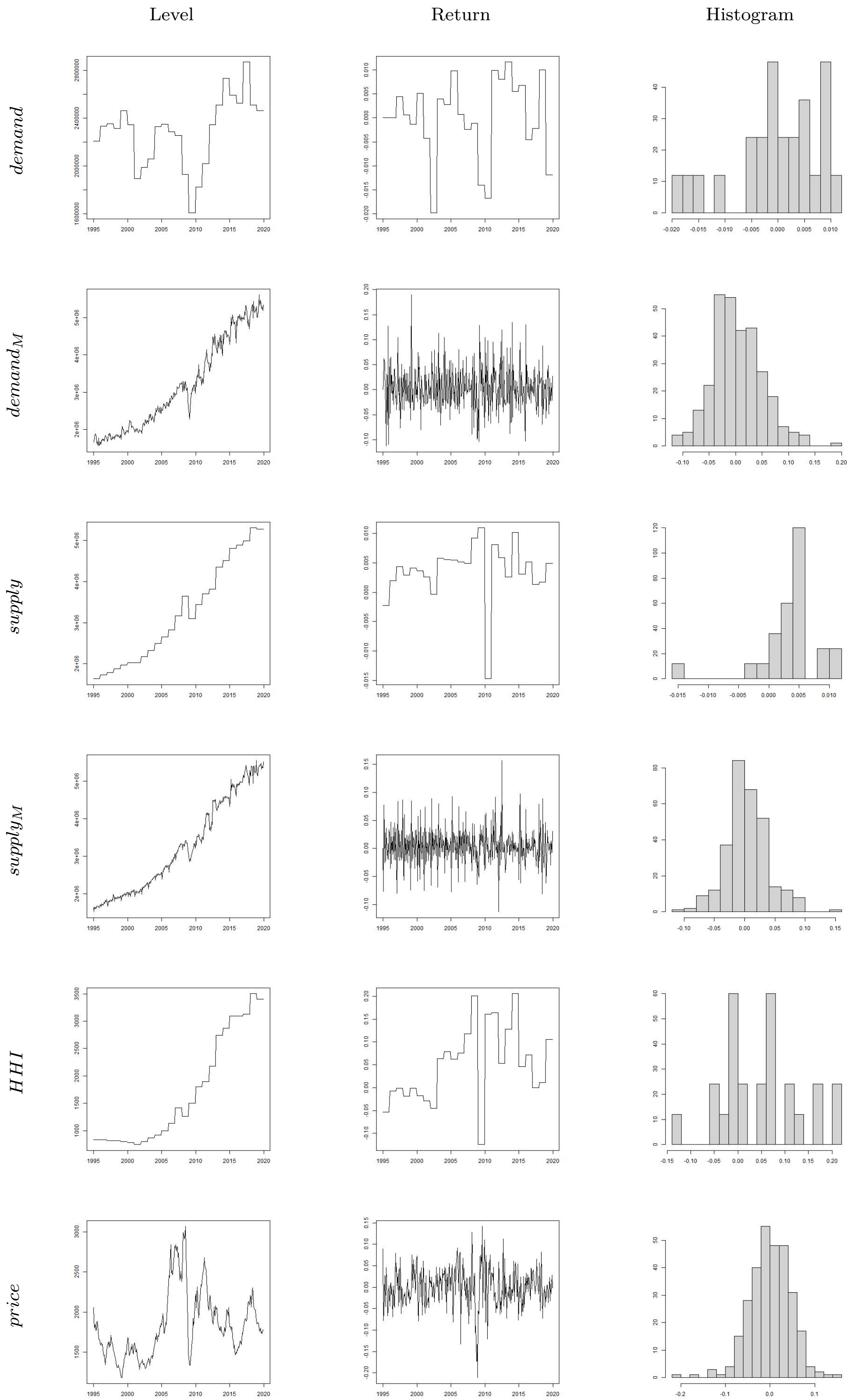


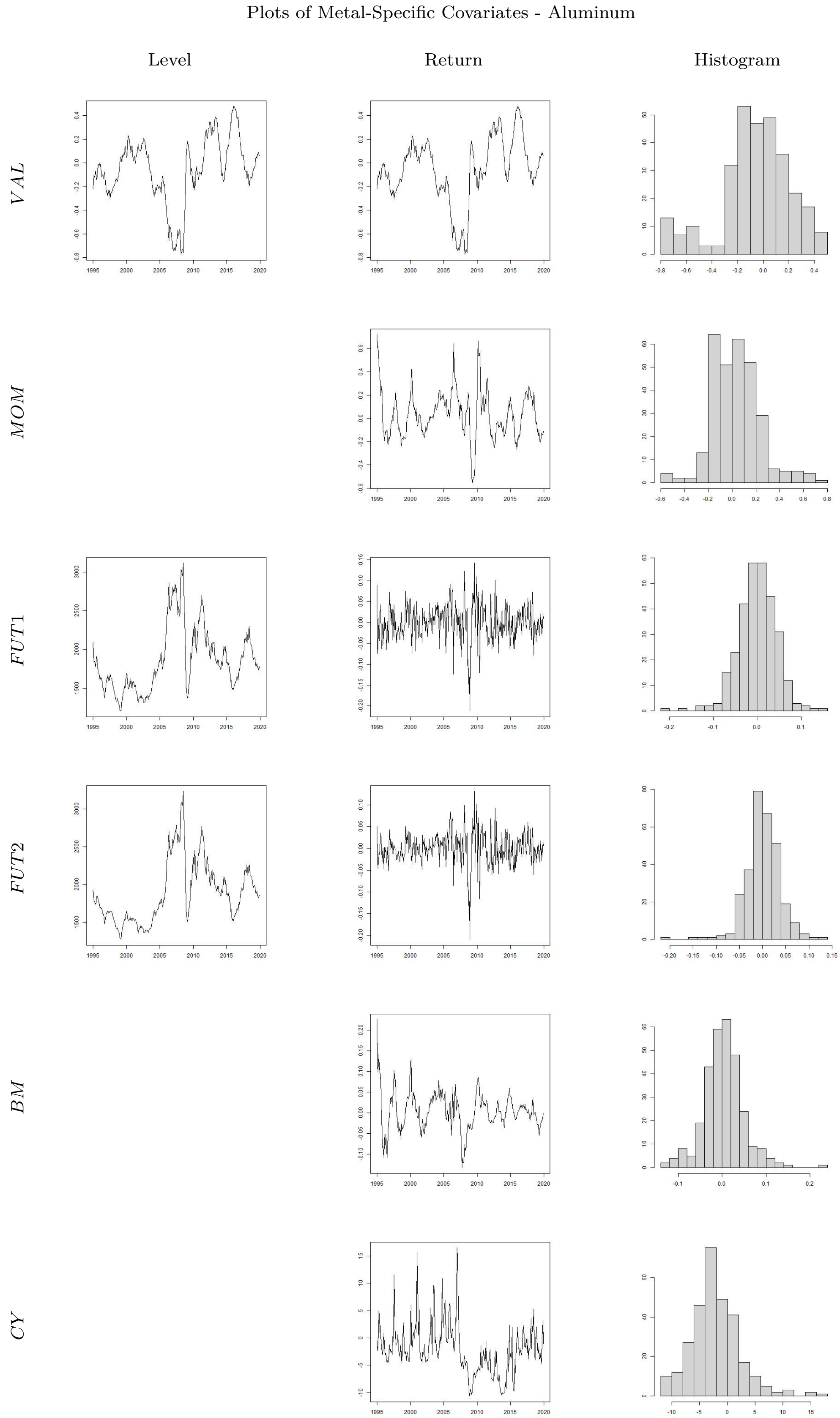
Plots of Metal-Specific Covariates - Platinum



This figure displays the time-series of the metal-specific price determinants for platinum in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

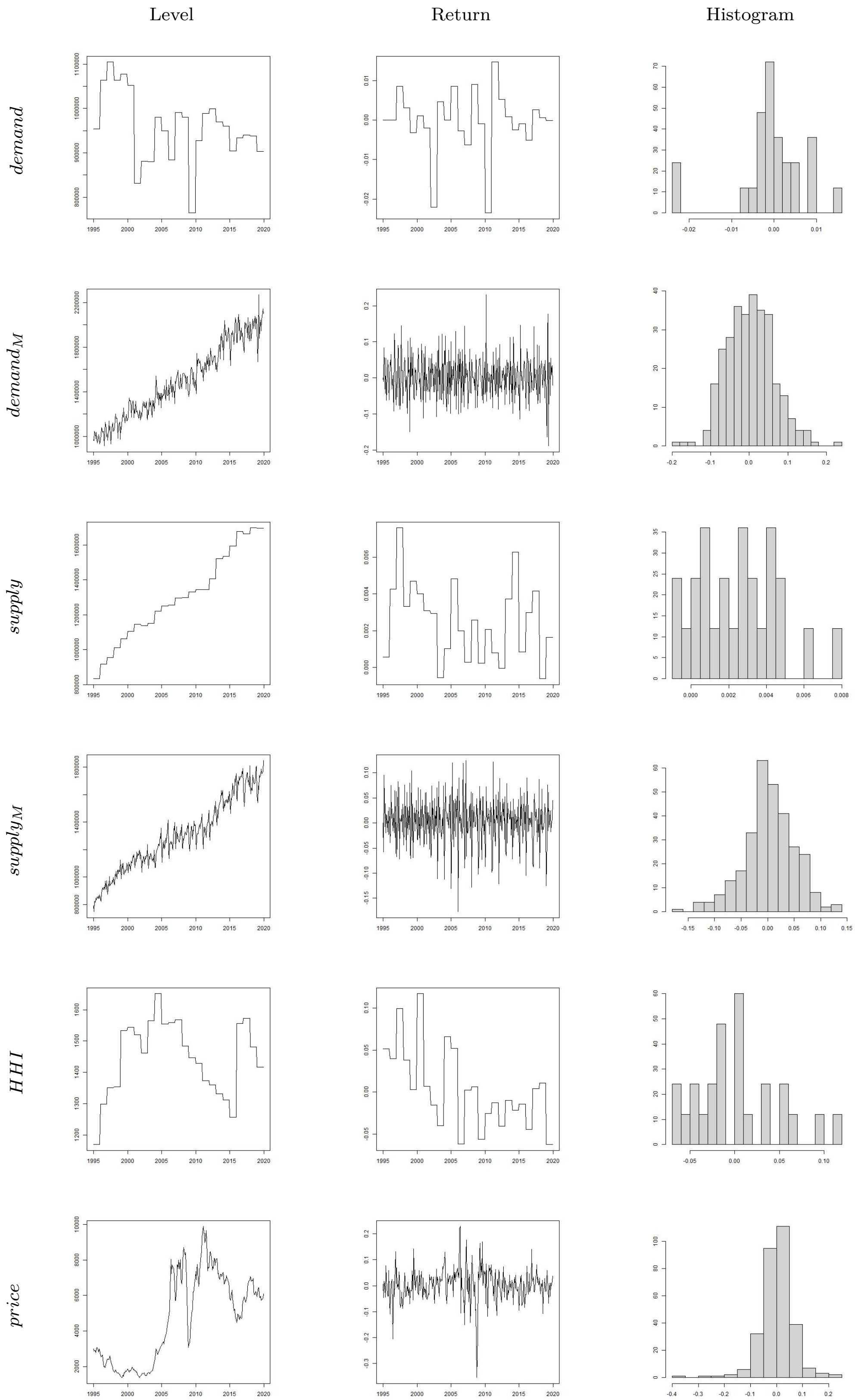
Figure C.4: Plots of Metal-Specific Covariates - Aluminum



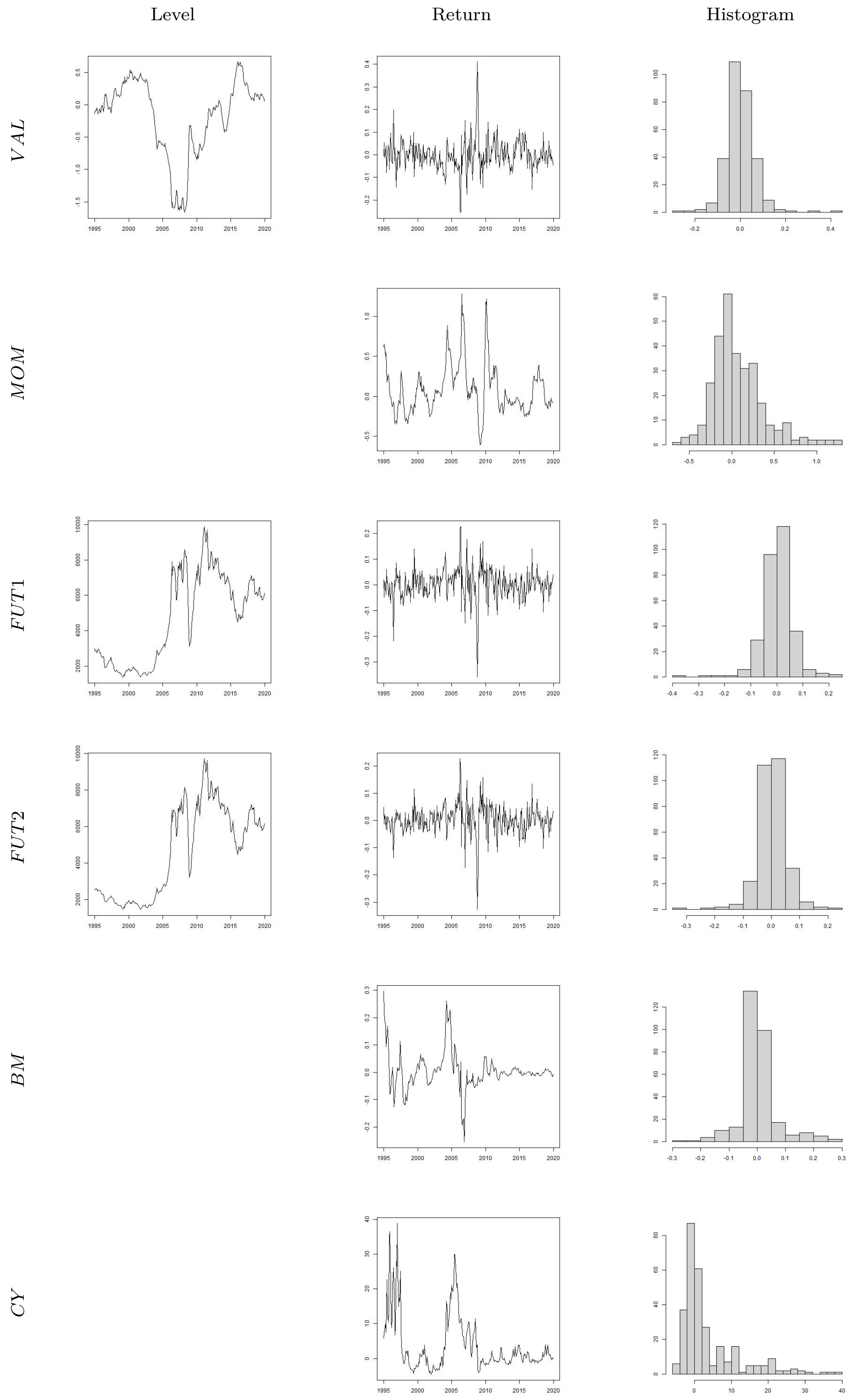


This figure displays the time-series of the metal-specific price determinants for aluminum in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.5: Plots of Metal-Specific Covariates - Copper

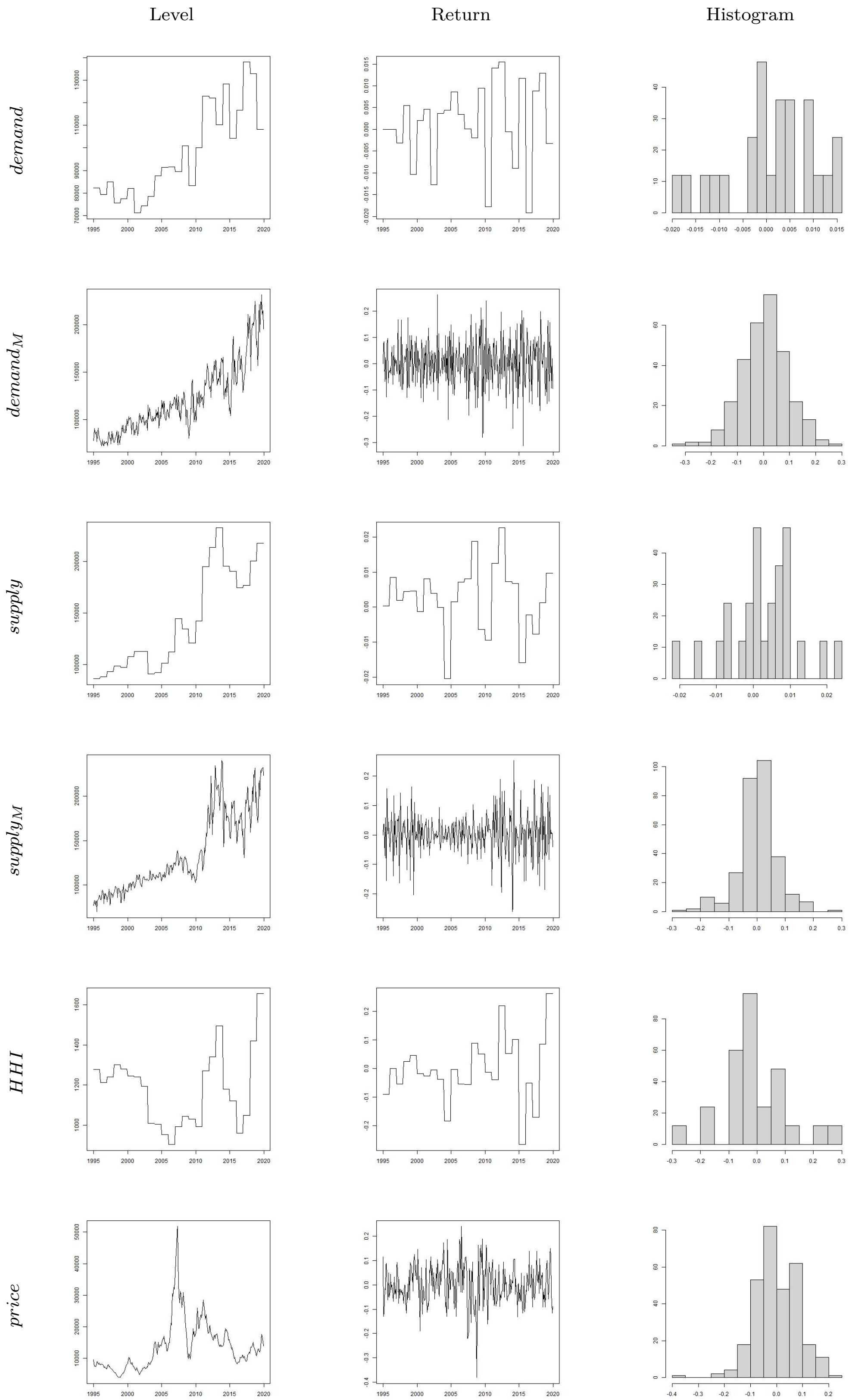


Plots of Metal-Specific Covariates - Copper

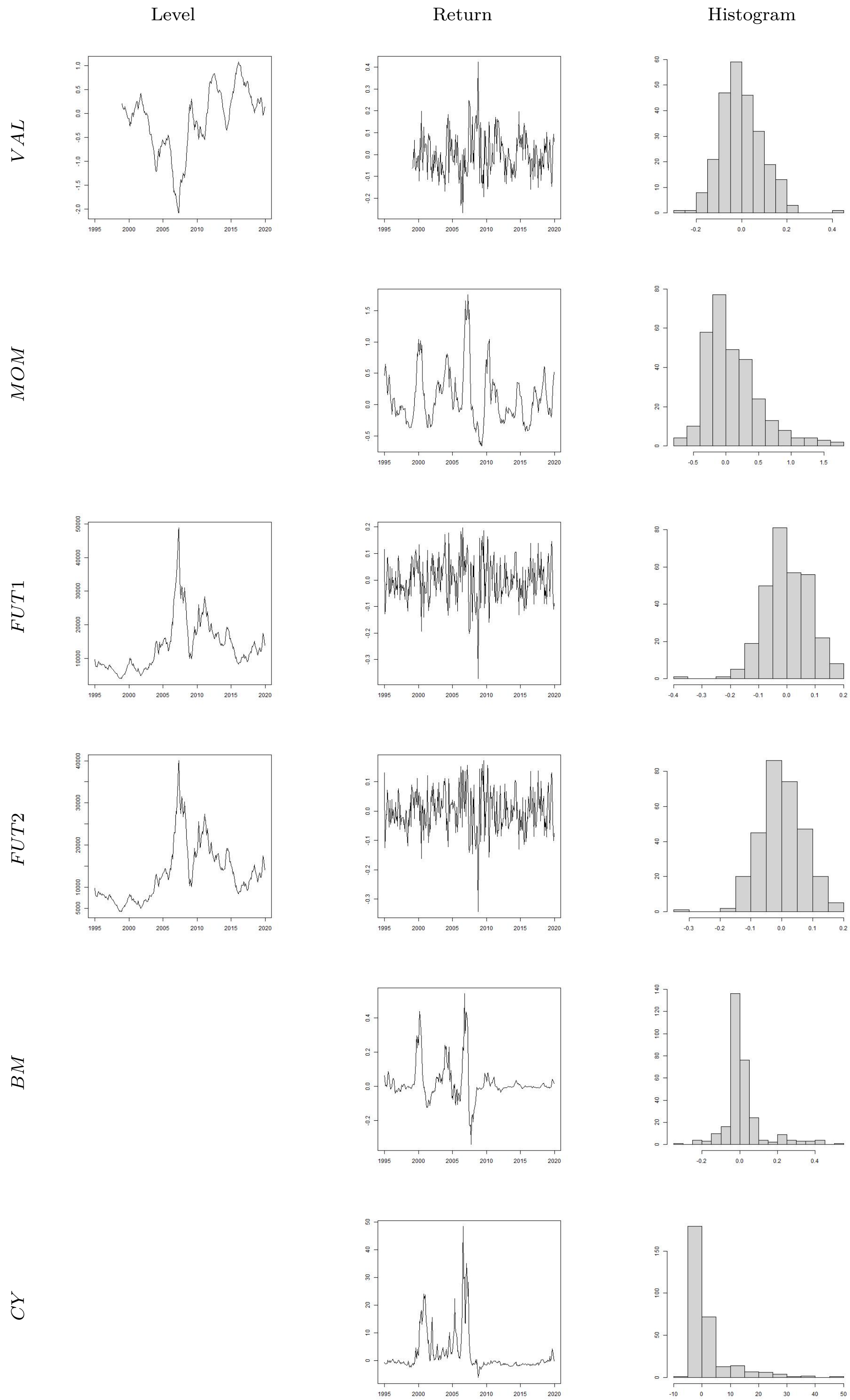


This figure displays the time-series of the metal-specific price determinants for copper in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.6: Plots of Metal-Specific Covariates - Nickel

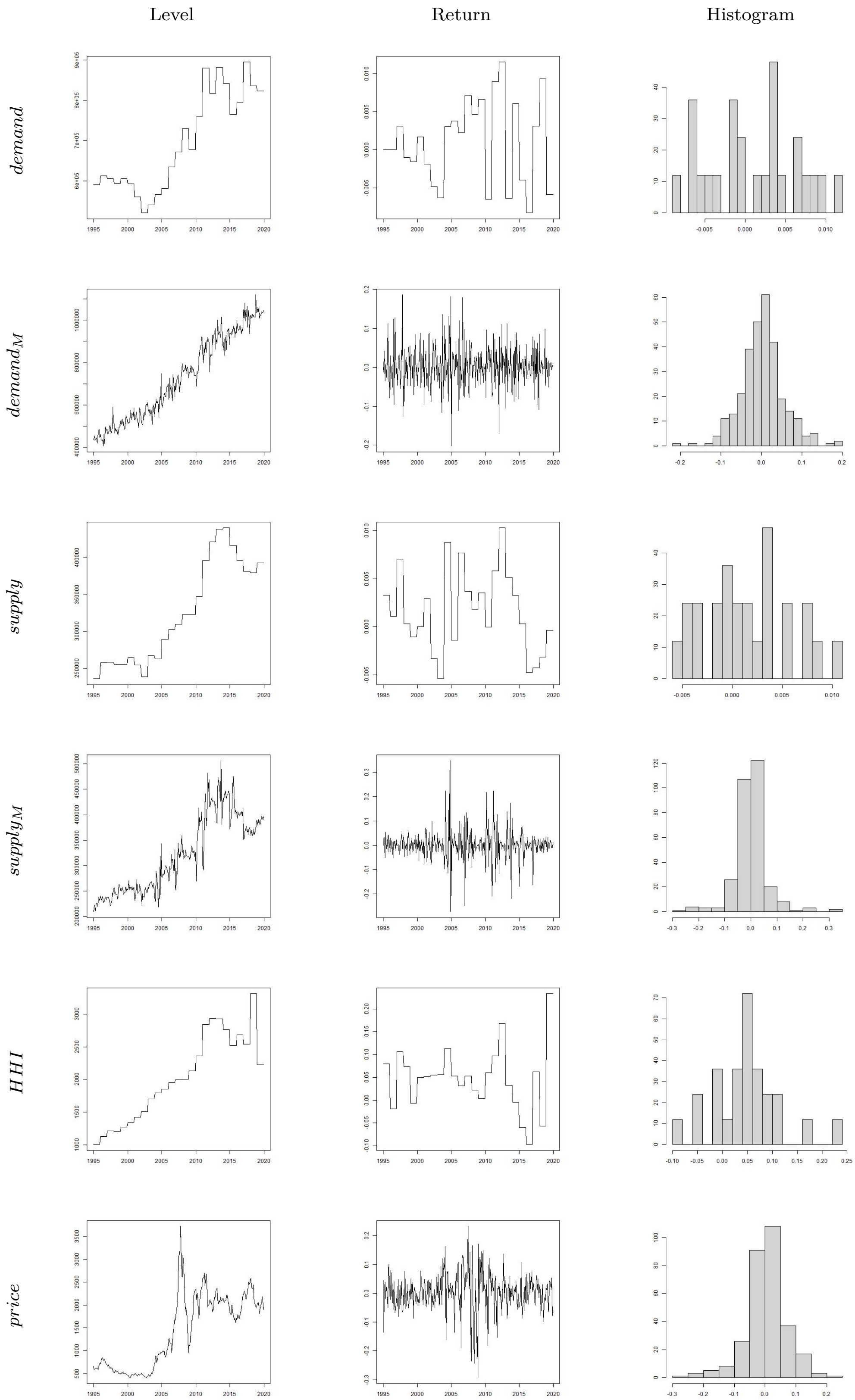


Plots of Metal-Specific Covariates - Nickel

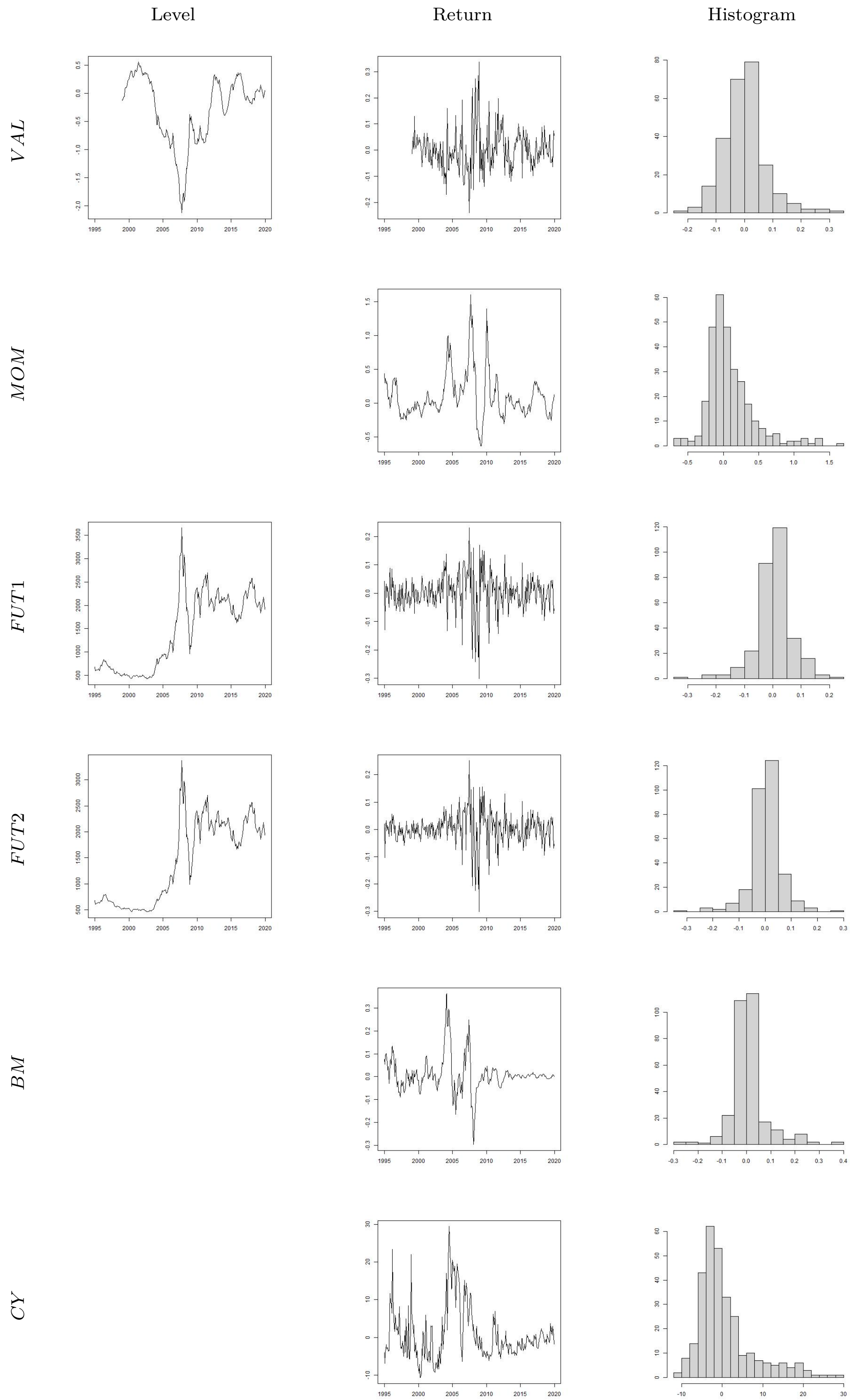


This figure displays the time-series of the metal-specific price determinants for nickel in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.7: Plots of Metal-Specific Covariates - Lead

