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Nowcasting Inflation at Quantiles: Causality from Commodities

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Abstract

This paper proposes a non-parametric test for Granger causality in quantiles to detect causality from a high-frequency driver to a low-frequency target. In an economic application, we examine Granger causality between inflation, as a low-frequency macroeconomic variable, and a selection of commodity futures, including gold, oil, and corn, as high-frequency financial variables. We find that logarithmic returns on given commodity futures are a prima facie cause of inflation at the lower quantiles of the distribution and marginally around the median. In the context of a nowcasting exercise, we find that incorporating commodity futures in the model with a polynomial function enhances short-term forecasting accuracy, leveraging timely data for more precise nowcasting of inflationary trends. [1] [2] [3]

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1 Introduction

A burgeoning body of research accentuates the pivotal role of financial market indicators in shaping macroeconomic trajectories and in channeling shocks to the real economy. Leading contributions include the contribution by Claessens et al. (2012) emphasizing the interconnections between financial and business cycles, particularly highlighting the direct correspondence between recessions and financial upheavals. Additionally, the contribution by Jermann and Quadrini (2012) elucidates how events within the financial sector manifest as constrictions in firms' financing conditions, a key factor contributing to the 2008-2009 recession. Furthermore, the contribution by Tamakoshi and Hamori (2012) posits that energy commodity prices, due to their causal linkages, serve as significant informational indicators for the overall price levels. Moreover, the very recent contribution by Foroni et al. (2023) underscores the necessity of incorporating macroeconomic variables when forecasting electricity prices to enhance accuracy in short-term point and density estimations.

Consequently, the information encapsulated in financial data or disseminated through financial markets holds substantial significance for comprehending macroeconomic shifts. The different nature of financial and macroeconomic variables coupled with the mismatch in their sampling frequencies certainly lie at the core of this relevance. Indeed, while most macroeconomic variables have a backward-looking nature and are low frequency, financial indicators are often forward-looking and are available at a much higher frequency. Accordingly, evaluating the potential impact of fluctuations in financial variables on macroeconomic indicators could yield valuable insights for policymakers and investors. This is mostly the case since the majority of macroeconomic variables are available only after the end of the reference month or quarter, whereas financial data often offers a degree of foresight prior to the release of macroeconomic indicators.

The framework proposed by Granger (1969) stands as a renowned approach to examining causality between economic variables, extensively studied and applied in research. The majority of research results focused on evaluating Granger causality in the conditional mean with data sampled at the same frequency. Jeong et al. (2012) were among the first authors proposing a non-parametric Granger causality test in quantiles, allowing for non-linearities to be considered when evaluating causal relations between two time series. Their contribution has been particularly valuable since the conditional mean might pose interpretative challenges, especially when the involved variables exhibit fat-tailed and non-elliptical distributions — characteristics commonly observed in financial returns. Indeed, existing studies suggest that while Granger causality might exhibit significance in tail quantiles, it might not necessarily manifest in the mean (Lee and Yang, 2014). While similar works have been conducted, the robustness and flexibility of the results offered by Jeong et al. (2012) remain unparalleled. [4]

While Jeong et al. (2012)'s work marked an important step forward in evaluating Granger causality, the mismatch in sampling frequencies of different variables remained unaddressed. The paramount significance of preserving the inherent high-frequency nature of financial data is crucial for leveraging the comprehensive information embedded within. Indeed, as highlighted by Ferrara et al. (2022), aggregation mechanisms employed to ensure the same frequency are likely to lead to biased estimates unless the underlying data-generating process features a flat aggregation scheme from high to low frequencies. Notably, to the best of our current knowledge, no test of Granger causality in quantiles with mixed frequency data is available yet.

Building upon the methodology proposed by Jeong et al. (2012), we present an updated version of their test, adapting it to accommodate both high- and low-frequency data without necessitating aggregation procedures. To perform the Granger causality test in quantiles with mixed-frequency data, we need to estimate the polynomial weights that allow the high-frequency variable to be accurately collapsed into a low-frequency one; this step would allow placing the causality testing within the framework of Jeong et al. (2012). To this aim, we estimate a Quantile-MIDAS model, which, in a second step, also allows us to evaluate the magnitude of the relationship between a financial and a macroeconomic variable. The seminal work by Ghysels et al. (2004), followed by Ghysels et al. (2006) and Ghysels et al. (2007), first introduced the idea of regressions involving time series data sampled at different frequencies, specifying conditional expectations as a distributed lag of regressors recorded at higher sampling frequencies. While a limited number of authors among which Lei et al. (2019), Xu et al. (2021), Ferrara et al. (2022) and Yang et al. (2023) resorted to Quantile-MIDAS models in their empirical works, the literature on this model is still at a relatively early stage yet. Thus, our first contribution is on the methodological side, as we introduce a practical approach to

[4]Other prominent contributions include Hong et al. (2009), Troster (2018) and Song and Taamouti (2021).

detect Granger causality at quantiles and, as a bi-product, to measure the intensity of the causality.

We apply our mixed-frequency Granger causality test in quantiles and our Quantile-MIDAS model to investigate whether futures on commodities, including gold, crude oil, and corn do impact inflation, that is if futures on commodities can be early warning indicators of inflation. As a matter of fact, while commodity prices are often regarded as a relevant cause for inflation risk, how to practically model a formal link between commodity prices and inflation remains an unresolved question (Garratt and Petrella, 2022). We believe that our contribution is relevant in filling this gap and addressing this much-debated question. We find that logarithmic returns on commodity futures are a prima facie cause for inflation in the lower quantiles of the distribution and marginally around the median. Particularly, starting with the future contract on gold, we find that the effect is larger in the left tail than in the center of the inflation distribution. This means that when inflation is very low, (i.e. in the 5^{th} and 25^{th} quantile of the distribution), if returns on gold futures increase by 1%, inflation increases by 0.06 units and 0.11 units, respectively. The application to future contracts on oil yields similar results. In the 5^{th} and 25^{th} quantile of the inflation distribution, if returns on oil futures increase by 1%, inflation increases by 0.31 units and 0.24 units. While there is causality between futures on agricultural commodities and inflation, the magnitude of the relationship is rather small. We conclude that precious metals and energy commodities have the most prominent impact on inflation. As a further step, we conduct a nowcasting exercise to assess how well commodity futures predict future inflation compared to using solely the inflation series. We find that incorporating futures on commodities significantly improves the predictive performance of inflation forecasts. Particularly integrating the whole monthly history without resorting to an aggregation mechanism, that is using a MIDAS specification as opposed to a specification that merely considers the monthly average, returns more accurate forecasts. This integration enables a more precise understanding of short-term fluctuations in inflation by leveraging the timely and informative nature of commodity futures data, thereby contributing to more accurate nowcasting of inflationary trends.

The remainder of the paper is organized as follows. Section 2 illustrates our methodology, where Section 2.1 describes the estimation of our Quantile-MIDAS model, Section 2.2 presents the Granger causality test in quantiles with mixed frequency data, and Section 2.3 shows how to conduct inference between two time series sampled at different frequencies. Section 3 considers the causal relations and inference between inflation and futures on commodities, where Section 3.1 looks at future contracts on gold, Section 3.2 at contracts on oil, and 3.3 at contracts on corn and wheat, as an economic application. Section 4 concludes.

2 Methodology

Our methodology consists of three main steps. Before delving into detailed explanations for each, we offer a brief overview to provide context and enhance clarity.

Jeong et al. (2012) developed a non-parametric test of Granger causality in quantile for data sampled at the same frequency. Our proposed methodology aims to extend their test to accommodate mixed-frequency data, enabling the detection of causality from a high-frequency driver to a low-frequency target quantile. To this aim, we collapse the high-frequency variable to the same frequency as the target variable. In order to mitigate potential biases inherent in simple aggregation mechanisms, we utilize a procedure reminiscent of finite one-side polynomials typically found in a MIDAS specification. Specifically, we use a functional form with two parameters as suggested by Ghysels et al. (2005). Defining this polynomial function requires the parameters that link a high-frequency variable to a low-frequency target and drive its behavior. We derive these parameters, which we will denote as (θ_1, θ_2), through the estimation of a Quantile-MIDAS model, which enables us to gain reasonable insights into their potential values. We store a grid ranging from the minimum to the maximum of the estimated value of each parameter, and we utilize it for the subsequent analysis stages.

Upon retrieving the parameters allowing to collapse the high-frequency driver into the same frequency as the low-frequency target, we are finally able to extend the test by Jeong et al. (2012), accommodating the inclusion of mixed-frequency data. Once we have defined our test statistic, we compute it for every possible combination of (θ_1, θ_2) in the grid that we stored and mark which pair returns the maximum value of our test statistic.

Finally, building on the two previous steps, we are able to perform a causal inference. We estimate the Quantile-MIDAS model again, fixing the parameters of the polynomial function at those values that maximize our test statistic. In this way, we are able to infer the relationship between a low-frequency macroeconomic variable and a high-frequency financial variable. [5]

Figure 1 stylizes our outlined methodology placing it into three main steps. The first two steps concern the methodology to retrieve the test statistic, while the final step centers on conducting the causal inference.

In the following section, we go through each of these explained steps in detail.

2.1 Preliminary Quantile-MIDAS Estimation

The first preliminary step of our methodology encompasses retrieving the parameters of the polynomial function, which is needed to collapse the high-frequency variable to the same frequency as the low-frequency target. To ascertain the potential ranges for these parameters, we estimate a Quantile-MIDAS model. This ensures that the parameters are based on logical and sought-after values.

We start from the standard quantile regression first introduced by Koenker and Bassett (1978). Building on Ghysels et al. (2004) and Ghysels et al. (2007), we add a MIDAS component, represented by $\tilde{B}(c;\boldsymbol{\theta}(\tau))$ in Equation (1) below. This function serves to align high-frequency financial data with macroeconomic data frequency and our focus in this preliminary step lies in determining the parameters $\boldsymbol{\theta}(\tau)$ governing this function. Since we are considering time series, it is reasonable to incorporate some lags of the dependent macroeconomic variable y_t into our model specification. To select the best autoregressive structure for y_t, we resort to the pseudo-R-Squared approach for quantile regressions suggested by Koenker and Machado (1999). To this aim, we availed ourselves of the `quantreg` function in MATLAB for quantile regressions with bootstrapping confidence intervals and we modified it including the calculation of the Pseudo-R-Squared dropping the polynomial order in the original function and in the code accordingly. [6]

Our Quantile-MIDAS model has the following specification:

$$y_t = \beta_0(\tau) + \sum_{n=1}^{N}[\beta_1(\tau)y_{t-n} + \beta_2(\tau)|y_{t-n}|] + \beta_3(\tau)\sum_{c=0}^{C-1}\tilde{B}(c;\boldsymbol{\theta}(\tau))\Gamma^{c/m}w_t + \epsilon(\tau)_t \tag{1}$$

[5] The whole code has been written in MATLAB and will be made available

[6] Aslak Grinsted (2008). quantreg(x,y,tau,order,Nboot) (https://www.mathworks.com/matlabcentral/fileexchange/32115-quantreg-x-y-tau-order-nboot), MATLAB Central File Exchange. Retrieved January 24, 2023.

where τ indicates the quantile considered; y_t is the low-frequency macroeconomic variable and, accordingly, y_{t-n} its lagged value with n being the lags; $\tilde{B}(c; \boldsymbol{\theta}(\tau)$ is a weighting function normalized to sum up to 1 that depends on a vector of parameters $\boldsymbol{\theta}(\tau)$, and a lag order $c = 0, ..., C-1$ treating the high-frequency nature of w; w_t is the high-frequency financial explanatory variable; $\Gamma^{c/m}$ is the standard lag operator, with m being the number of high-frequency observation available in one low-frequency period; and $\epsilon(\tau)_t$ is the residual of the model.

To parsimoniously estimate the model in Equation (1), the lagged coefficients of $\tilde{B}(c; \boldsymbol{\theta}(\tau))$ needs to be parametrized. Otherwise, the number of lags of w_t would be quite large, and major drawbacks from the elevated number of parameters would arise (Breiman and Freedman, 1983). One of the more parsimonious fashions to parametrize the lags of $\tilde{B}(c; \boldsymbol{\theta}(\tau))$ are finite one-sided polynomials. In the distributed lag literature, the exponential Almon lag polynomial is one of the most common (Almon, 1965) since it has two important properties. Namely, it provides positive coefficients and it sums up to unity, which are both desirable properties for economic and financial applications. [7] Equation (2) defines the exponential Almon lag polynomial. Following Ghysels et al. (2005), we use a functional form with two parameters, that is $\theta = (\theta_1, \theta_2)$:

$$\tilde{B}(k; \theta(\tau)_1; \theta(\tau)_2) = \frac{e^{\theta(\tau)_1 k + \theta(\tau)_2 k^2}}{\sum_{k=1}^{K} e^{\theta(\tau)_1 k + \theta(\tau)_2 k^2}} \tag{2}$$

where k is an index tracking every high-frequency observation in one period, that is ranging from 1 to k, and (θ_1, θ_2) are the parameters to be estimated which differ for every quantile τ that one might consider. [8] Through the function in (2) we are able to significantly decrease the number of parameters to be estimated and therefore the model becomes parsimonious. In fact,the numbers of parameters to be estimated for the high-frequency variable of our model reduces to only two, that is the polynomial weights θ_1 and θ_2. The weighting function in Equation (2) yields a vector of weights with dimensions m x 1, with m being the number of high-frequency observations corresponding to one low-frequency observation. Multiplying the matrix of the high-frequency information times this vector of weights allows us to insert both components in our model, collapsing the high-frequency

[7] Another common finite one-sided polynomial is the Beta Lag polynomial. This function is though less used in the literature and therefore we stick to the Almon Lag.

[8] If low-frequency data are available monthly and high-frequency data daily, k=1:22, if we assume that there are 22 days in a month where information is available; if low-frequency data are available quarterly, k=1:60; etc.

variable to the same frequency of the low-frequency dependent variable.

At this point, having inserted in the model the MIDAS component, we can estimate the conditional quantiles. We proceed as suggested by Koenker and Hallock (2001) and minimize a sum of asymmetrical weighted absolute residuals, assigning different weights to negative and positive residuals. That is, positive residuals are multiplied by the quantile τ and negative residuals by $\tau - 1$. To obtain conditional quantiles we solve the optimization problem in Equation 3 replacing absolute values by $\rho_\tau(\cdot)$:

$$\min_{\beta \in \mathbb{R}^\rho} \sum \rho_\tau(y_i - \xi(x_i, \beta)) \tag{3}$$

where $\rho_\tau(\cdot)$ is the tilted absolute value function yielding the τth sample quantile as its solution and $\xi(x_i, \beta)$ is a parametric function.

2.2 Mixed-Frequency Granger Causality Test in Quantiles

In the first preliminary step of our methodology described in Section 2.1 we retrieved the possible ranges that the parameters governing the weights could take. At this point, we can move to the second step of our methodology which concerns performing the Granger causality test for mixed-frequency data in quantiles. This test is non-parametric, that is it depends on the aggregation weights, which we just estimated. Since the exact values are not known, we consider a values grid for the weights and we determine which combination of weights yields the maximum value of the test statistic at every quantile.

Following Jeong et al. (2012), a time series w_t does not Granger cause another time series y_t in the τth quantile as to $z_t =\{\ y_{t-1}, ..., y_{t-p}, w_{t-1}, ..., w_{t-q}\}$ if

$$Q_\tau(y_t|z_t) = Q_\tau(y_t|x_t) \tag{4}$$

On the contrary, w_t is a prima facie cause in the τth quantile if:

$$Q_\tau(y_t|z_t) \neq Q_\tau(y_t|x_t) \tag{5}$$

where $x_t = \{y_{t-1}, ..., y_{t-p}\}$ and $Q_\tau(y_t|\cdot)$ is the τth conditional quantile of y_t given $\cdot$. Accordingly, to establish causality, we need to test the following set of hypotheses:

$$H0 : P\{F_{y|z}(Q_\tau(x_t)|z_t) = \tau\} = 1 \tag{6}$$

$$H1 : P\{F_{y|z}(Q_\tau(x_t)|z_t) = \tau\} < 1 \tag{7}$$

The null hypothesis in Equation (6) is only true if $1\{y_t \leqslant Q_\tau(x_t)\} = \tau + \epsilon_t$, where $F_{y|z}(\cdot)$ is the conditional distribution function of y_t given $z_t(x_t)$ and $1(\cdot)$ is the indicator function.

While different distant measures exist to test this hypothesis, we follow Jeong et al. (2012) and consider $J \equiv E[\{F_{y|z}(Q_\tau(x_t)|z_t) - \tau)\}f_z(z_t)]$, where $f_z(z_t)$ is the marginal density function of z_t. Since $F_{y|z}(Q_\tau(x_t)|z_t) - \tau) = E(\epsilon_t|z_t)$, we can rewrite:

$$J = E\{\epsilon_t E(\epsilon_t|z_t) f_z(z_t)\} \tag{8}$$

J in Equation (8) above can be used to test the hypotheses in Equation (6) and (7) since it is strictly positive and the equality in Equation (8) holds if and only if the H0 in Equation (6) is true.

At this point, we estimate the density-weighted conditional expectation $E(\epsilon_t|z_t)f_z(z_t)$ with the kernel method:

$$\hat{E}(\epsilon_t|z_t)\hat{f}_z(z_t) = \frac{1}{(T-1)h^d} \sum_{s \neq t}^{T} K_{ts}\epsilon_s \tag{9}$$

where $d = p+q$ is the dimension of z; $K_{ts} = K\{\frac{(z_t - z_s)}{h}\}$ is the kernel function, and h is the bandwidth, which we optimally choose for x_t and derive for z_t accordingly. Replacing Equation (9) in Equation (8), we obtain the test-statistic:

$$\begin{aligned} J_T &= \frac{1}{T(T-1)h^d} \sum_{t=1}^{T} \sum_{s \neq t}^{T} K_{ts}\epsilon_t\epsilon_s \\ &= \frac{1}{T(T-1)h^d} \sum_{t=1}^{T} \sum_{s \neq t}^{T} K_{ts}[1\{y_t \leqslant Q_\tau(x_t)\} - \tau][1\{y_s \leqslant Q_\tau(x_s)\} - \tau] \end{aligned} \tag{10}$$

To have a feasible kernel based J_T, we can estimate $Q_\tau(x_s)$, the τth conditional quantile of y_s given x_s, using the nonparametric kernel method Jeong et al. (2012). Accordingly, the error ϵ is computed as $\hat{\epsilon}_t = I\{y_t \leqslant \hat{Q}_\tau(x_t)\} - \tau$ and replaced in Equation (10). [9]

Having defined the test statistic J_T, we now need to deal with the high-frequency nature of the financial variable w_t and insert it into the test. We start from the estimation of the Quantile-MIDAS model described in Section 2.1 and perform the estimation for every quantile $\tau \in [0.05 : 0.95]$ with a step of 0.05. This allows us to gain extensive insights into potential polynomial weights for the weighting function in Equation (2). This is particularly important since the test is rather sensible to the polynomial weights since they determine the value of the collapsed high-frequency variable. Deriving them from the Quantile-MIDAS estimation allows us to assign them based on some presumable knowledge and information. Considering the minimum and maximum value of the estimated polynomial weights, we define a range for (θ_1, θ_2) and we specify a value grid for every combination of both weights. [10] We consider each and every one of these combinations to collapse the high-frequency variable w_t, ending up with different possible versions of the collapsed w_t. We compute the test statistic J_T in Equation (10) for every version of the collapsed high-frequency variable and we store a matrix with the maximum value of J_T at every quantile τ. At this point, considering the standard critical value of 1.96 we check if the high-frequency variable causes the low-frequency variable at various quantiles.