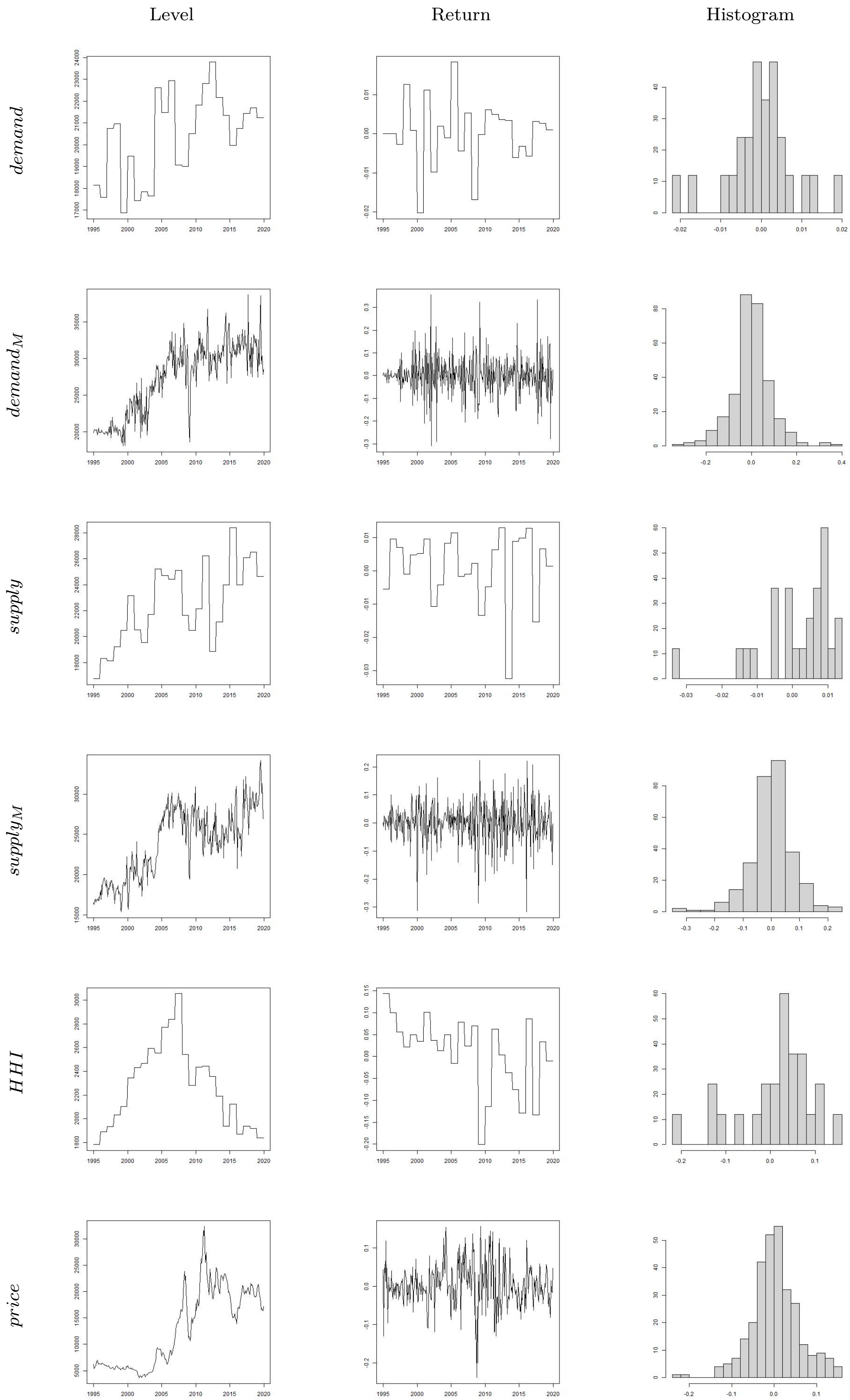


Plots of Metal-Specific Covariates - Lead

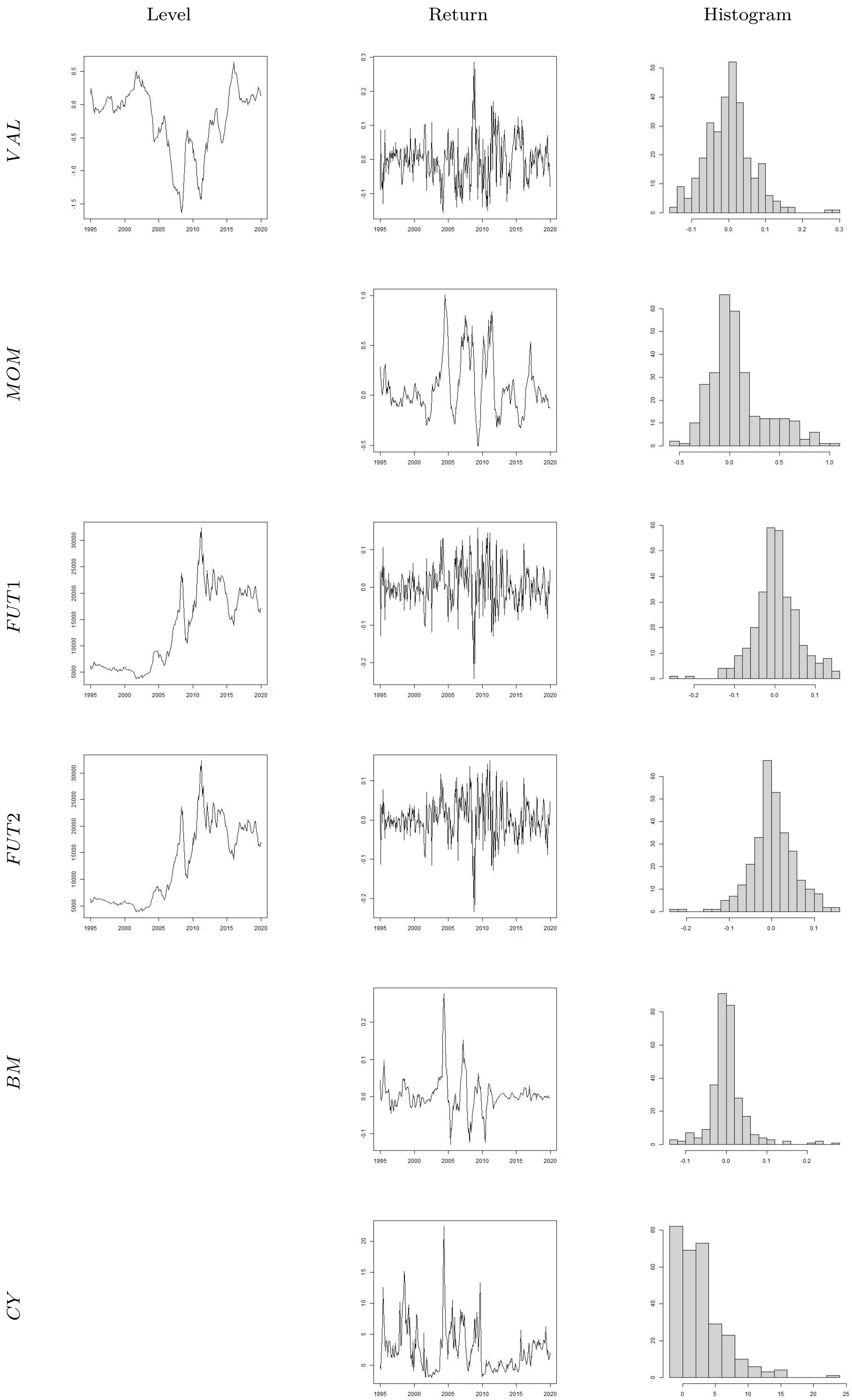


This figure displays the time-series of the metal-specific price determinants for lead in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.8: Plots of Metal-Specific Covariates - Tin

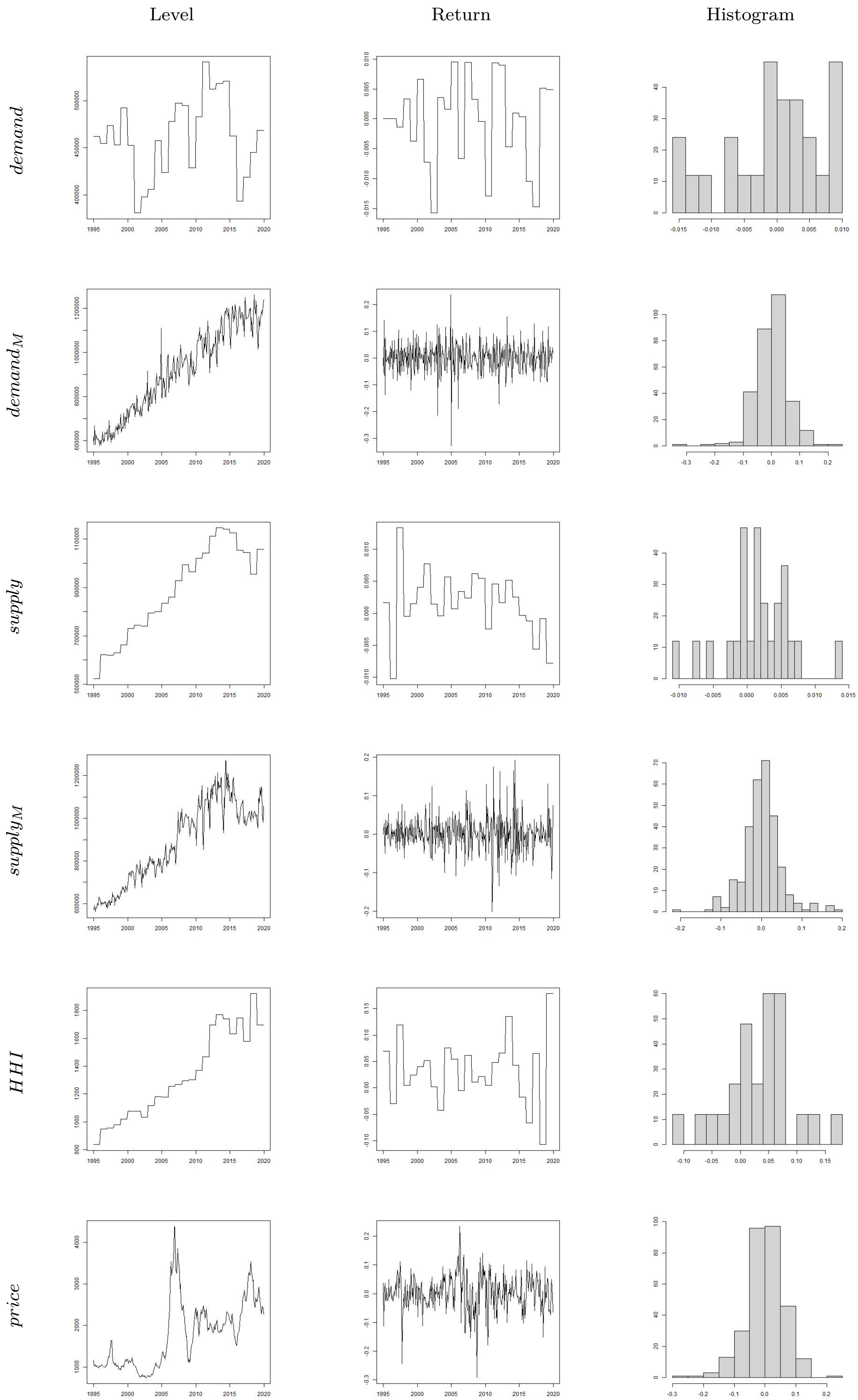


Plots of Metal-Specific Covariates - Tin

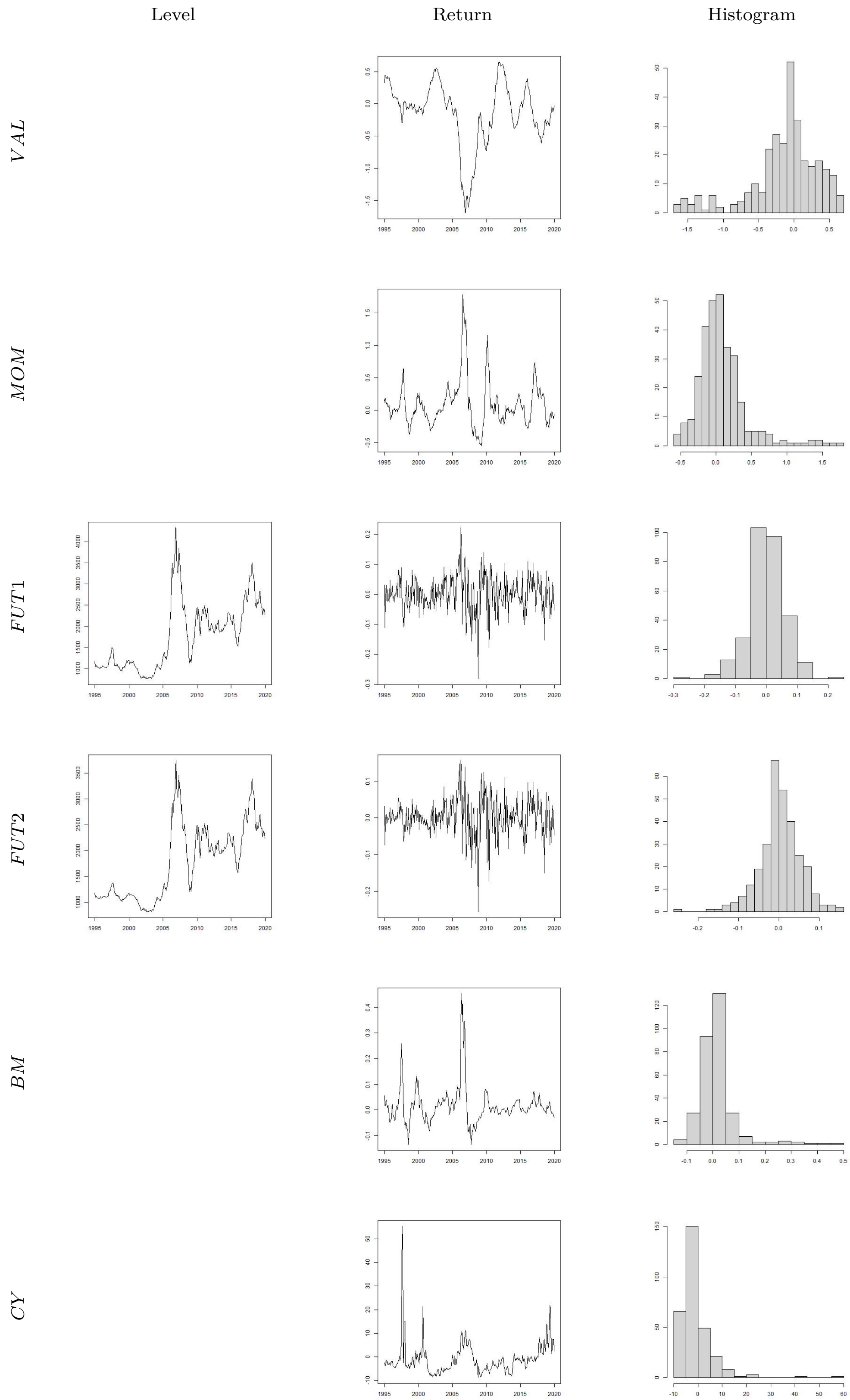


This figure displays the time-series of the metal-specific price determinants for tin in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.9: Plots of Metal-Specific Covariates - Zinc

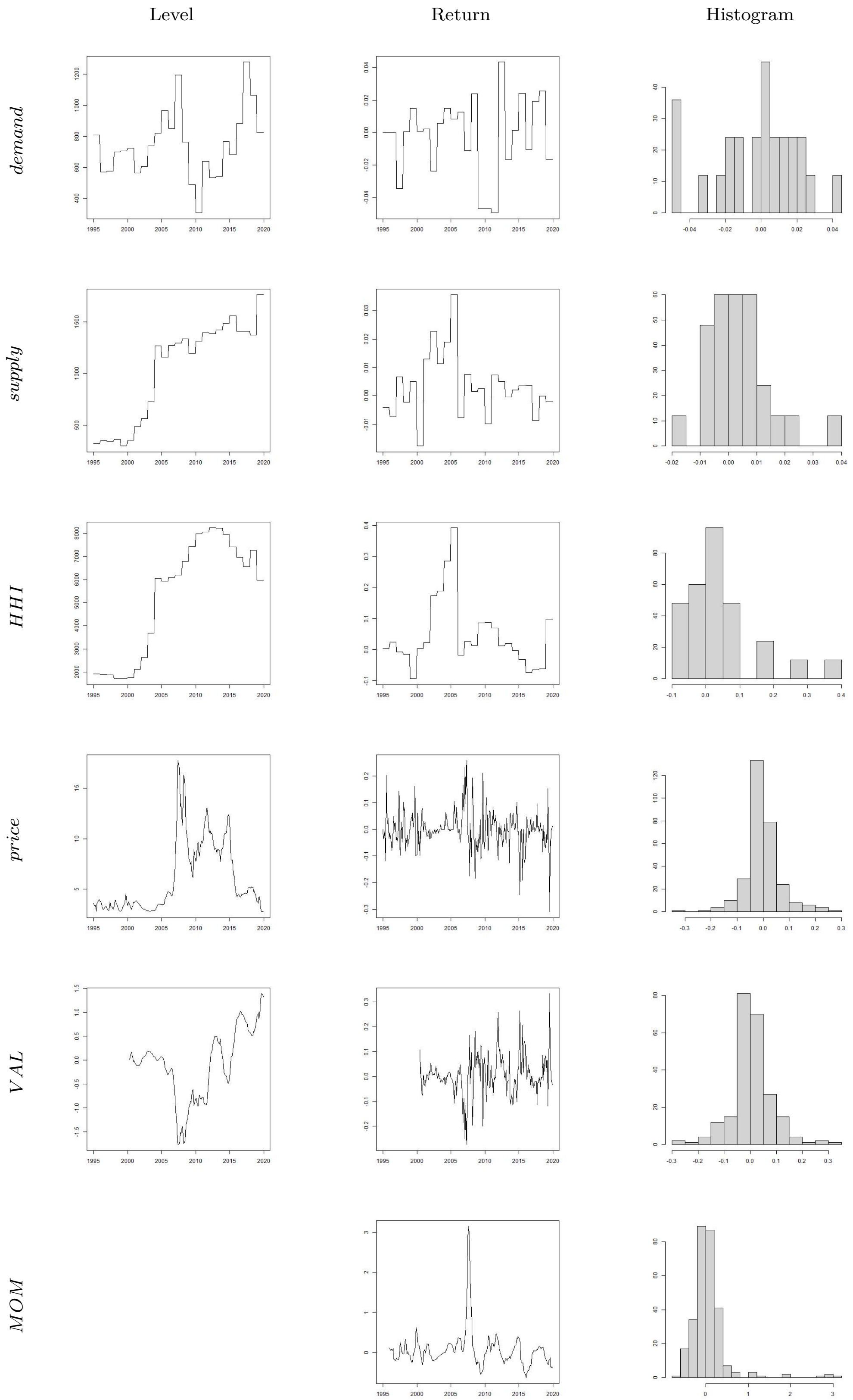


Plots of Metal-Specific Covariates - Zinc



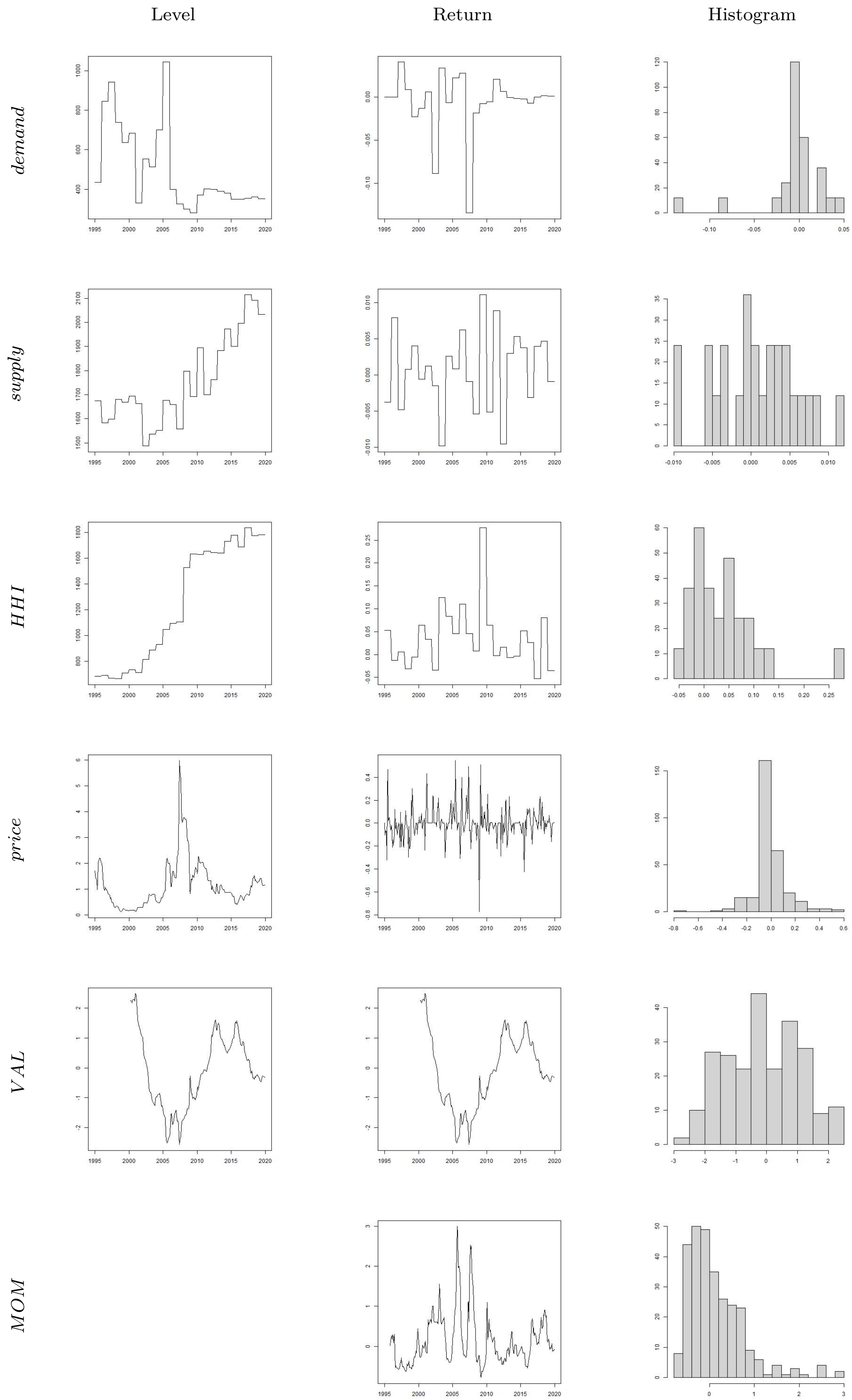
This figure displays the time-series of the metal-specific price determinants for zinc in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.10: Plots of Metal-Specific Covariates - Bismuth



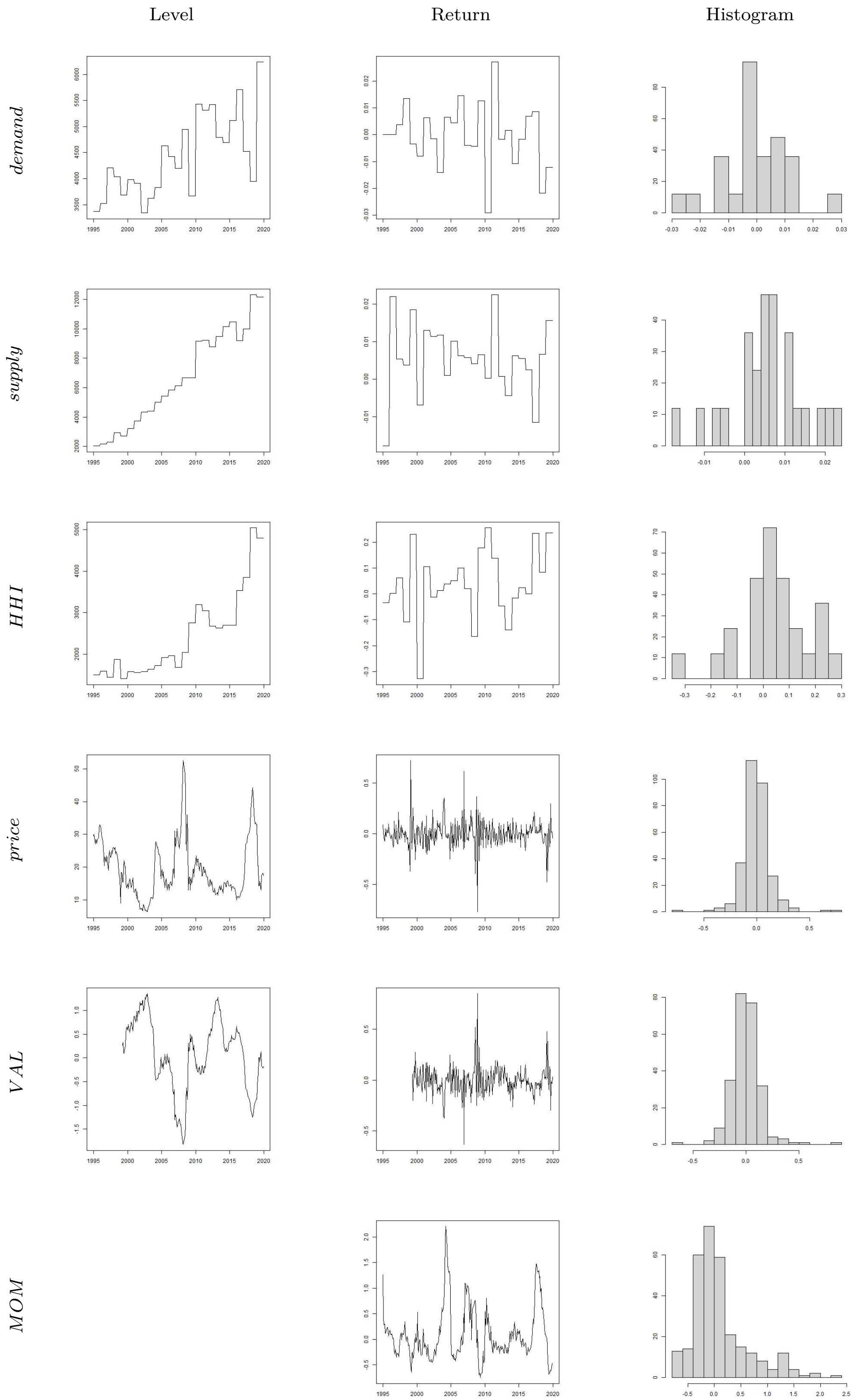
This figure displays the time-series of the metal-specific price determinants for bismuth in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.11: Plots of Metal-Specific Covariates - Cadmium



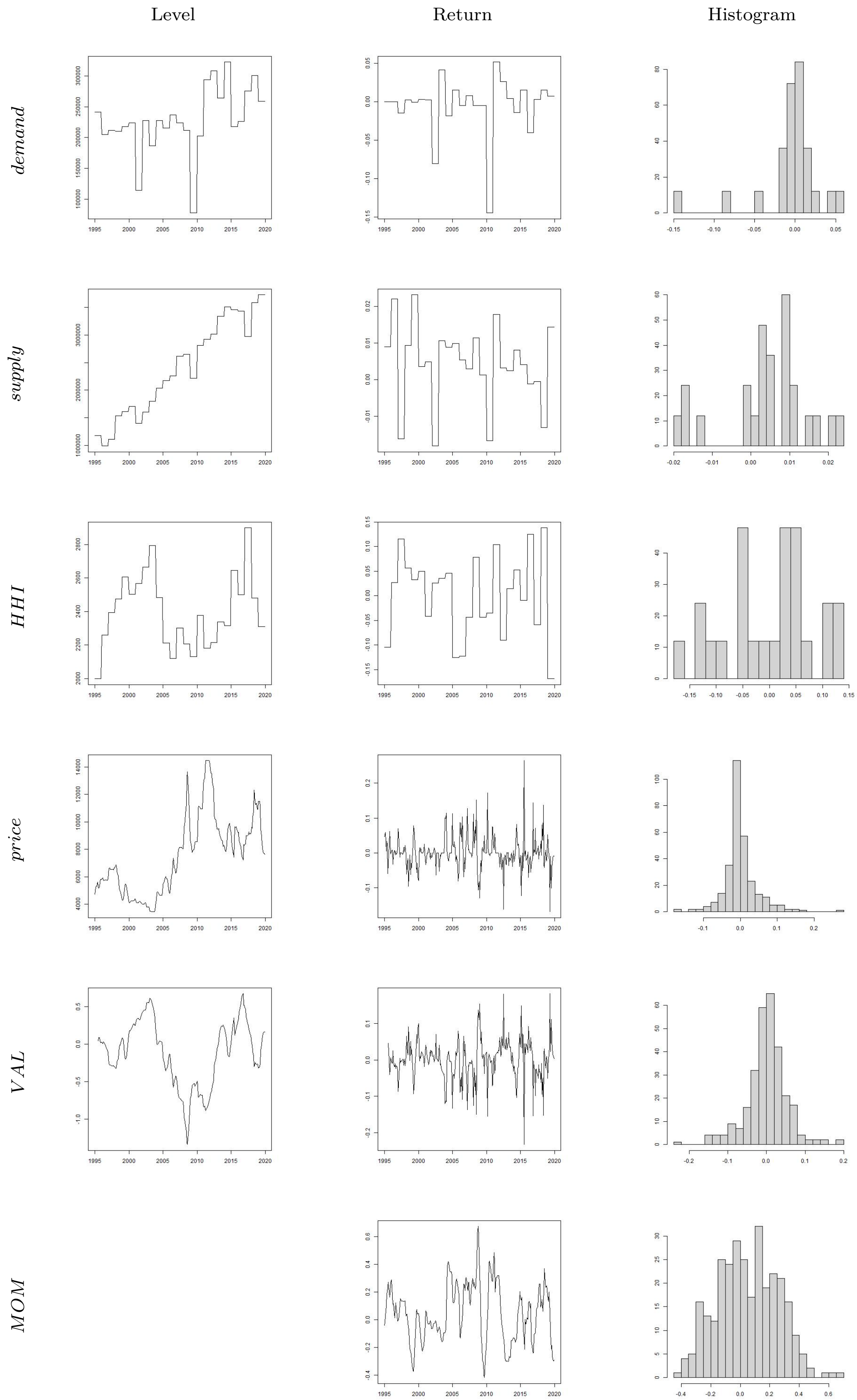
This figure displays the time-series of the metal-specific price determinants for cadmium in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.12: Plots of Metal-Specific Covariates - Cobalt



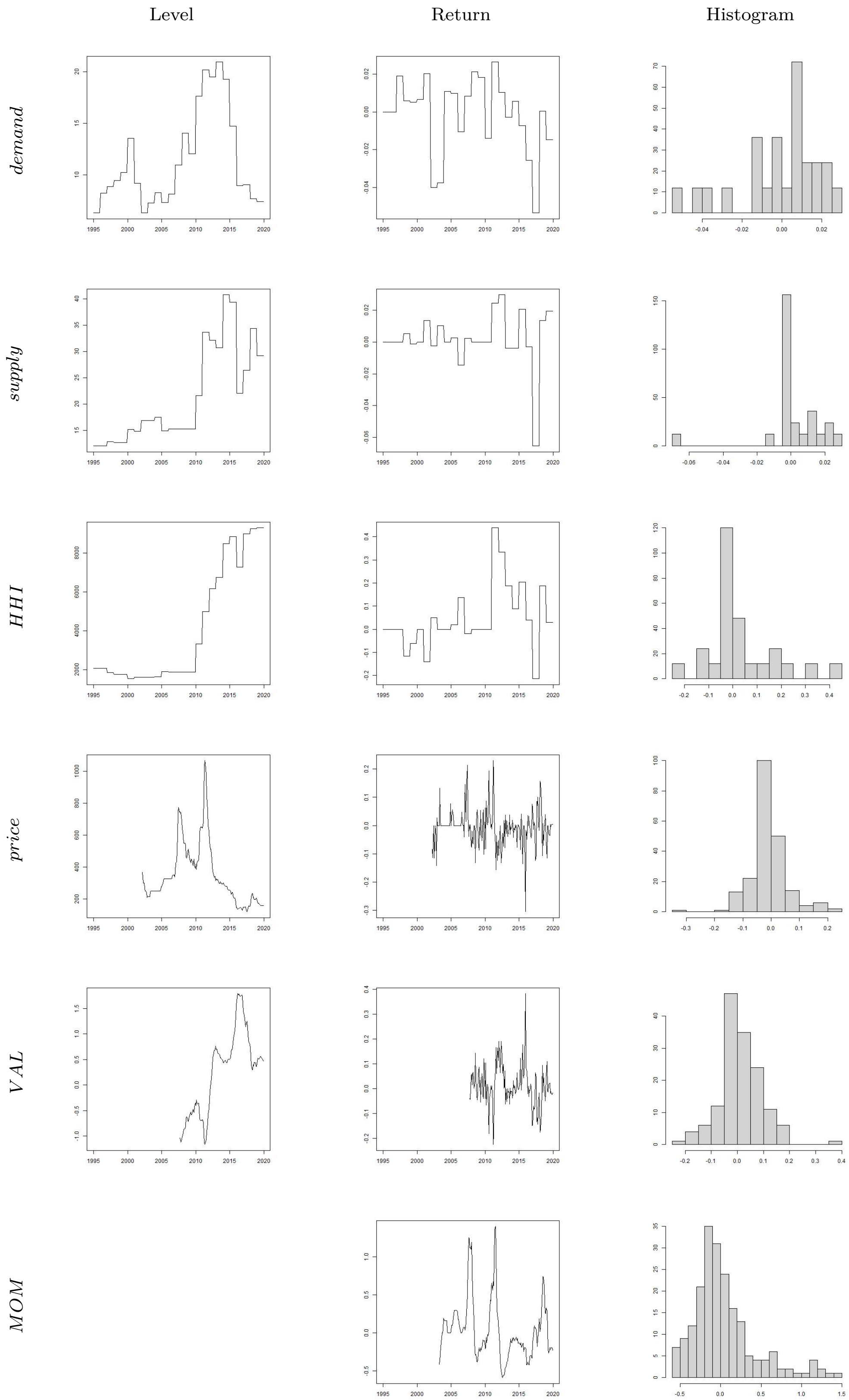
This figure displays the time-series of the metal-specific price determinants for cobalt in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.13: Plots of Metal-Specific Covariates - Chromium



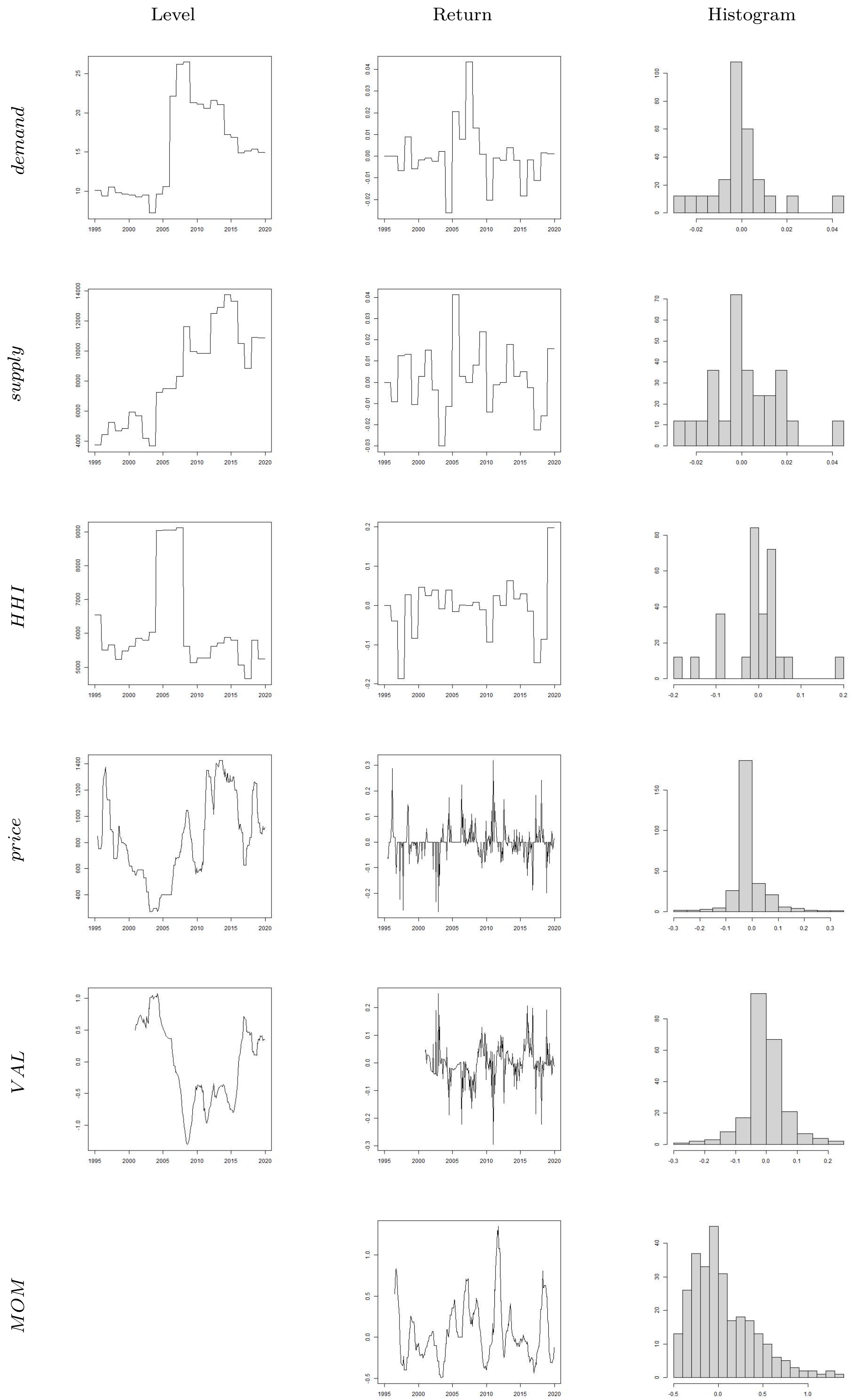
This figure displays the time-series of the metal-specific price determinants for chromium in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.14: Plots of Metal-Specific Covariates - Gallium



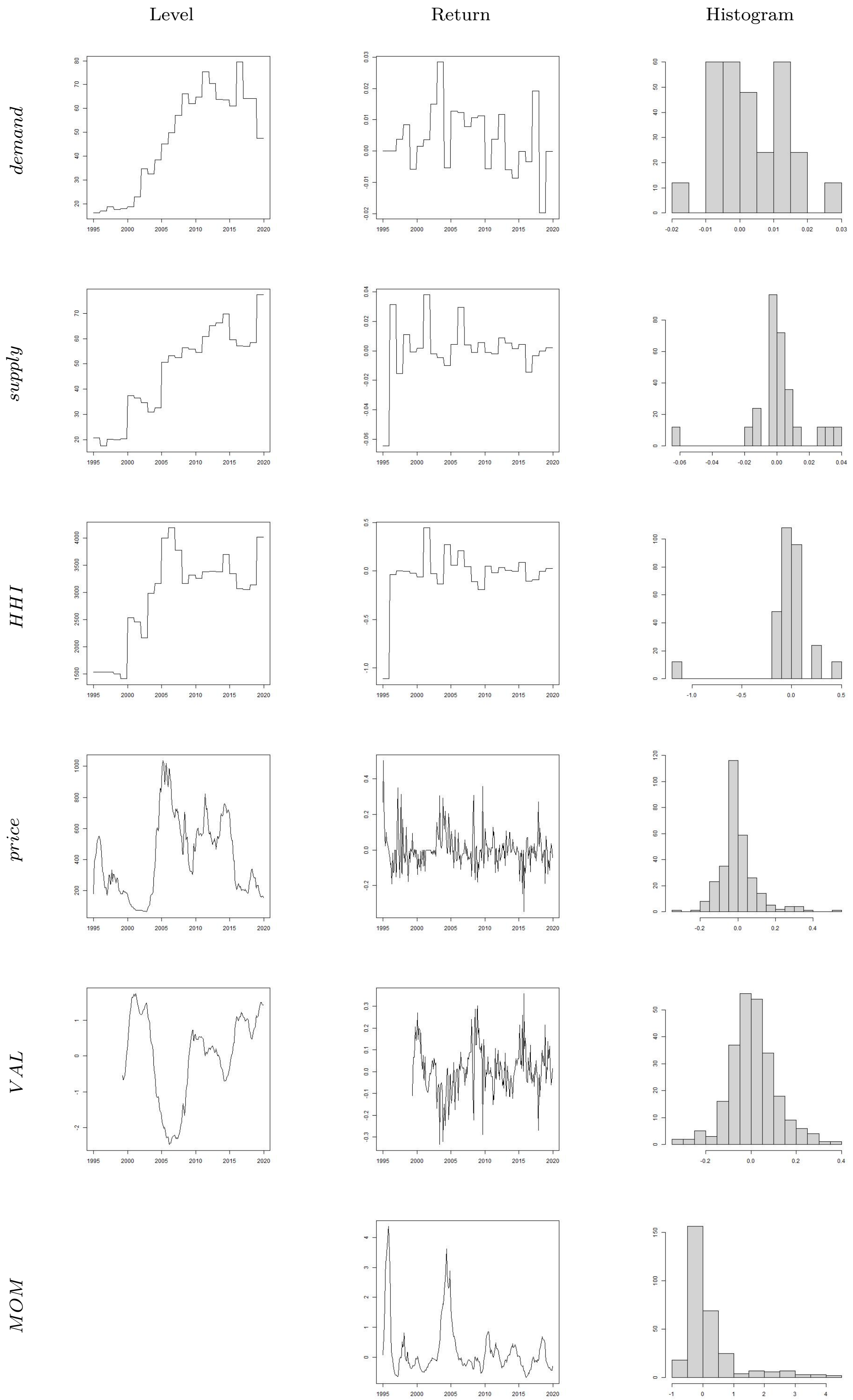
This figure displays the time-series of the metal-specific price determinants for gallium in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.15: Plots of Metal-Specific Covariates - Germanium



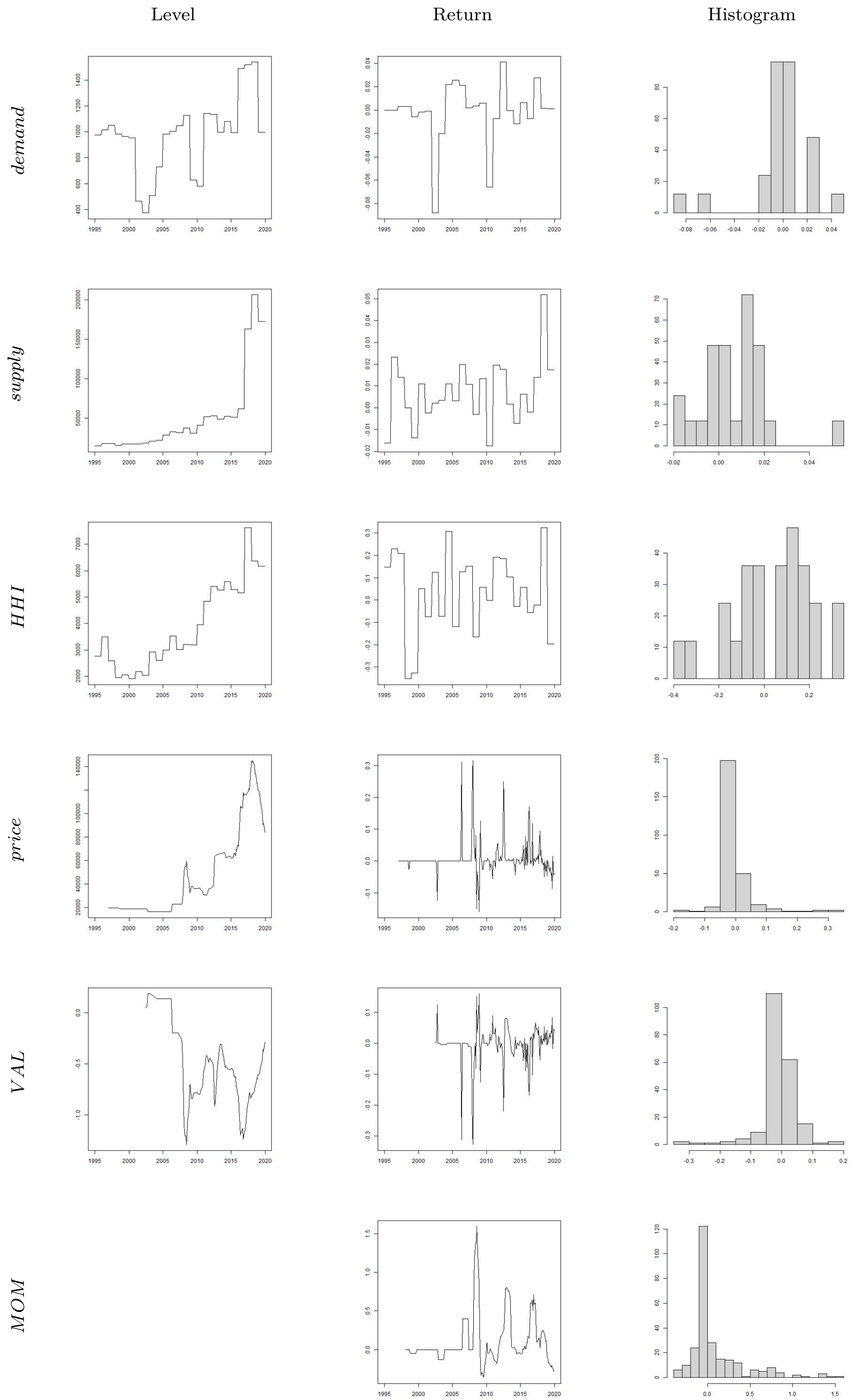
This figure displays the time-series of the metal-specific price determinants for germanium in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.16: Plots of Metal-Specific Covariates - Indium



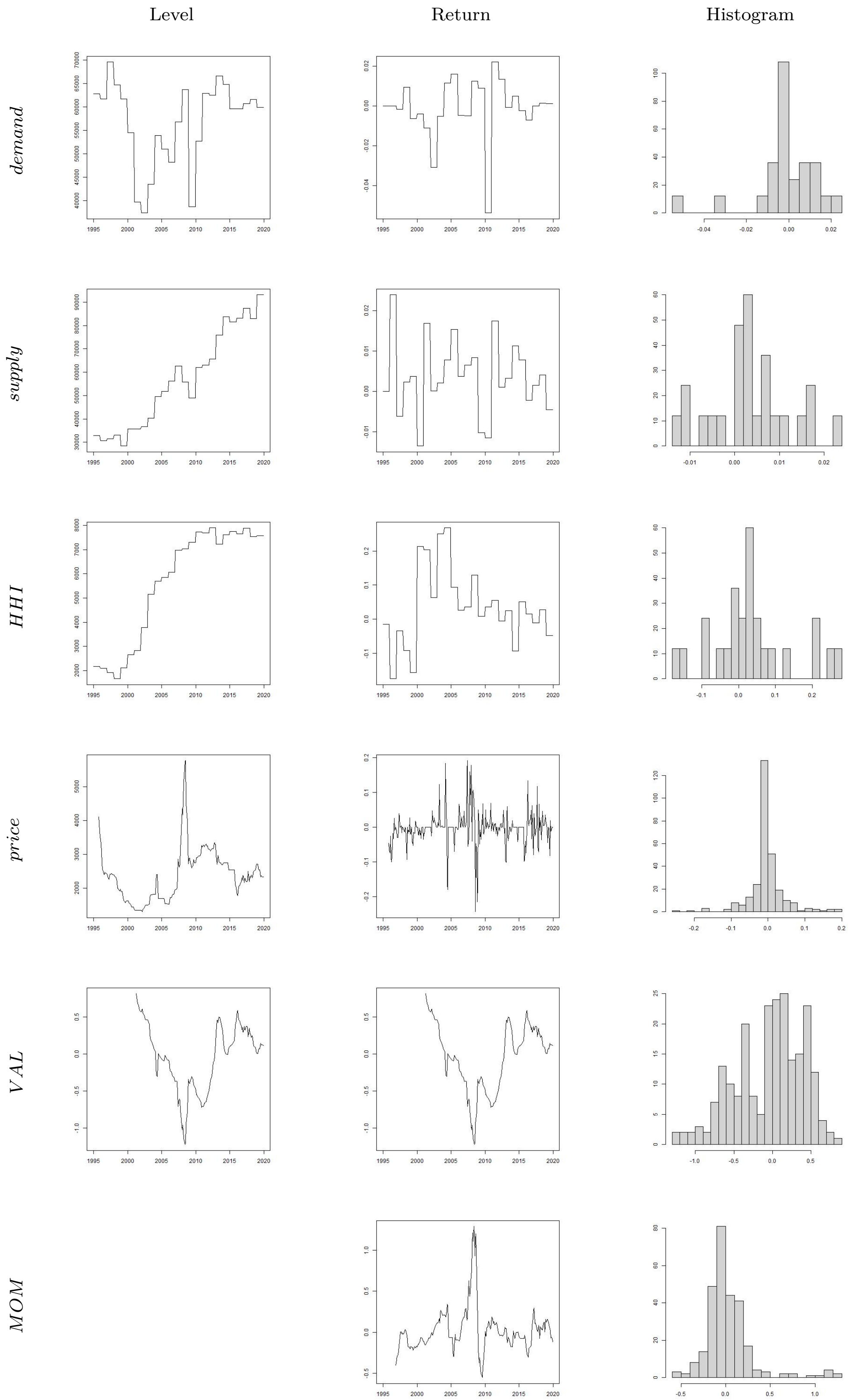
This figure displays the time-series of the metal-specific price determinants for indium in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.17: Plots of Metal-Specific Covariates - Lithium



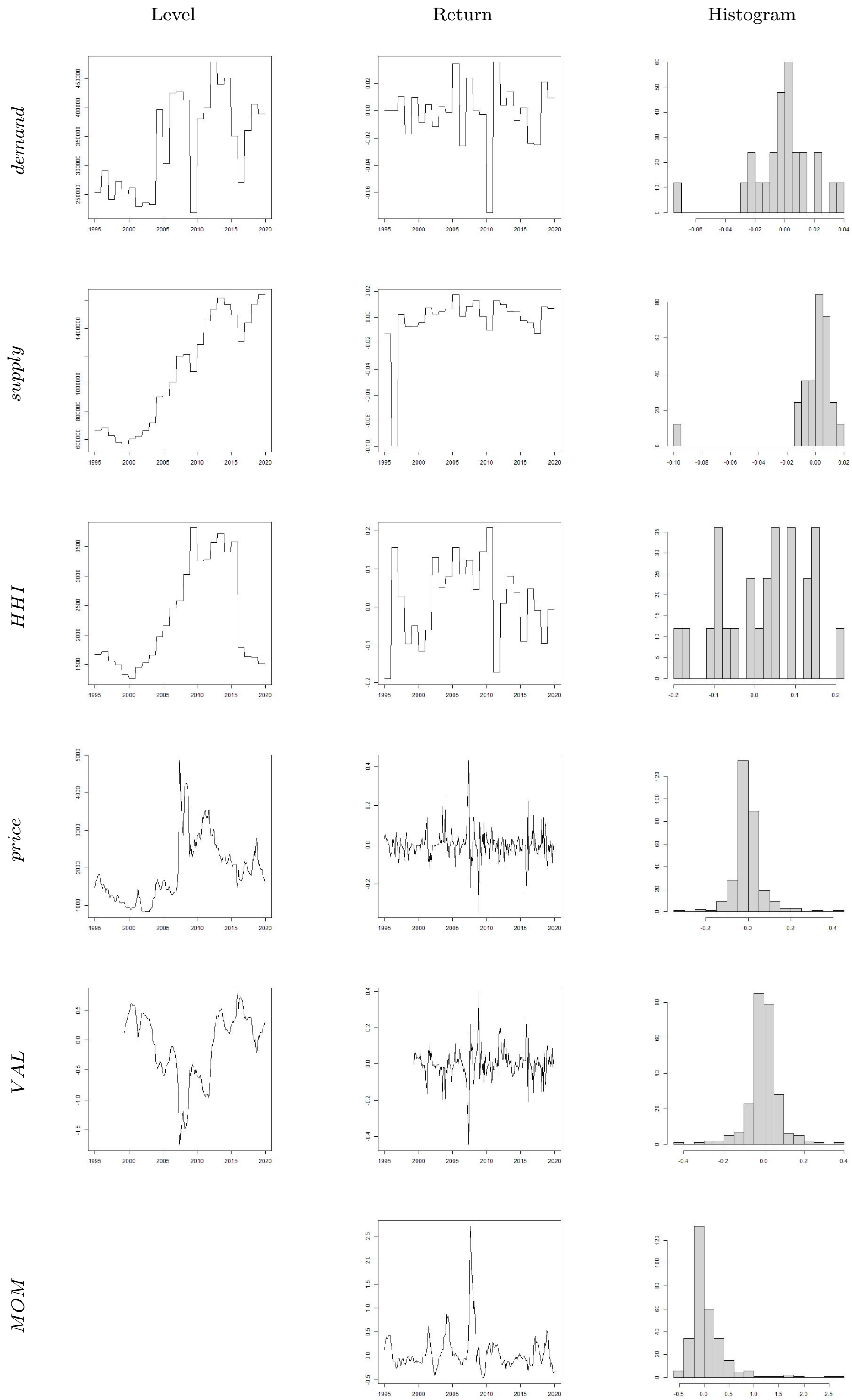
This figure displays the time-series of the metal-specific price determinants for lithium in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.18: Plots of Metal-Specific Covariates - Magnesium



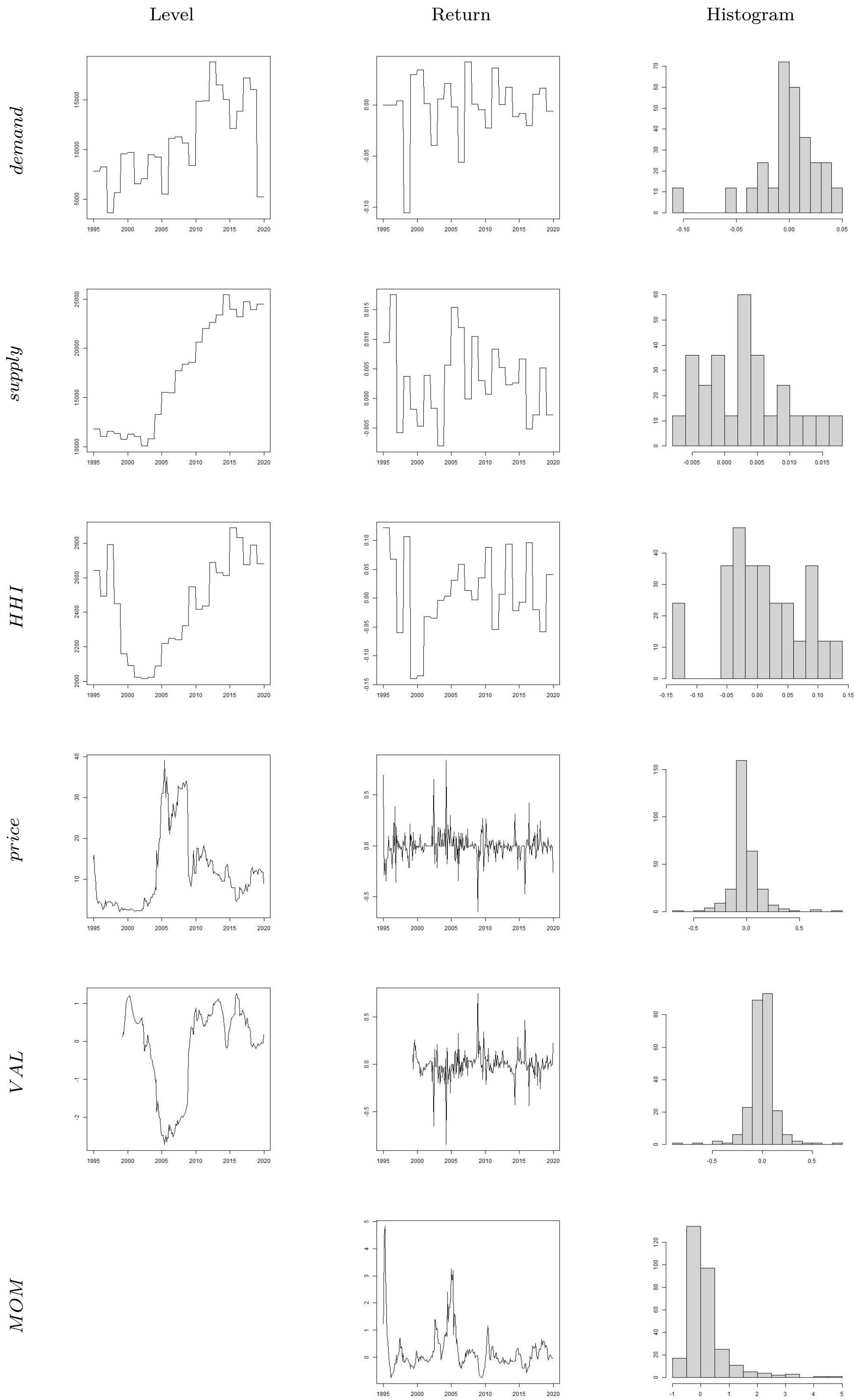
This figure displays the time-series of the metal-specific price determinants for magnesium in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.19: Plots of Metal-Specific Covariates - Manganese



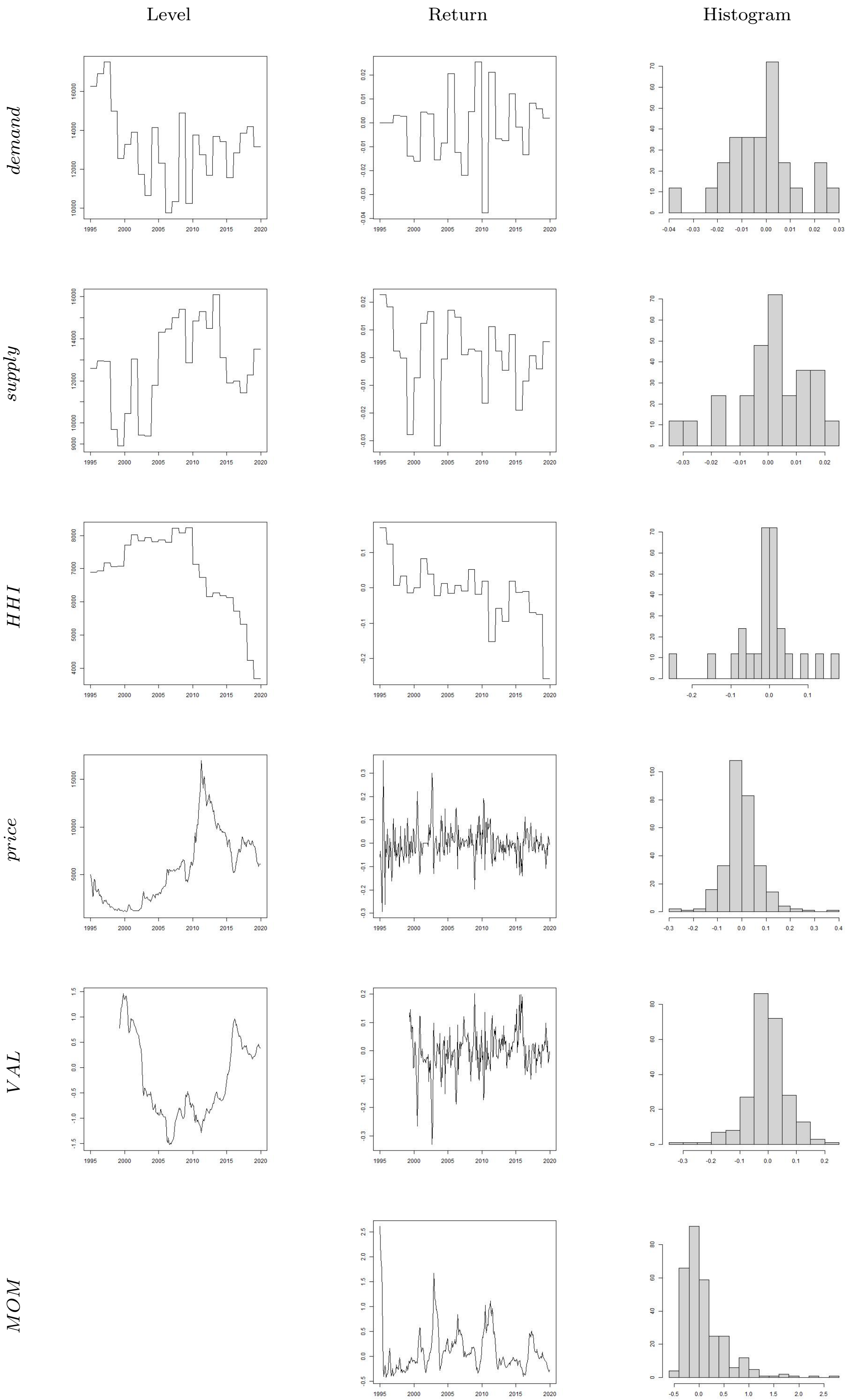
This figure displays the time-series of the metal-specific price determinants for manganese in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.20: Plots of Metal-Specific Covariates - Molybdenum



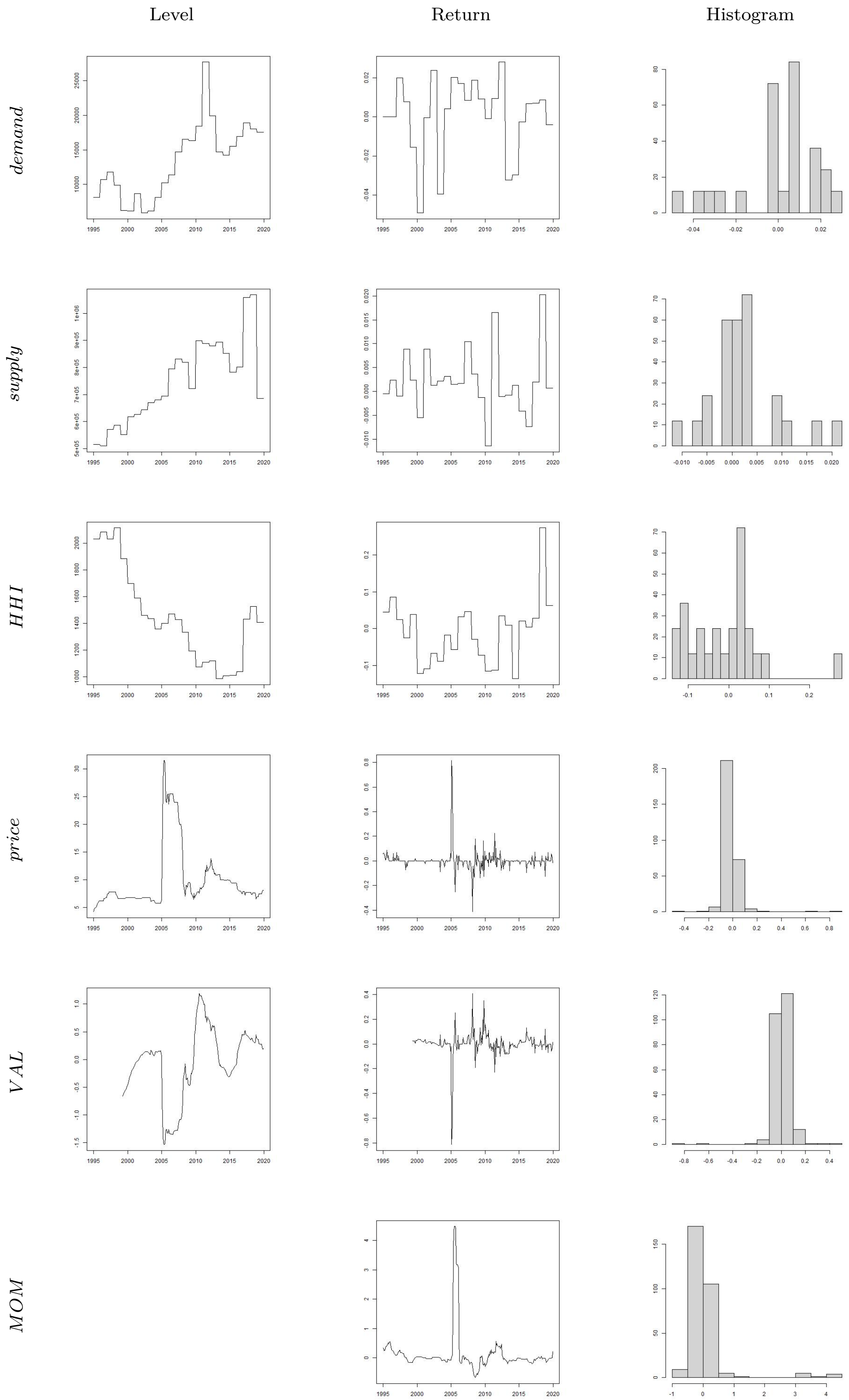
This figure displays the time-series of the metal-specific price determinants for molybdenum in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.21: Plots of Metal-Specific Covariates - Antimomy