2.3 Causal Inference

At this point, we can move to the third part of our methodology to finally infer about the relationship between a low-frequency macroeconomic variable and a high-frequency financial variable.

The procedure described in Section 2.1 allows us to estimate a Quantile-MIDAS model at various quantiles along with the respective polynomial weights. The Granger causality test in quantiles adapted to mixed-frequency data described in Section 2.2 allows us to establish a formal link between a macroeconomic low-frequency variable and a high-frequency financial variable, ascertaining if there is a causal relation between the two variables. This is a crucial step since establishing Granger causality justifies forecasting one variable based on another. The last step of our methodology aims

[9] Up to this point we replicated the code written by Jeong et al. (2012) in MATLAB. We successfully reproduced their code and their empirical application to confirm that our version of their code was correct and in line with their work. Minor modifications have been applied to smooth the code, but by and large, we remained faithful to their version. What comes next is our original contribution.

[10] In defining a value range, we consider a reasonable step ending up with approximately 300 combinations of (θ_1, θ_2)

at inferring the magnitude of the relationship between a low-frequency macroeconomic variable and a high-frequency financial variable. To do so, we estimate the Quantile-MIDAS model in Equation (1) again, fixing (θ_1, θ_2) to those value maximizing the test-static J_T at every quantile considered. First we extract the combinations of polynomial weights as follow:

$$J_T(w_t(\hat{\boldsymbol{\theta}})) = \max(J_T) \tag{11}$$

where J_T is the test statistic of Equation (10) computed at every $\tau \in [0.01 : 0.99]$; $\hat{\boldsymbol{\theta}}$ is the estimated combination of (θ_1, θ_2) that yields the maximum value of J_T; and w_t is the high-frequency variable. Then, we re-estimate the model in Equation (1) with these polynomial weights, thus estimating only the parameters related to the lagged values of the low-frequency dependent variable and the one applied to the explanatory high-frequency variable without its weights:

$$y_t = \beta_0(\tau) + \sum_{n=1}^{N}[\beta_1(\tau)y_{t-n} + \beta_2(\tau)|y_{t-n}|] + \beta_3(\tau)\sum_{c=0}^{C-1}\tilde{B}(c;\hat{\boldsymbol{\theta}}(\tau))\Gamma^{c/m}w_t + \epsilon(\tau)_t \tag{12}$$

In this way, we are able to quantify the relationship between these two variables at different quantiles, that is considering the whole distribution of the low-frequency dependent variable.

3 Empirical Analysis

Having defined how to model a formal link between a low-frequency macroeconomic variable and a high-frequency financial variable, we now apply our framework to a much-debated question in the literature. That is, do commodity prices contain helpful insights to predict inflation? Can commodity prices be regarded as early warning signals of inflation changes?

To answer these questions, we measured inflation as the monthly change in the Consumer Price Index (in short CPI) in percentage points. We considered the period ranging from September 2009 up until April 2022, hence covering a period of roughly 13 years. We downloaded it from FRED and considered the CPI for all urban consumers indexed for $1982 - 1984 = 100$. We used the seasonally adjusted version of this CPI index to remove the effects of seasonal change, including production cycles, weather, etc. [11] For a graphical representation of how it evolves over time, please refer to the line plot in Figure A in Appendix A Inflation will be our macroeconomic low-frequency variable since it is available once per month.

Instead, we use futures on commodities as our high-frequency variable. Indeed, various studies underscore that commodity price futures, compared to commodity spot prices, better reflect movements in inflation in the medium-long run and can be fully informative about future economic developments (Chinn and Coibion (2014), Gospodinov and Ng (2013), Hong and Yogo (2012) and Deschamps et al. (2021)). We downloaded a selection of future continuous contracts from Kibot and we picked one commodity for each main category. That is, we selected gold for the precious metals, crude oil for energy, and corn for agriculture. In light of the recent Ukrainian-Russia war and its repercussions on the economy, we decided to look at corn, alongside wheat as the main agriculture commodity, to rule out any bias coming from this extreme event.

Then, we calculated the logarithmic returns of each of the given commodities, and we relied on these figures for our analysis. We considered continuous contracts for every commodity. Similarly to inflation, we considered the period ranging from September 2009 to April 2022. Commodity future prices are available daily, thus we set $m = 21$, setting that there are 21 high-frequency observations for one low-frequency observation, namely for a monthly value of inflation.

The Pseudo-R Square suggests that the optimal autoregressive structure for inflation has two lags. Accordingly, we consider a Quantile-MIDAS model with two lags for all the applications. That is, we set $n = 2$ in Equation (1) and (12).

3.1 Inflation & Gold Futures Contracts

We begin our empirical analysis, by investigating the relationship between gold and inflation. Gold is one of the most important commodities, both for governments and private investors, with trading taking place 24 hours a day worldwide and daily transactions comprising billions of dollars occurring on a regular basis. Gold has historically been regarded as one of the most sage inflation hedge

[11] U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, January 29, 2023.

commodities, with its prices rising considerably at times of high inflation, such as those preceding the great financial crisis Dempster and Artigas (2010). Indeed, Junttila et al. (2018) have found that gold is among the commodities providing the safest hedge against economic and financial risks. Specifically, gold has proved to be a safe haven during periods when investors are wary of a recession or concerned about credit markets, target rate cuts, and uncertain about changing inflation rates, as highlighted by Tuysuz (2013), Baur and McDermott (2010). Accordingly, while gold as a commodity bears a monetary nature and is very sensitive to inflation and interest rate changes (Batten et al., 2014), a formal causal gold-inflation linkage has not been established yet. We believe that this is a relevant gap to fill, to be able to better hedge and foresee inflation.

Preliminary Quantile-MIDAS Estimation. Following our methodology in Section 2, we begin estimating the Quantile-MIDAS model in Equation 1. The estimation results in Table 1 suggests that $\theta_1 \in [-0.006; 0.2]$ and $\theta_2 \in [-0.008; 0.15]$. To obtain a reasonable range of values of polynomial weights, we select a step of 0.01 for both, thus considering 21x16=336 possible combinations of (θ_1, θ_2). These are reported in the first two columns of Table B1 in Appendix B

Mixed-Frequency Granger Causality Test in Quantiles. To establish if gold Granger causes inflation, we compute the test statistic J_T in Equation (10) at each and every one of these combinations and we extrapolate the maximum value of J_T at every quantile, collecting which combinations of (θ_1, θ_2) yield given values of J_T. These combinations are reported in Table 2. Table B1 in Appendix B reports all the values of J_T for every pairs of (θ_1, θ_2) in the range indicated above. Then, to evaluate the causal relation between Gold and Inflation throughout the whole distribution, we plot J_T at various quantiles. Figure 3 suggests that J_T exceeds the critical value 2.57 when $0 \leq \tau \leq 0.26$, $0.39 \leq \tau \leq 0.64$, and $0.84 \leq \tau \leq 0.97$. Therefore, we derive that returns on gold futures are a prima facie cause for inflation in these intervals and they are not in the remaining intervals. J_T indicates that causality is strongest in the left tail, suggesting that low returns impact inflation the most. Accordingly, looking at the results in Figure 3, we find that returns on gold futures have a significant predictive power for extreme changes in inflation. Therefore, we provide strong evidence justifying the usage of gold futures to hedge inflation movements. To rule out any concern arising

Table 1: Quantile-MIDAS Preliminary Analysis: Estimating Weights for Gold Returns Collapse

	Quantiles				
y_t: **Inflation**	*0.05*	*0.25*	*0.50*	*0.75*	*0.95*
β_0 : *intercept*	-0.263***	-0.032***	0.014***	0.093***	0.307***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$\beta_1 : y_{t-1}$	1.161***	0.404***	0.572***	0.546***	0.559***
	[0.000]	[0.000]	[0.000]	[0.004]	[0.000]
$\beta_2 : y_{t-2}$	-0.944***	-0.248***	0.227***	0.202***	0.312***
	[0.000]	[0.000]	[0.000]	[0.003]	[0.000]
$\beta_3 : \lvert y_{t-1}\rvert$	-0.217***	-0.198***	-0.335***	-0.204***	-0.176***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]
$\beta_4 : \lvert y_{t-2}\rvert$	0.567***	0.053***	0.289***	0.370***	0.073***
	[0.001]	[0.001]	[0.000]	[0.001]	[0.000]
β_5: Gold Log Returns	11.675***	3.711***	3.665***	3.783***	7.998***
	[0.000]	[0.001]	[0.008]	[0.008]	[0.000]
θ_1	0.045***	0.002***	0.004	0.002***	0.199***
	[0.000]	[0.001]	[0.065]	[0.000]	[0.000]
θ_2	0.017***	0.061***	0.132***	0.147***	-0.008***
	[0.001]	[0.000]	[0.002]	[0.001]	[0.000]
Pseudo R Squared	0.17	0.18	0.21	0.25	0.24
*Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*					

Note: This table displays the estimated conditional quantiles along the columns and the independent variables used in our model along the rows. Each cell contains the estimated coefficients, with their respective p-values presented in square brackets underneath. These p-values are to be interpreted using the significance codes provided in the table. The polynomial weights, which are pivotal at this stage, have been highlighted in grey.

Table 2: Table showing the maximum values of J_T at every quantile along with the combinations of (θ_1, θ_2)

$\boldsymbol{\tau}$	J_T	θ_1	θ_2
0.05	40.89	0.194	0.142
0.25	2.97	-0.006	0.002
0.50	4.90	0.194	0.012
0.75	1.36	-0.006	-0.008
0.95	6.45	-0.006	0.032

from simultaneously computing several inferences, we apply the Bonferroni correction. By setting the significance cut-off at $\frac{\alpha}{n}$, where α is the aggregated significance level and n is the number of tests performed, we compensate for the probability of running into a type I error with the confidence intervals being larger (Dunn, 1961).

Causal Inference. To investigate the relation between gold futures and inflation in a more precise way, we estimate the Quantile-MIDAS model again, fixing (θ_1, θ_2) at the values indicated in Table 2, which returns the results depicted in Table 3. Looking at the coefficient β_5, we conclude that

Table 3: Table showing Quantile-MIDAS regression results with fixed polynomial weights.

	Quantiles				
y_t**: Inflation**	*0.05*	*0.25*	*0.50*	*0.75*	*0.95*
β_0: intercept	-0.230*** [0.000]	-0.031*** [0.000]	0.022*** [0.000]	0.119*** [0.000]	0.349*** [0.000]
$\beta_1 : y_t - 1$	1.258*** [0.000]	0.552*** [0.000]	0.552*** [0.000]	0.416*** [0.004]	0.629*** [0.000]
$\beta_2 : y_t - 2$	-1.035*** [0.000]	0.074*** [0.000]	0.197*** [0.000]	0.323*** [0.003]	0.379*** [0.000]
$beta_3 : \lvert y_t - 1 \rvert$	-0.225*** [0.000]	-0.168*** [0.001]	-0.330*** [0.000]	-0.183*** [0.000]	-0.227*** [0.000]
$\beta_4 : \lvert y_t - 2 \rvert$	0.540*** [0.000]	0.101*** [0.001]	0.299*** [0.000]	0.295*** [0.001]	-0.043*** [0.000]
$\boldsymbol{\beta_5}$: **Gold Log Returns**	**6.833***** [0.000]	**10.739***** [0.001]	**3.920***** [0.001]	**0.064***** [0.001]	**−2.708***** [0.003]
Pseudo R Squared	0.27	0.17	0.22	0.25	0.27
*Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*					

Note: This table displays the estimated conditional quantiles along the columns and the independent variables used in our model along the rows. Each cell contains the estimated coefficients, with their respective p-values presented in square brackets underneath. These p-values are to be interpreted using the significance codes provided in the table. The coefficient of the MIDAS polynomial function is reported in bold, as it is the key element in this stage.

the impact of gold futures log returns on inflation is larger in the left tail than in the center of the inflation distribution and in the right tail. Accordingly, when inflation is very low, returns on gold futures have the highest positive impact on inflation, increasing it by 0.07 units in the 5^{th} quantile and by 0.11 units 25^{th}. In the upper quantile of the inflation distribution (i.e. at $\tau = 0.95$), the coefficient takes a negative sign. This means that if inflation is very high, log returns on gold futures decrease it by 0.03 units. Figure 4 below shows the estimated conditional quantiles against the actual data, attesting that our model captures the observations fairly well.

As a robustness check, we estimate an unrestricted Quantile-MIDAS model as well and our causality test accordingly. The estimation results and the test statistic across the whole distribution are reported in Appendix C2 in Table C2 and he results of the Granger causality quantiles at all quantiles is reported in Figure C1. The estimation results show that the significance is fading, with almost no coefficient being statistically different from zero. This is the case since, using this model specification, our time series become very short and there are too many parameters. In any case, the causality test is very similar to the one performed with the polynomial weights and confirm the results discussed above.

Significance of the Weighting Function. The combinations of weights that return the maximum value of test statistics across the distribution, indicated in Figure 3, assume the polynomial shape depicted in Figure 5. These plots suggest that in the tails and in the center of the distribution, the last days of the months matter the most in explaining variations in inflation.

To further investigate the pieces of information revealed by the graphs in Figure 5, we check if the underlying weighting function is significant at every quantile and how its significance evolves throughout the monthly time series. For the baseline case, we evaluate the significance of the Almong Lag polynomial function. To this aim, we resort to the δ-Method firstly introduced by Dorfman (1938) to approximate the variance of the weighting function and to ultimately evaluate the significance of the MIDAS expansion dictated by the Almon Lag polynomial.

We begin by computing the gradient of the weighting function relative to θ_1 and θ_2 analytically. Then, we compute the gradient at those values of θ_1 and θ_2 reported in Table 2, that is those we used for the causal inference. Next, we retrieve the variance-covariance matrix at every quantile from the estimation results in table 3 and we extract only the grids relative to the polynomial weights, that is (θ_1, θ_2). Finally, we approximate the standard error of the MIDAS expansion (i.e. of the Almon Lag polynomial as a weighting function) multiplying the gradient of the function at the (θ_1, θ_2) maximizing our test statistic, times the variance-covariance matrix, times the same gradient transposed. Results are reported in Figure 6 below. Interestingly, we can see that in the tails of the distribution, almost every day is important to predict inflation. Instead, at the center of the distribution, only the last days of the month are in fact relevant.

Nowcasting Inflation at Quantiles: Causality from Gold. To complete the analysis of the relationship between gold and inflation, we perform a nowcasting exercise following Adrian et al. (2019), Bańbura et al. (2013) and Giannone et al. (2008). We analyze and compare 3 different models, that is our Quantile-MIDAS model (QMIDAS), a Quantile model where the high-frequency part is simply collapsed to the average (QAVG), and a Quantile Autoregressive model with 2 lags (QAR(2)), which we refer to as the benchmark. For all them we consider 19 quantiles, ranging from 0.05 to 0.95, equally spaced with a step of 0.05. In line with the rest of our intuition, we take advantage of the high-frequency nature of returns on gold futures to produce real-time forecasts. Indeed, we use a one-step expanding window updating both the inflation information and the daily return on gold futures, meaning that for each monthly observation, we can produce 21 forecasts. Since we have 149 monthly inflation observations, we set the length of the in-sample period to 96 months, corresponding to observations until December 2017. Accordingly, the out-of-sample periods starts at January 2018, corresponding to the latest 53 months in the sample, thus ending in April 2022. For each of these 53 months, though, we have daily information regarding returns on gold futures, and accordingly, we are able to produce 21 forecast for each of these 53 months.

To begin our nowcasting analysis, we compare the three models with quantile scores. Results are reported in Table 4 below, where the different quantiles are detailed on the columns, and our three different models on the rows. For the full selection of quantiles, please refer to Table D1 in Appendix D. Table 4 also reports the outcome of the Diebold-Mariano test against the benchmark (the univariate and autoregressive model with two lags of inflation only) and the model confidence set at 5% with respect to all the models. These results show that both our model and the QAVG, that is the model with the average monthly return on gold futures, perform better than QAR(2). This implies that returns on gold futures are relevant when predicting inflation.

Table 4: Table showing quantile scores for different quantiles (on the columns) and for three different models (on the rows). ***, ** and * indicate that ratios are significantly different from 1 at 1%, 5% and 10%, according to the Diebold-Mariano test. The model in italic is our benchmark model.

τ	0.05	0.10	0.25	0.50	*0.75*	*0.90*	*0.95*
QAR(2)	*1.971*	*3.342*	*4.911*	*3.819*	*1.495*	*0.313*	*0.085*
QMIDAS	0.954***	0.964***	0.985***	0.971***	0.943***	0.981***	0.978***
QAVG	0.968***	0.988***	0.999***	0.995***	0.996***	0.982***	0.966***

To understand which one performs better, we look at the cumulative sum of the differences between the quantile scores of our model (QMIDAS) and the model with the average (QAVG) over the out-of-sample period. Results are plotted in Figure 7. For the sake of readability, we reported a selection of quantiles only. Please refer to Appendix D for the complete distribution. While both quantile scores are above 0, the blue line, hence the one corresponding to our QMIDAS model, is consistently above the red line, corresponding to the QAVG model. This indicates that our QMIDAS model is consistently outperforming the QAVG model over the out-of-sample period.

3.2 Inflation & Crude Oil Futures Contracts

As a second application, we look at another rather impactful commodity, that is crude oil. Various studies highlight that oil prices move along with a country's economic growth and that they mirror a country's economic conditions (Darby (1982) and Kilian and Vigfusson (2017)). Indeed, under ordinary times, as the economy grows, so does the demand for oil, and when a country is in a recession or is under distress, oil prices are likely to shrink, as happened after the global crisis in 2020 and the subsequent lockdowns in fairly every country worldwide. More recently, the growing tensions between Russia and Ukraine, and the rest of the world are fomenting fears about a crude oil supply shortage. In turn, these events considerably contribute to rising inflation, among other important economic indicators. Indeed, some works have highlighted that crude oil price fluctuations are a major driver of inflation variability, but there is a strong asymmetric relationship between crude oil prices and inflation, both for oil-importing and -exporting countries (Chen (2009), Raheem et al. (2020) and Álvarez et al. (2011)). We gather that while it is clear that this relationship exist and has crucial relevance, a formal link between the two variables hasn't been established yet. With this application, we aim to fill this gap and shed light onto this important, yet still rather fuzzy relation.