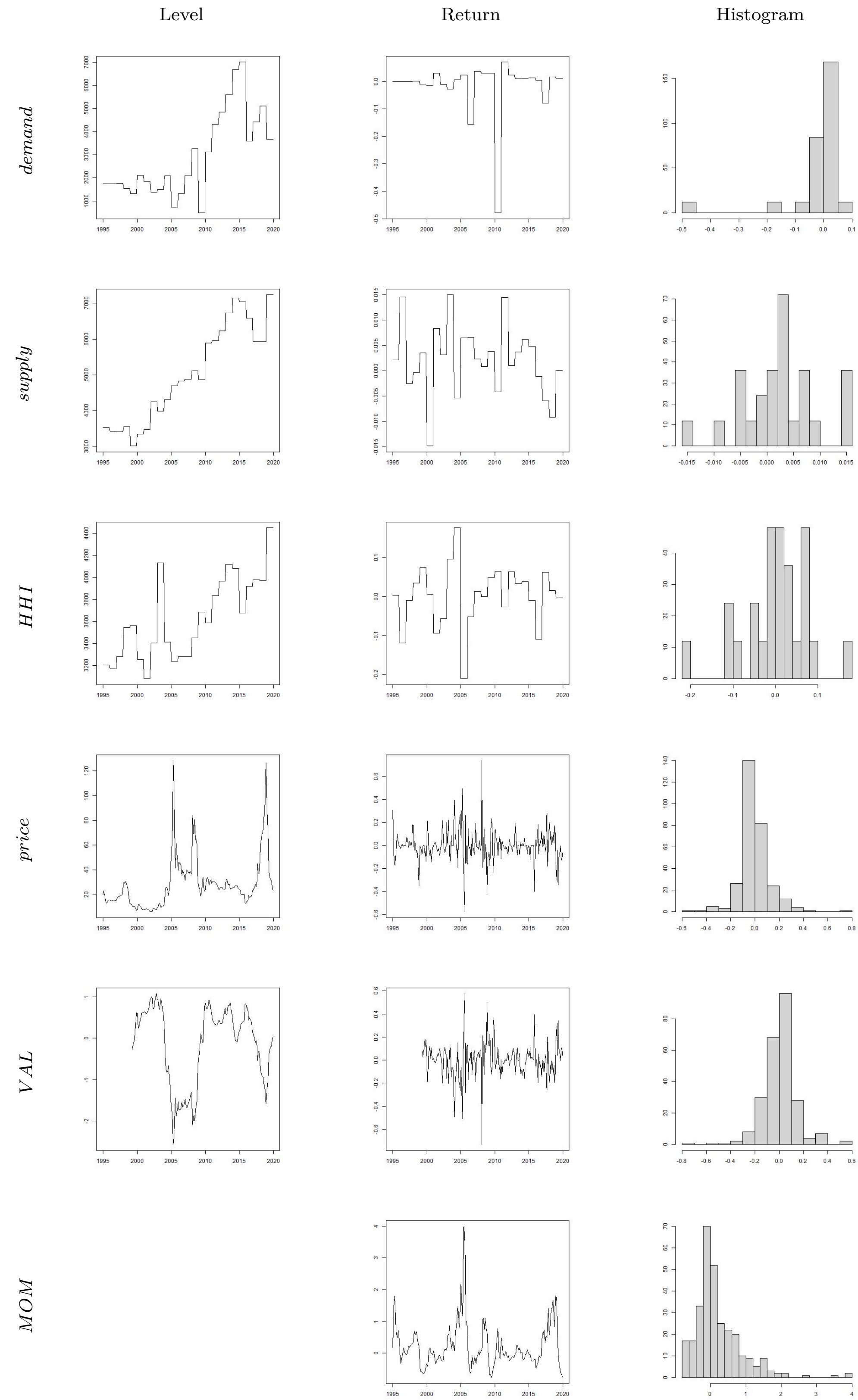
This figure displays the time-series of the metal-specific price determinants for antimony in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.22: Plots of Metal-Specific Covariates - Titanium



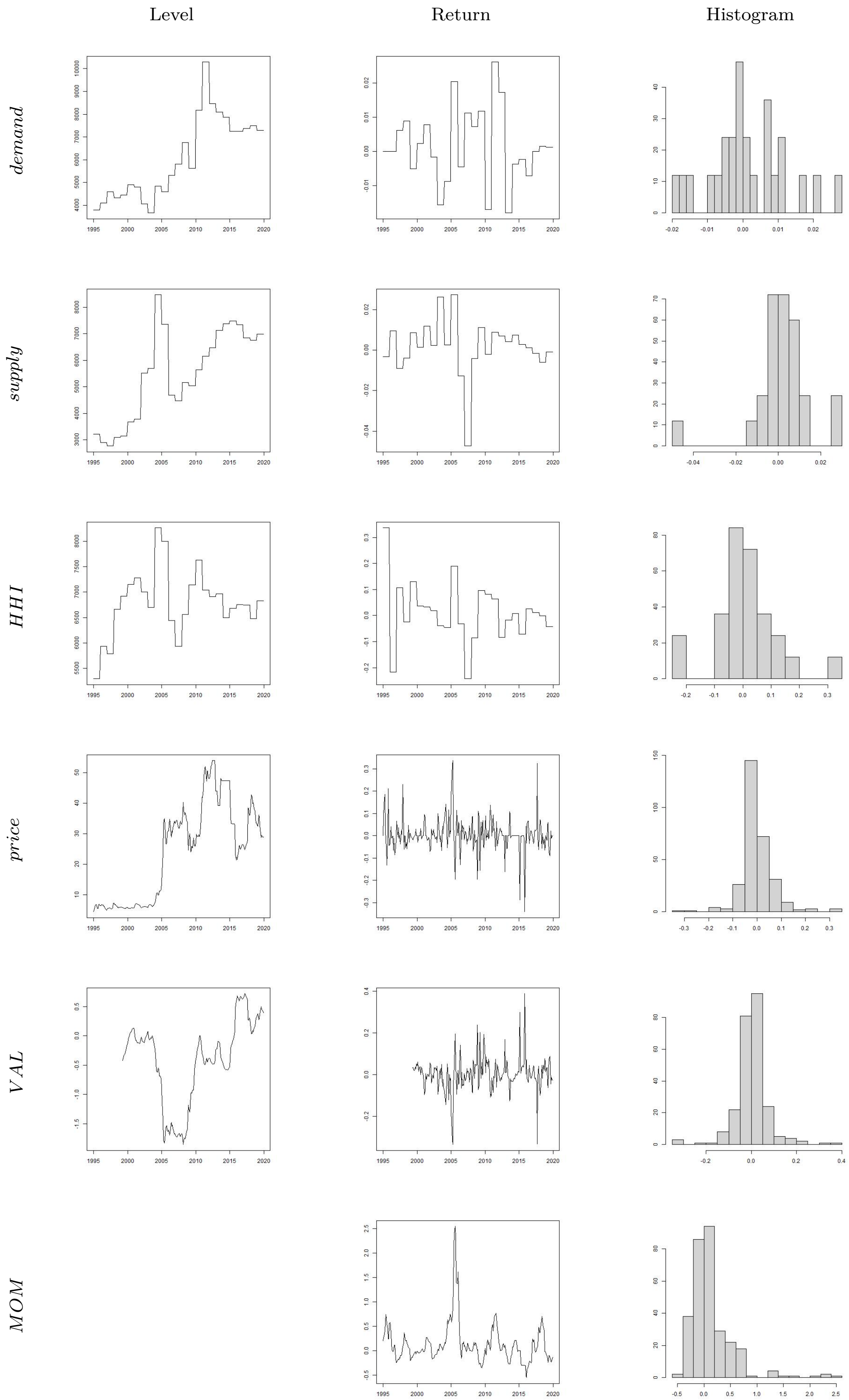
This figure displays the time-series of the metal-specific price determinants for titanium in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

Figure C.23: Plots of Metal-Specific Covariates - Vanadium



This figure displays the time-series of the metal-specific price determinants for vanadium in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

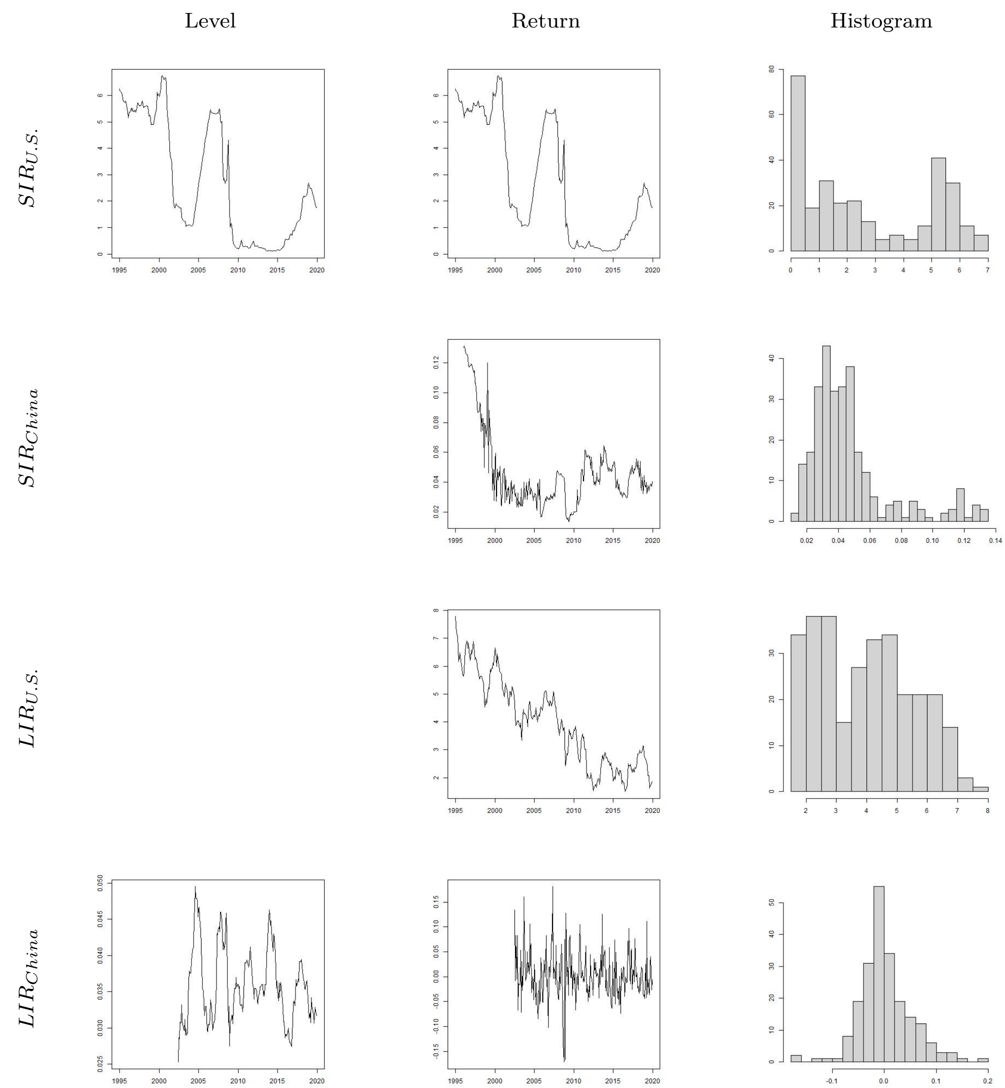
Figure C.24: Plots of Metal-Specific Covariates - Tungsten



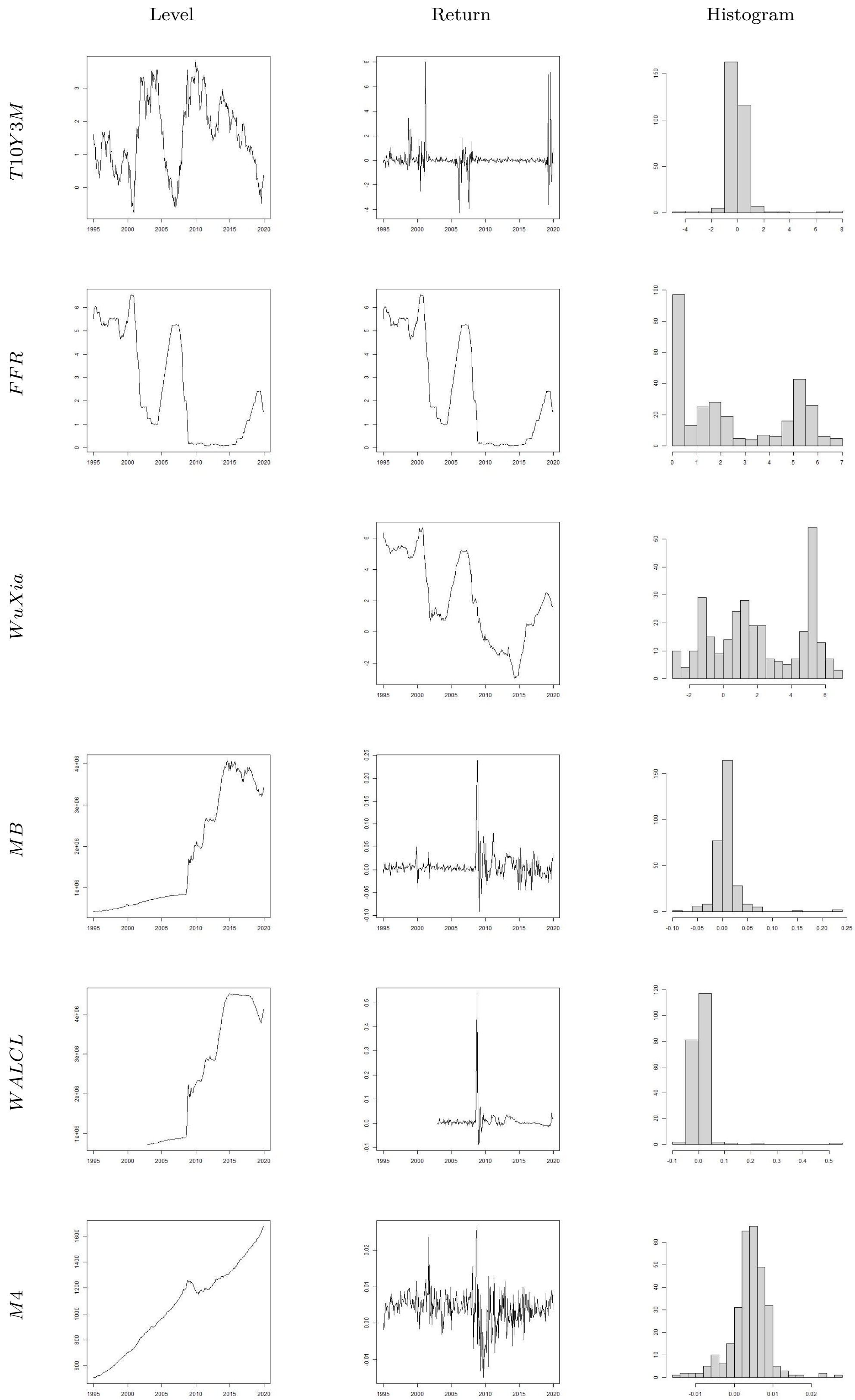
This figure displays the time-series of the metal-specific price determinants for tungsten in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

D Plots of General Metal Price Determinants

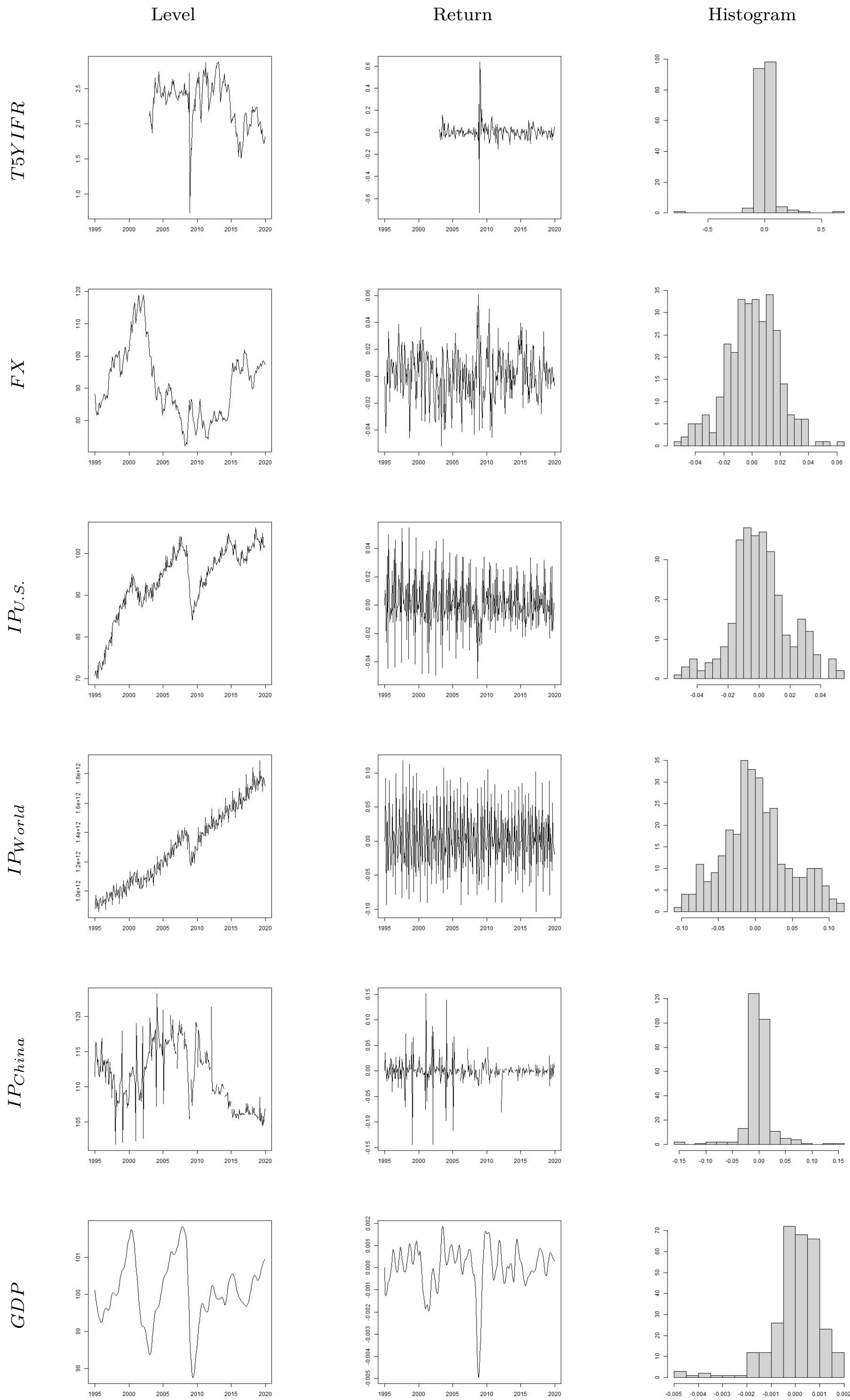
Figure D.1: Plots of General Metal Price Determinants



Plots of General Metal Price Determinants



Plots of General Metal Price Determinants



Plots of General Metal Price Determinants

Level | Return | Histogram

EAKilian

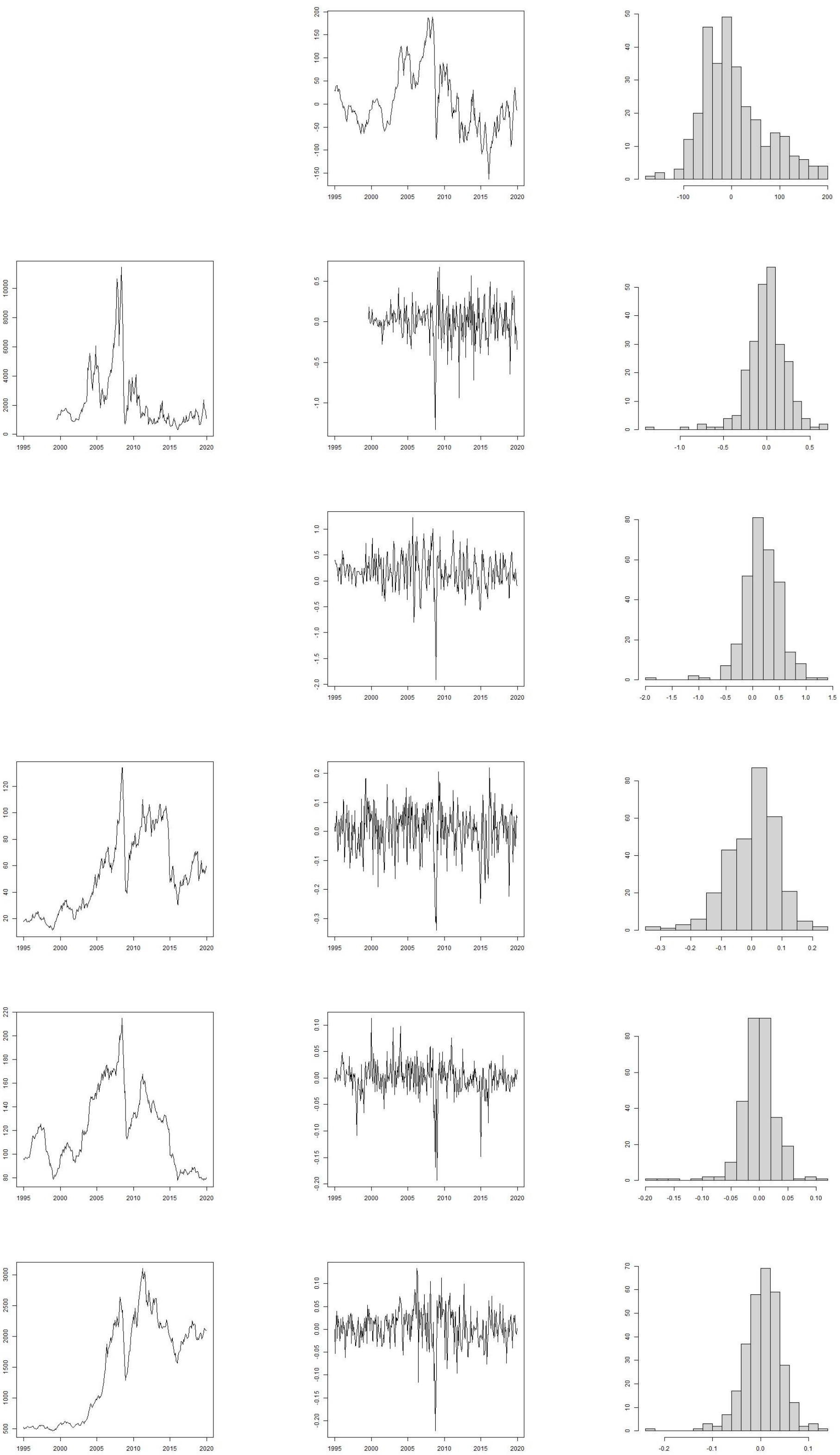
BDI

CPI

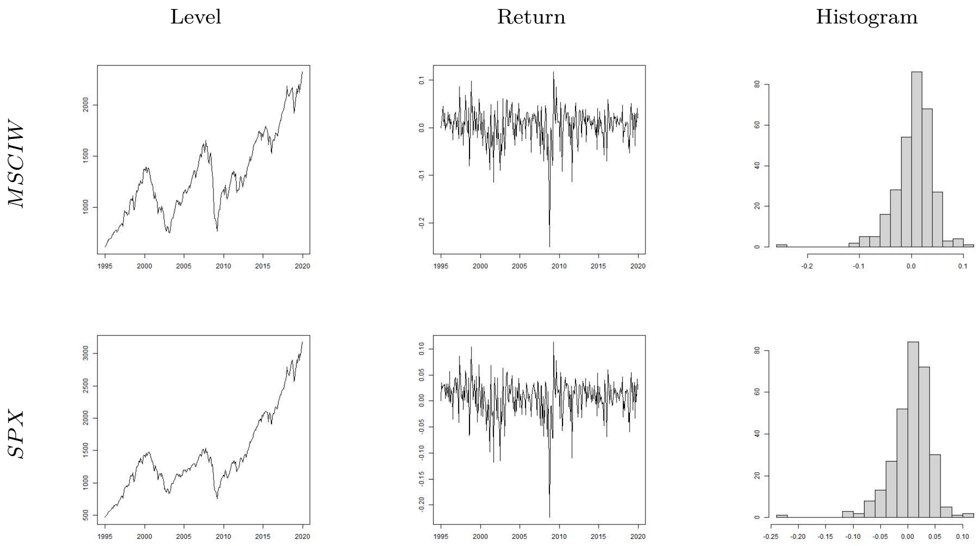
OIL

BCOM

RICIM



Plots of General Metal Price Determinants

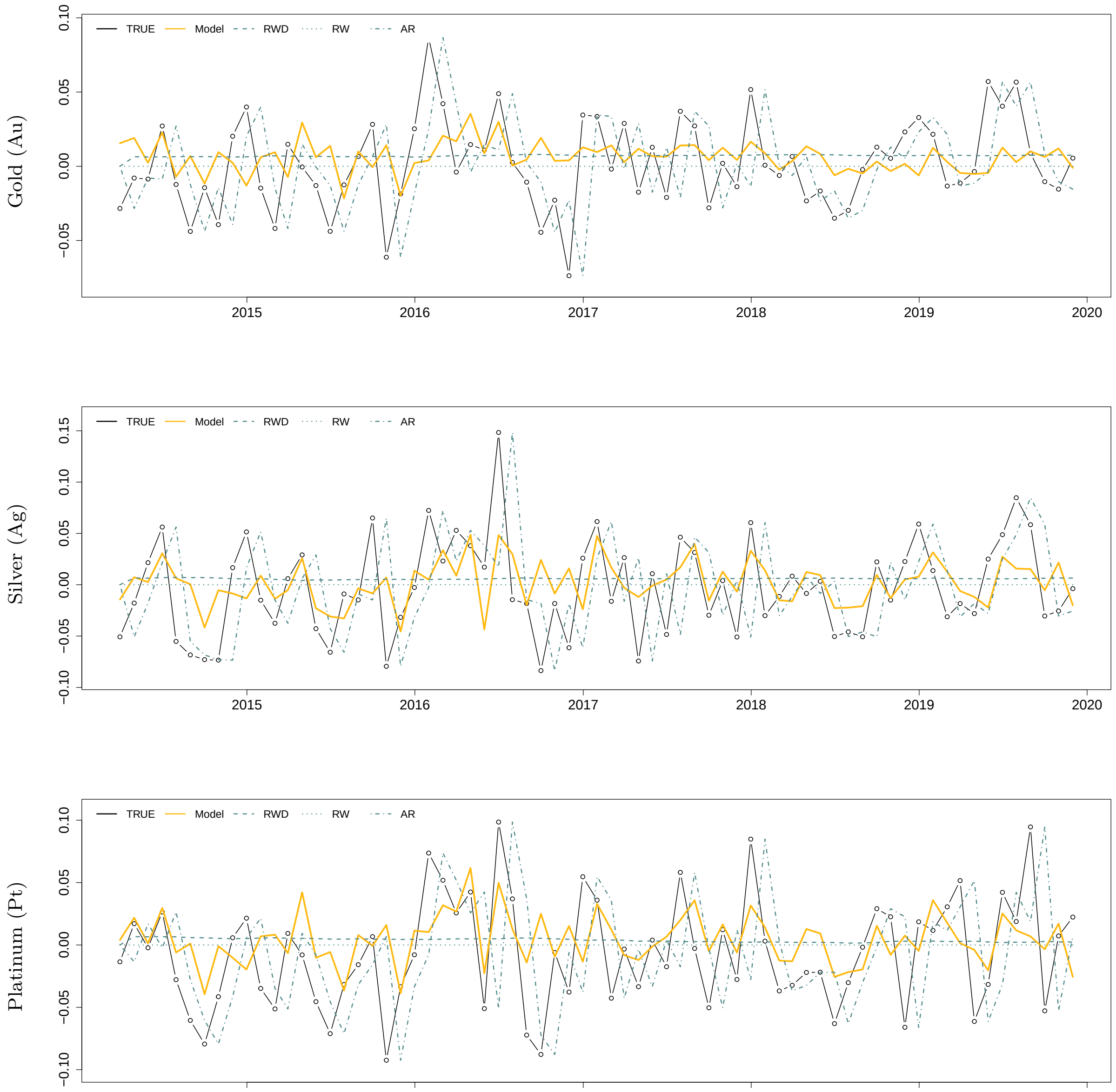


This figure displays the time-series of the general metal price determinants in level, as well as the adjusted return series and the corresponding histogram. In case the co-variate is stationary in level, the level plot is not displayed.

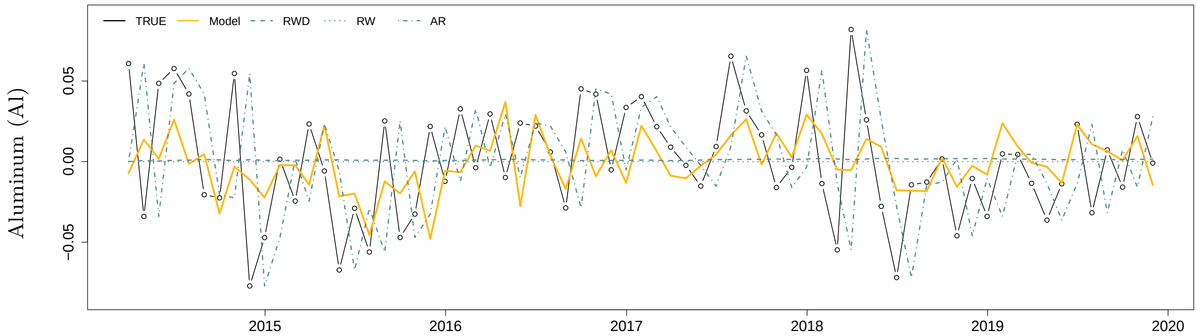
E Additional Empirical Results

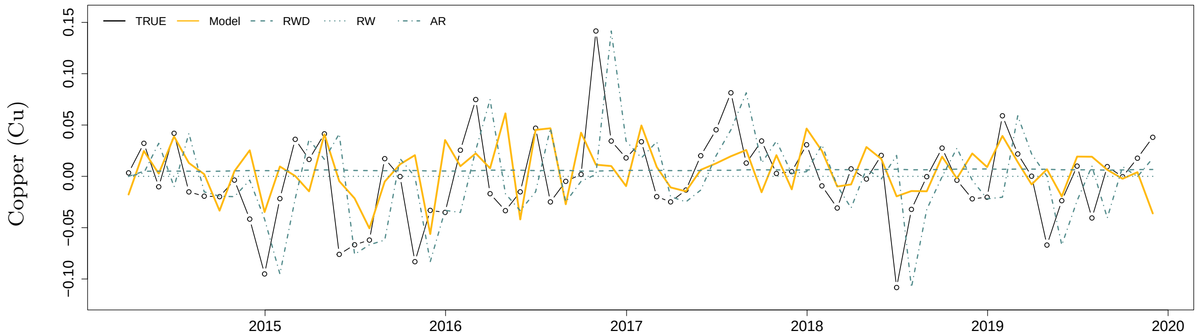
E.1 Plots of Metal-Specific Price Predictions

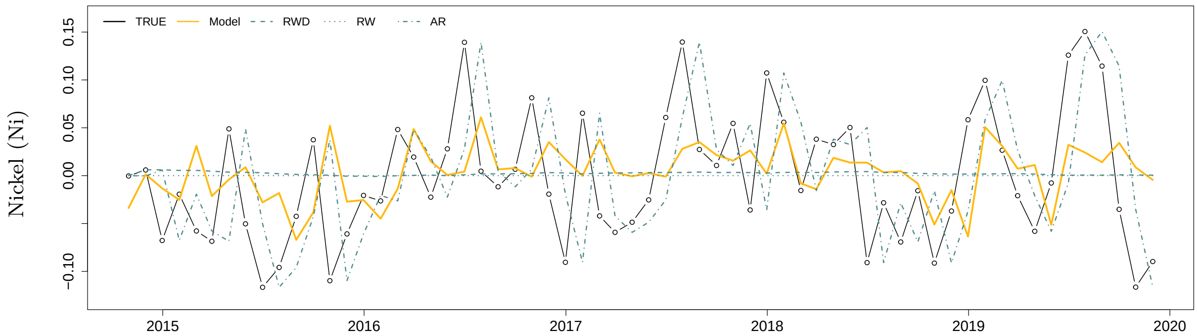
Figure E.1: Plots of Metal-Specific Price Predictions