Preliminary Quantile-MIDAS Estimation Similarly to the previous section, we begin our empirical analysis by estimating our Quantile-MIDAS model in Equation 1. Estimations results are reported in Table 5 and suggest that $\theta_1 \in [-0.1; 0.25]$ and $\theta_2 \in [-0.006; 0.02]$, where each value represent the minimum and maximum value that resulted statistically significant in the estimation. To obtain a reasonable value grid of polynomial weights we select a step of 0.02 for θ_1 and of 0.002 θ_2, ending up with 18x14=252 combinations. These are reported in the first two columns of Table B2 in Appendix B

Mixed-Frequency Granger Causality Test in Quantiles At this point, to establish a formal link between crude oil and inflation, that is to investigate whether crude oil prices Granger cause inflation, we compute the test statistic J_T in Equation (10) at various quantiles. We extrapolate the maximum value of J_T at every quantile considered and we mark which combination of polynomial weights return given values of J_T. We report them in Table 6. Table B2 in Appendix B reports all the values of J_T for every pairs of (θ_1, θ_2) in the range indicated above. In Figure 8 we show how

Table 5: Quantile-MIDAS Preliminary Analysis: Estimating Weights for Crude Oil Returns Collapse

	Quantiles				
y_t: **Inflation**	*0.05*	*0.25*	*0.50*	*0.75*	*0.95*
β_0: Intercept	-0.208 [9.815]	0.008*** [0.000]	0.062*** [0.000]	0.117*** [0.000]	0.281*** [0.000]
$\beta_1 : y_t - 1$	0.929 [21987]	0.645*** [0.000]	0.387*** [0.000]	0.355*** [0.000]	0.283*** [0.000]
$\beta_2 : y_t - 2$	-0.305 [30401]	-0.073*** [0.001]	0.232*** [0.000]	0.384*** [0.000]	0.372*** [0.000]
$\beta_3 : \lvert y_t - 1\rvert$	-0.282 [44220]	-0.046** [0.015]	0.002*** [0.000]	-0.067*** [0.000]	0.145*** [0.000]
$\beta_4 : \lvert y_t - 2\rvert$	0.091 [48460]	-0.108*** [0.015]	-0.021*** [0.000]	0.113*** [0.001]	-0.070*** [0.000]
β_5: Crude Oil Log Returns	19.786 [68161]	25.506*** [0.024]	19.978*** [0.008]	21.533*** [0.000]	19.272*** [0.003]
θ_1	-0.195 [107.43]	0.104*** [0.000]	0.074 [0.065]	-0.022*** [0.000]	0.232*** [0.000]
θ_2	0.014*** [0.001]	-0.001*** [0.000]	-0.003*** [0.002]	0.02*** [0.000]	-0.006*** [0.000]
Pseudo R Squared	0.30	0.29	0.29	0.34	0.43
Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'					

Note: This table displays the estimated conditional quantiles along the columns and the independent variables used in our model along the rows. Each cell contains the estimated coefficients, with their respective p-values presented in square brackets underneath. These p-values are to be interpreted using the significance codes provided in the table. The polynomial weights, which are pivotal at this stage, have been highlighted in grey.

Granger causality between crude oil prices and inflation evolves throughout the whole distribution. We can see that the test statistic J_T is always above the critical value 2.57, hence indicating that crude oil prices are a prima facie cause for inflation at any price level. J_T only drops below 2.57 at the very end of the distribution (i.e. at $\tau = 0.96$), hence indicating that extremely high returns on crude oil futures do not Granger cause inflation to abruptly change. Consequently, returns on crude oil futures have significant predictive power for extreme, as well as non-extreme, movements in inflation and could reliably be used as hedging instruments against inflation. As a robustness, similar to the gold application, we applied the Bonferroni correction to rule out concerns arising from multiple testing.

Causal Inference. Then, to further investigate the relationship between log returns on crude oil futures and inflation, we estimate our Quantile-MIDAS model again fixing (θ_1, θ_2) at the values

Table 6: Table showing the maximum values of J_T at every quantile along with the combinations of (θ_1, θ_2)

τ	J_T	θ_1	θ_2
0.05	45.79	0.10	-0.006
0.25	5.99	0.04	-0.002
0.50	8.82	-0.10	0.004
0.75	2.94	0.20	0.018
0.95	10.65	0.22	0.018

indicated in Table 6. Table 7 reports the estimation of our Quantile-MIDAS model with fixed polynomial weights. The coefficient β_5 relative to Crude Oil Log Returns takes a positive sign throughout the whole distribution and is significant at every quantile considered. We can notice that, while it remains rather large at any inflation status, it takes on more sizable values in the left tail of the distribution, the magnitude of which then gradually decreases as the right tail is approached. This is in line with the causality test depicted in Figure 8, where it appeared that the causal relation was strongest on the left tail, that is up until $\tau = 0.20$, while it was weaker, yet still present, in the rest of the distribution. It follows that, when inflation is very low, log returns on crude oil futures, do have the biggest impact on inflation, increasing it by 0.32 units at $\tau = 0.05$ and by 0.24 units at $\tau = 0.25$. The effect is still fairly large around the median, where if crude oil futures increase by 1%, inflation increases by 0.18 units. Toward the end of the distribution, the effect shrinks but is still significant and positive. At $\tau = 0.75$, inflation increases by 0.05 units if crude oil futures increase by 1%, whereas at $\tau = 0.95$, by 0.06 units. In short, we gather that at times of low inflation, crude oil futures are powerful instruments to foresee how inflation will move in the future.

To have a graphical intuition of our model fit, we plot the conditional quantiles of our estimated model, against the actual data. The model captures the actual data (the blue dots) pretty well. Moreover, we observe that conditional quantiles do not cross, implying that the conditional quantile function satisfied the imposed monotonicity constraint.

Similarly to the section above, as robustness, we estimate an unrestricted Quantile-MIDAS model as well and perform our mixed-frequency Granger causality test accordingly. Results hold. Please consult Appendix C.2 for the estimation and test results. The same reasoning explained in the previous sub-section applies.

Table 7: Table showing Quantile-MIDAS regression results with fixed polynomial weights.

	Quantiles				
y_t: **Inflation**	*0.05*	*0.25*	*0.50*	*0.75*	*0.95*
β_0: intercept	-0.116*** [0.000]	0.012*** [0.000]	0.054*** [0.005]	0.173*** [0.000]	0.318*** [0.000]
$\beta_1 : y_t - 1$	0.354*** [0.000]	0.661*** [0.001]	0.330 [0.280]	0.494*** [0.000]	0.709*** [0.000]
$\beta_2 : y_t - 2$	-0.258*** [0.000]	-0.143*** [0.001]	0.266 [0.283]	0.164*** [0.000]	0.299*** [0.000]
$\beta_3 : \|y_t - 1\|$	-0.102*** [0.000]	0.009*** [0.001]	0.037 [0.286]	-0.119*** [0.001]	-0.123*** [0.000]
$\beta_4 : \|yt - 2\|$	0.080*** [0.000]	-0.064*** [0.001]	0.008 [0.283]	0.095*** [0.000]	-0.121*** [0.000]
$\boldsymbol{\beta_5}$: **Crude Oil Log Returns**	**31.979***** [0.000]	**24.428***** [0.001]	**18.457***** [0.001]	**5.531***** [0.000]	**6.423***** [0.000]
Pseudo R Squared	0.29	0.23	0.25	0.32	0.42
Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'					

Note: This table displays the estimated conditional quantiles along the columns and the independent variables used in our model along the rows. Each cell contains the estimated coefficients, with their respective p-values presented in square brackets underneath. These p-values are to be interpreted using the significance codes provided in the table. The coefficient of the MIDAS polynomial function is reported in bold, as it is the key element in this stage.

Significance of the Weighting Function. Figure 10 plots the exponential Almon lag polynomial function of Equation (2) using given polynomial weights as inputs. This function takes a concave shape in the left tail of the distribution (i.e. at $\tau = 0.05$ and $\tau = 0.25$), and a convex shape around the median, suggesting that in times of low inflation, the first 10 days have more predictive power than the last 11 days, whereas at $\tau = 0.5$, the first and the last 5 days of the month are those that matter the most. Instead, when inflation is very high (i.e. at $\tau = 0.75$ and $\tau = 0.95$), the last 5 days of the month are those with the largest predictive power.

Similar to the previous section, we evaluate the significance of the MIDAS expansion according to the Almon Lag Polynomial specification. As shown in the plots in Figure 11, when evaluating the relevance of crude oil in predicting inflation, throughout nearly the whole distribution, every day of the month is relevant.

Nowcasting Inflation at Quantiles: Causality from Crude Oil. As a last step of our empirical analysis on crude oil, we perform the nowcasting exercise explained in the previous Subsection 3.1.

We compare our model (QMIDAS) and an average model (QAVG) model against the benchmark of the AR(2) model for inflation using quantile scores. A snapshot of results is reported in Table 8; for the whole selection of quantiles, please refer to Table D2. Results show that both models perform significantly better than the benchmark at all quantiles, suggesting that when predicting inflation, returns on crude oil futures are indeed relevant.

Table 8: Table showing quantile scores for different quantiles (on the columns) and for three different models (on the rows). ***, ** and * indicate that ratios are significantly different from 1 at 1%, 5% and 10%, according to the Diebold-Mariano test. The model in italic is our benchmark model.

τ	0.05	0.10	0.25	0.50	*0.75*	*0.90*	*0.95*
QAR(2)	*1.971*	*3.342*	*4.911*	*3.819*	*1.495*	*0.313*	*0.085*
QMIDAS	0.799***	0.861***	0.892***	0.864***	0.887***	0.910***	0.891***
QAVG	0.815***	0.827***	0.847***	0.866***	0.891***	0.936***	0.955***

To understand which model perform better, we look at the cumulative sum of the differences between the quantile scores of our model and the QAVG model. Results are shown in Figure 12. While there aren't significant differences in the performance of the two models in the center and in the left tail of the distribution, in the most right tail of the distribution, our model performs better than the QAVG model.

3.3 Inflation & Corn Future Contracts

Table 9: Quantile-MIDAS Preliminary Analysis: Estimating Weights for Crude Oil Collapse

	Quantiles				
y_t: **Inflation**	*0.05*	*0.25*	*0.50*	*0.75*	*0.95*
β_0: intercept	-0.149*** [0.000]	-0.010*** [0.000]	0.018*** [0.000]	0.119*** [0.000]	0.317*** [0.000]
$\beta_1 : y_t - 1$	1.195*** [0.000]	0.507*** [0.001]	0.569*** [0.000]	0.417*** [0.000]	0.565*** [0.000]
$\beta_2 : y_t - 2$	-0.816*** [0.000]	0.169*** [0.001]	0.221*** [0.000]	0.324*** [0.000]	0.388*** [0.000]
$\beta_3 : \lvert y_t - 1\rvert$	-0.247*** [0.000]	-0.176** [0.000]	-0.336*** [0.000]	-0.183*** [0.000]	-0.204*** [0.000]
$\beta_4 : \lvert y_t - 2\rvert$	0.259*** [0.000]	-0.044*** [0.000]	0.286*** [0.000]	0.295*** [0.000]	0.030** [0.000]
β_5: Crude Oil Log Returns	0.118*** [68161]	1.177*** [0.001]	0.017*** [0.000]	0.040*** [0.000]	0.045*** [0.003]
θ_1	0.000 [0.001]	0.222*** [0.000]	0.003*** [0.000]	0.004*** [0.000]	0.016*** [0.000]
θ_2	0.022*** [0.000]	-0.008*** [0.000]	0.125*** [0.000]	0.140*** [0.000]	0.012*** [0.000]
Pseudo R Squared	0.14	0.17	0.21	0.25	0.18
Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'					

Note: This table displays the estimated conditional quantiles along the columns and the independent variables used in our model along the rows. Each cell contains the estimated coefficients, with their respective p-values presented in square brackets underneath. These p-values are to be interpreted using the significance codes provided in the table. The polynomial weights, which are pivotal at this stage, have been highlighted in grey.

For the last empirical application, we look at two main food commodities, namely corn and wheat future contracts. While corn is the most produced and consumed crop worldwide with nearly 1.1 billion tons harvested every year, wheat comes near, especially in the region of Europe and Central Asia, as opposed to the U.S., with nearly 800 million tons produced yearly. Since the market for wheat endured major disruptions following the Russia-Ukraine war, we decided to focus on corn for our empirical application. There is a general consensus that food commodity prices are relevant to predict inflation and, more generally, that they could be powerful instruments to foresee economic trends. In fact, some countries are predominantly driven by the exports of essential crops, such as corn, wheat, soybean and, accordingly, changes in the market and prices for these commodities would yield a major impact on the underlying economy and especially inflation. Nevertheless, very few studies have focused on establishing a formal link between inflation and food commodities. Cecchetti and Moessner (2008) suggested that suggests that rising food commodity prices have generally not spawned strong second-round effects on inflation. Furceri et al. (2016) showed that global food price shocks have a great impact on domestic inflation in a large group of countries, increasing it on average by 0.5 percentage points after a year. Peersman (2022) corroborated these results and found that exogenous shifts in food prices indirectly trigger inflationary effects via rising wages and that they explain almost 30% of the euro-area inflation volatility. None of these studies, though, approached the issue dealing with the mismatch in the frequency of inflation and commodity prices. We aim to fill this gap and establish a formal link between preserving the original frequency to obtain real-time indications about inflation starting from futures on food commodities.

Quanile-MIDAS Estimation. Similarly to the previous sections, we begin estimating our Quantile-MIDAS model of Equation (1). The estimation results are reported in Table 9 and suggest that $\theta_1 \in [-0.07; 0.32]$ and $\theta_2 \in [-0.18; 0.14]$, where each value represent the minimum, and maximum value that proved to be statistically significant. To obtain a value grid out of these boundary values, we selected a step of 0.03 for both θ_1 and θ_2, for a total of 14x11=154 combinations. These are reported in the first two columns of Table B3 in Appendix B

Mixed-Frequency Granger Causality Test in Quantiles. At this point, having gained insights into the polynomial weights (θ_1, θ_2), we can proceed with the Granger causality test. We compute the test statistic J_T in Equation (10) for every combination and at various quantiles. We extrapolate the maximum value of the test statistic at every quantile considered and we mark which combination of $(\theta_1; \theta_2)$ return given values of J_T. We report them in Table 10. Table B3 in Appendix B reports all the values of J_T for every pairs of (θ_1, θ_2) in the range indicated above. Figure 13 shows how Granger causality between futures on corn and inflation evolves across the whole distribution. J_T is beyond the critical value 2.57 when $0 \leq \tau \leq 0.27$, $0.38 \leq \tau \leq 0.64$, $0.79 \leq \tau \leq 0.96$. Therefore, e gather that returns on corn futures are a prima facie cause for inflation in these intervals, whilw they are not when $0.28 \leq \tau \leq 0.37$ and $0.80 \leq \tau \leq 0.95$, and at th last three percentiles of the distribution. Figure 13 suggests that causality is stronger in the left tail, rather than in the center of the

Table 10: Table showing the maximum values of J_T at every quantile along with the combinations of (θ_1, θ_2)

τ	J_T	θ_1	θ_2
0.05	65.36	0.32	0.12
0.25	3.82	0.29	0.12
0.50	5.49	0.32	0.03
0.75	0.61	0.32	0
0.95	9.96	-0.04	0

distribution since the value of J_T peaks at the lower quantiles and slowly decreases at the end of the distribution. Thus, low returns on corn futures cause inflation to abruptly change. More generally, returns on corn futures have significant predictive power for extreme, as well as non-extreme changes in inflation and could be used as hedging instruments against inflation. As a robustness, similar to the gold application, we applied the Bonferroni correction to rule out concerns arising from multiple testing.

Table 11: Table showing Quantile-MIDAS regression results with fixed polynomial weights.

	Quantiles				
y_t: **Inflation**	*0.05*	*0.25*	*0.50*	*0.75*	*0.95*
β_0: intercept	-0.157*** [0.000]	-0.022*** [0.000]	0.019*** [0.000]	0.105*** [0.000]	0.320*** [0.000]
$\beta_1 : y_t - 1$	1.173 [8713]	0.517 [1321]	0.573*** [0.000]	0.384*** [0.000]	0.686*** [0.000]
$\beta_2 : y_t - 2$	-0.856 [8713]	0.118 [1321]	0.225*** [0.000]	0.332*** [0.000]	0.394*** [0.000]
$beta_3 : \|y_t - 1\|$	-0.213*** [0.000]	-0.175*** [0.002]	-0.339*** [0.000]	-0.151*** [0.000]	-0.230*** [0.000]
$\beta_4 : \|y_t - 2\|$	0.332*** [0.000]	0.033*** [0.002]	0.282*** [0.000]	0.327*** [0.000]	0.010*** [0.000]
$\boldsymbol{\beta_5}$: **Corn Log Returns**	**0.055***** [0.000]	**0.275***** [0.000]	**0.022***** [0.000]	**0.176***** [0.000]	**-0.405***** [0.000]
Pseudo R Squared	0.12	0.17	0.21	0.25	0.29
Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'					

Note: This table displays the estimated conditional quantiles along the columns and the independent variables used in our model along the rows. Each cell contains the estimated coefficients, with their respective p-values presented in square brackets underneath. These p-values are to be interpreted using the significance codes provided in the table. The coefficient of the MIDAS polynomial function is reported in bold, as it is the key element in this stage.

Causal Inference. Having established that there is indeed causality, namely that returns on corn futures Granger cause inflation at various quantiles, we now examine this linkage in more depth. To this aim, we estimate our Quantile-MIDAS model of Equation (12) fixing (θ_1, θ_2) at the values reported in Table 10. Table 11 reports the estimation result of our Quantile-MIDAS model with fixed polynomial weights. The coefficient β_5 relative to Corn log returns is significant throughout the whole distribution. It always returns a positive sign, except on the left tail (i.e. at $\tau = 0.95$), where the coefficient is negative. Compared to the other two commodities considered, that is gold and crude oil, the relationship between inflation and corn futures is weaker. Indeed, in Table 11, we can observe that the coefficients on corn log returns are rather small, yet strongly significant. Accordingly, while futures on corn Granger cause inflation to change as shown in Figure 13, the impact that the former has on the latter is minor. Indeed, when inflation is low (i.e. at $\tau = 0.05$ and $\tau = 0.25$), if log returns on corn futures increase by 1%, inflation increases by 0.0005 units and 0.003 units respectively. When inflation lies at a median level (i.e. at $\tau = 0.5$), a 1% increase in corn futures returns leads to a 0.0002 units increase in inflation. When inflation is rather high (i.e. at $\tau = 0.75$), a 1% increase in corn futures leads to a 0.002 units increase in inflation. Instead, if inflation is very high (i.e. at $\tau = 0.95$), a 1% increase in corn futures returns will bring down inflation by 0.004 units. We conclude that while food commodities can relate about inflation movements, gold and crude oil are more powerful and leads to larger changes in inflation.

To have a graphical intuition of our model fit, in Figure 14 we plot the conditional quantiles of our estimated model, against the actual data. The model captures the actual data (the blue dots) pretty well. We observe that conditional quantiles do not cross, implying that the conditional quantile function satisfied the imposed monotonicity constraint.

As a robustness check, we estimate an unrestricted Quantile-MIDAS model as well and our causality test accordingly. Please refer to Appendix C.3 for the estimation results in Table C3 and the test statistic development throughout the whole distribution in Figure C6.

Significance of the Weighting Function. Figure 15 plots the exponential Almon lag polynomial function in Equation 2 using as input the combinations of (θ_1, θ_2) that maximize J_T, that is those reported in Table 10. This function is increasing up until $\tau = 0.75$ and decreasing at $\tau = 0.95$. These shapes suggest that when inflation is very low and when it lies around the median value, it at

$\tau = 0.05$ through $\tau = 0.75$, the last 5 days of the month entail the largest predictive power, compared to the first days. At $\tau = 0.95$, that is at left tail of the distribution, the function becomes decreasing, suggesting that the first days of the month matter the most to foresee inflation, while as the end of the month approaches, information becomes gradually less insightful.

To better understand this trend, we evaluate the significance of the MIDAS expansion function, that is of the Almon Lag Polynomial for our baseline case. The plots in Figure 16 show that around the median and at $\tau = 0.75$, only the last day of the month (i.e. $m = 21$), is relevant to predict inflation. Nevertheless, when the left tail of the distribution is considered, as well as $\tau = 0.95$, every day in the month is statistically significant. This result predominantly demonstrates the importance of analyzing the whole distribution and a MIDAS specification when trying to evaluate the relationship between a macroeconomic and a financial variable such as inflation and returns on commodities.

Table 12: Table showing quantile scores for different quantiles (on the columns) and for three different models (on the rows). ***, ** and * indicate that ratios are significantly different from 1 at 1%, 5% and 10%, according to the Diebold-Mariano test. The model in italic is our benchmark model.

τ	0.05	0.10	0.25	0.50	*0.75*	*0.90*	*0.95*
QAR(2)	*1.971*	*3.342*	*4.911*	*3.819*	*1.495*	*0.313*	*0.085*
QMIDAS	0.961***	0.960***	0.973***	0.992***	0.978***	0.981***	0.943***
QAVG	0.903***	0.923***	0.961***	0.996***	0.999***	0.986***	0.987***

Nowcasting Inflation at Quantiles: Causality from Corn. As a last step of our empirical analysis on corn, we perform a nowcasting exercise as discussed and described in the previous subsections. We compare our model (QMIDAS) and the QAVG model against the usual benchmark of AR(2) for inflation with compare quantile scores. A snapshot of results is reported in Table 12, while the full selection of quantiles is reported in Table D3 in Appendix D. It shows that both QMIDAS and QAVG are significantly better then the benchmark across the whole distribution, suggesting that, once again, returns on corn futures are relevant to predict inflationary trends. To understand which model specification works better, we plot the cumulative sum of the differences between the quantile scores of our model and the QAVG model. Results are displayed in Figure 17. We conclude that at the center of the distribution and up until $\tau = 0.75$, our model performs better. Nevertheless, in the left tail of the distribution QAVG performs better. Instead, at the utmost right tail, the two models perform equally accurately.

4 Concluding Remarks

By extending the nonparametric causality test in quantiles initially proposed by Jeong et al. (2012), we introduce a modified version of this test capable of accommodating mixed-frequency data. The appealing feature of our test statistic lies in its ability to explore Granger causality between two variables sampled at different frequencies across various conditional quantiles.

We estimate the polynomial weights to accurately collapse the high-frequency variable into a low-frequency one via a Quantile-MIDAS model, hence placing the causality testing within the framework of Jeong et al. (2012). We then use the so-estimated weights to evaluate the magnitude of the relationship between two mixed-frequency variables. Our first contribution is thus on the methodological side, as we introduce a practical approach to detect Granger causality at quantiles, and as a bi-product, to measure the intensity of the causality.

We then apply our proposed methodology to investigate Granger causality between inflation and returns on futures on commodities, that is gold, crude oil, and corn continuous contracts. We find that logarithmic returns on commodity futures are a prima facie cause for inflation in the lower quantiles of the distribution and marginally around the median. Particularly, starting with the future contract on gold, we find that the effect is larger in the left tail than in the center of the inflation distribution. This means that when inflation is very low (i.e. in the 5^{th}) and 25^{th} quantile of the distribution, if returns on gold futures increase by 1%, inflation increases by 0.06 units and 0.11 units, respectively. The application to future contracts on oil yields similar results. In the 5^{th} and 25^{th} quantile of the inflation distribution, if returns on oil futures increase by 1%, inflation increases by 0.31 units and 0.24 units. While there is causality between futures on agricultural commodities and inflation, the magnitude of the relationship is rather small. We conclude that precious metals and energy commodities have the most prominent impact on inflation.

Our proposed framework can be favorably used by investors and policymakers to anticipate inflation movements through the lens of financial market perception and, as an example, through futures on commodities. This is particularly relevant since financial data are available at a very high frequency and the information they entail could offer a head start on inflation movements, which would otherwise be known only after the end of the month or quarter.

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Figures

Figure 1: Stylized methodology

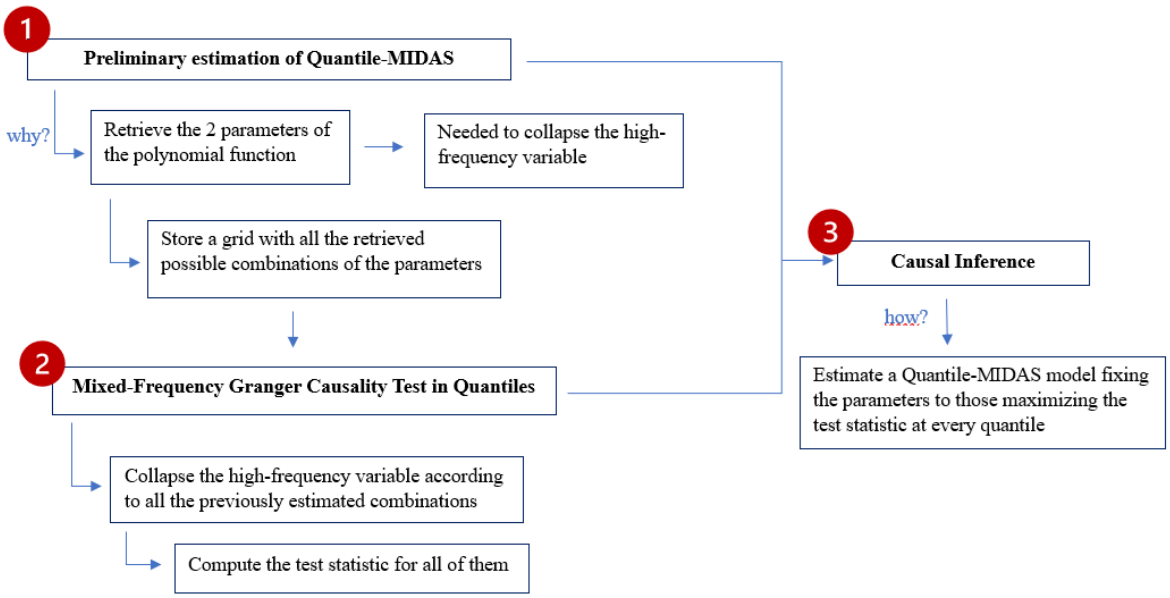


Figure 2: Plot of the daily gold (solid blue line), crude oil (dash-dotted orange line), corn (dotted green line), and wheat (dashed purple line) prices from 2009 to 2022

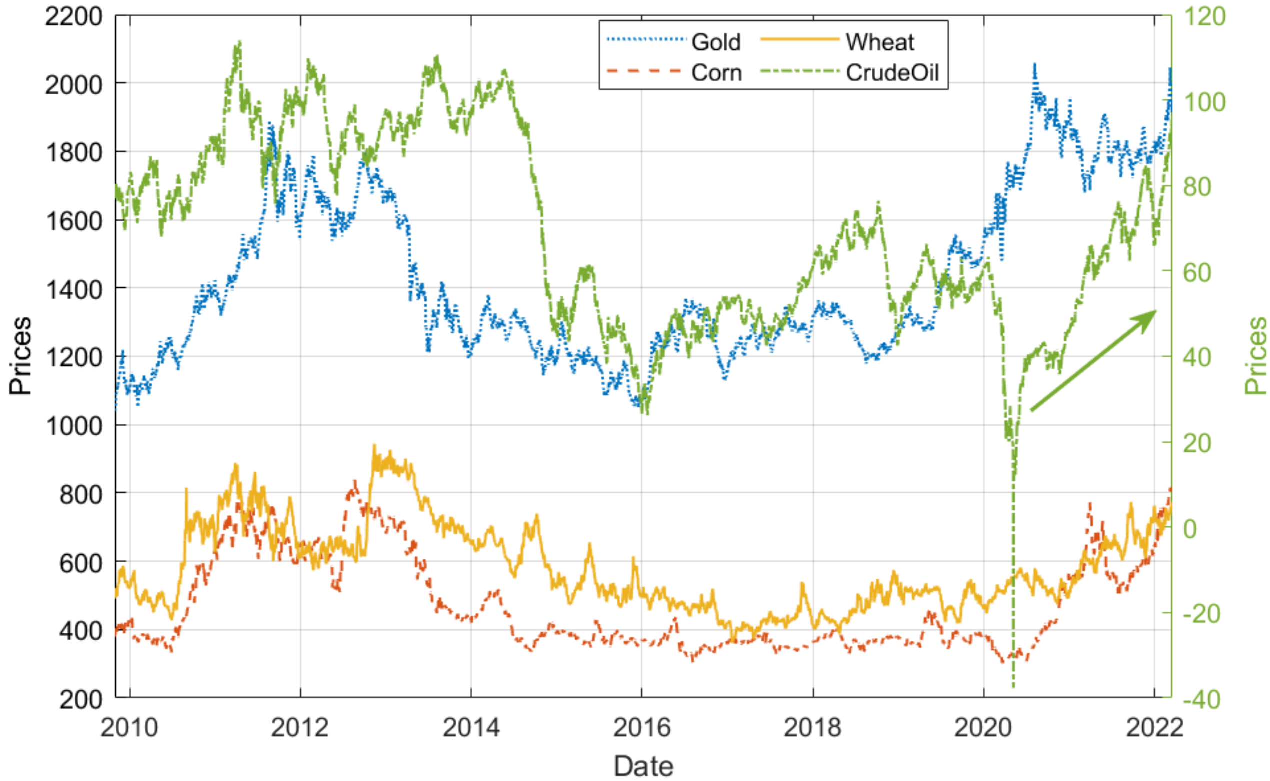


Figure 3: Test statistic J_T with respect to various quantiles. The blue solid line represents the test statistic based on the Almon Lag polynomial. The red dashed line marks the aggregated critical value at $\alpha = 0.01$ and the associated standard normal critical value of 2.57. The green dotted line marks the significance level increased as per the Bonferroni correction (i.e. at $\alpha = 0.00003$ and an associated critical value of 3.98).

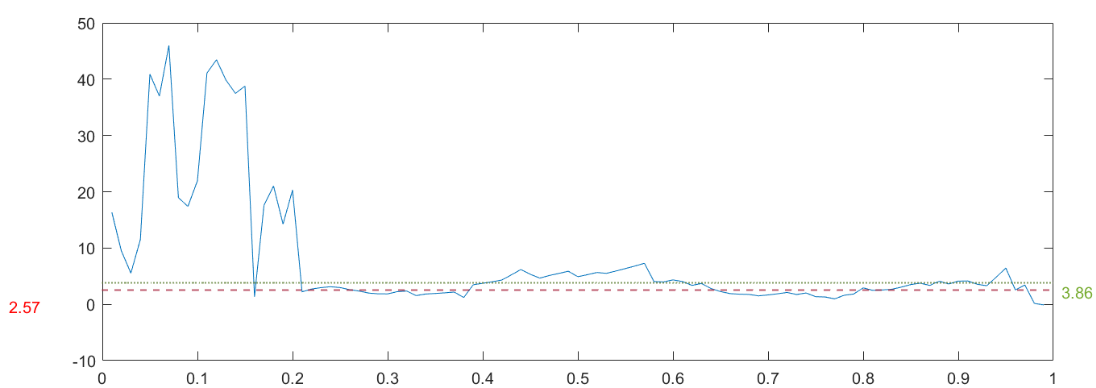


Figure 4: Conditional Quantiles and actual data.

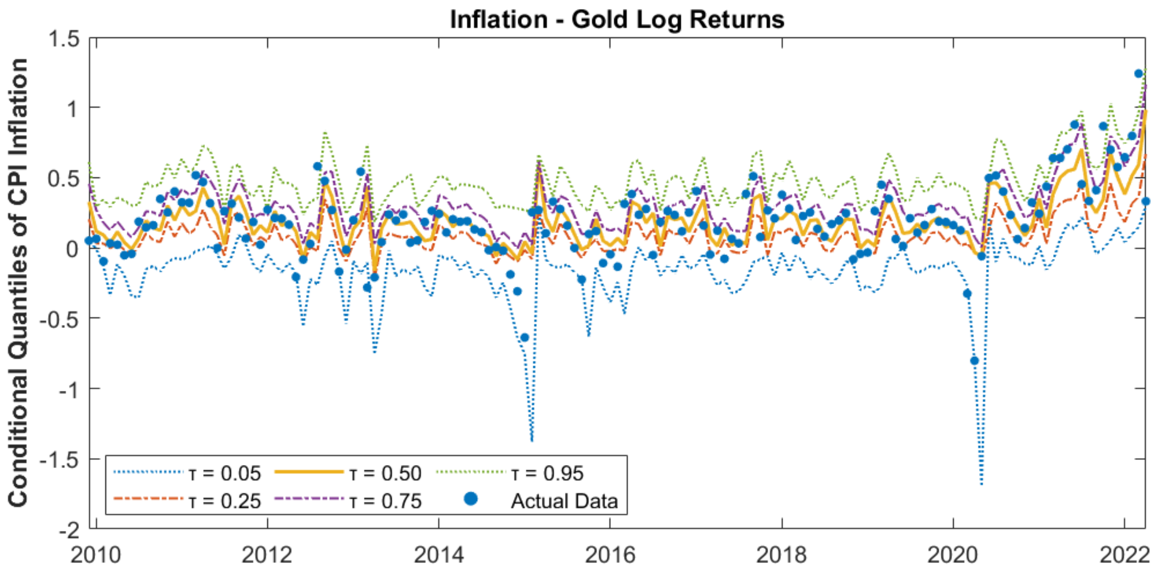


Figure 5: Almon Polynomial Shape for the combination of (θ_1, θ_2) that maximize J_T at various quantiles τ indicated above each plot.

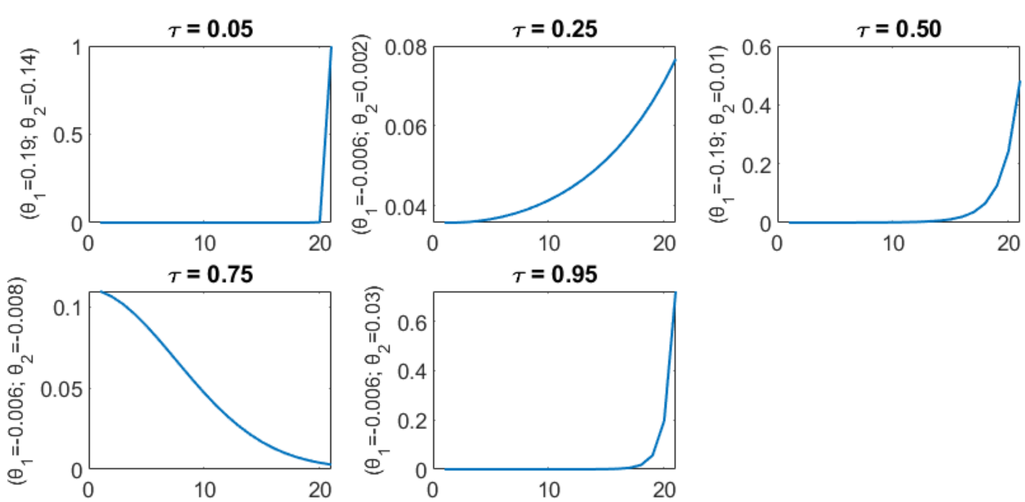


Figure 6: These plots show the significance of the Almon Lag Polynomial as a weighting function for the MIDAS component at different quantiles. The y-axis reports the z-scores and the x-axis each day m in a month. The blue squares indicate the z-scores within the $[-1.96, 1.96]$ range, that is the non-significant days. The green dots indicate the z-scores that are above or below the confidence interval, that is the significant days.

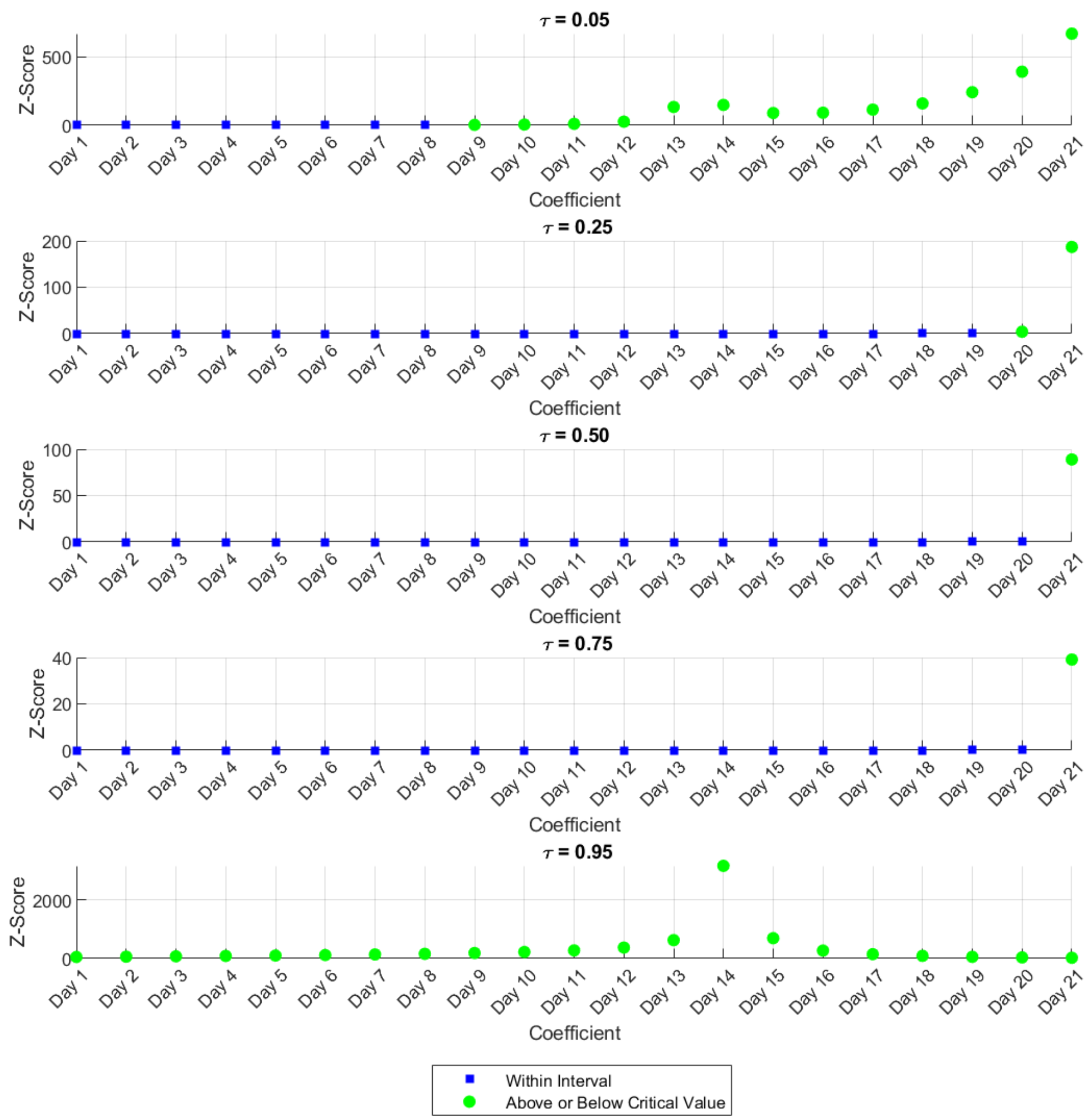


Figure 7: Quantile Scores of QMIDAS vs QAVG model in the out-of-sample period. The blue line refers to the QMIDAS model; the red one to the QAVG model.