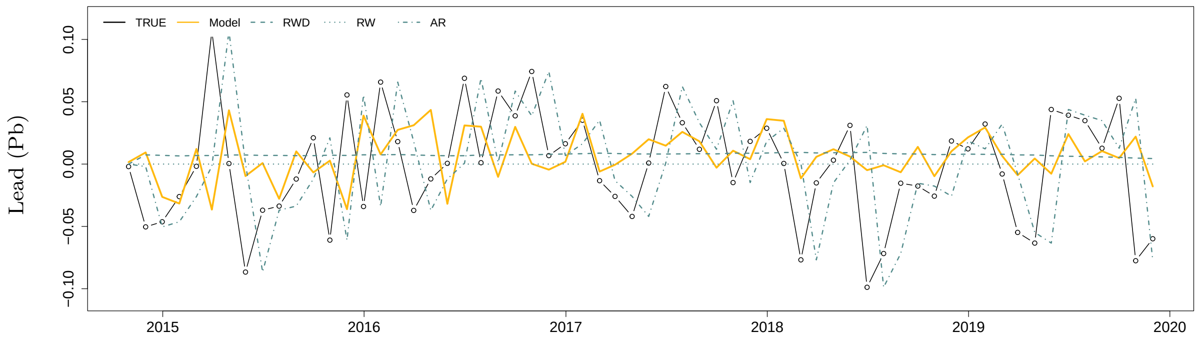


Plots of Metal-Specific Price Predictions

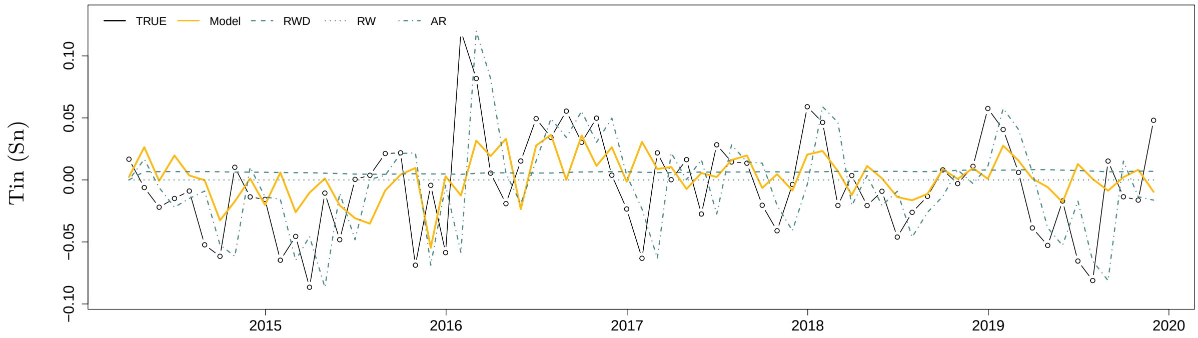


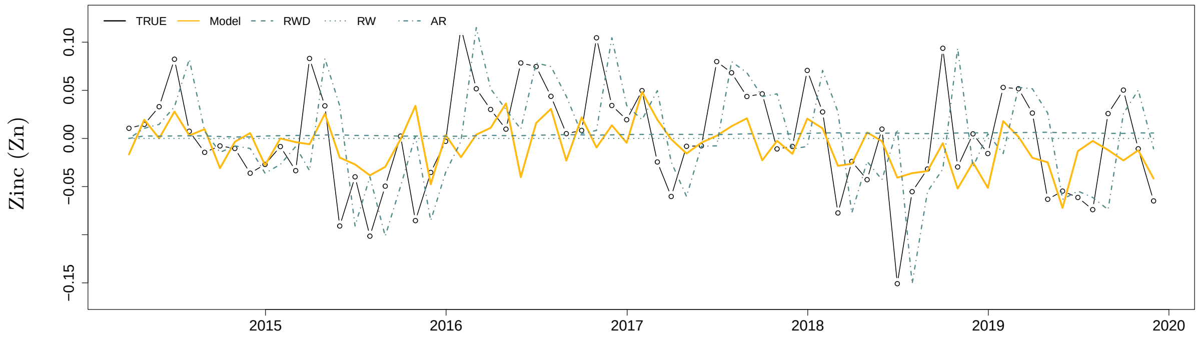


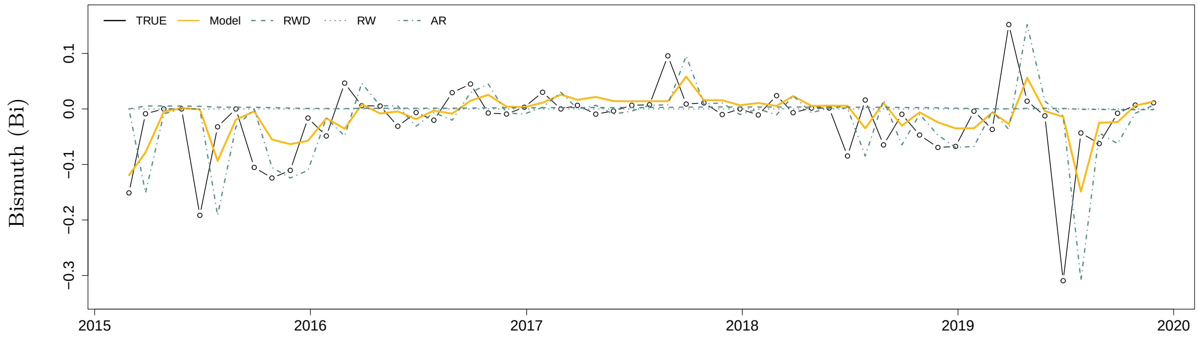


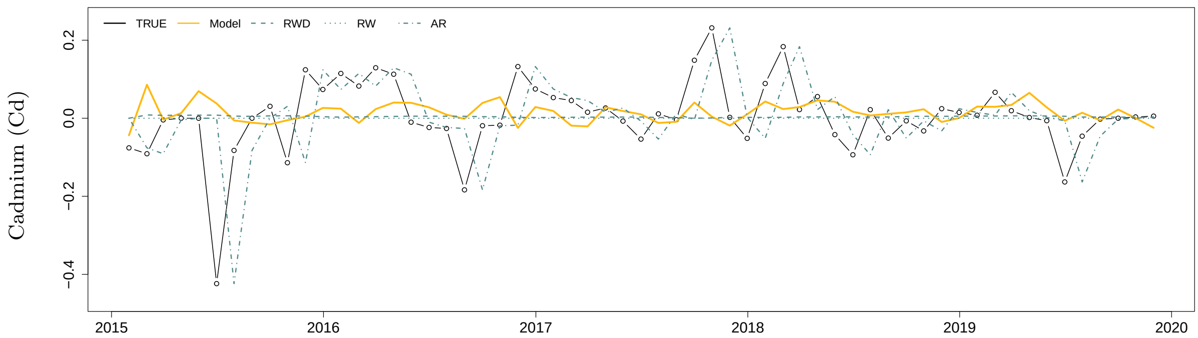


Plots of Metal-Specific Price Predictions

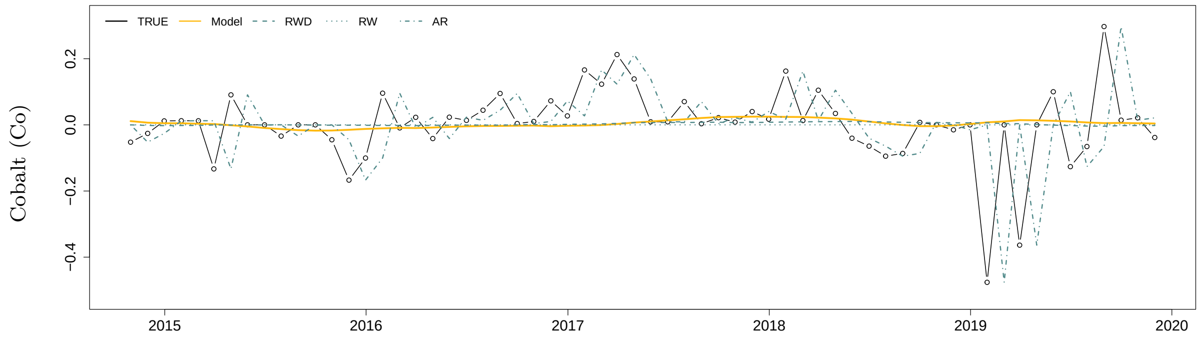


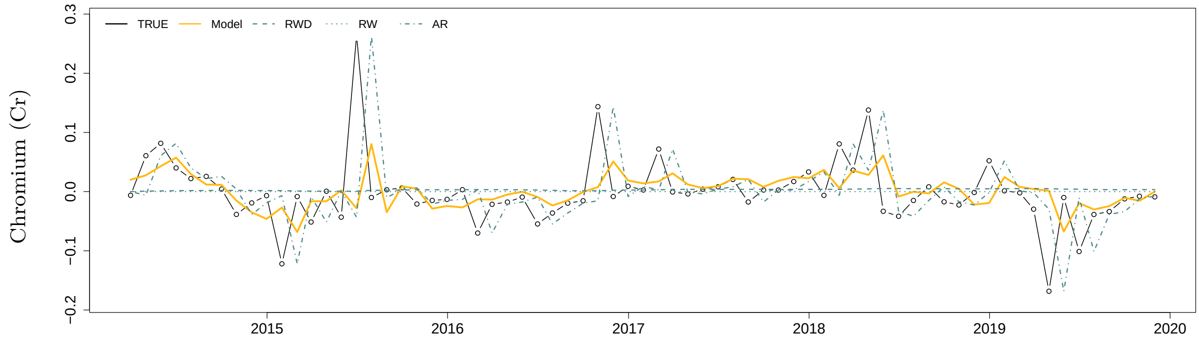


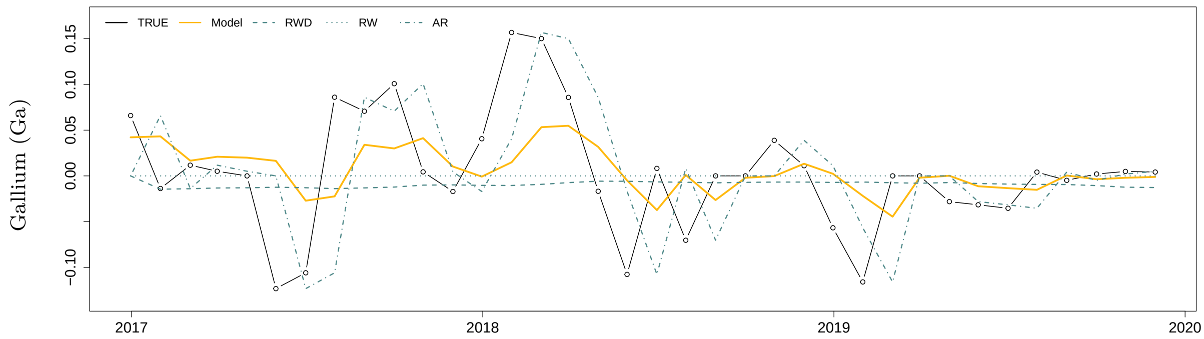


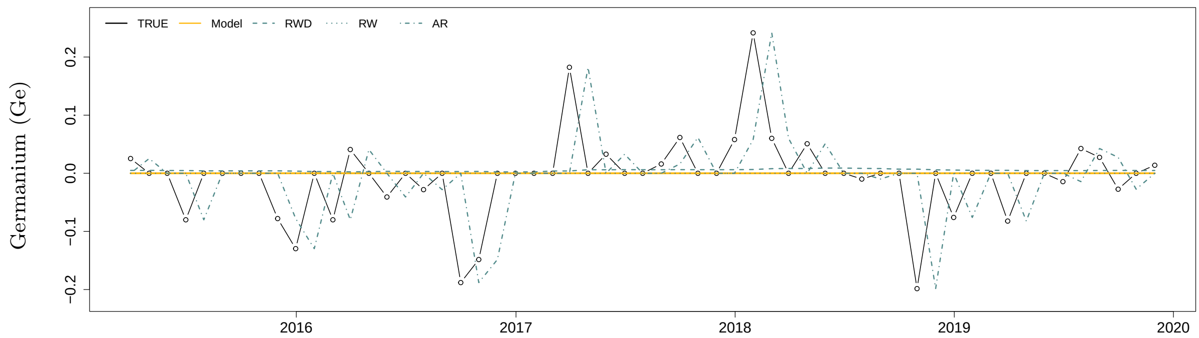


Plots of Metal-Specific Price Predictions

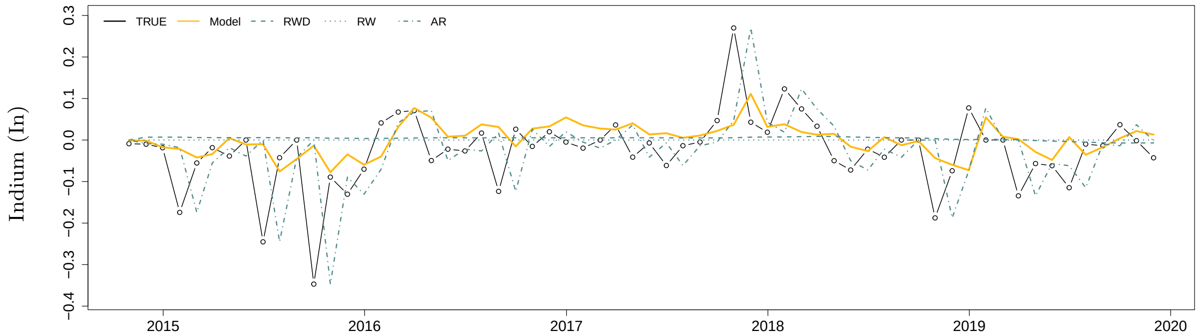


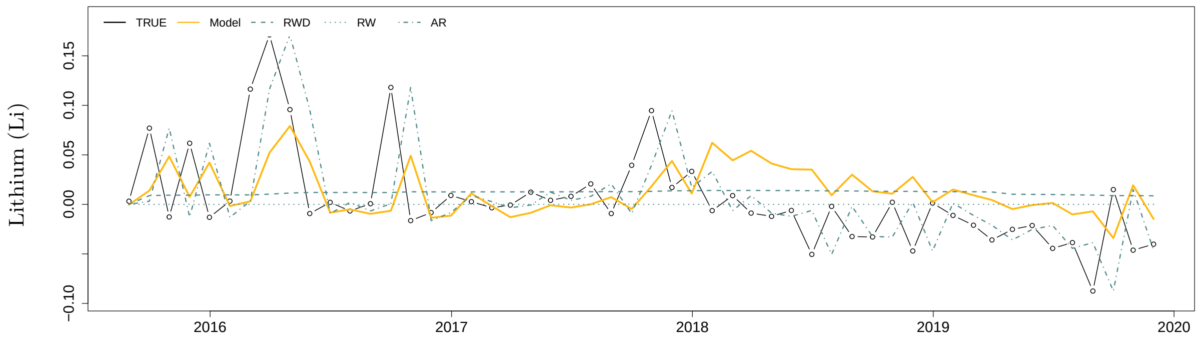


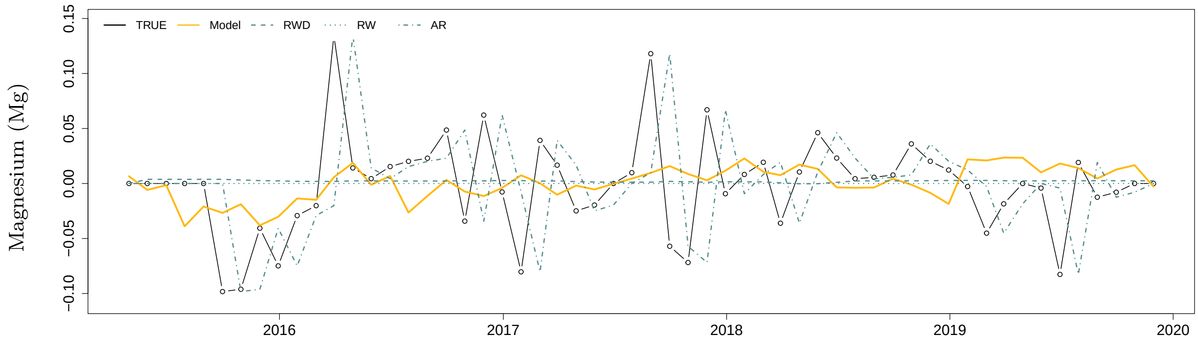


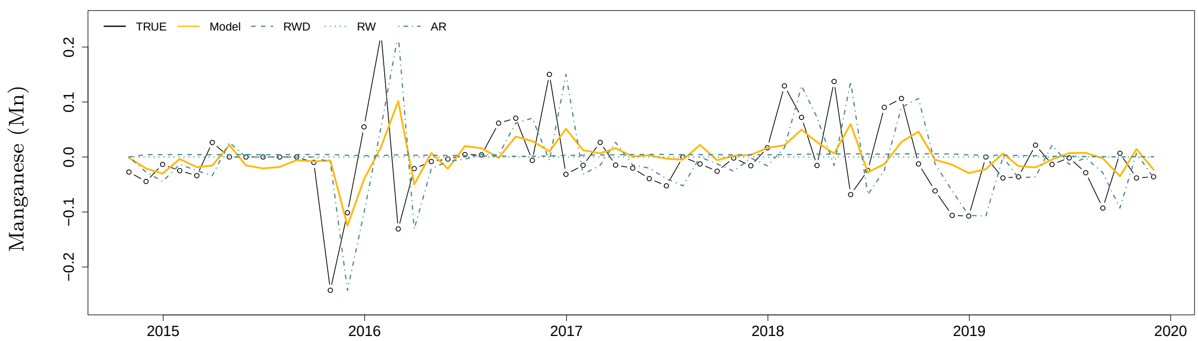


Plots of Metal-Specific Price Predictions

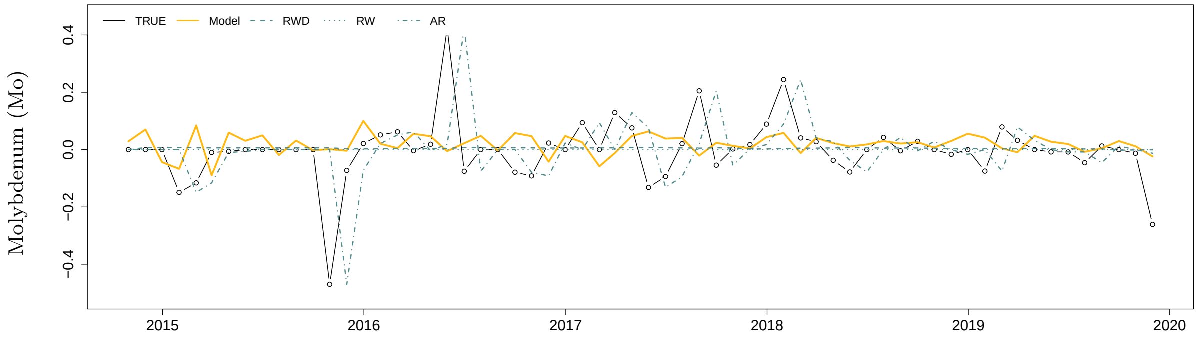


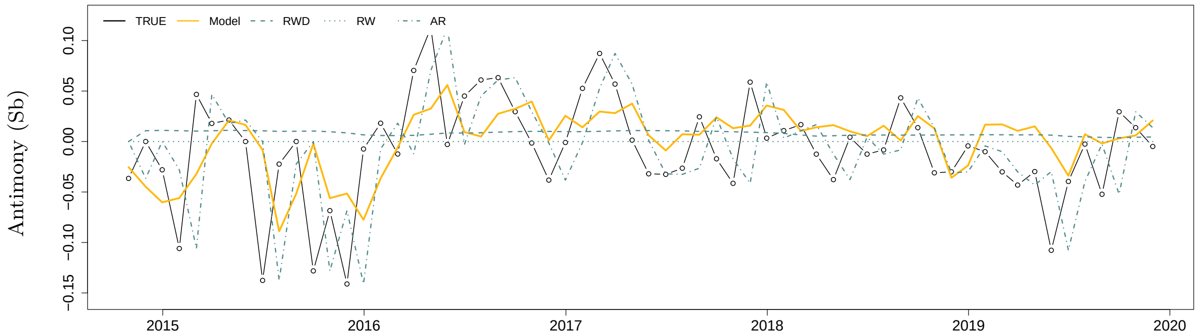


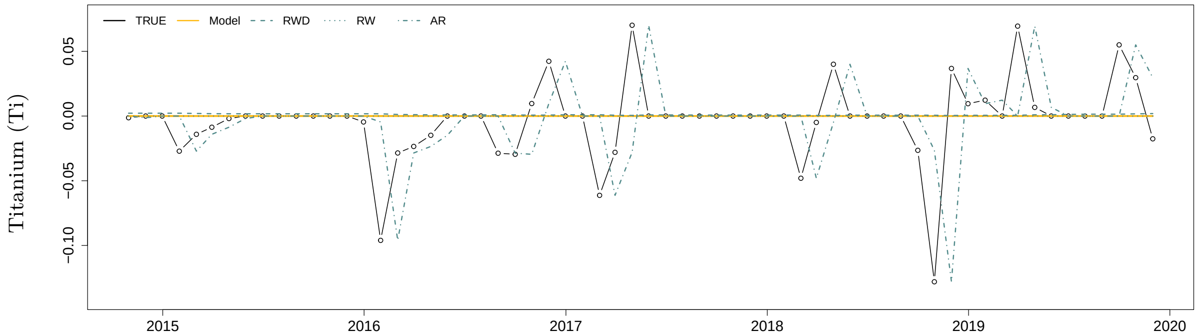


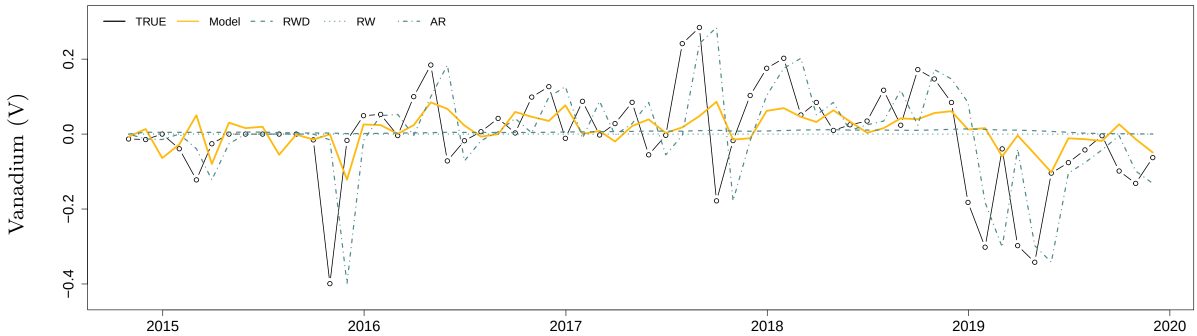


Plots of Metal-Specific Price Predictions

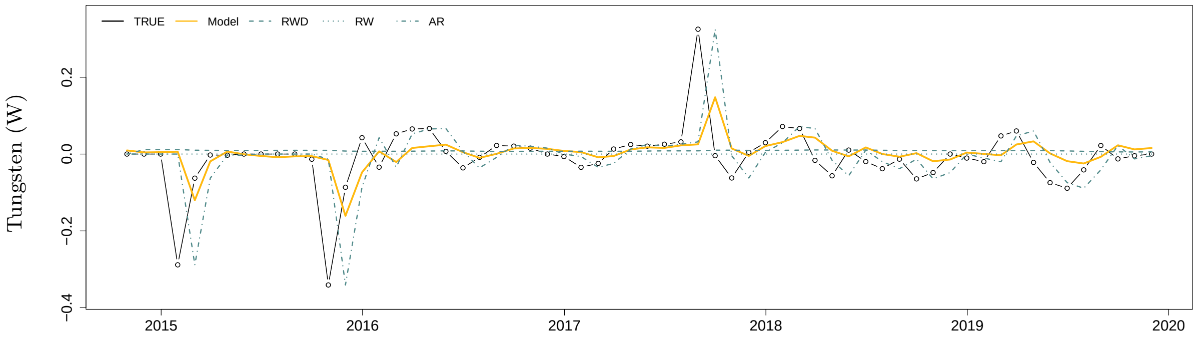








Plots of Metal-Specific Price Predictions



This figure displays the metal-specific out-of-sample predictions (Model) in comparison to the actual return series (TRUE), as well as the corresponding random-walk (RW), random-walk with drift (RWD) and AR(1) (AR) benchmarks.

E.2 Additional Linear Regression Specifications

Table E.1: Linear Regression Results for the Metal Price Predictors - Total-Sample

	$supply$	hhi	$demand$	VAL	$Price_{t-1}$	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
Ag								-0.01 (0.02)																							0.31 (0.01)		0.08
Au								-0.01 (0.00)																					0.17 (0.11)				0.12
Pt						-0.04 (0.04)	0.26 (0.02)																						0.41 (0.01)				0.19
Al		-0.11 (0.01)																						13.27 (0.00)					0.28 (0.00)				0.20
Cu							0.30 (0.00)				-0.80 (0.01)					-0.36 (0.03)		-2.44 (0.01)															0.25
Ni				-0.29 (0.00)														-3.04 (0.02)															0.14
Pb									0.19 (0.03)							-0.42 (0.11)				-0.71 (0.04)													0.12
Sn				-0.29 (0.00)														-1.9 (0.05)															0.13
Zn					0.26 (0.00)			-0.00 (0.09)	0.14 (0.09)									-2.59 (0.01)															0.21
Bi					0.50 (0.00)																									0.34 (0.00)			0.34
Cd					0.27 (0.00)											-0.93 (0.14)																	0.16
Co																				-1.48 (0.01)												0.62 (0.08)	0.08
Cr				-0.38 (0.00)														-1.25 (0.01)										0.10 (0.01)					0.39
Ga				-0.34 (0.00)																													0.14
Ge																																	
In	-1.36 (0.00)			-0.31 (0.00)																											0.51 (0.00)		0.32
Li					0.51 (0.00)																												0.26
Mg					0.34 (0.00)																										0.38 (0.01)		0.22
Mn				-0.36 (0.00)																										0.24 (0.10)			0.28
Mo																-1.29 (0.00)				-1.66 (0.00)													0.17
Sb					0.34 (0.00)																							0.16 (0.00)					0.23
Ti					0.44 (0.01)																												0.19
V					0.28 (0.02)											-0.68 (0.01)													0.86 (0.01)				0.24
W					0.44 (0.00)															-0.76 (0.01)													0.30

This table displays the averaged β-coefficients and corresponding p-values of the metal price predictors in the total-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability. The lagged return ($Price_{t-1}$) of each metal has been included as additional predictor.

Table E.2: Linear Regression Results for the Metal Price Determinants - Total-Sample

	supply	hhi	demand	VAL	MOM	FUT1	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	T10Y3M	FFR	WuXia	MB	WALCL	M4	T5YIFR	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	EAKilian	BDI	CPI	OIL	BCOM	RICIM	MSCIW	SPX	$Adj.R^2$
Ag						1.01 (0.00)	+0.00 (0.00)																										0.99
Au				-0.00 (0.31)		1.01 (0.00)	+0.00 (0.00)																										0.99
Pt				-0.61 (0.00)		0.28 (0.00)																								0.11 (0.00)			0.93
Al						1.02 (0.00)	+0.00 (0.03)																										0.98
Cu						1.02 (0.00)																											0.99
Ni						1.05 (0.00)	+0.00 (0.35)																							-0.06 (0.00)			0.99
Pb						1.06 (0.00)																								-0.07 (0.00)			0.99
Sn						1.03 (0.00)														0.05 (0.02)									0.02 (0.02)	-0.04 (0.01)			0.99
Zn						1.02 (0.00)																											0.96
Bi				-0.78 (0.00)																				5.11 (0.00)									0.86
Cd			-0.48 (0.18)										0.03 (0.14)			-0.91 (0.06)												0.32 (0.04)					0.19
Co				-0.91 (0.00)																				-13.1 (0.00)									0.93
Cr				-0.84 (0.00)														-0.53 (0.00)						-3.51 (0.00)									0.91
Ga	0.86 (0.00)			-0.83 (0.00)						-0.52 (0.04)																							0.92
Ge																																	
In	-1.29 (0.00)			-0.77 (0.00)	-0.01 (0.00)										+0.00 (0.29)																		0.81
Li	0.63 (0.00)			-0.90 (0.00)										-0.00 (0.00)																			0.90
Mg														0.01 (0.02)										10.97 (0.01)			0.04 (0.00)						0.19
Mn				-0.82 (0.00)																													0.88
Mo				-0.86 (0.00)																													0.86
Sb				-0.81 (0.00)									-0.00 (0.12)																				0.84
Ti																																	
V				-0.86 (0.00)																													0.87
W		0.11 (0.00)		-0.82 (0.00)																					+0.00 (0.03)								0.89

This table displays the averaged β-coefficients and corresponding p-values of the metal price determinants in the total-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability. Value factor (VAL), Futures Prices ($FUT1$) and RICI Metals Index ($RICIM$) specifically been included.