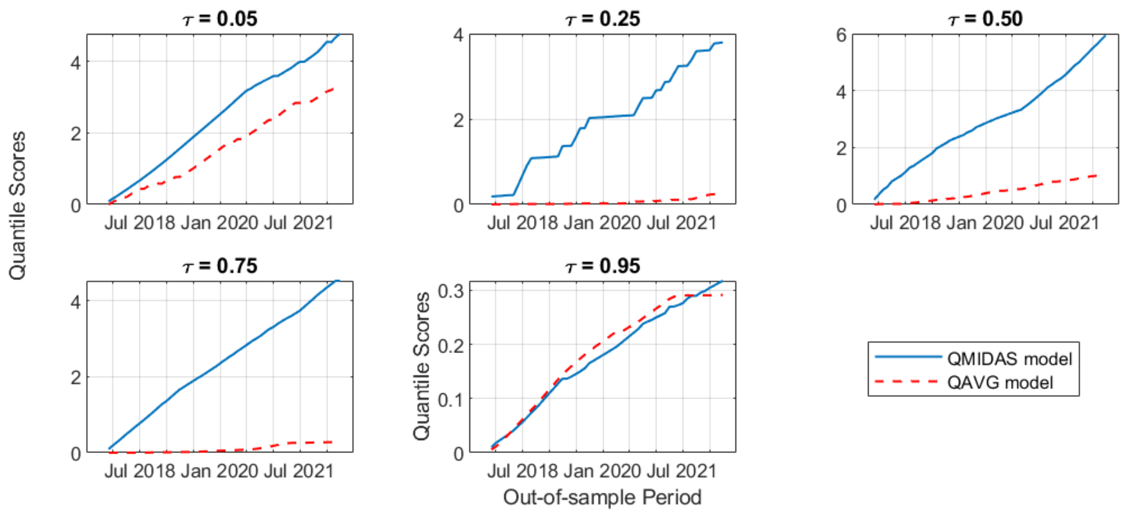


Figure 8: Test statistic J_T with respect to various quantiles. The red dashed line marks the aggregated critical value at $\alpha = 0.01$ and the associated standard normal critical value of 2.57. The green dotted line marks the significance level increased as per the Bonferroni correction (i.e. at $\alpha = 0.00003$ and an associated critical value of 3.86).

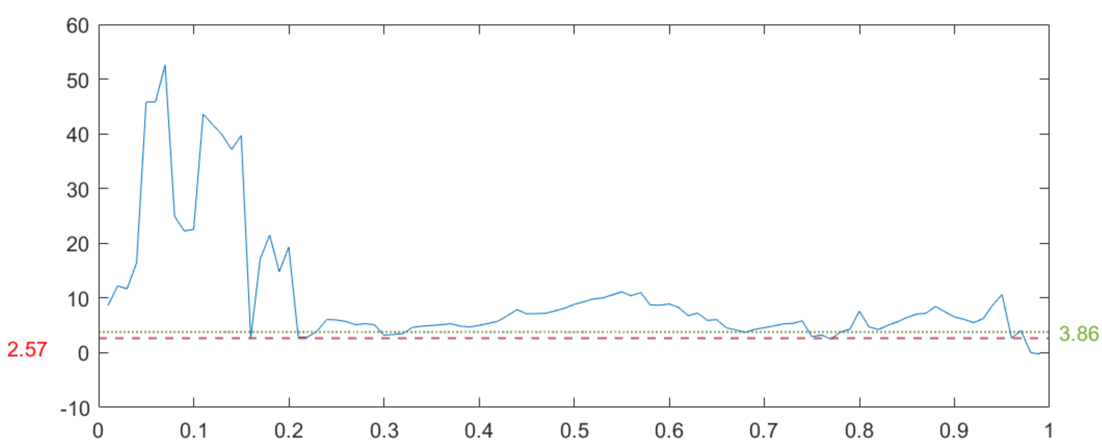


Figure 9: Conditional Quantiles and actual data.

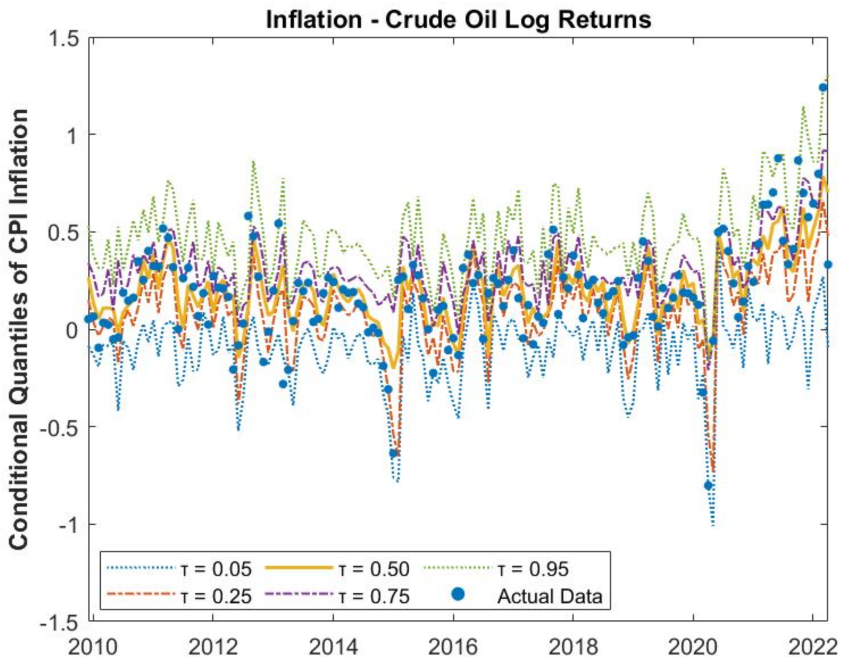


Figure 10: Almon Polynomial Shape for the combination of (θ_1, θ_2) that maximize J_T at various quantiles τ indicated above each plot.

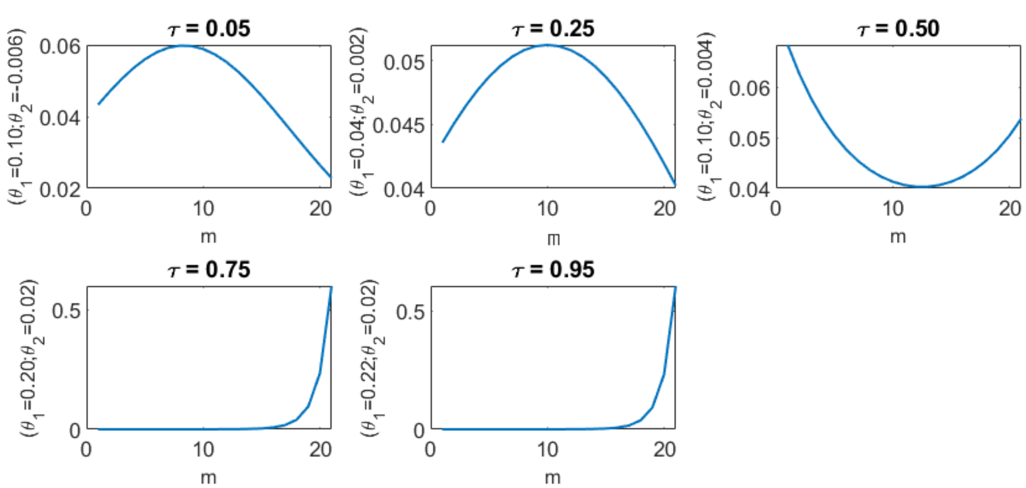


Figure 11: These plots show the significance of the Almon Lag Polynomial as a weighting function for the MIDAS component at different quantiles. The y-axis reports the z-scores and the x-axis each day m in a month. The blue squares indicate the z-scores within the $[-1.96, 1.96$, that is the non-significant days. The green dots indicate the z-scores that are above or below the confidence interval, that is the significant days.

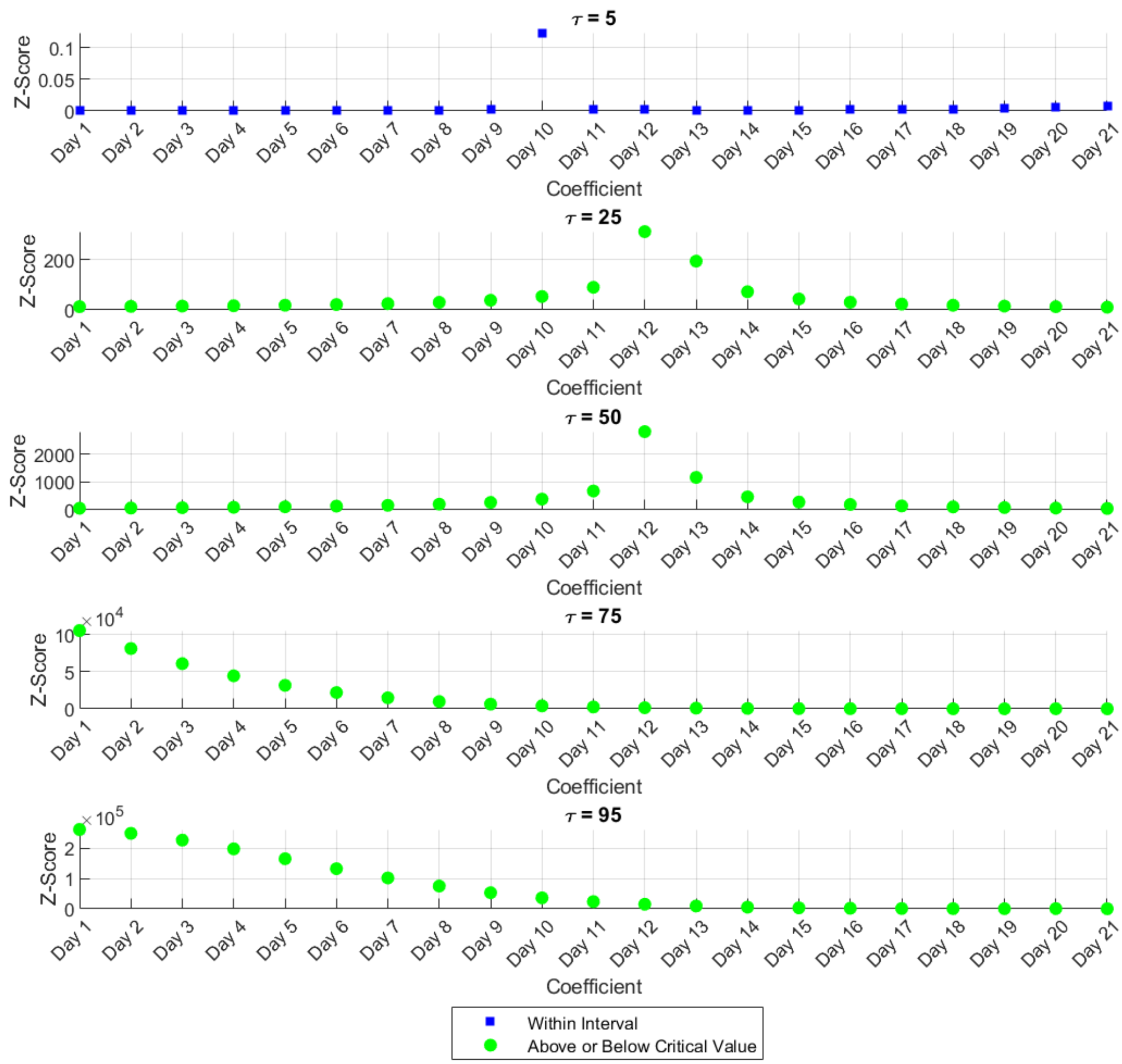


Figure 12: Quantile Scores of QMIDAS vs QAVG model in the out-of-sample period. The blue line refers to the QMIDAS model; the red one to the QAVG model.

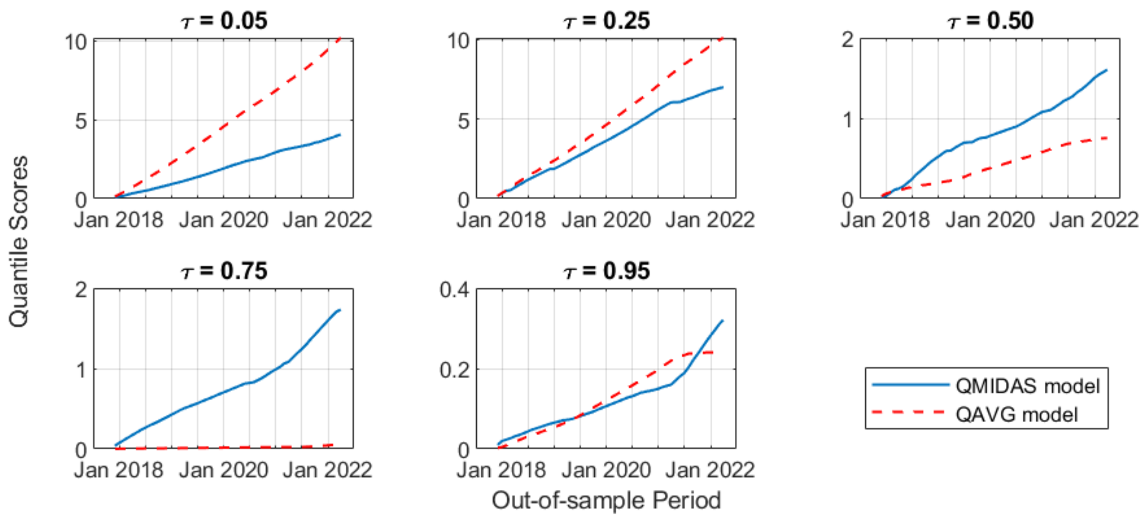


Figure 13: Test statistic J_T with respect to various quantiles. The red dashed line marks the aggregated critical value at $\alpha = 0.01$ and the associated standard normal critical value of 2.57. The green dotted line marks the significance level increased as per the Bonferroni correction (i.e. at $\alpha = 0.00003$ and an associated critical value of 3.82).

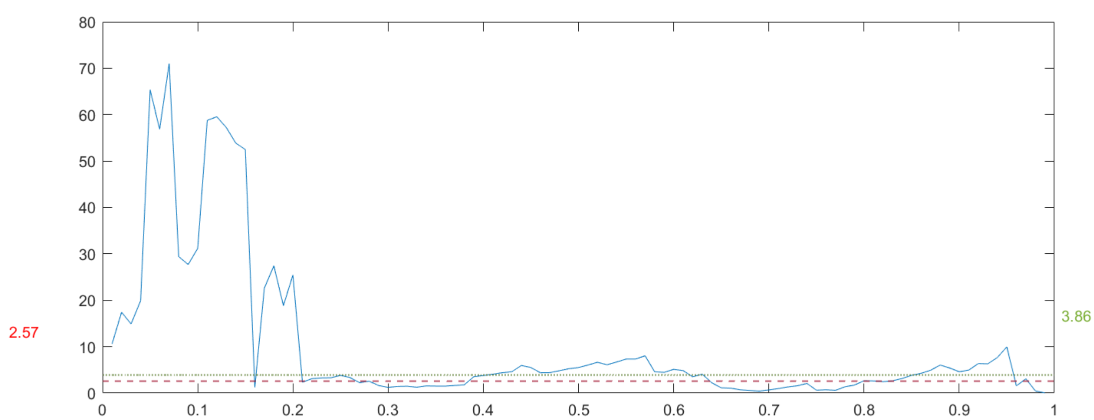


Figure 14: Conditional Quantiles and actual data.

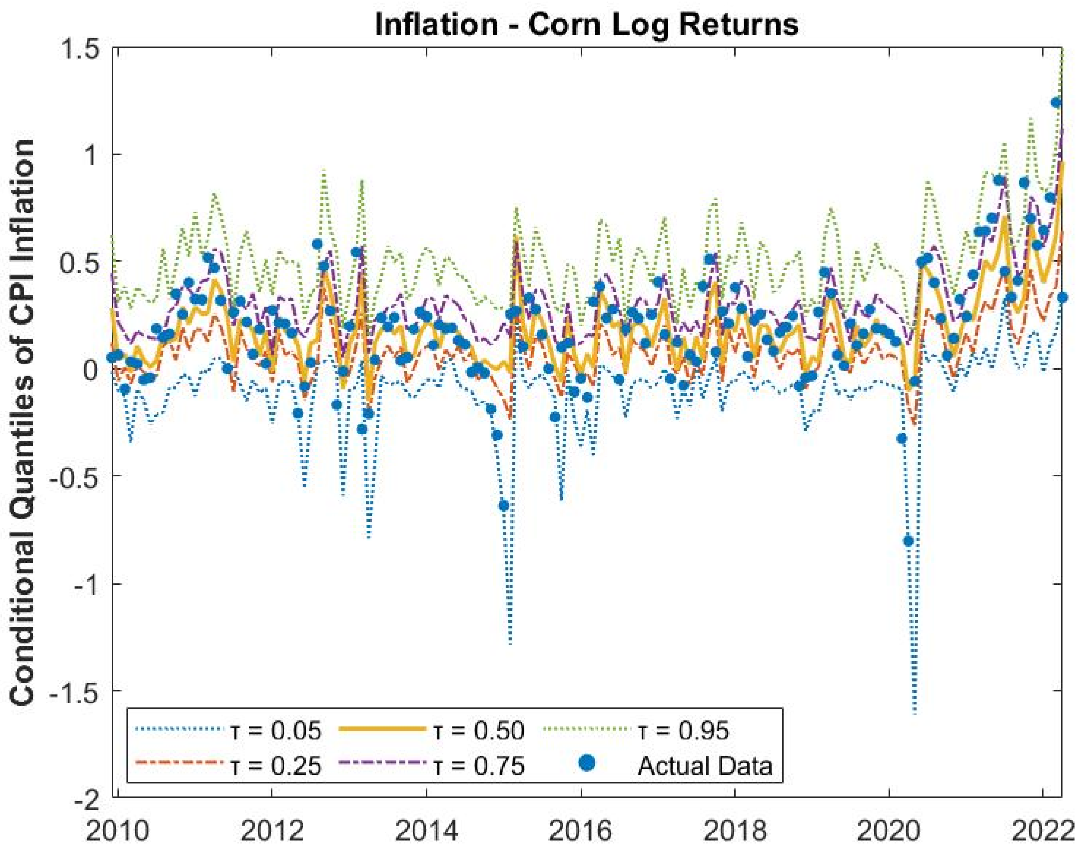


Figure 15: Almon Polynomial Shape for the combination of (θ_1, θ_2) that maximize J_T at various quantiles τ indicated above each plot.

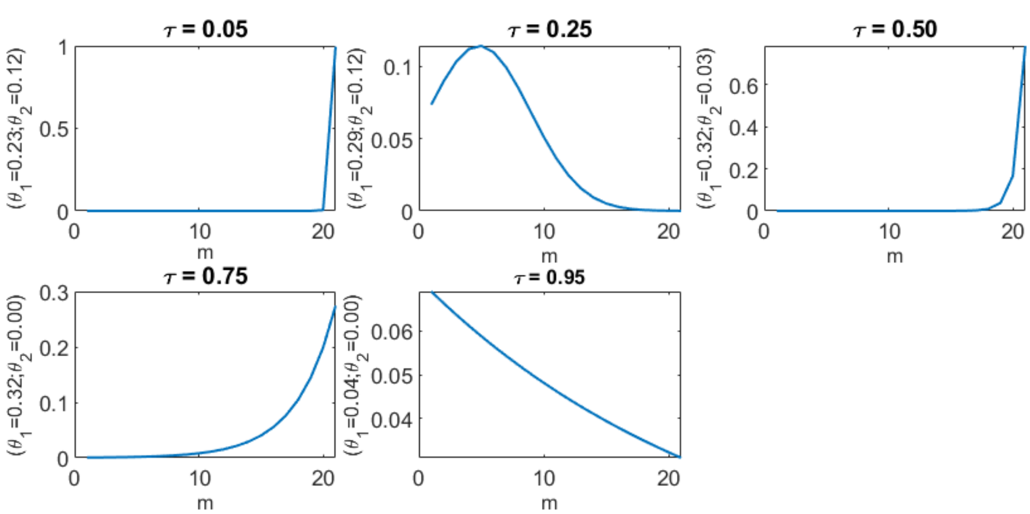


Figure 16: These plots show the significance of the Almon Lag Polynomial as a weighting function for the MIDAS component at different quantiles. The y-axis reports the z-scores and the x-axis each day m in a month. The blue squares indicate the z-scores within the $[-1.96, 1.96$, that is the non-significant days. The green dots indicate the z-scores that are above or below the confidence interval, that is the significant days.

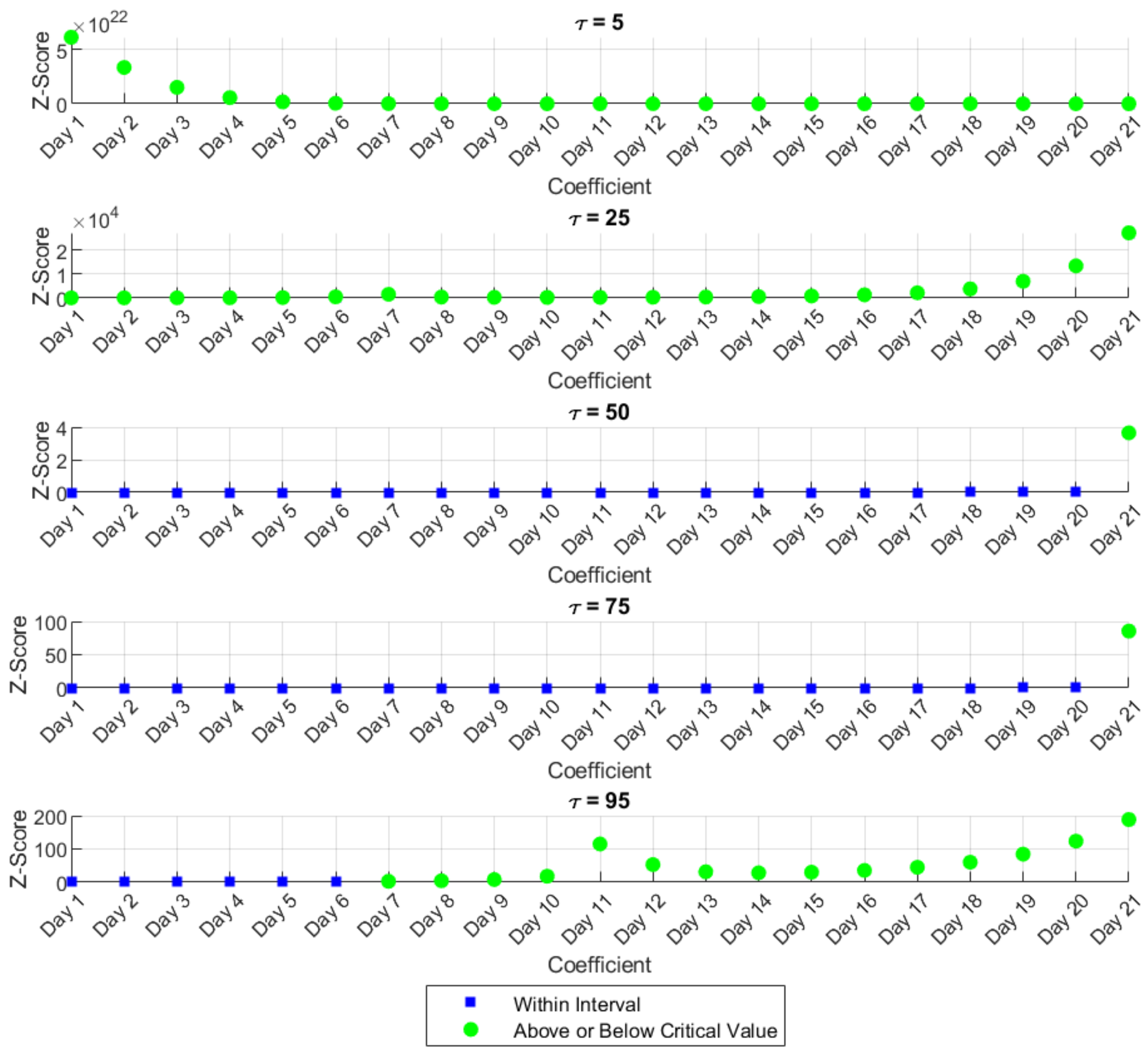
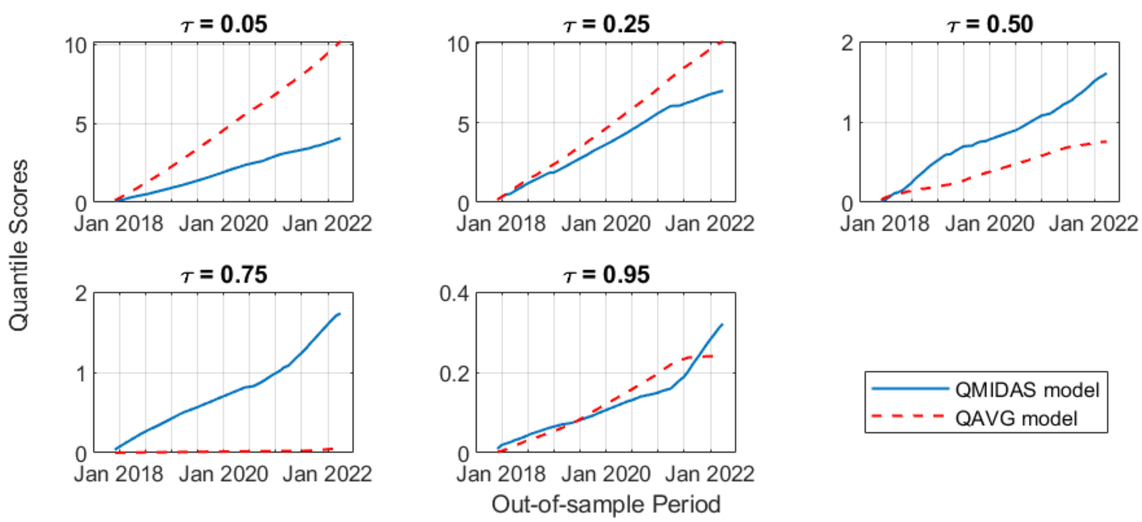


Figure 17: Quantile Scores of QMIDAS vs QAVG model in the out-of-sample period. The blue solid line refers to the QMIDAS model; the red dotted one to the QAVG model.



A Inflation

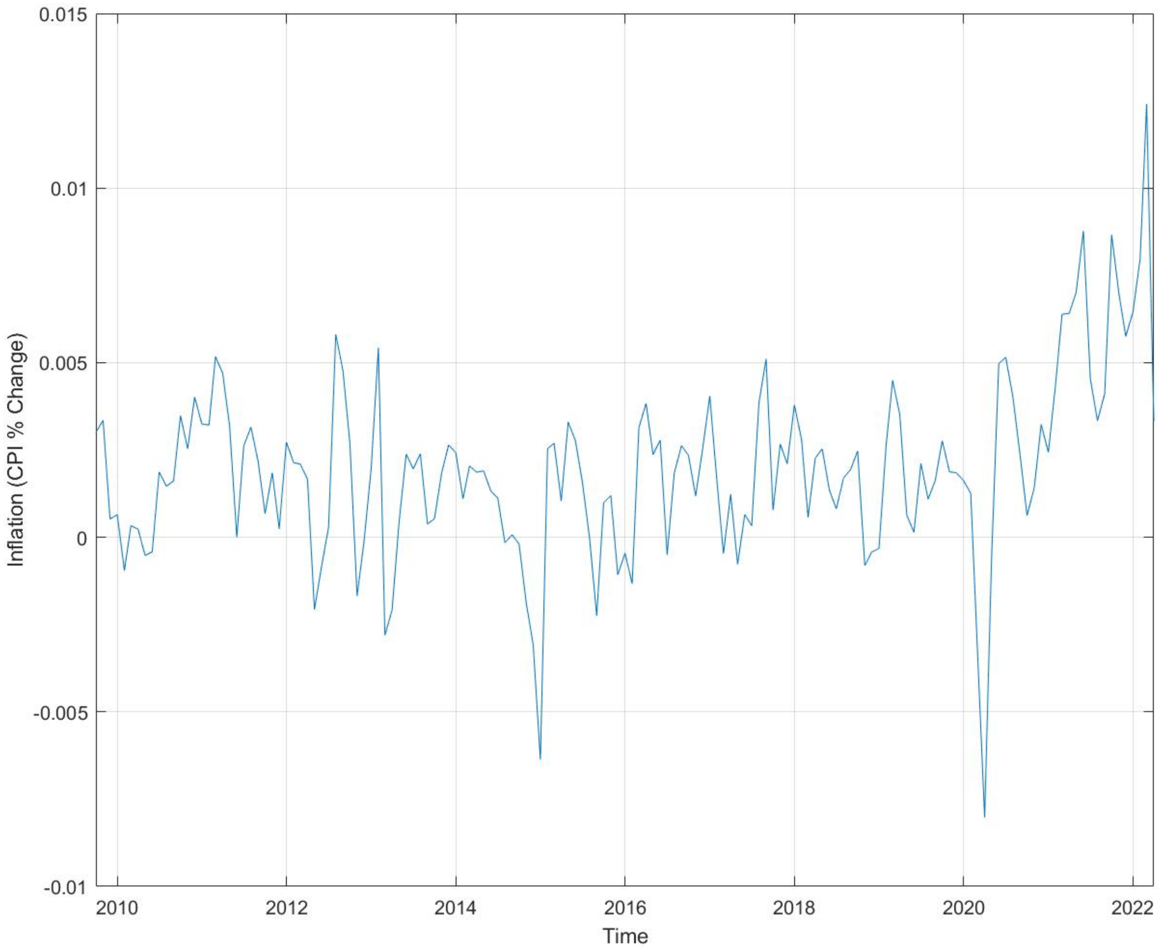


Figure A1: Line plot showing how inflation evolves over time

B Values Grids for J_T

Table B1: Table showing all possible outcomes of the test statistic J_T for the causal relation between futures on gold and inflation at various quantiles (on the columns) for all plausible pairs of the polynomial weights (θ_1, θ_2) (on the rows). The pairs yielding the maximum values of J_T at every quantile considered are indicated in bold.

		Quantiles																		
θ_1	θ_2	*0.05*	*0.1*	*0.15*	*0.2*	*0.25*	*0.3*	*0.35*	*0.4*	*0.45*	*0.5*	*0.55*	*0.6*	*0.65*	*0.7*	*0.75*	*0.8*	*0.85*	*0.9*	*0.95*
-0.006	***-0.008***	34.68	17.69	37.98	17.12	1.18	0.30	-0.12	1.88	3.35	2.34	3.67	2.01	-0.74	-0.65	**1.36**	2.76	2.35	2.41	4.09
-0.006	***0.002***	37.67	19.84	33.17	17.03	**2.98**	1.48	1.24	2.02	3.19	3.87	4.91	2.80	0.21	0.75	0.95	1.68	0.31	1.66	2.15
-0.006	*0.012*	30.07	16.24	32.37	15.01	1.68	1.31	0.95	2.70	4.14	4.08	5.27	2.81	0.46	-0.19	-0.03	1.18	2.07	2.93	3.42
-0.006	***0.022***	32.59	16.85	34.77	17.06	2.31	**1.86**	1.92	3.73	5.32	4.88	6.28	**4.34**	**2.27**	1.60	0.83	2.91	3.15	3.56	5.52
-0.006	***0.032***	34.49	17.74	36.50	18.89	2.03	1.31	1.27	3.25	4.85	4.38	5.58	4.06	1.52	1.38	0.52	2.80	**3.51**	3.46	**6.45**
-0.006	*0.042*	37.95	20.41	37.64	20.12	2.13	1.18	1.13	2.95	4.51	4.13	5.30	3.94	1.04	1.09	0.39	2.65	3.04	3.14	5.77
-0.006	*0.052*	38.92	21.45	37.34	20.28	2.42	1.08	1.22	2.90	4.45	4.12	5.37	4.13	0.94	1.13	0.53	2.43	2.54	2.74	4.82
-0.006	*0.062*	39.50	21.74	36.95	20.28	2.50	0.89	1.16	2.80	4.35	3.98	5.31	4.20	0.87	1.14	0.57	2.26	2.20	2.48	4.27
-0.006	*0.072*	39.96	21.84	36.72	20.29	2.46	0.71	1.03	2.70	4.24	3.82	5.18	4.16	0.77	1.07	0.49	2.12	1.97	2.33	4.03
-0.006	*0.082*	40.29	21.89	36.59	20.29	2.41	0.58	0.92	2.61	4.15	3.70	5.06	4.10	0.68	0.99	0.40	2.01	1.81	2.25	3.92
-0.006	*0.092*	40.51	21.91	36.51	20.30	2.36	0.49	0.84	2.55	4.08	3.61	4.97	4.05	0.61	0.92	0.32	1.93	1.70	2.20	3.88
-0.006	*0.102*	40.65	21.93	36.47	20.30	2.33	0.43	0.79	2.50	4.03	3.55	4.91	4.01	0.56	0.87	0.26	1.88	1.63	2.17	3.86
-0.006	*0.112*	40.75	21.94	36.44	20.30	2.31	0.39	0.75	2.48	4.00	3.52	4.87	3.98	0.53	0.84	0.22	1.84	1.59	2.16	3.85
-0.006	*0.122*	40.81	21.94	36.42	20.30	2.29	0.36	0.73	2.46	3.98	3.49	4.84	3.96	0.51	0.81	0.20	1.81	1.55	2.15	3.85
-0.006	*0.132*	40.85	21.95	36.40	20.30	2.28	0.35	0.71	2.44	3.97	3.47	4.83	3.94	0.49	0.80	0.18	1.80	1.53	2.14	3.85
-0.006	*0.142*	40.88	21.95	36.39	20.30	2.27	0.34	0.70	2.43	3.96	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.004	-0.008	34.61	17.59	37.93	17.07	1.14	0.36	-0.12	1.90	3.38	2.35	3.66	1.97	-0.80	-0.70	1.26	2.55	2.16	2.25	3.85
0.004	*0.002*	37.16	19.78	32.67	16.67	2.81	1.25	1.11	1.88	3.05	3.90	4.69	2.83	0.36	0.74	0.86	1.83	0.35	2.06	2.37
0.004	*0.012*	30.32	16.33	32.47	15.09	1.67	1.34	0.96	2.76	4.20	4.10	5.32	2.88	0.53	-0.15	0.00	1.22	2.14	3.09	3.56

0.004	*0.022*	32.56	16.81	34.78	17.09	2.32	1.85	1.93	3.73	5.32	4.87	6.26	4.33	2.27	1.62	0.83	2.91	3.16	3.55	5.55
0.004	*0.032*	34.60	17.81	36.55	18.94	2.02	1.30	1.26	3.23	4.84	4.36	5.56	4.06	1.50	1.37	0.51	2.80	3.50	3.45	6.45
0.004	*0.042*	37.99	20.45	37.64	20.13	2.14	1.18	1.13	2.95	4.51	4.13	5.30	3.94	1.04	1.09	0.39	2.64	3.03	3.13	5.75
0.004	*0.052*	38.94	21.47	37.33	20.28	2.42	1.08	1.22	2.90	4.45	4.11	5.37	4.13	0.94	1.13	0.53	2.43	2.53	2.73	4.80
0.004	*0.062*	39.52	21.75	36.94	20.28	2.50	0.89	1.15	2.80	4.35	3.98	5.30	4.20	0.87	1.14	0.57	2.25	2.19	2.47	4.27
0.004	*0.072*	39.97	21.84	36.71	20.29	2.46	0.71	1.03	2.69	4.24	3.82	5.17	4.16	0.77	1.07	0.49	2.12	1.96	2.33	4.02
0.004	*0.082*	40.29	21.89	36.59	20.29	2.41	0.58	0.92	2.61	4.14	3.70	5.06	4.10	0.68	0.99	0.40	2.01	1.81	2.25	3.92
0.004	*0.092*	40.51	21.91	36.51	20.30	2.36	0.49	0.84	2.55	4.08	3.61	4.97	4.05	0.61	0.92	0.32	1.93	1.70	2.20	3.88
0.004	*0.102*	40.66	21.93	36.47	20.30	2.33	0.43	0.79	2.50	4.03	3.55	4.91	4.01	0.56	0.87	0.26	1.88	1.63	2.17	3.86
0.004	*0.112*	40.75	21.94	36.44	20.30	2.31	0.39	0.75	2.47	4.00	3.51	4.87	3.98	0.53	0.84	0.22	1.84	1.58	2.16	3.85
0.004	*0.122*	40.81	21.94	36.42	20.30	2.29	0.36	0.73	2.46	3.98	3.49	4.84	3.96	0.50	0.81	0.20	1.81	1.55	2.15	3.85
0.004	*0.132*	40.85	21.95	36.40	20.30	2.28	0.35	0.71	2.44	3.97	3.47	4.83	3.94	0.49	0.80	0.18	1.79	1.53	2.14	3.85
0.004	*0.142*	40.88	21.95	36.39	20.30	2.27	0.34	0.70	2.43	3.96	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.014	*-0.008*	34.57	17.50	37.95	17.05	1.09	0.39	-0.12	1.92	3.40	2.35	3.63	1.88	-0.86	-0.75	1.14	2.31	1.92	2.07	3.60
0.014	*0.002*	35.98	19.43	32.01	16.19	2.54	0.97	0.94	1.68	2.86	3.79	4.39	2.71	0.42	0.58	0.64	1.85	0.36	2.38	2.40
0.014	*0.012*	30.59	16.45	32.58	15.17	1.66	1.36	0.97	2.81	4.26	4.13	5.38	2.95	0.59	-0.10	0.03	1.28	2.22	3.25	3.68
0.014	***0.022***	32.53	16.78	34.80	17.13	2.33	1.85	**1.93**	3.73	5.33	4.85	6.24	4.32	2.26	1.63	0.83	2.92	3.18	3.54	5.58
0.014	*0.032*	34.71	17.88	36.59	18.98	2.02	1.29	1.25	3.22	4.82	4.35	5.55	4.05	1.49	1.36	0.50	2.79	3.49	3.45	6.45
0.014	*0.042*	38.03	20.50	37.65	20.14	2.15	1.18	1.13	2.95	4.51	4.13	5.30	3.94	1.03	1.09	0.39	2.64	3.01	3.12	5.72
0.014	*0.052*	38.95	21.48	37.32	20.28	2.43	1.08	1.22	2.90	4.45	4.11	5.37	4.14	0.94	1.13	0.54	2.42	2.52	2.72	4.78
0.014	*0.062*	39.53	21.75	36.93	20.28	2.50	0.88	1.15	2.80	4.35	3.98	5.30	4.20	0.86	1.14	0.57	2.25	2.18	2.47	4.26
0.014	*0.072*	39.98	21.84	36.71	20.29	2.46	0.70	1.03	2.69	4.23	3.82	5.17	4.16	0.77	1.07	0.49	2.11	1.96	2.33	4.02
0.014	*0.082*	40.30	21.89	36.59	20.30	2.41	0.57	0.92	2.61	4.14	3.69	5.05	4.10	0.68	0.99	0.40	2.01	1.81	2.24	3.92
0.014	*0.092*	40.52	21.91	36.51	20.30	2.36	0.49	0.84	2.54	4.08	3.61	4.97	4.05	0.61	0.92	0.32	1.93	1.70	2.20	3.88
0.014	*0.102*	40.66	21.93	36.47	20.30	2.33	0.43	0.79	2.50	4.03	3.55	4.91	4.01	0.56	0.87	0.26	1.87	1.63	2.17	3.86
0.014	*0.112*	40.75	21.94	36.44	20.30	2.31	0.39	0.75	2.47	4.00	3.51	4.87	3.98	0.53	0.84	0.22	1.84	1.58	2.16	3.85