Table E.3: Linear Regression Results for the Metal Price Predictors - Total-Sample

	$supply_M$	hhi	$demand_M$	VAL	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
Al																								12.28 (0.00)					0.30 (0.00)				0.15
Cu						0.34 (0.00)										-0.34 (0.05)		-2.53 (0.01)															0.23
Ni				-0.29 (0.00)														-3.04 (0.02)															0.14
Pb								0.19 (0.03)								-0.42 (0.11)				-0.71 (0.04)													0.12
Sn				-0.29 (0.00)														-1.91 (0.04)															0.13
Zn						0.26 (0.00)	-0.00 (0.07)	0.14 (0.08)										-2.54 (0.01)															0.20

This table displays the averaged β-coefficients and corresponding p-values of the metal price predictors in the total-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table E.4: Linear Regression Results for the Metal Price Determinants - Total-Sample

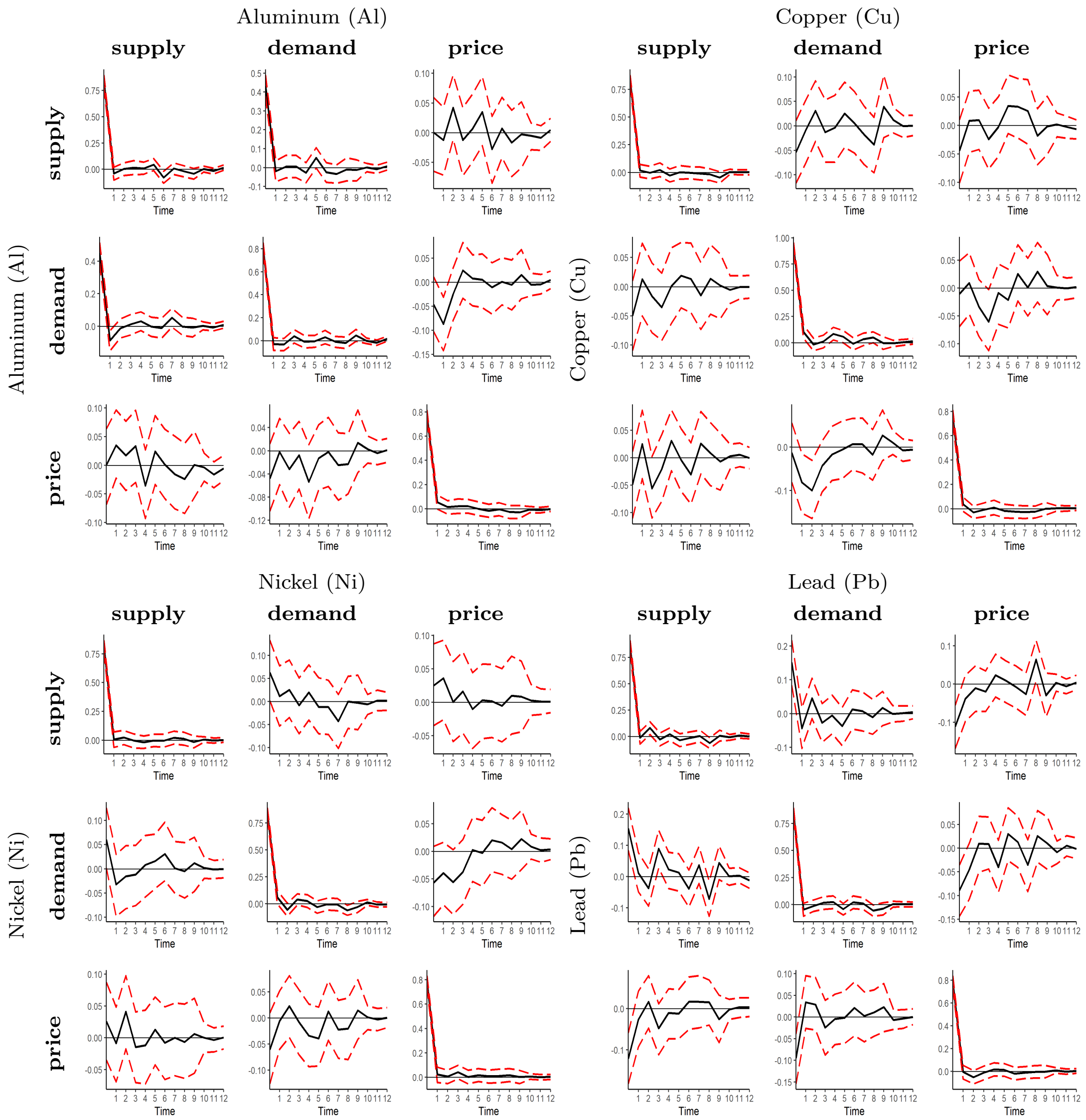
	$supply_M$	hhi	$demand_M$	VAL	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
Al							+0.00 (0.00)													-0.42 (0.03)								0.10 (0.08)	0.30 (0.00)		0.33 (0.00)		0.41
Cu										-0.67 (0.01)						-0.44 (0.00)												0.18 (0.00)	0.31 (0.06)		0.49 (0.00)		0.42
Ni		-0.11 (0.01)						0.17 (0.00)																				0.19 (0.00)			0.85 (0.00)		0.35
Pb							+0.00 (0.01)	0.19 (0.03)								-0.40 (0.07)				-0.89 (0.00)											0.40 (0.00)		0.28
Sn																				-0.57 (0.03)					+0.00 (0.06)		0.02 (0.12)		0.28 (0.07)		0.50 (0.00)		0.32
Zn								0.24 (0.00)												-0.74 (0.00)											0.61 (0.00)		0.32

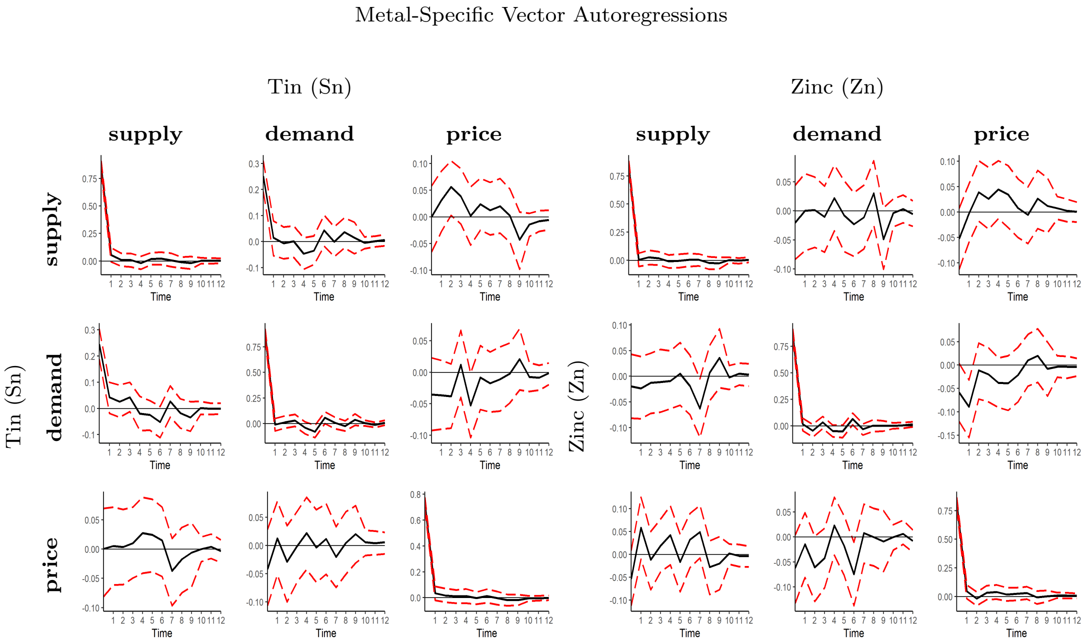
This table displays the averaged β-coefficients and corresponding p-values of the metal price determinants in the total-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

E.3 Plots of Generalized Impulse Response Functions

E.3.1 Metal-Specific Vector Autoregressions

Figure E.2: GIRFs of Metal-Specific Vector Autoregressions

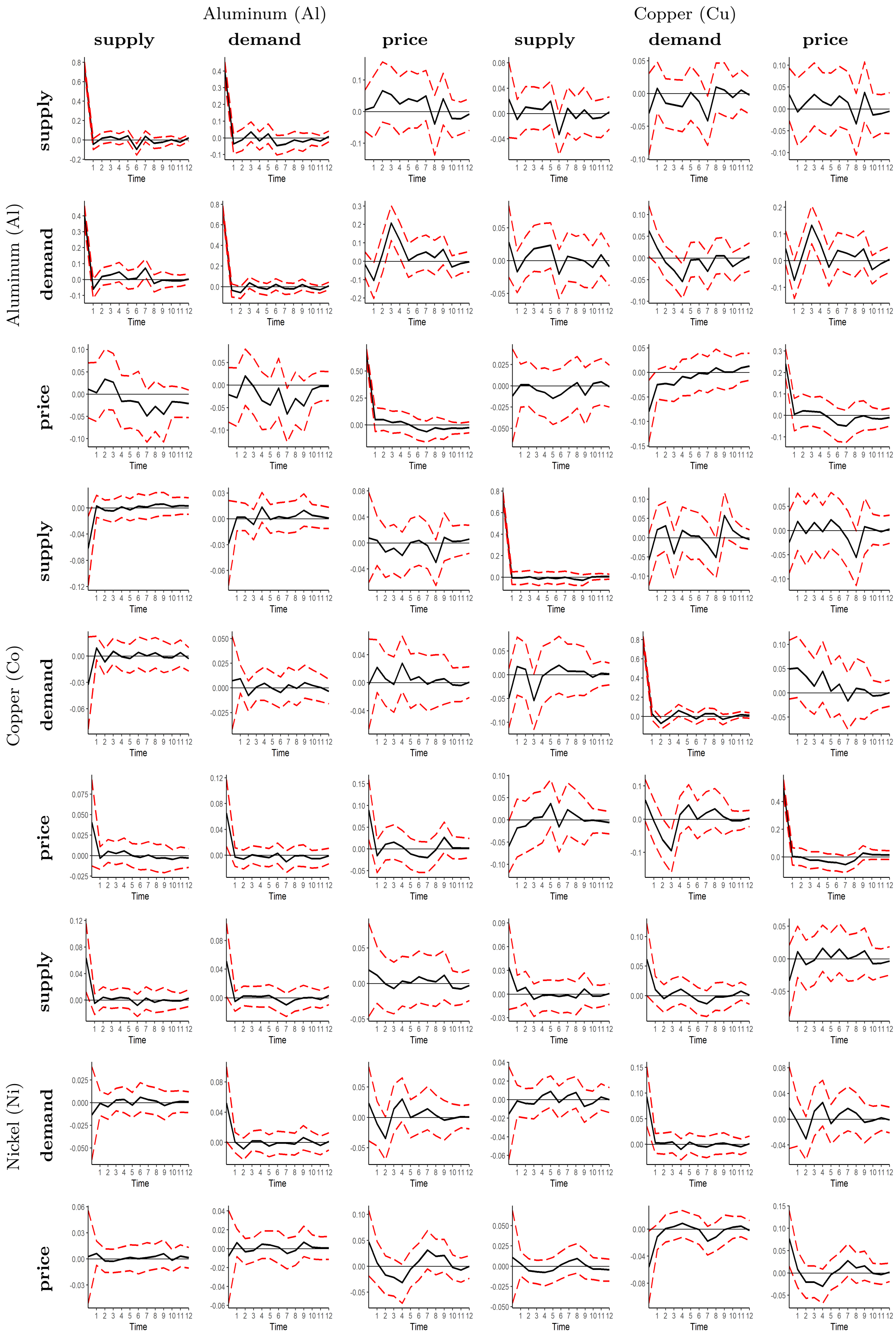




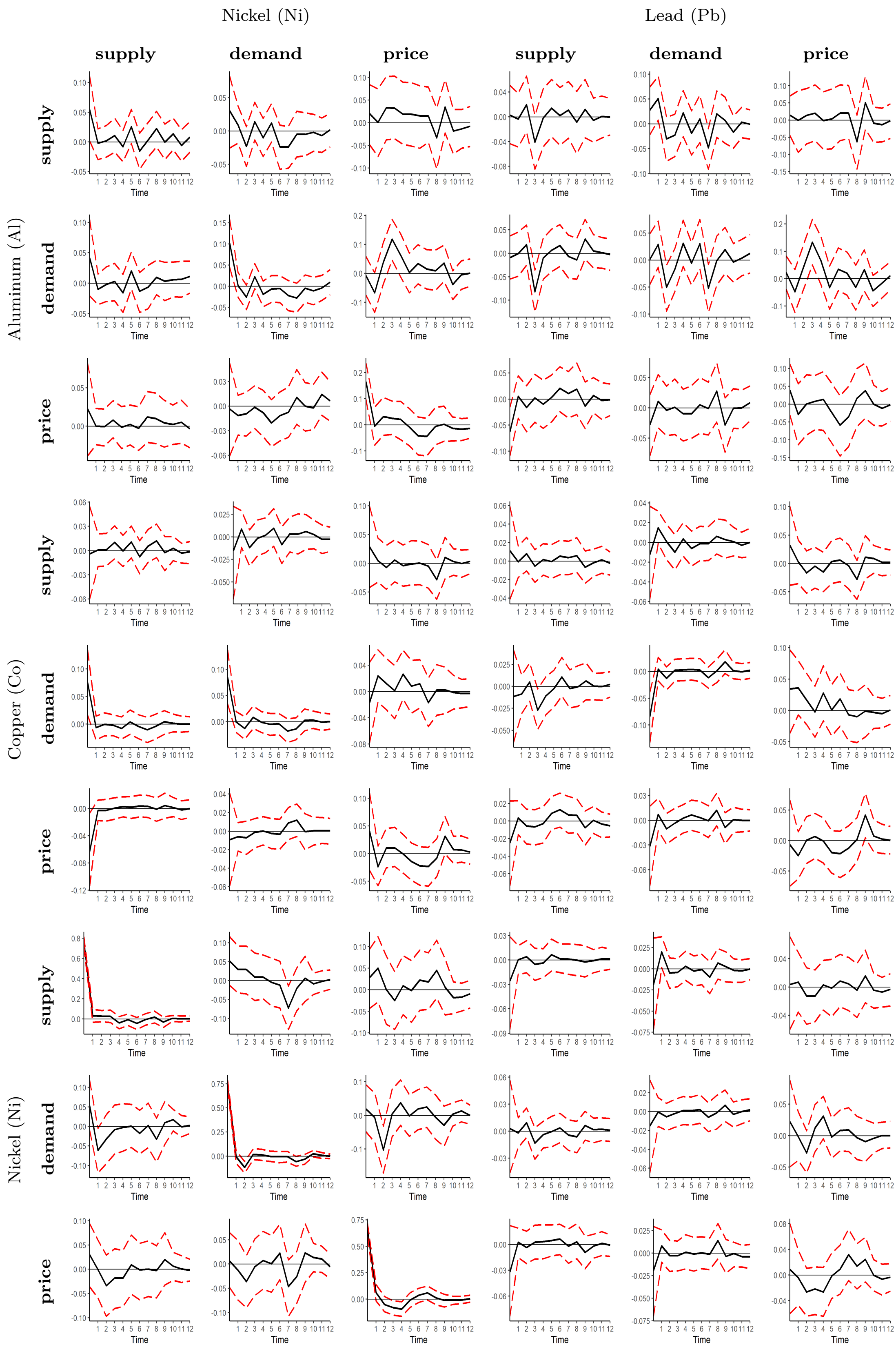
This figure displays the generalized impulse response function results of the metal-specific vector autoregressions. Hereby, we display the response of the column variable to a one-standard deviation shock in the row variable **supply**, **demand** or **price**. The black, solid line represents the average response, whereas the red lines display the 68% confidence intervals.

E.3.2 Global Vector Autoregressions

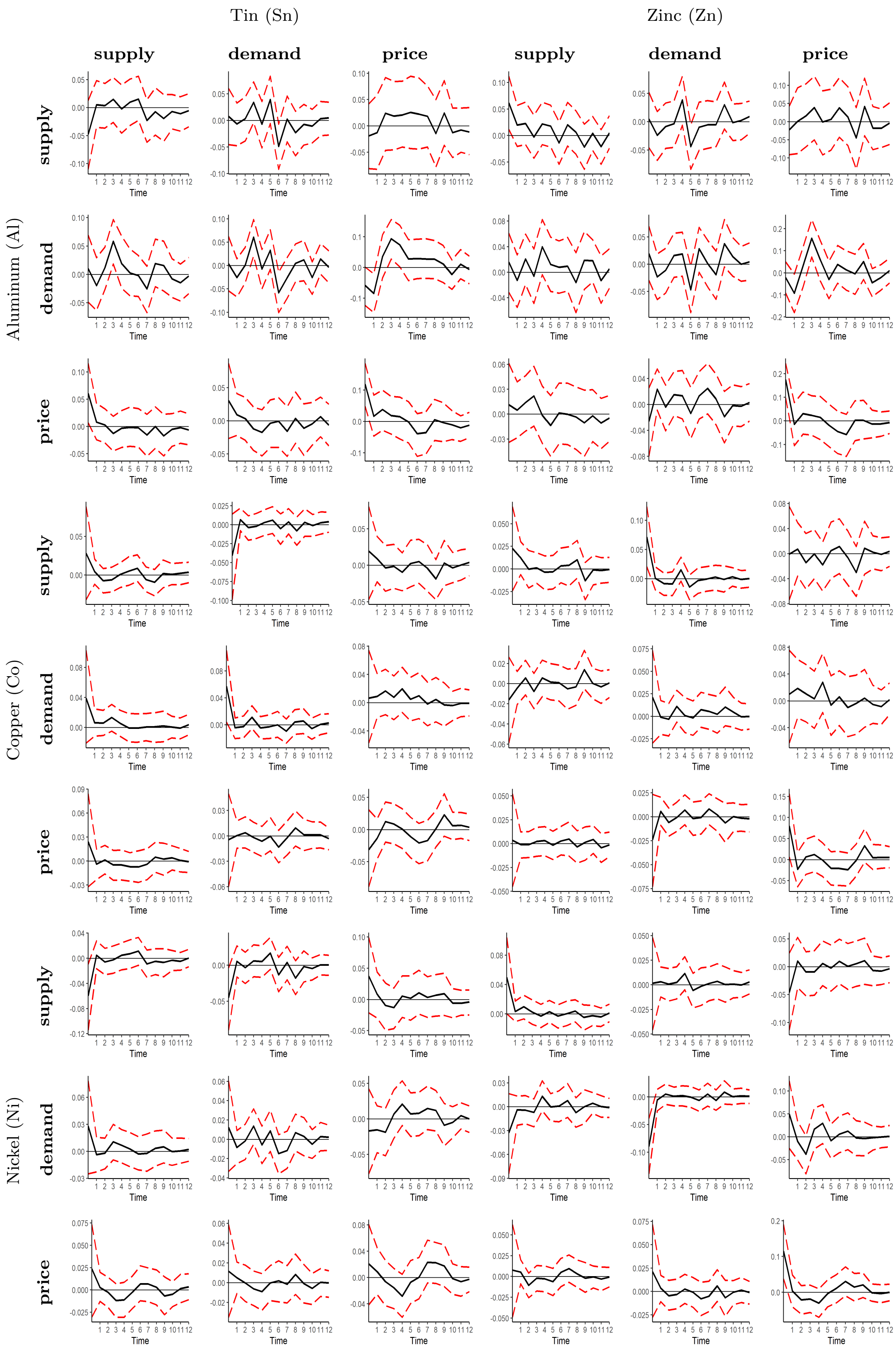
Figure E.3: GIRFs of Global Vector Autoregression - Weight Matrix Supply



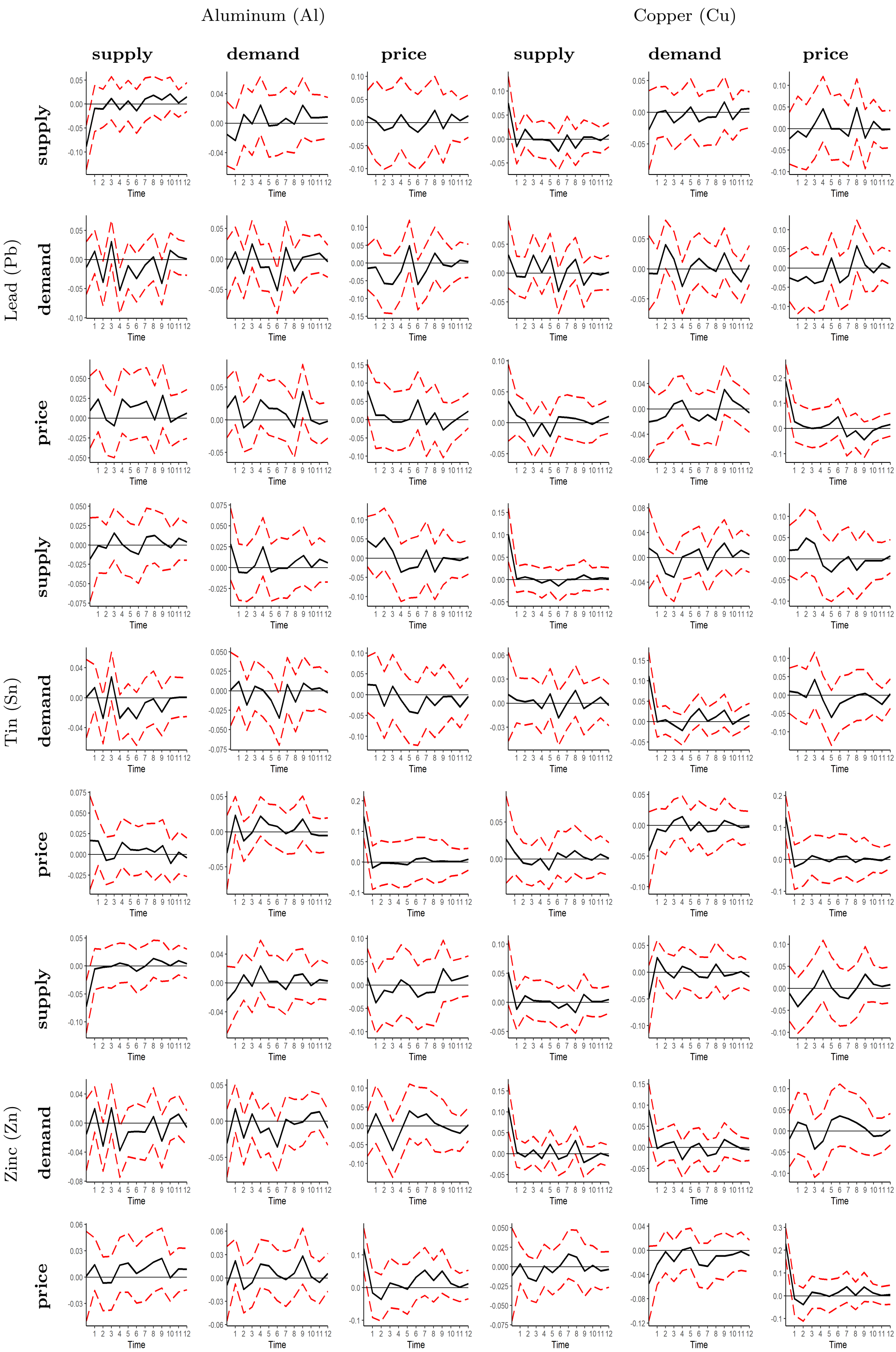
GIRFs of Global Vector Autoregression - Weight Matrix Supply



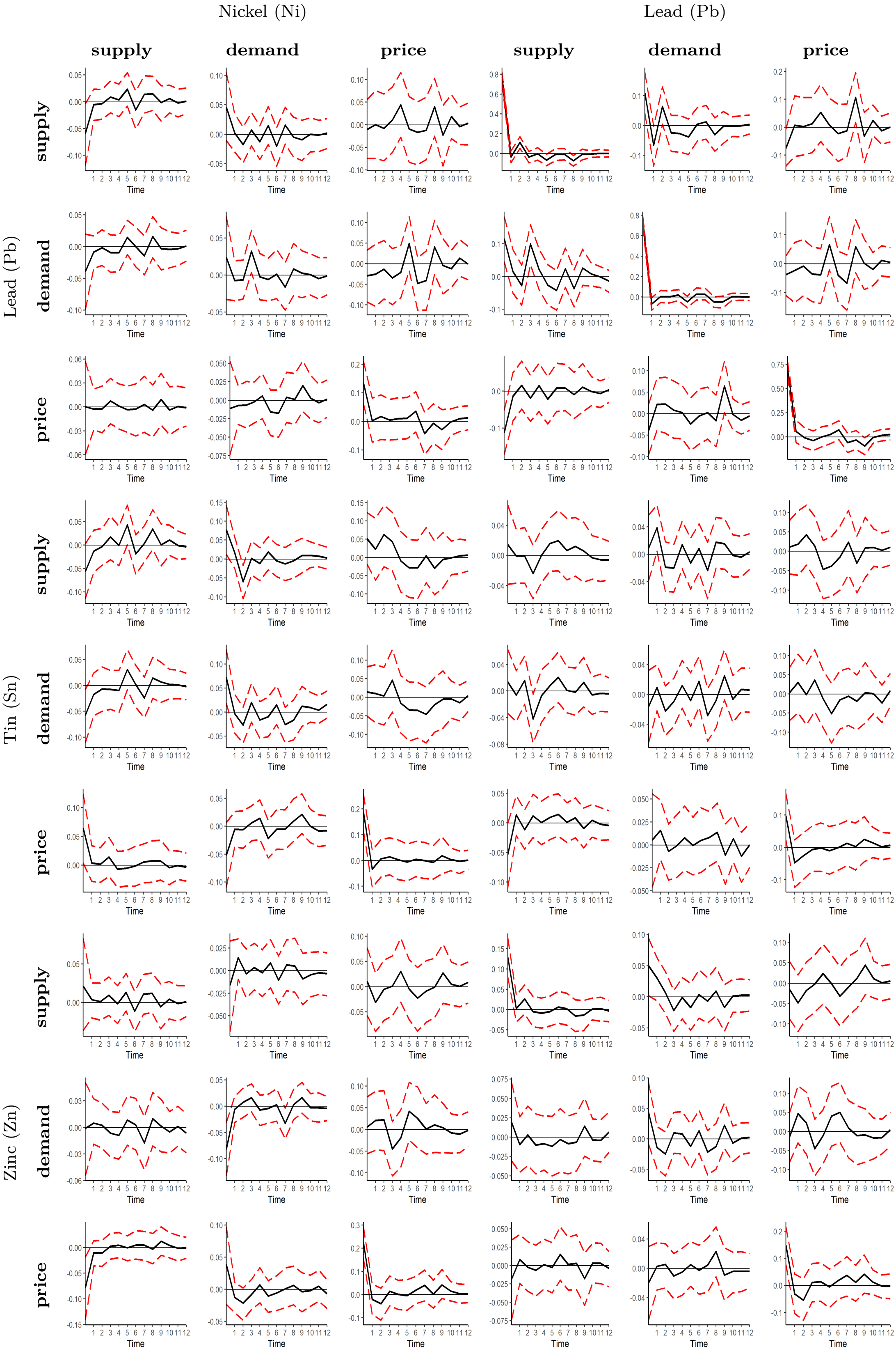
GIRFs of Global Vector Autoregression - Weight Matrix Supply



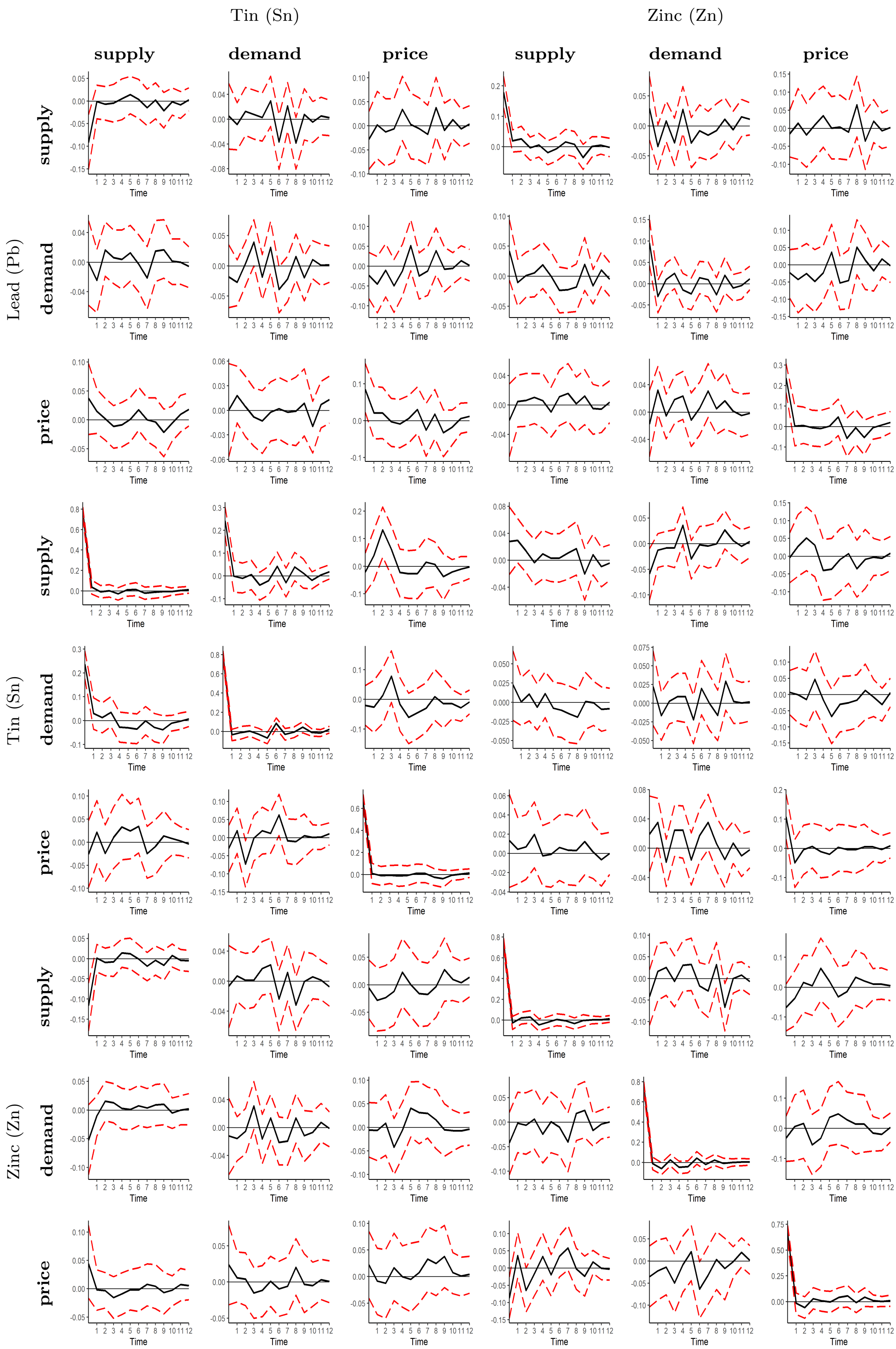
GIRFs of Global Vector Autoregression - Weight Matrix Supply



GIRFs of Global Vector Autoregression - Weight Matrix Supply

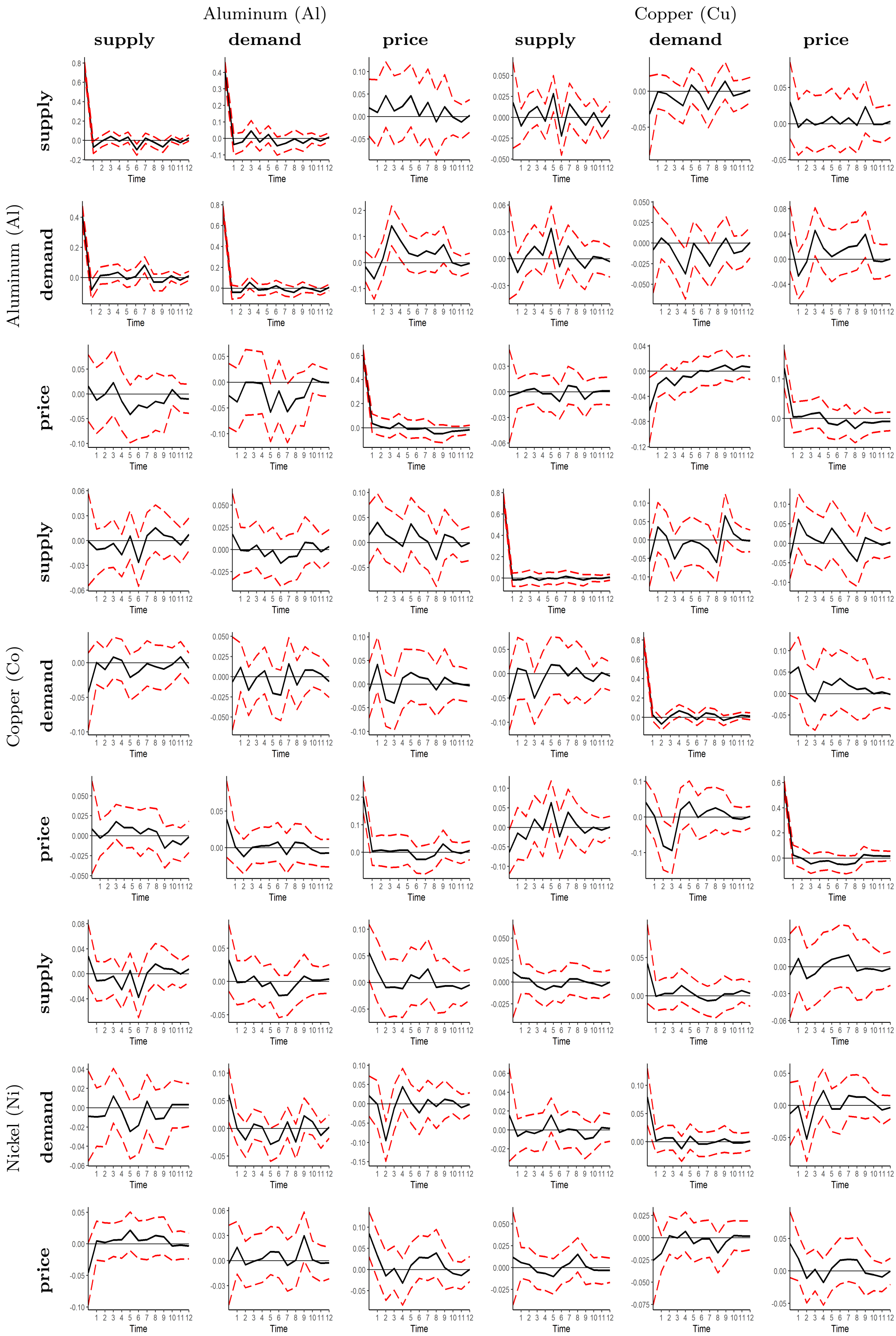


GIRFs of Global Vector Autoregression - Weight Matrix Supply

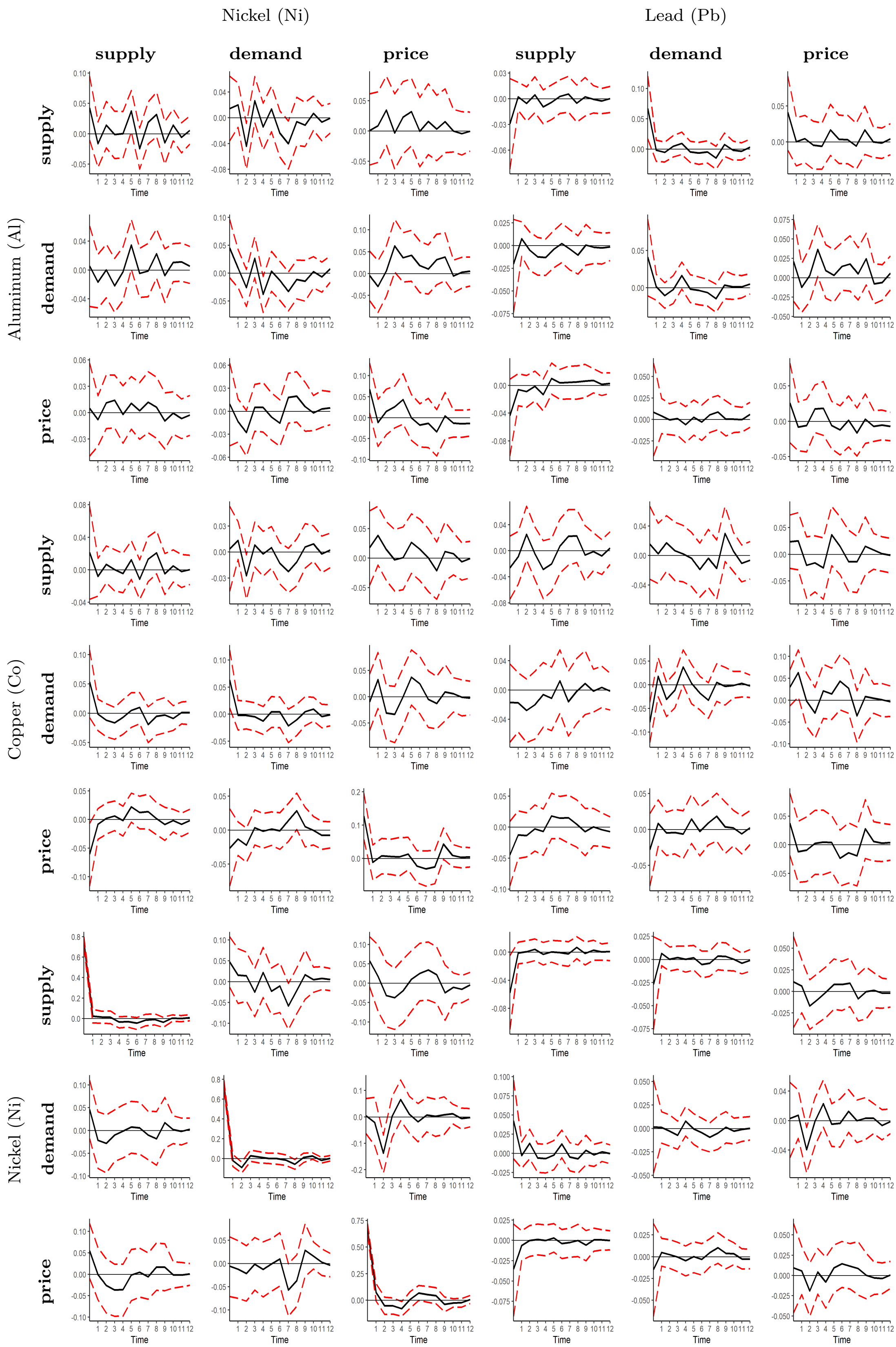


This figure displays the generalized impulse response function results of the global vector autoregression using the supply weight matrix. Hereby, we display the response of the column variable to a one-standard deviation shock in the row variable **supply**, **demand** or **price**. The black, solid line represents the average response, whereas the red lines display the 68% confidence intervals.

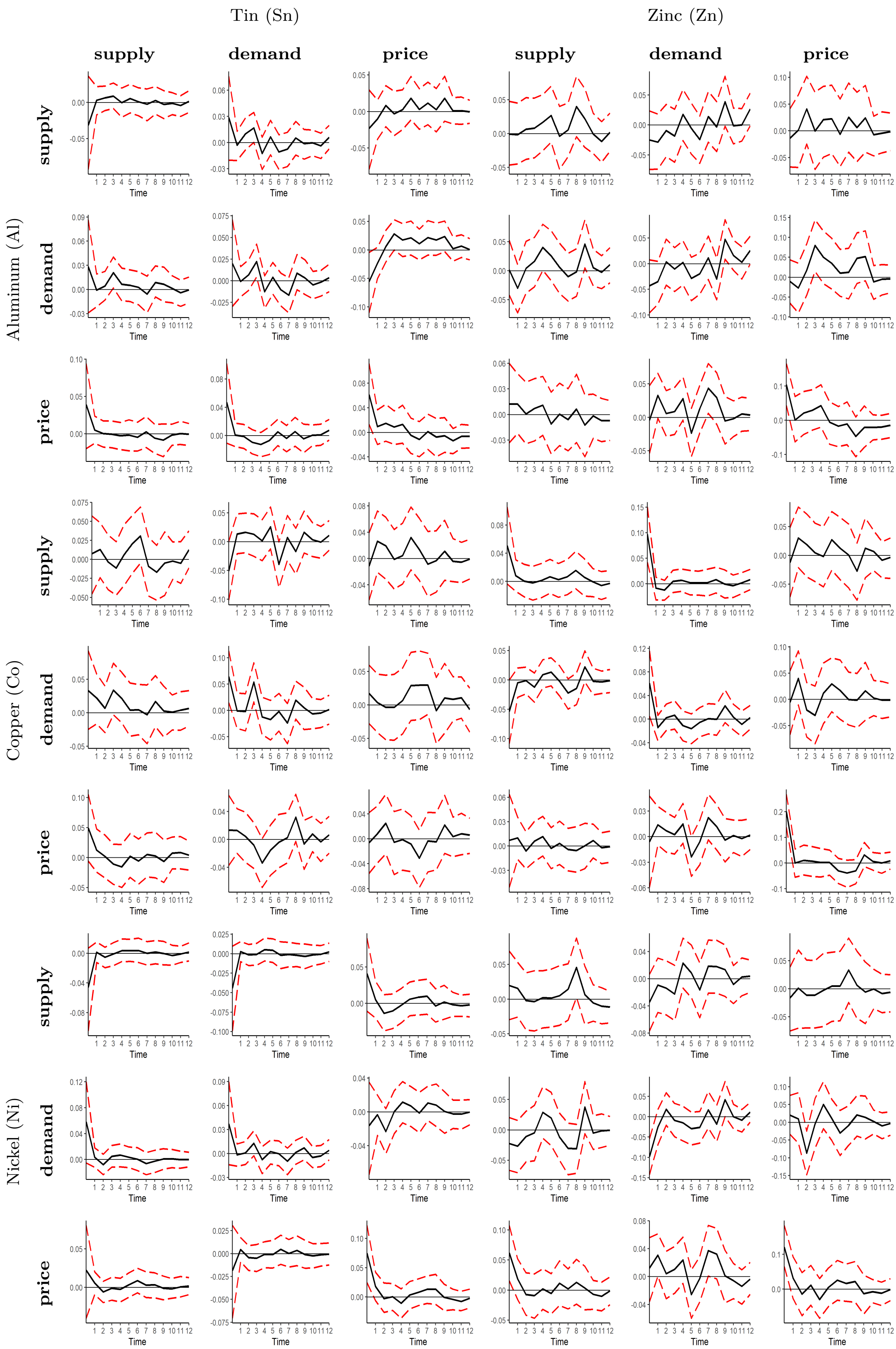
Figure E.4: GIRFs of Global Vector Autoregression - Weight Matrix Demand



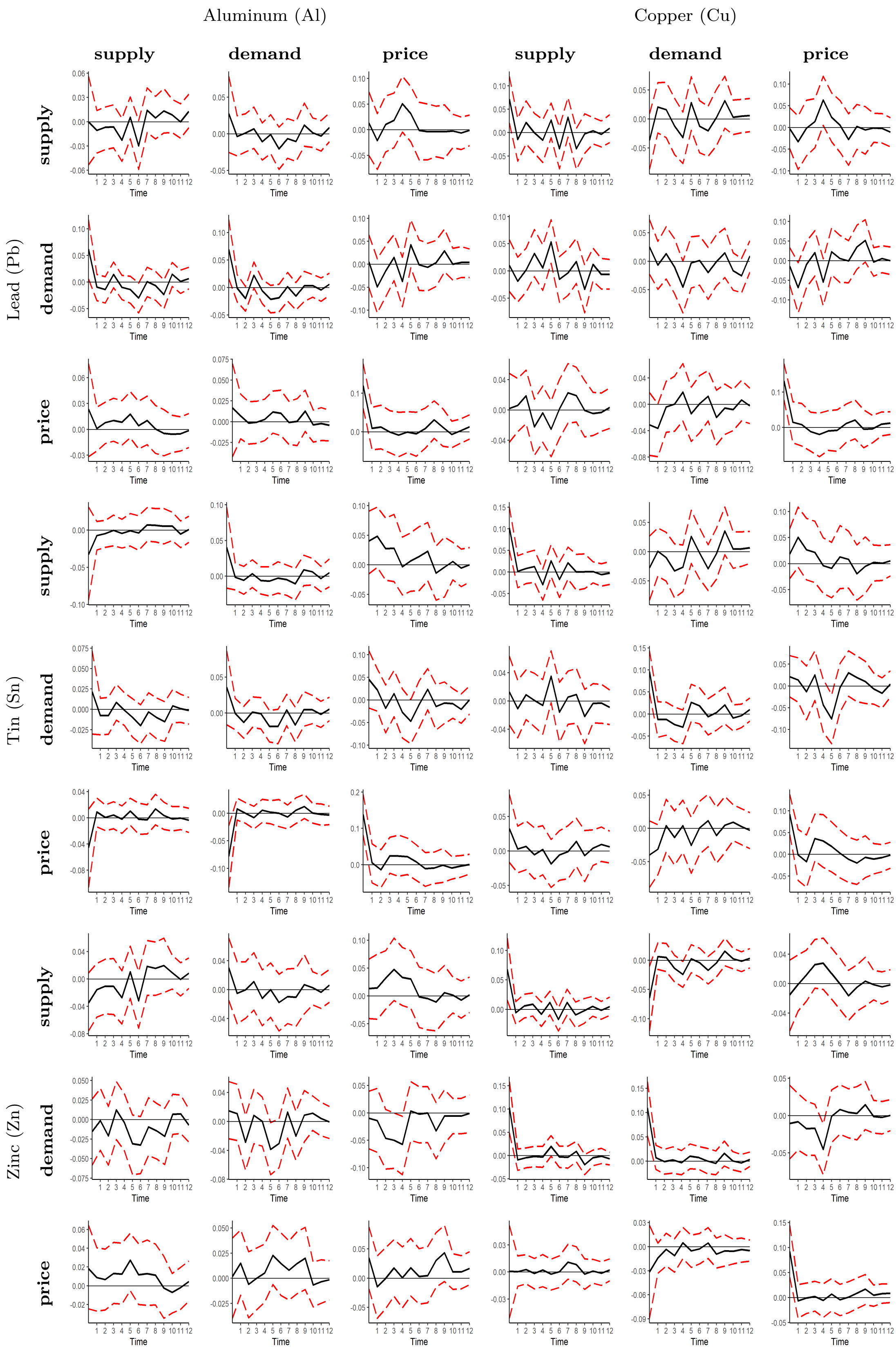
GIRFs of Global Vector Autoregression - Weight Matrix Demand



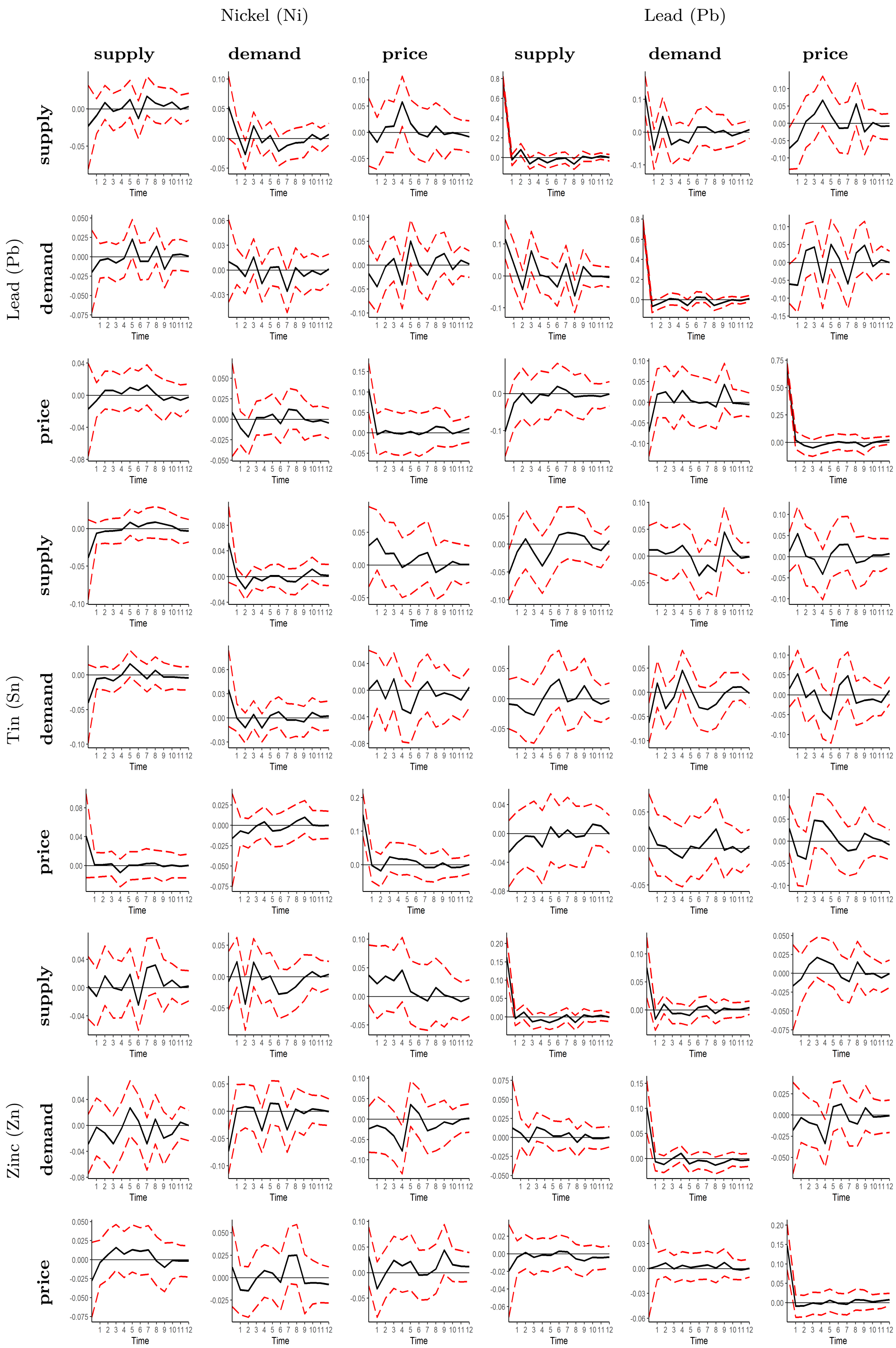
GIRFs of Global Vector Autoregression - Weight Matrix Demand



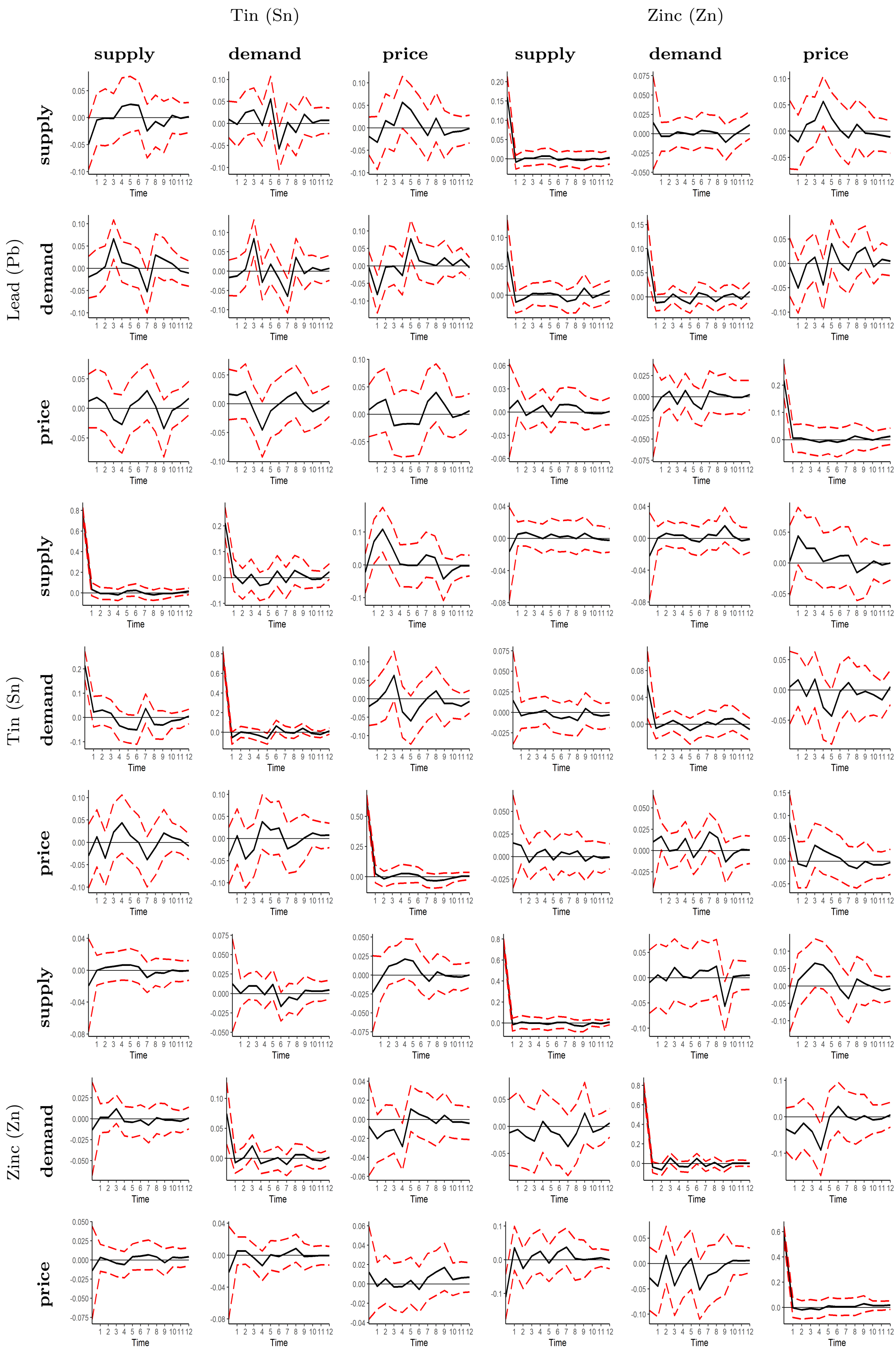
GIRFs of Global Vector Autoregression - Weight Matrix Demand



GIRFs of Global Vector Autoregression - Weight Matrix Demand

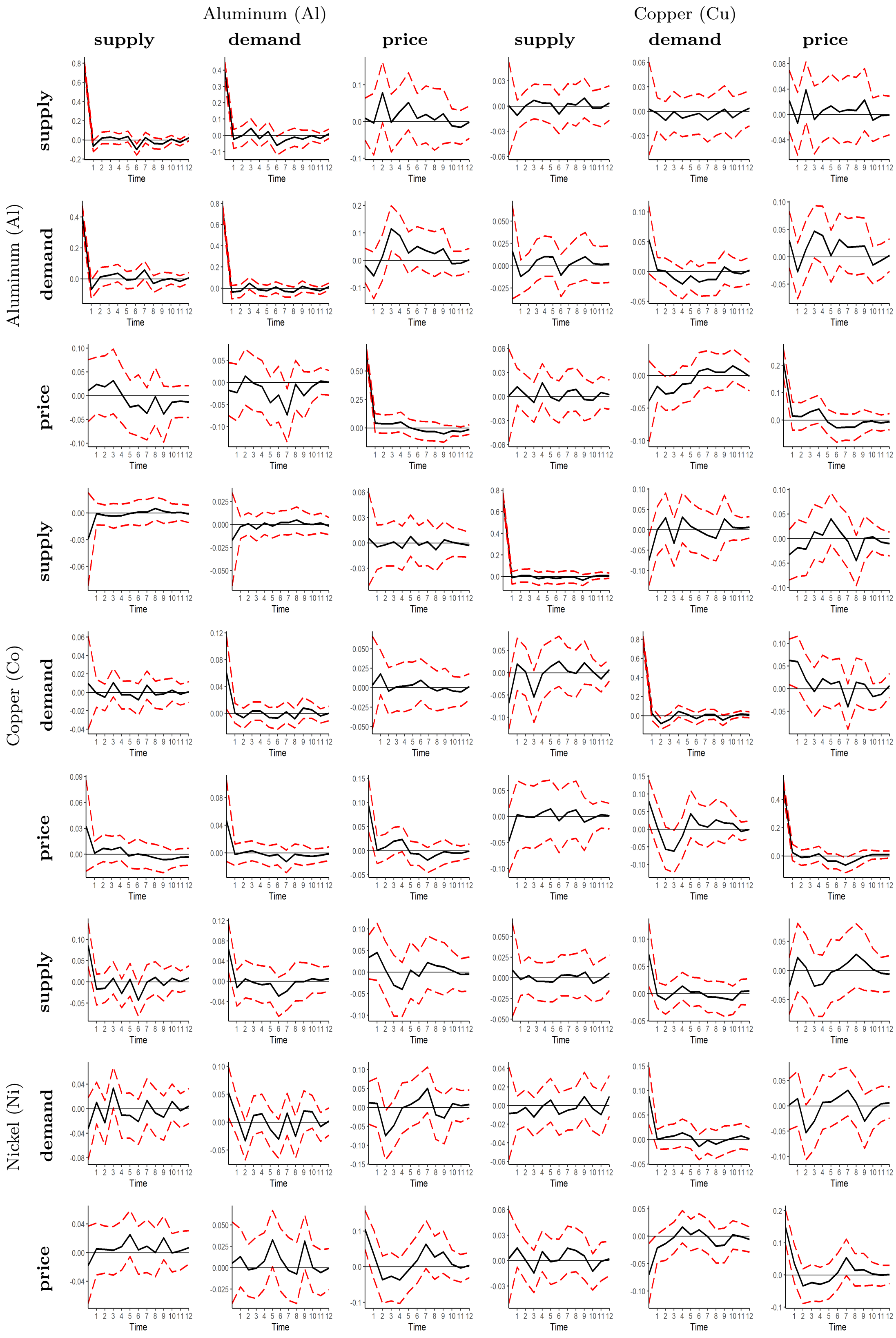


GIRFs of Global Vector Autoregression - Weight Matrix Demand

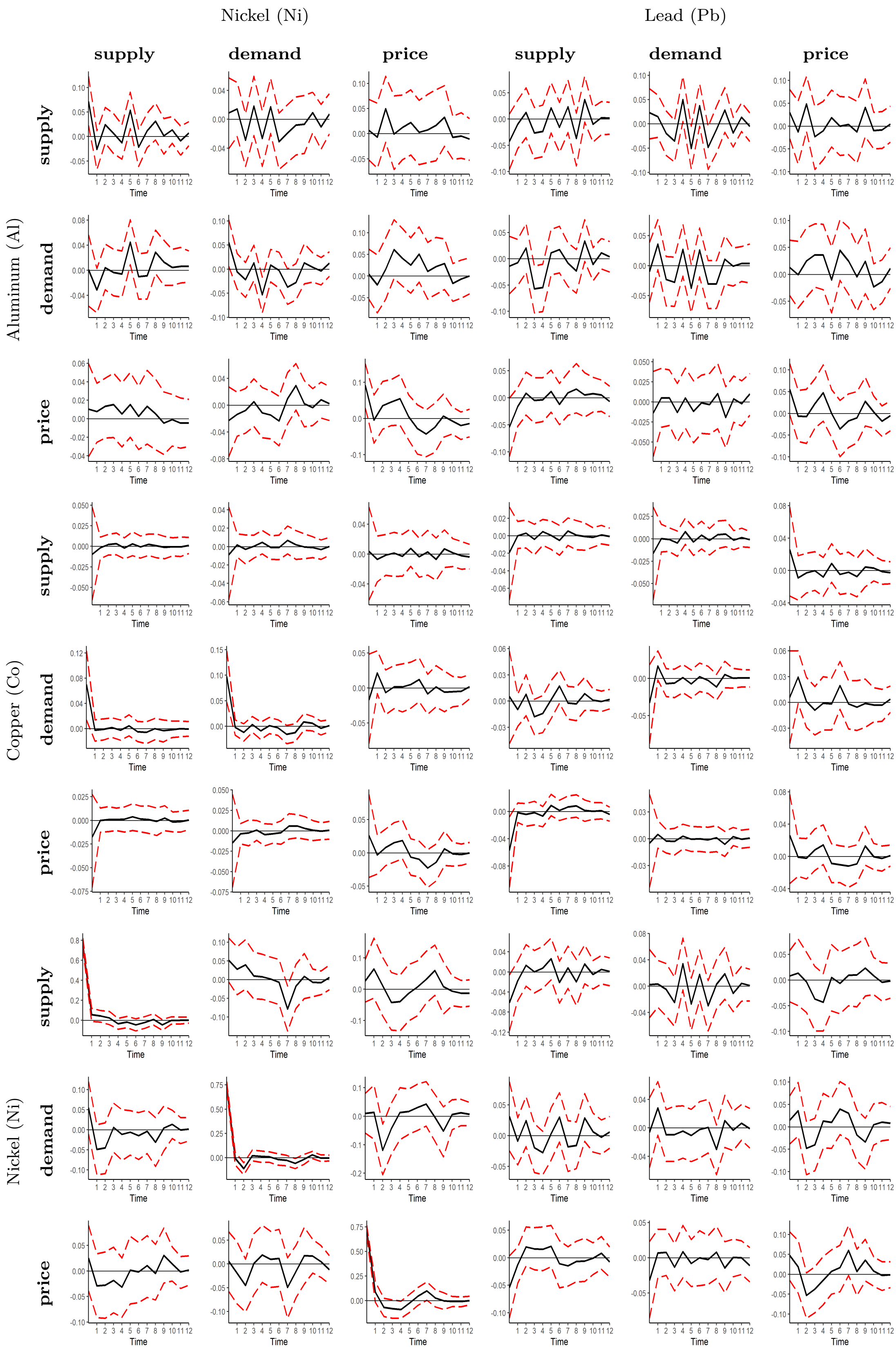


This figure displays the generalized impulse response function results of the global vector autoregression using the demand weight matrix. Hereby, we display the response of the column variable to a one-standard deviation shock in the row variable **supply**, **demand** or **price**. The black, solid line represents the average response, whereas the red lines display the 68% confidence intervals.

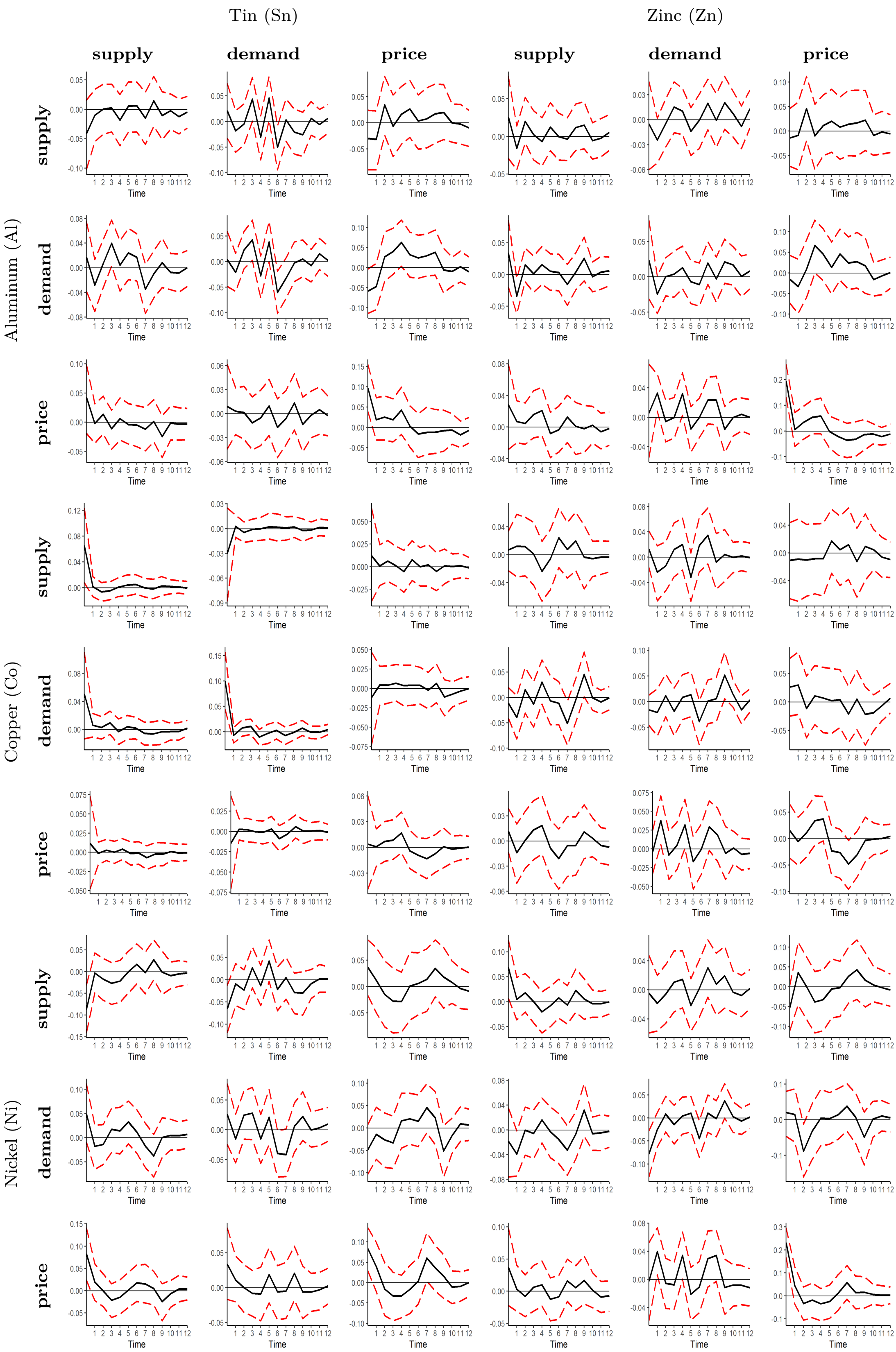
Figure E.5: GIRFs of Global Vector Autoregression - Weight Matrix Trading



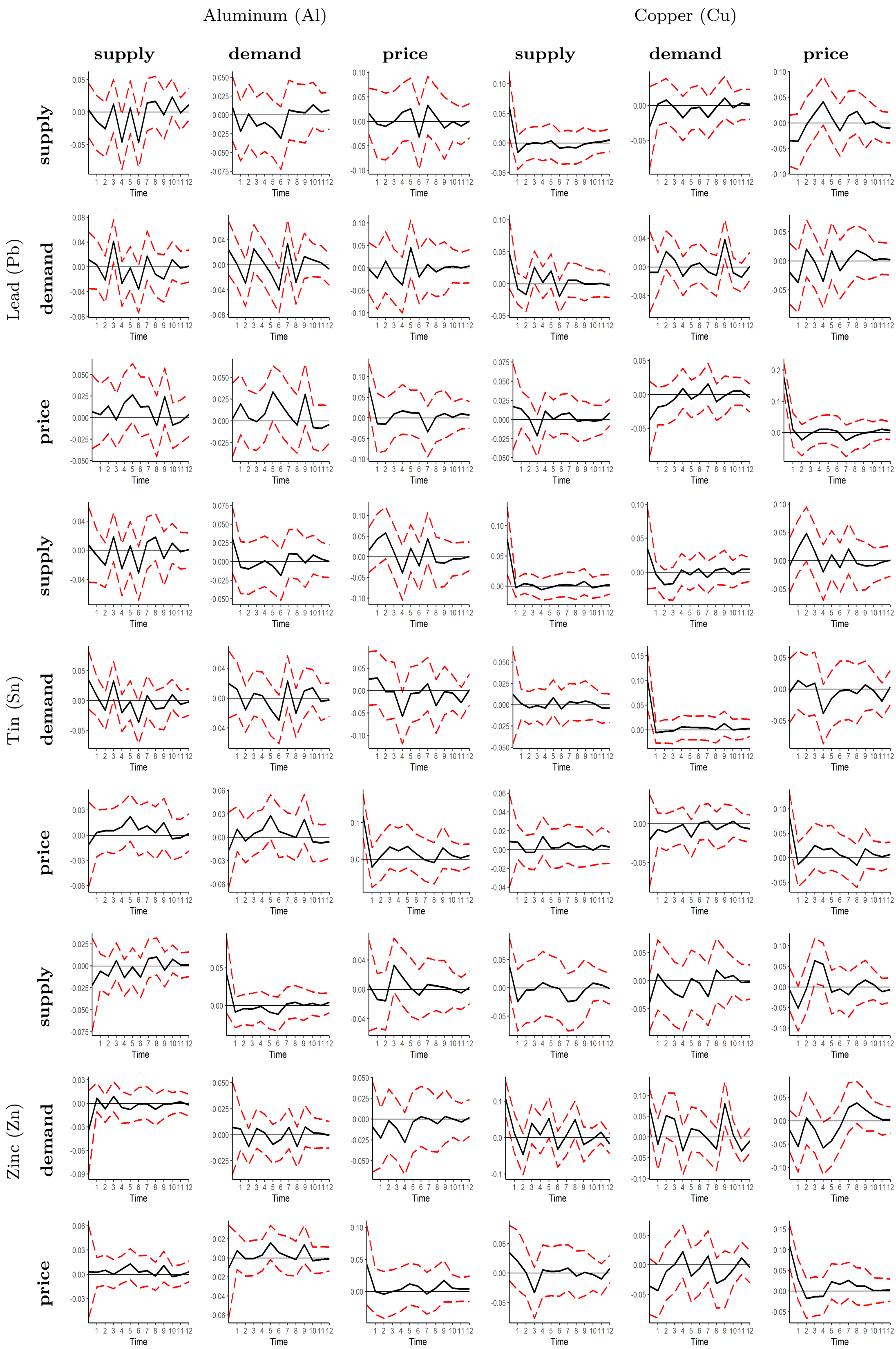
GIRFs of Global Vector Autoregression - Weight Matrix Trading