0.014	*0.122*	40.81	21.94	36.42	20.30	2.29	0.36	0.73	2.45	3.98	3.49	4.84	3.96	0.50	0.81	0.20	1.81	1.55	2.15	3.85
0.014	*0.132*	40.85	21.95	36.40	20.30	2.28	0.35	0.71	2.44	3.96	3.47	4.83	3.94	0.49	0.80	0.18	1.79	1.53	2.14	3.85
0.014	*0.142*	40.88	21.95	36.39	20.30	2.27	0.34	0.70	2.43	3.96	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.024	*-0.008*	34.56	17.45	38.06	17.08	1.03	0.41	-0.13	1.95	3.44	2.34	3.59	1.77	-0.92	-0.78	1.00	2.03	1.65	1.87	3.38
0.024	*0.002*	34.40	18.84	31.14	15.54	2.16	0.68	0.70	1.42	2.61	3.58	4.08	2.50	0.41	0.32	0.39	1.68	0.31	2.53	2.26
0.024	*0.012*	30.87	16.58	32.68	15.25	1.66	1.38	0.99	2.86	4.32	4.17	5.44	3.03	0.66	-0.05	0.07	1.33	2.29	3.38	3.80
0.024	*0.022*	32.50	16.75	34.82	17.16	2.34	1.85	1.93	3.74	5.33	4.84	6.22	4.32	2.25	1.64	0.83	2.92	3.20	3.53	5.62
0.024	*0.032*	34.83	17.95	36.64	19.03	2.01	1.28	1.23	3.20	4.81	4.34	5.54	4.04	1.47	1.35	0.50	2.79	3.49	3.44	6.44
0.024	*0.042*	38.07	20.54	37.65	20.15	2.16	1.18	1.13	2.95	4.50	4.13	5.30	3.95	1.03	1.09	0.40	2.63	3.00	3.11	5.69
0.024	*0.052*	38.97	21.49	37.30	20.28	2.43	1.07	1.22	2.89	4.45	4.11	5.37	4.14	0.93	1.13	0.54	2.42	2.51	2.71	4.77
0.024	*0.062*	39.54	21.75	36.92	20.28	2.50	0.88	1.15	2.80	4.34	3.97	5.30	4.20	0.86	1.14	0.57	2.24	2.18	2.46	4.25
0.024	*0.072*	39.99	21.84	36.70	20.29	2.46	0.70	1.02	2.69	4.23	3.81	5.17	4.16	0.76	1.07	0.49	2.11	1.95	2.32	4.02
0.024	*0.082*	40.31	21.89	36.58	20.30	2.41	0.57	0.92	2.60	4.14	3.69	5.05	4.10	0.67	0.99	0.39	2.01	1.80	2.24	3.92
0.024	*0.092*	40.52	21.91	36.51	20.30	2.36	0.48	0.84	2.54	4.07	3.61	4.97	4.05	0.61	0.92	0.32	1.93	1.70	2.20	3.88
0.024	*0.102*	40.66	21.93	36.46	20.30	2.33	0.43	0.79	2.50	4.03	3.55	4.91	4.00	0.56	0.87	0.26	1.87	1.63	2.17	3.86
0.024	*0.112*	40.75	21.94	36.43	20.30	2.31	0.39	0.75	2.47	4.00	3.51	4.87	3.98	0.53	0.84	0.22	1.84	1.58	2.16	3.85
0.024	*0.122*	40.81	21.94	36.41	20.30	2.29	0.36	0.73	2.45	3.98	3.49	4.84	3.96	0.50	0.81	0.20	1.81	1.55	2.15	3.85
0.024	*0.132*	40.85	21.95	36.40	20.30	2.28	0.35	0.71	2.44	3.96	3.47	4.83	3.94	0.49	0.80	0.18	1.79	1.53	2.14	3.85
0.024	*0.142*	40.88	21.95	36.39	20.30	2.27	0.34	0.70	2.43	3.96	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.034	*-0.008*	34.60	17.45	38.25	17.17	1.00	0.41	-0.12	1.99	3.48	2.33	3.56	1.64	-0.95	-0.78	0.86	1.76	1.36	1.68	3.25
0.034	*0.002*	33.01	18.29	30.38	14.89	1.77	0.41	0.48	1.22	2.41	3.37	3.85	2.31	0.40	0.09	0.20	1.46	0.30	2.62	2.08
0.034	*0.012*	31.16	16.72	32.79	15.33	1.67	1.41	1.02	2.92	4.38	4.21	5.50	3.11	0.73	0.01	0.10	1.39	2.36	3.51	3.91
0.034	***0.022***	32.49	16.73	34.85	17.20	2.35	1.84	1.92	**3.74**	5.33	4.83	6.21	4.31	2.24	1.65	0.83	2.92	3.22	3.53	5.65
0.034	*0.032*	34.94	18.03	36.69	19.07	2.01	1.27	1.22	3.19	4.79	4.33	5.52	4.03	1.45	1.34	0.49	2.79	3.48	3.44	6.44
0.034	*0.042*	38.11	20.58	37.65	20.16	2.16	1.18	1.14	2.95	4.50	4.13	5.30	3.95	1.02	1.08	0.40	2.63	2.98	3.09	5.67
0.034	*0.052*	38.98	21.50	37.29	20.28	2.44	1.07	1.22	2.89	4.45	4.11	5.37	4.15	0.93	1.13	0.54	2.41	2.50	2.70	4.75

0.034	*0.062*	39.55	21.76	36.92	20.28	2.50	0.87	1.14	2.79	4.34	3.97	5.29	4.20	0.86	1.13	0.56	2.24	2.17	2.46	4.24
0.034	*0.072*	40.00	21.84	36.70	20.29	2.46	0.70	1.02	2.69	4.23	3.81	5.16	4.16	0.76	1.06	0.48	2.11	1.95	2.32	4.01
0.034	*0.082*	40.31	21.89	36.58	20.30	2.40	0.57	0.91	2.60	4.14	3.69	5.05	4.10	0.67	0.98	0.39	2.00	1.80	2.24	3.92
0.034	*0.092*	40.53	21.91	36.51	20.30	2.36	0.48	0.84	2.54	4.07	3.60	4.97	4.04	0.61	0.92	0.31	1.93	1.70	2.20	3.88
0.034	*0.102*	40.66	21.93	36.46	20.30	2.33	0.43	0.78	2.50	4.03	3.55	4.91	4.00	0.56	0.87	0.26	1.87	1.63	2.17	3.86
0.034	*0.112*	40.76	21.94	36.43	20.30	2.31	0.39	0.75	2.47	4.00	3.51	4.87	3.98	0.53	0.84	0.22	1.84	1.58	2.15	3.85
0.034	*0.122*	40.82	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.98	3.49	4.84	3.96	0.50	0.81	0.20	1.81	1.55	2.15	3.85
0.034	*0.132*	40.86	21.95	36.40	20.30	2.28	0.35	0.71	2.44	3.96	3.47	4.83	3.94	0.49	0.80	0.18	1.79	1.53	2.14	3.85
0.034	*0.142*	40.88	21.95	36.39	20.30	2.27	0.34	0.70	2.43	3.96	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.044	*-0.008*	34.67	17.50	38.48	17.28	1.01	0.41	-0.09	2.04	3.53	2.34	3.54	1.53	-0.94	-0.74	0.74	1.51	1.09	1.53	3.24
0.044	*0.002*	32.07	17.88	29.86	14.34	1.44	0.21	0.30	1.10	2.31	3.21	3.75	2.18	0.37	-0.11	0.06	1.29	0.37	2.72	1.94
0.044	*0.012*	31.46	16.87	32.91	15.42	1.68	1.43	1.05	2.97	4.44	4.26	5.56	3.19	0.81	0.06	0.14	1.46	2.43	3.62	4.02
0.044	*0.022*	32.47	16.71	34.87	17.24	2.35	1.83	1.92	3.73	5.33	4.81	6.19	4.30	2.23	1.66	0.82	2.92	3.24	3.52	5.69
0.044	*0.032*	35.05	18.10	36.74	19.12	2.00	1.27	1.21	3.18	4.78	4.32	5.51	4.02	1.43	1.33	0.48	2.78	3.47	3.43	6.44
0.044	*0.042*	38.14	20.61	37.65	20.17	2.17	1.18	1.14	2.94	4.50	4.13	5.31	3.96	1.02	1.08	0.40	2.62	2.97	3.08	5.64
0.044	*0.052*	39.00	21.51	37.28	20.28	2.44	1.06	1.22	2.89	4.44	4.11	5.37	4.15	0.93	1.13	0.54	2.41	2.49	2.70	4.73
0.044	*0.062*	39.57	21.76	36.91	20.28	2.50	0.87	1.14	2.79	4.34	3.96	5.29	4.20	0.86	1.13	0.56	2.24	2.16	2.45	4.23
0.044	*0.072*	40.01	21.85	36.70	20.29	2.46	0.69	1.02	2.68	4.22	3.81	5.16	4.16	0.76	1.06	0.48	2.10	1.95	2.32	4.01
0.044	*0.082*	40.32	21.89	36.58	20.30	2.40	0.57	0.91	2.60	4.14	3.69	5.05	4.10	0.67	0.98	0.39	2.00	1.80	2.24	3.91
0.044	*0.092*	40.53	21.92	36.51	20.30	2.36	0.48	0.84	2.54	4.07	3.60	4.96	4.04	0.60	0.92	0.31	1.93	1.69	2.20	3.88
0.044	*0.102*	40.67	21.93	36.46	20.30	2.33	0.42	0.78	2.50	4.03	3.55	4.91	4.00	0.56	0.87	0.26	1.87	1.63	2.17	3.86
0.044	*0.112*	40.76	21.94	36.43	20.30	2.31	0.39	0.75	2.47	4.00	3.51	4.87	3.97	0.52	0.83	0.22	1.84	1.58	2.15	3.85
0.044	*0.122*	40.82	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.98	3.49	4.84	3.96	0.50	0.81	0.19	1.81	1.55	2.15	3.85
0.044	*0.132*	40.86	21.95	36.40	20.30	2.28	0.35	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.80	0.18	1.79	1.53	2.14	3.85
0.044	*0.142*	40.88	21.95	36.39	20.30	2.27	0.34	0.70	2.43	3.96	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.054	*-0.008*	34.72	17.57	38.67	17.39	1.03	0.40	-0.05	2.09	3.58	2.37	3.54	1.44	-0.88	-0.65	0.65	1.32	0.88	1.44	3.37

0.054	*0.002*	31.51	17.59	29.59	13.96	1.18	0.08	0.18	1.09	2.31	3.14	3.76	2.10	0.30	-0.31	-0.09	1.19	0.46	2.81	1.87
0.054	*0.012*	31.75	17.02	33.04	15.51	1.70	1.46	1.08	3.02	4.49	4.31	5.63	3.27	0.88	0.12	0.18	1.52	2.49	3.72	4.12
0.054	***0.022***	32.46	16.69	34.90	17.28	2.36	1.83	1.92	3.73	**5.33**	4.80	6.17	4.30	2.22	1.66	0.82	**2.92**	3.26	3.51	5.73
0.054	*0.032*	35.16	18.17	36.78	19.16	2.00	1.26	1.20	3.17	4.76	4.31	5.49	4.01	1.42	1.32	0.48	2.78	3.46	3.43	6.43
0.054	*0.042*	38.17	20.65	37.64	20.18	2.18	1.17	1.14	2.94	4.50	4.13	5.31	3.96	1.01	1.08	0.40	2.62	2.96	3.07	5.62
0.054	*0.052*	39.01	21.52	37.27	20.28	2.44	1.06	1.22	2.89	4.44	4.10	5.37	4.15	0.93	1.13	0.55	2.40	2.48	2.69	4.71
0.054	*0.062*	39.58	21.76	36.90	20.28	2.50	0.86	1.14	2.79	4.34	3.96	5.29	4.20	0.85	1.13	0.56	2.23	2.16	2.45	4.22
0.054	*0.072*	40.02	21.85	36.69	20.29	2.46	0.69	1.01	2.68	4.22	3.80	5.16	4.16	0.76	1.06	0.48	2.10	1.94	2.32	4.01
0.054	*0.082*	40.33	21.89	36.58	20.30	2.40	0.56	0.91	2.60	4.13	3.68	5.05	4.09	0.67	0.98	0.39	2.00	1.79	2.24	3.91
0.054	*0.092*	40.53	21.92	36.51	20.30	2.36	0.48	0.83	2.54	4.07	3.60	4.96	4.04	0.60	0.91	0.31	1.92	1.69	2.19	3.87
0.054	*0.102*	40.67	21.93	36.46	20.30	2.33	0.42	0.78	2.50	4.03	3.55	4.91	4.00	0.56	0.87	0.26	1.87	1.62	2.17	3.86
0.054	*0.112*	40.76	21.94	36.43	20.30	2.31	0.39	0.75	2.47	4.00	3.51	4.87	3.97	0.52	0.83	0.22	1.83	1.58	2.15	3.85
0.054	*0.122*	40.82	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.98	3.49	4.84	3.96	0.50	0.81	0.19	1.81	1.55	2.15	3.85
0.054	*0.132*	40.86	21.95	36.40	20.30	2.28	0.35	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.80	0.18	1.79	1.53	2.14	3.85
0.054	*0.142*	40.88	21.95	36.39	20.30	2.27	0.34	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.064	***-0.008***	34.69	17.62	**38.78**	17.43	1.06	0.37	-0.02	2.13	3.61	2.42	3.56	1.38	-0.77	-0.52	0.60	1.22	0.76	1.43	3.65
0.064	*0.002*	31.22	17.40	29.55	13.72	1.00	0.02	0.12	1.17	2.40	3.18	3.85	2.05	0.20	-0.51	-0.27	1.11	0.53	2.83	1.87
0.064	*0.012*	32.05	17.16	33.17	15.60	1.72	1.48	1.11	3.07	4.54	4.36	5.69	3.35	0.96	0.17	0.22	1.59	2.56	3.81	4.22
0.064	*0.022*	32.46	16.68	34.93	17.32	2.36	1.82	1.91	3.73	5.33	4.79	6.15	4.29	2.20	1.67	0.81	2.92	3.27	3.51	5.76
0.064	*0.032*	35.28	18.25	36.83	19.21	1.99	1.25	1.19	3.15	4.75	4.30	5.48	4.01	1.40	1.31	0.47	2.77	3.45	3.42	6.42
0.064	*0.042*	38.21	20.69	37.64	20.19	2.19	1.17	1.14	2.94	4.50	4.13	5.31	3.97	1.01	1.08	0.41	2.61	2.94	3.06	5.59
0.064	*0.052*	39.03	21.53	37.26	20.28	2.45	1.05	1.22	2.89	4.44	4.10	5.37	4.15	0.93	1.14	0.55	2.40	2.47	2.68	4.70
0.064	*0.062*	39.59	21.77	36.90	20.28	2.50	0.86	1.14	2.79	4.33	3.96	5.29	4.20	0.85	1.13	0.56	2.23	2.15	2.45	4.22
0.064	*0.072*	40.02	21.85	36.69	20.29	2.45	0.68	1.01	2.68	4.22	3.80	5.15	4.15	0.75	1.06	0.48	2.10	1.94	2.31	4.00
0.064	*0.082*	40.33	21.89	36.57	20.30	2.40	0.56	0.91	2.60	4.13	3.68	5.04	4.09	0.67	0.98	0.38	2.00	1.79	2.24	3.91
0.064	*0.092*	40.54	21.92	36.51	20.30	2.36	0.48	0.83	2.54	4.07	3.60	4.96	4.04	0.60	0.91	0.31	1.92	1.69	2.19	3.87

0.064	*0.102*	40.67	21.93	36.46	20.30	2.33	0.42	0.78	2.50	4.03	3.55	4.90	4.00	0.56	0.87	0.26	1.87	1.62	2.17	3.86
0.064	*0.112*	40.76	21.94	36.43	20.30	2.30	0.39	0.75	2.47	4.00	3.51	4.87	3.97	0.52	0.83	0.22	1.83	1.58	2.15	3.85
0.064	*0.122*	40.82	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.98	3.49	4.84	3.95	0.50	0.81	0.19	1.81	1.55	2.14	3.85
0.064	*0.132*	40.86	21.95	36.40	20.30	2.28	0.35	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.80	0.18	1.79	1.53	2.14	3.85
0.064	*0.142*	40.88	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.074	*-0.008*	34.48	17.59	38.75	17.39	1.06	0.29	-0.01	2.14	3.61	2.46	3.59	1.33	-0.64	-0.37	0.59	1.21	0.75	1.52	4.08
0.074	*0.002*	31.06	17.27	29.55	13.54	0.91	0.02	0.12	1.29	2.55	3.30	3.97	2.01	0.11	-0.68	-0.44	1.06	0.56	2.80	1.91
0.074	*0.012*	32.33	17.30	33.31	15.70	1.74	1.51	1.15	3.11	4.59	4.41	5.76	3.43	1.04	0.23	0.26	1.66	2.61	3.89	4.31
0.074	*0.022*	32.46	16.66	34.96	17.36	2.37	1.81	1.90	3.73	5.33	4.77	6.13	4.29	2.19	1.67	0.81	2.92	3.29	3.51	5.80
0.074	*0.032*	35.39	18.32	36.87	19.25	1.99	1.25	1.18	3.14	4.74	4.29	5.47	4.00	1.39	1.30	0.46	2.77	3.44	3.42	6.41
0.074	*0.042*	38.24	20.72	37.64	20.19	2.20	1.17	1.15	2.94	4.50	4.13	5.31	3.97	1.01	1.08	0.41	2.61	2.93	3.05	5.57
0.074	*0.052*	39.05	21.54	37.25	20.28	2.45	1.05	1.22	2.89	4.44	4.10	5.37	4.16	0.93	1.14	0.55	2.39	2.46	2.67	4.68
0.074	*0.062*	39.60	21.77	36.89	20.28	2.50	0.85	1.13	2.78	4.33	3.95	5.28	4.20	0.85	1.13	0.56	2.23	2.14	2.44	4.21
0.074	*0.072*	40.03	21.85	36.69	20.29	2.45	0.68	1.01	2.68	4.22	3.80	5.15	4.15	0.75	1.06	0.48	2.10	1.93	2.31	4.00
0.074	*0.082*	40.34	21.89	36.57	20.30	2.40	0.56	0.91	2.60	4.13	3.68	5.04	4.09	0.67	0.98	0.38	1.99	1.79	2.24	3.91
0.074	*0.092*	40.54	21.92	36.50	20.30	2.36	0.48	0.83	2.54	4.07	3.60	4.96	4.04	0.60	0.91	0.31	1.92	1.69	2.19	3.87
0.074	*0.102*	40.68	21.93	36.46	20.30	2.33	0.42	0.78	2.50	4.03	3.54	4.90	4.00	0.55	0.87	0.26	1.87	1.62	2.17	3.86
0.074	*0.112*	40.76	21.94	36.43	20.30	2.30	0.38	0.75	2.47	4.00	3.51	4.87	3.97	0.52	0.83	0.22	1.83	1.58	2.15	3.85
0.074	*0.122*	40.82	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.98	3.49	4.84	3.95	0.50	0.81	0.19	1.81	1.55	2.14	3.85
0.074	*0.132*	40.86	21.95	36.40	20.30	2.28	0.35	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.80	0.18	1.79	1.53	2.14	3.85
0.074	*0.142*	40.88	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.084	*-0.008*	34.01	17.44	38.48	17.23	0.99	0.17	-0.07	2.08	3.55	2.47	3.60	1.28	-0.51	-0.25	0.61	1.26	0.81	1.69	4.59
0.084	*0.002*	31.00	17.18	29.47	13.37	0.90	0.05	0.15	1.42	2.70	3.43	4.11	2.01	0.10	-0.77	-0.51	1.05	0.63	2.80	1.97
0.084	*0.012*	32.60	17.44	33.46	15.80	1.77	1.53	1.19	3.16	4.64	4.46	5.83	3.51	1.12	0.29	0.30	1.73	2.67	3.95	4.39
0.084	***0.022***	32.46	16.66	35.00	17.41	2.37	1.80	1.89	3.72	5.33	4.76	6.12	4.28	2.17	**1.67**	0.80	2.92	3.31	3.50	5.83
0.084	*0.032*	35.50	18.40	36.92	19.29	1.99	1.24	1.17	3.13	4.72	4.28	5.46	3.99	1.37	1.29	0.46	2.77	3.43	3.41	6.41