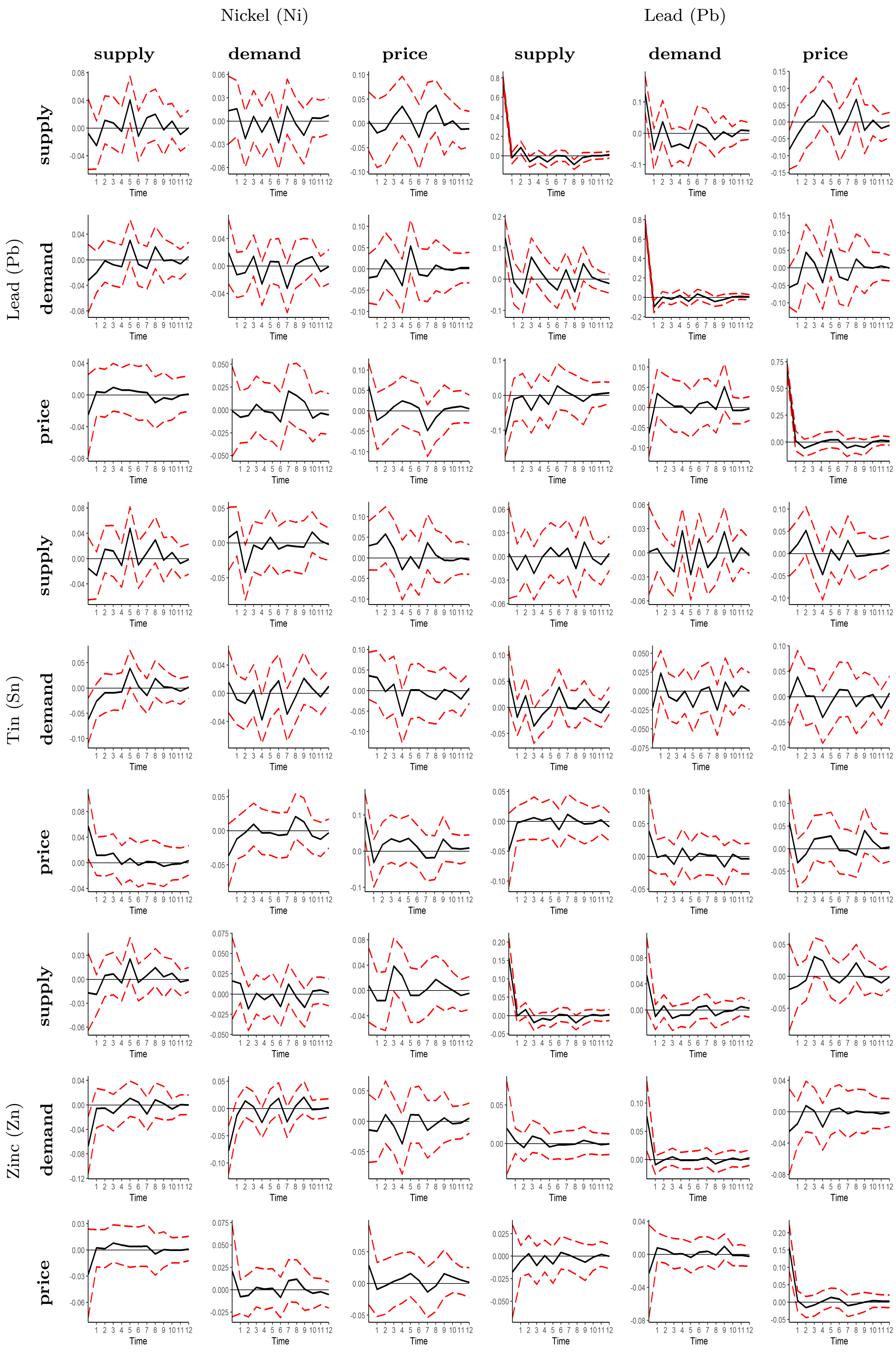
GIRFs of Global Vector Autoregression - Weight Matrix Trading



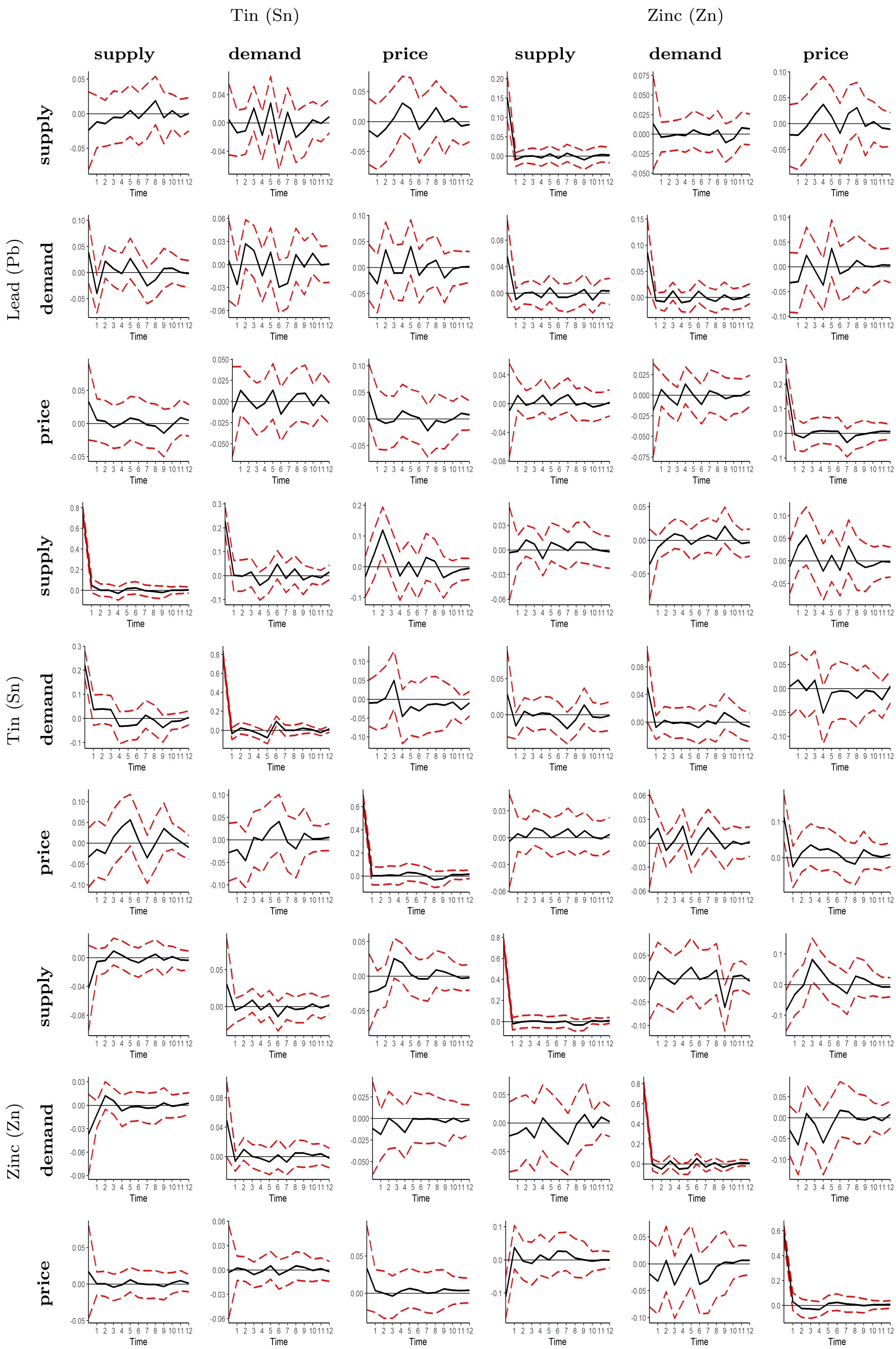
GIRFs of Global Vector Autoregression - Weight Matrix Trading



GIRFs of Global Vector Autoregression - Weight Matrix Trading

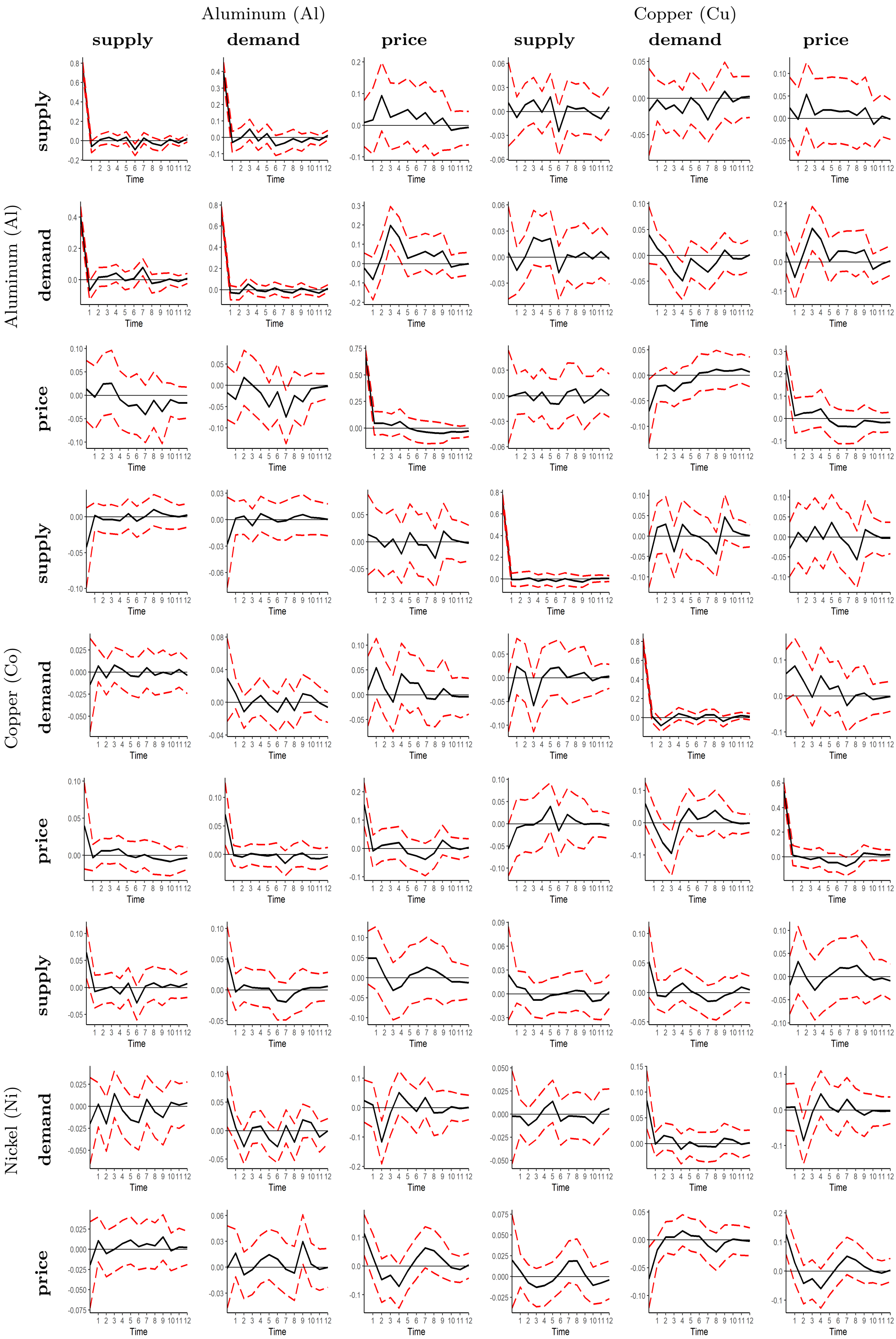


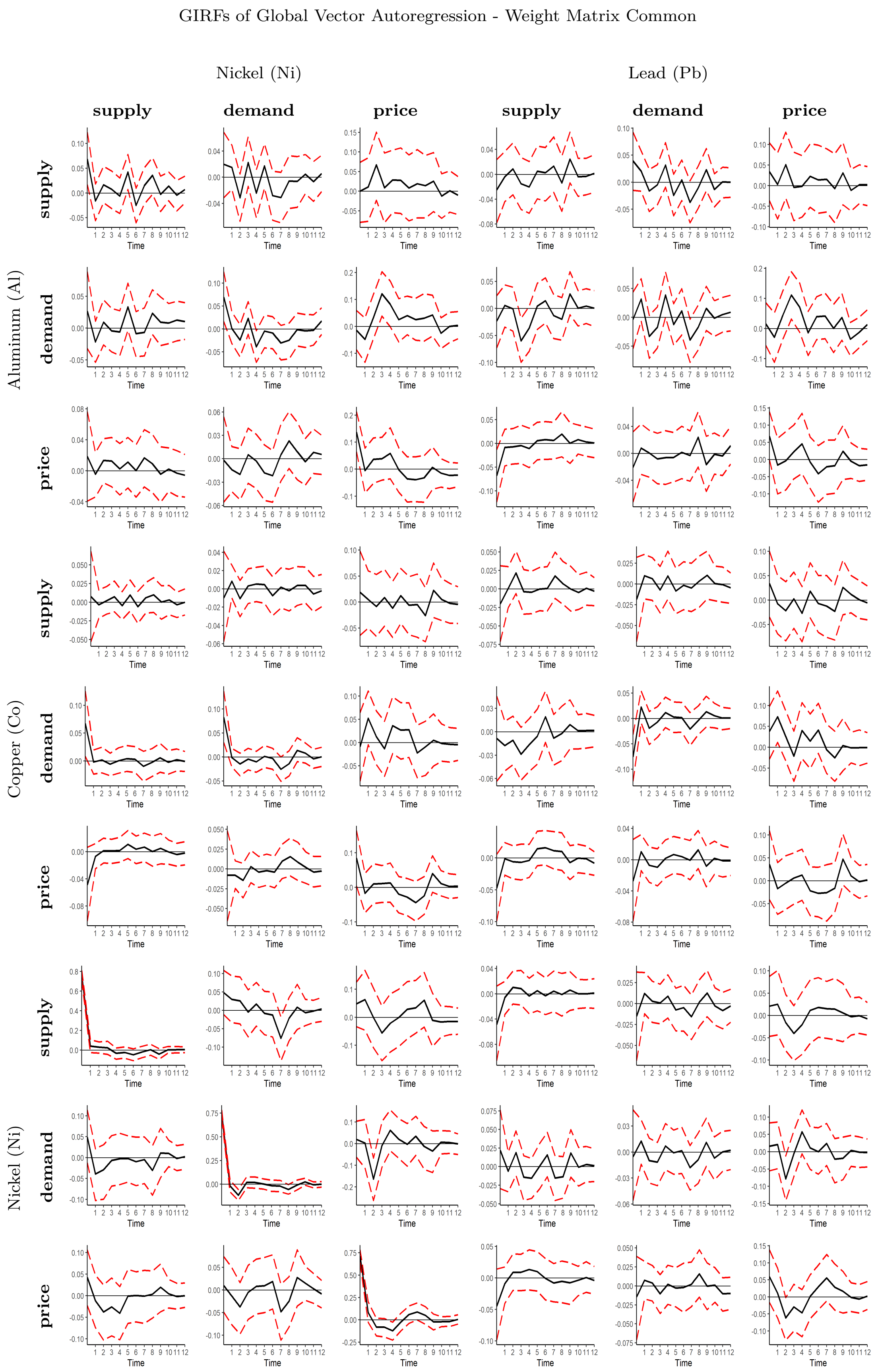
GIRFs of Global Vector Autoregression - Weight Matrix Trading



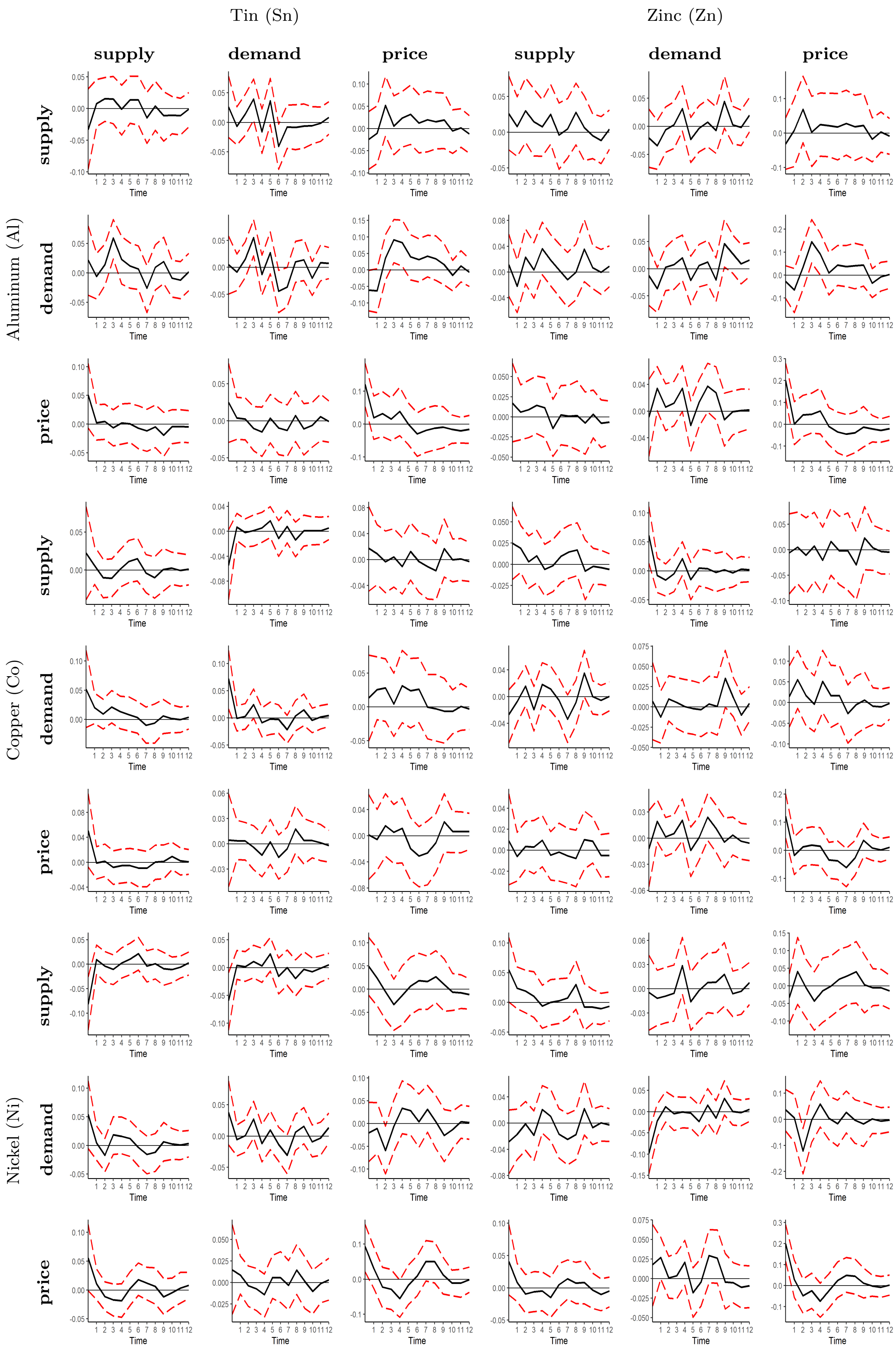
This figure displays the generalized impulse response function results of the global vector autoregression using the trading weight matrix. Hereby, we display the response of the column variable to a one-standard deviation shock in the row variable **supply**, **demand** or **price**. The black, solid line represents the average response, whereas the red lines display the 68% confidence intervals.

Figure E.6: GIRFs of Global Vector Autoregression - Weight Matrix Common

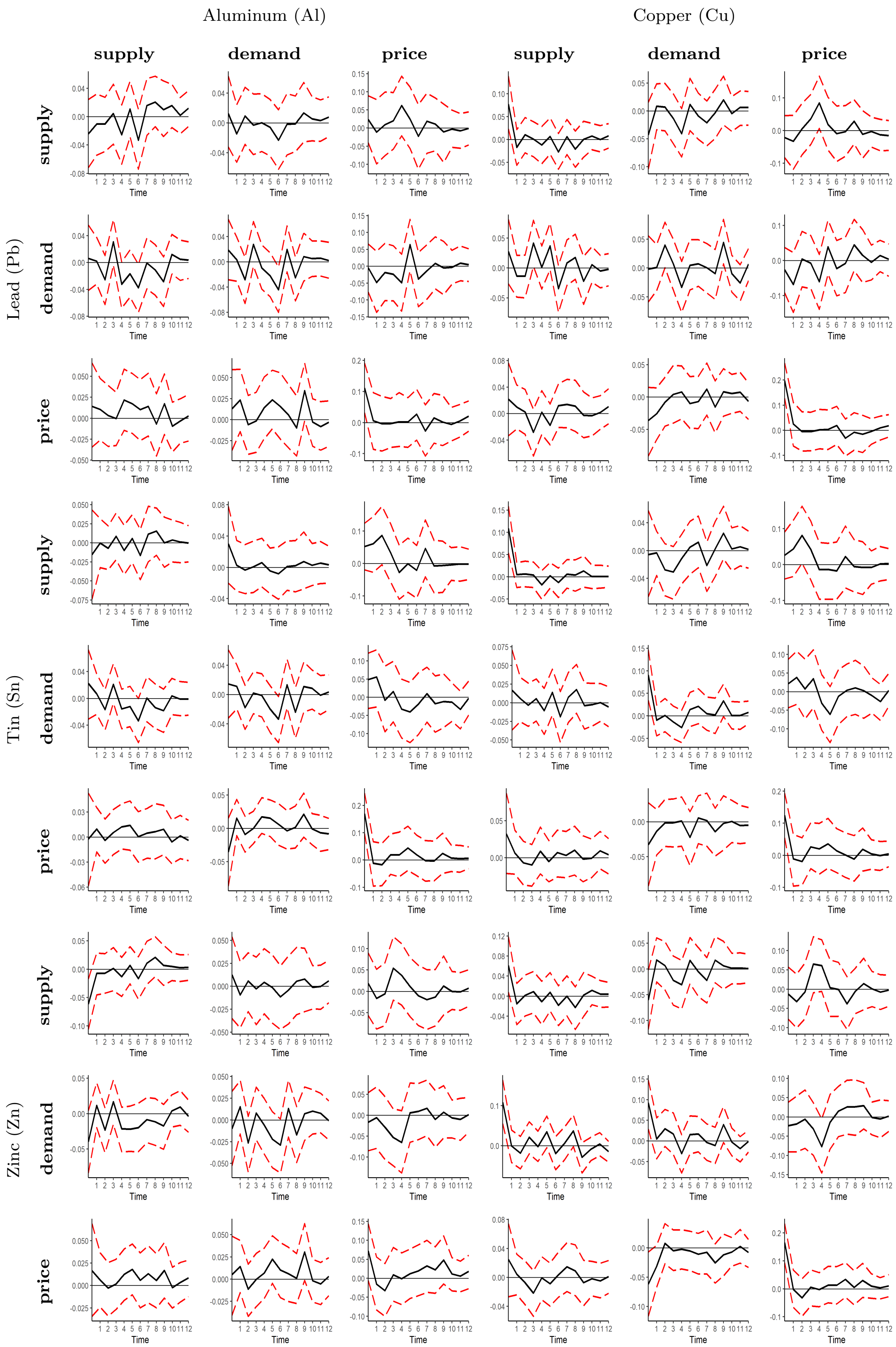



GIRFs of Global Vector Autoregression - Weight Matrix Common
Nickel (Ni)
Lead (Pb)
supply
demand
price
supply
demand
price
Aluminum (Al)
Copper (Co)
Nickel (Ni)
supply
demand
price
Time

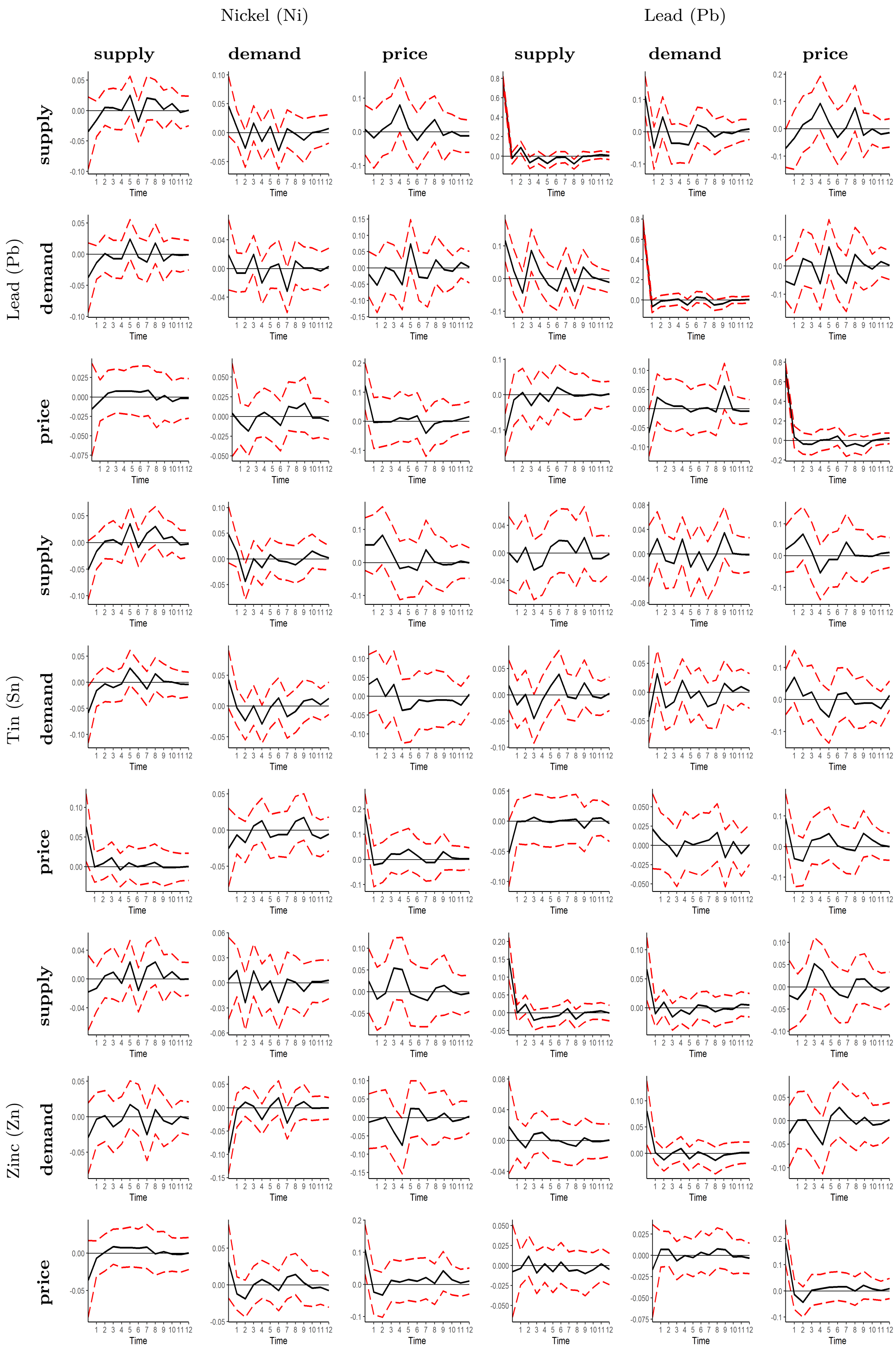
GIRFs of Global Vector Autoregression - Weight Matrix Common



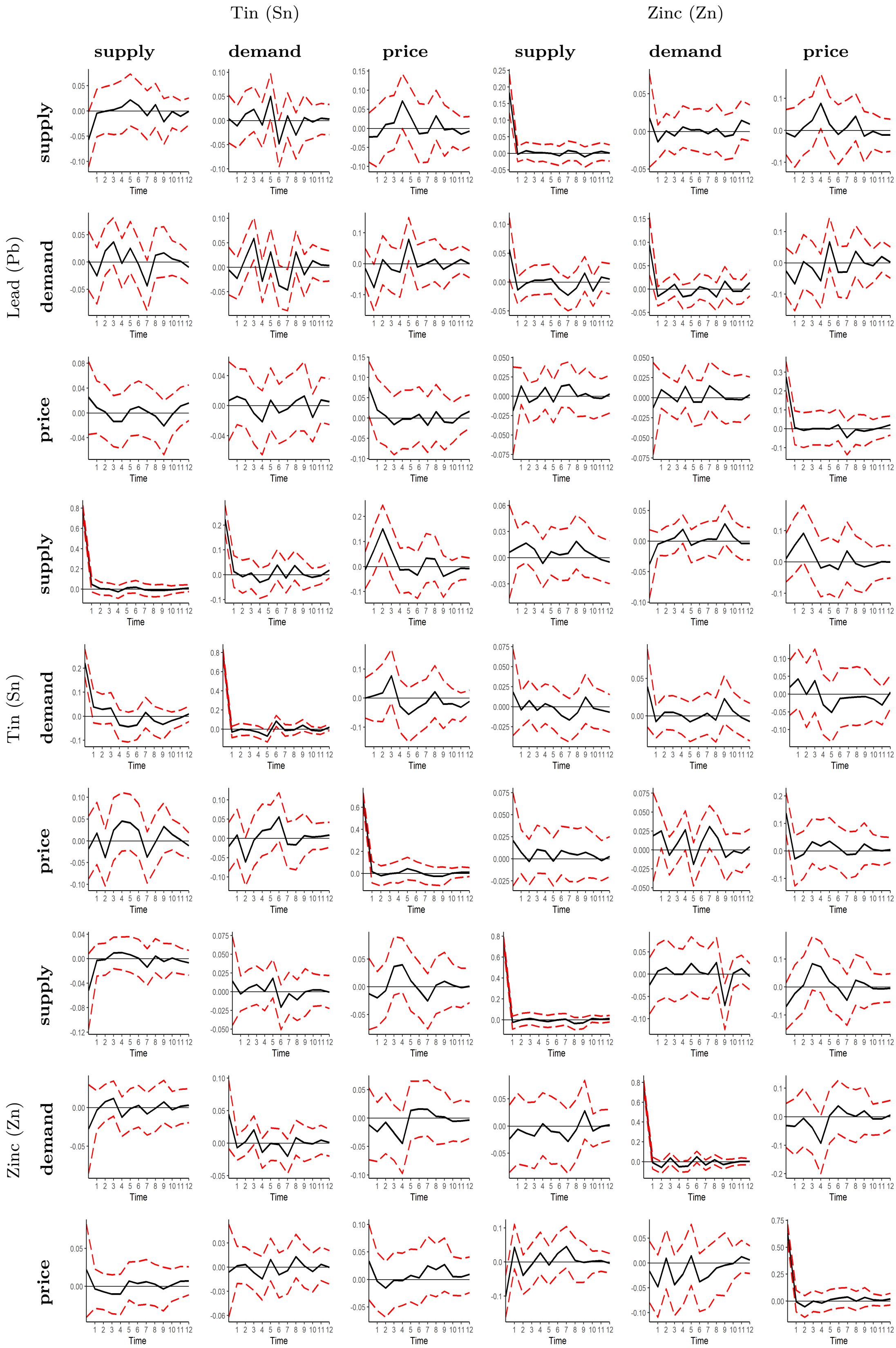
GIRFs of Global Vector Autoregression - Weight Matrix Common



GIRFs of Global Vector Autoregression - Weight Matrix Common



GIRFs of Global Vector Autoregression - Weight Matrix Common



This figure displays the generalized impulse response function results of the global vector autoregression using the common weight matrix. Hereby, we display the response of the column variable to a one-standard deviation shock in the row variable **supply**, **demand** or **price**. The black, solid line represents the average response, whereas the red lines display the 68% confidence intervals.

Acknowledgements

None of the lines of this thesis I could not have written without the support of numerous people, whom I would like to thank sincerely at this point.

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