0.084	*0.042*	38.27	20.76	37.63	20.20	2.20	1.17	1.15	2.94	4.49	4.13	5.31	3.98	1.00	1.08	0.41	2.60	2.92	3.04	5.54
0.084	*0.052*	39.06	21.55	37.24	20.28	2.45	1.05	1.22	2.88	4.44	4.10	5.37	4.16	0.93	1.14	0.55	2.39	2.45	2.67	4.66
0.084	*0.062*	39.62	21.77	36.88	20.28	2.50	0.85	1.13	2.78	4.33	3.95	5.28	4.20	0.85	1.13	0.56	2.22	2.14	2.44	4.20
0.084	*0.072*	40.04	21.85	36.68	20.29	2.45	0.68	1.01	2.67	4.22	3.79	5.15	4.15	0.75	1.05	0.47	2.09	1.93	2.31	4.00
0.084	*0.082*	40.34	21.89	36.57	20.30	2.40	0.56	0.90	2.59	4.13	3.68	5.04	4.09	0.66	0.97	0.38	1.99	1.78	2.23	3.91
0.084	*0.092*	40.55	21.92	36.50	20.30	2.36	0.47	0.83	2.54	4.07	3.60	4.96	4.04	0.60	0.91	0.31	1.92	1.69	2.19	3.87
0.084	*0.102*	40.68	21.93	36.46	20.30	2.33	0.42	0.78	2.50	4.02	3.54	4.90	4.00	0.55	0.86	0.25	1.87	1.62	2.17	3.86
0.084	*0.112*	40.76	21.94	36.43	20.30	2.30	0.38	0.75	2.47	4.00	3.51	4.87	3.97	0.52	0.83	0.22	1.83	1.58	2.15	3.85
0.084	*0.122*	40.82	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.98	3.49	4.84	3.95	0.50	0.81	0.19	1.81	1.55	2.14	3.85
0.084	*0.132*	40.86	21.95	36.40	20.30	2.28	0.34	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.79	0.18	1.79	1.53	2.14	3.85
0.084	*0.142*	40.88	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.79	0.17	1.78	1.52	2.14	3.85
0.094	*-0.008*	33.25	17.17	37.96	17.00	0.87	0.01	-0.16	1.97	3.44	2.46	3.61	1.23	-0.41	-0.17	0.60	1.33	0.89	1.89	5.09
0.094	*0.002*	31.15	17.18	29.44	13.30	0.96	0.12	0.22	1.55	2.83	3.56	4.28	2.08	0.18	-0.76	-0.45	1.14	0.79	2.90	2.01
0.094	*0.012*	32.86	17.56	33.60	15.90	1.79	1.56	1.23	3.20	4.69	4.52	5.89	3.59	1.19	0.35	0.34	1.80	2.72	4.01	4.47
0.094	*0.022*	32.47	16.65	35.04	17.45	2.37	1.78	1.88	3.72	5.32	4.75	6.10	4.28	2.15	1.67	0.79	2.92	3.33	3.50	5.87
0.094	*0.032*	35.61	18.47	36.96	19.33	1.99	1.24	1.16	3.12	4.71	4.27	5.44	3.98	1.36	1.28	0.45	2.76	3.42	3.41	6.40
0.094	*0.042*	38.30	20.79	37.63	20.21	2.21	1.17	1.15	2.94	4.49	4.13	5.32	3.98	1.00	1.08	0.42	2.60	2.90	3.03	5.51
0.094	*0.052*	39.08	21.56	37.23	20.28	2.46	1.04	1.21	2.88	4.43	4.09	5.37	4.16	0.93	1.14	0.55	2.38	2.44	2.66	4.65
0.094	*0.062*	39.63	21.77	36.88	20.28	2.50	0.84	1.13	2.78	4.32	3.94	5.28	4.20	0.85	1.13	0.56	2.22	2.13	2.43	4.19
0.094	*0.072*	40.05	21.85	36.68	20.29	2.45	0.67	1.00	2.67	4.21	3.79	5.15	4.15	0.75	1.05	0.47	2.09	1.92	2.31	3.99
0.094	*0.082*	40.35	21.89	36.57	20.30	2.40	0.55	0.90	2.59	4.13	3.67	5.04	4.09	0.66	0.97	0.38	1.99	1.78	2.23	3.91
0.094	*0.092*	40.55	21.92	36.50	20.30	2.36	0.47	0.83	2.54	4.07	3.59	4.96	4.04	0.60	0.91	0.31	1.92	1.68	2.19	3.87
0.094	*0.102*	40.68	21.93	36.46	20.30	2.32	0.42	0.78	2.50	4.02	3.54	4.90	4.00	0.55	0.86	0.25	1.87	1.62	2.17	3.86
0.094	*0.112*	40.77	21.94	36.43	20.30	2.30	0.38	0.74	2.47	4.00	3.51	4.86	3.97	0.52	0.83	0.22	1.83	1.58	2.15	3.85
0.094	*0.122*	40.82	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.98	3.49	4.84	3.95	0.50	0.81	0.19	1.81	1.55	2.14	3.85
0.094	*0.132*	40.86	21.95	36.40	20.30	2.28	0.34	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.79	0.18	1.79	1.53	2.14	3.85

0.094	*0.142*	40.88	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.52	2.14	3.85
0.104	*-0.008*	32.34	16.85	37.25	16.74	0.74	-0.14	-0.25	1.84	3.31	2.45	3.62	1.18	-0.33	-0.17	0.55	1.36	0.90	2.03	5.45
0.104	*0.002*	31.57	17.33	29.62	13.40	1.10	0.23	0.32	1.66	2.95	3.69	4.51	2.21	0.35	-0.69	-0.30	1.31	1.04	3.09	2.03
0.104	*0.012*	33.10	17.67	33.75	16.00	1.82	1.58	1.27	3.24	4.73	4.57	5.95	3.66	1.27	0.41	0.38	1.87	2.77	4.05	4.55
0.104	*0.022*	32.49	16.65	35.08	17.49	2.36	1.77	1.87	3.71	5.32	4.74	6.08	4.27	2.13	1.67	0.79	2.91	3.35	3.50	5.90
0.104	*0.032*	35.72	18.55	37.00	19.37	1.99	1.24	1.16	3.11	4.70	4.26	5.43	3.98	1.34	1.27	0.45	2.76	3.41	3.40	6.39
0.104	*0.042*	38.33	20.82	37.63	20.21	2.22	1.17	1.16	2.94	4.49	4.13	5.32	3.98	1.00	1.08	0.42	2.59	2.89	3.02	5.49
0.104	*0.052*	39.09	21.57	37.22	20.28	2.46	1.04	1.21	2.88	4.43	4.09	5.37	4.17	0.92	1.14	0.56	2.38	2.43	2.65	4.63
0.104	*0.062*	39.64	21.78	36.87	20.28	2.49	0.84	1.12	2.77	4.32	3.94	5.27	4.20	0.84	1.13	0.55	2.22	2.13	2.43	4.19
0.104	*0.072*	40.06	21.85	36.68	20.29	2.45	0.67	1.00	2.67	4.21	3.79	5.14	4.15	0.74	1.05	0.47	2.09	1.92	2.30	3.99
0.104	*0.082*	40.36	21.89	36.57	20.30	2.40	0.55	0.90	2.59	4.13	3.67	5.03	4.09	0.66	0.97	0.38	1.99	1.78	2.23	3.91
0.104	*0.092*	40.55	21.92	36.50	20.30	2.35	0.47	0.83	2.53	4.06	3.59	4.95	4.04	0.60	0.91	0.30	1.92	1.68	2.19	3.87
0.104	*0.102*	40.68	21.93	36.46	20.30	2.32	0.42	0.78	2.50	4.02	3.54	4.90	4.00	0.55	0.86	0.25	1.87	1.62	2.17	3.86
0.104	*0.112*	40.77	21.94	36.43	20.30	2.30	0.38	0.74	2.47	3.99	3.51	4.86	3.97	0.52	0.83	0.22	1.83	1.58	2.15	3.85
0.104	*0.122*	40.82	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.98	3.48	4.84	3.95	0.50	0.81	0.19	1.81	1.55	2.14	3.85
0.104	*0.132*	40.86	21.95	36.40	20.30	2.28	0.34	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.79	0.18	1.79	1.53	2.14	3.85
0.104	*0.142*	40.88	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.52	2.14	3.85
0.114	*-0.008*	31.55	16.65	36.52	16.57	0.68	-0.23	-0.30	1.73	3.18	2.47	3.65	1.18	-0.26	-0.25	0.43	1.31	0.80	2.07	5.58
0.114	*0.002*	32.21	17.60	29.99	13.64	1.30	0.36	0.46	1.77	3.06	3.82	4.76	2.38	0.54	-0.58	-0.10	1.53	1.34	3.32	2.03
0.114	*0.012*	33.31	17.77	33.90	16.10	1.84	1.60	1.31	3.27	4.77	4.62	6.01	3.73	1.34	0.46	0.41	1.94	2.81	4.08	4.62
0.114	*0.022*	32.50	16.65	35.12	17.54	2.36	1.76	1.85	3.70	5.31	4.72	6.06	4.27	2.12	1.66	0.78	2.91	3.37	3.50	5.93
0.114	*0.032*	35.83	18.63	37.04	19.41	1.99	1.23	1.15	3.10	4.69	4.25	5.42	3.97	1.33	1.26	0.44	2.76	3.40	3.39	6.37
0.114	*0.042*	38.35	20.86	37.62	20.22	2.23	1.16	1.16	2.93	4.49	4.13	5.32	3.99	0.99	1.08	0.42	2.59	2.88	3.01	5.46
0.114	*0.052*	39.11	21.58	37.21	20.28	2.46	1.03	1.21	2.88	4.43	4.09	5.37	4.17	0.92	1.14	0.56	2.37	2.42	2.64	4.62
0.114	*0.062*	39.65	21.78	36.86	20.28	2.49	0.83	1.12	2.77	4.32	3.94	5.27	4.20	0.84	1.12	0.55	2.21	2.12	2.43	4.18
0.114	*0.072*	40.07	21.85	36.67	20.29	2.45	0.67	1.00	2.67	4.21	3.78	5.14	4.15	0.74	1.05	0.47	2.08	1.92	2.30	3.99

0.114	*0.082*	40.36	21.90	36.56	20.30	2.39	0.55	0.90	2.59	4.12	3.67	5.03	4.09	0.66	0.97	0.37	1.99	1.78	2.23	3.91
0.114	*0.092*	40.56	21.92	36.50	20.30	2.35	0.47	0.83	2.53	4.06	3.59	4.95	4.04	0.60	0.91	0.30	1.91	1.68	2.19	3.87
0.114	*0.102*	40.69	21.93	36.46	20.30	2.32	0.42	0.78	2.49	4.02	3.54	4.90	4.00	0.55	0.86	0.25	1.86	1.62	2.17	3.86
0.114	*0.112*	40.77	21.94	36.43	20.30	2.30	0.38	0.74	2.47	3.99	3.51	4.86	3.97	0.52	0.83	0.22	1.83	1.57	2.15	3.85
0.114	*0.122*	40.83	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.98	3.48	4.84	3.95	0.50	0.81	0.19	1.81	1.55	2.14	3.85
0.114	*0.132*	40.86	21.95	36.40	20.30	2.28	0.34	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.79	0.18	1.79	1.53	2.14	3.85
0.114	*0.142*	40.89	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.52	2.14	3.85
0.124	*-0.008*	31.18	16.70	35.97	16.59	0.72	-0.23	-0.28	1.65	3.10	2.53	3.71	1.21	-0.21	-0.36	0.26	1.17	0.60	1.97	5.41
0.124	*0.002*	32.93	17.92	30.38	13.93	1.54	0.50	0.61	1.87	3.15	3.94	4.99	2.52	0.68	-0.47	0.09	1.73	1.61	3.51	2.02
0.124	*0.012*	33.51	17.86	34.03	16.19	1.87	1.63	1.35	3.31	4.81	4.66	6.07	3.80	1.42	0.52	0.45	2.01	2.85	4.10	4.68
0.124	*0.022*	32.52	16.65	35.16	17.59	2.36	1.74	1.84	3.69	5.31	4.71	6.05	4.26	2.10	1.66	0.77	2.91	3.38	3.50	5.97
0.124	*0.032*	35.93	18.70	37.08	19.45	1.99	1.23	1.15	3.09	4.68	4.24	5.41	3.96	1.31	1.25	0.43	2.75	3.39	3.39	6.36
0.124	*0.042*	38.38	20.89	37.61	20.22	2.24	1.16	1.16	2.93	4.49	4.13	5.32	3.99	0.99	1.08	0.43	2.58	2.86	3.00	5.44
0.124	*0.052*	39.12	21.59	37.20	20.28	2.47	1.03	1.21	2.88	4.43	4.08	5.37	4.17	0.92	1.14	0.56	2.37	2.41	2.64	4.60
0.124	*0.062*	39.66	21.78	36.86	20.28	2.49	0.83	1.12	2.77	4.31	3.93	5.27	4.20	0.84	1.12	0.55	2.21	2.11	2.42	4.17
0.124	*0.072*	40.08	21.86	36.67	20.29	2.45	0.66	0.99	2.67	4.21	3.78	5.14	4.15	0.74	1.05	0.46	2.08	1.91	2.30	3.98
0.124	*0.082*	40.37	21.90	36.56	20.30	2.39	0.55	0.90	2.59	4.12	3.67	5.03	4.08	0.66	0.97	0.37	1.98	1.77	2.23	3.90
0.124	*0.092*	40.56	21.92	36.50	20.30	2.35	0.47	0.82	2.53	4.06	3.59	4.95	4.03	0.59	0.91	0.30	1.91	1.68	2.19	3.87
0.124	*0.102*	40.69	21.93	36.46	20.30	2.32	0.42	0.78	2.49	4.02	3.54	4.90	4.00	0.55	0.86	0.25	1.86	1.62	2.17	3.86
0.124	*0.112*	40.77	21.94	36.43	20.30	2.30	0.38	0.74	2.47	3.99	3.51	4.86	3.97	0.52	0.83	0.21	1.83	1.57	2.15	3.85
0.124	*0.122*	40.83	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.97	3.48	4.84	3.95	0.50	0.81	0.19	1.81	1.55	2.14	3.85
0.124	*0.132*	40.86	21.95	36.40	20.30	2.28	0.34	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.79	0.17	1.79	1.53	2.14	3.85
0.124	*0.142*	40.89	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.52	2.14	3.85
0.134	*-0.008*	31.33	17.04	35.65	16.78	0.87	-0.16	-0.18	1.62	3.05	2.65	3.81	1.29	-0.17	-0.48	0.07	0.98	0.34	1.74	4.97
0.134	*0.002*	33.62	18.21	30.68	14.17	1.78	0.64	0.77	1.95	3.23	4.06	5.17	2.59	0.73	-0.41	0.22	1.85	1.81	3.59	2.01
0.134	*0.012*	33.67	17.92	34.16	16.28	1.89	1.65	1.39	3.34	4.85	4.71	6.12	3.86	1.49	0.57	0.48	2.07	2.88	4.12	4.74

0.134	*0.022*	32.55	16.65	35.21	17.63	2.35	1.73	1.82	3.69	5.30	4.70	6.03	4.26	2.08	1.65	0.76	2.90	3.40	3.50	6.00
0.134	*0.032*	36.04	18.77	37.12	19.49	1.99	1.23	1.14	3.08	4.67	4.24	5.40	3.96	1.30	1.24	0.43	2.75	3.38	3.38	6.35
0.134	*0.042*	38.40	20.92	37.61	20.23	2.24	1.16	1.16	2.93	4.49	4.13	5.32	4.00	0.99	1.08	0.43	2.57	2.85	2.99	5.41
0.134	*0.052*	39.13	21.60	37.19	20.28	2.47	1.02	1.21	2.87	4.42	4.08	5.36	4.17	0.92	1.14	0.56	2.37	2.40	2.63	4.59
0.134	*0.062*	39.67	21.79	36.85	20.28	2.49	0.83	1.11	2.77	4.31	3.93	5.26	4.20	0.84	1.12	0.55	2.20	2.11	2.42	4.17
0.134	*0.072*	40.09	21.86	36.67	20.29	2.44	0.66	0.99	2.66	4.20	3.78	5.13	4.14	0.74	1.04	0.46	2.08	1.91	2.30	3.98
0.134	*0.082*	40.37	21.90	36.56	20.30	2.39	0.54	0.89	2.59	4.12	3.66	5.03	4.08	0.65	0.97	0.37	1.98	1.77	2.23	3.90
0.134	*0.092*	40.56	21.92	36.50	20.30	2.35	0.47	0.82	2.53	4.06	3.59	4.95	4.03	0.59	0.90	0.30	1.91	1.68	2.19	3.87
0.134	*0.102*	40.69	21.93	36.46	20.30	2.32	0.41	0.77	2.49	4.02	3.54	4.90	4.00	0.55	0.86	0.25	1.86	1.61	2.17	3.86
0.134	*0.112*	40.77	21.94	36.43	20.30	2.30	0.38	0.74	2.47	3.99	3.51	4.86	3.97	0.52	0.83	0.21	1.83	1.57	2.15	3.85
0.134	*0.122*	40.83	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.97	3.48	4.84	3.95	0.50	0.81	0.19	1.81	1.55	2.14	3.85
0.134	*0.132*	40.86	21.95	36.40	20.30	2.28	0.34	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.79	0.17	1.79	1.53	2.14	3.85
0.134	*0.142*	40.89	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.52	2.14	3.85
0.144	*-0.008*	31.82	17.48	35.41	17.04	1.12	-0.03	-0.03	1.62	3.02	2.79	3.92	1.39	-0.14	-0.58	-0.13	0.77	0.06	1.41	4.36
0.144	*0.002*	34.22	18.46	30.85	14.32	1.99	0.77	0.93	2.01	3.28	4.16	5.27	2.58	0.70	-0.40	0.29	1.90	1.90	3.53	2.01
0.144	***0.012***	33.81	17.98	34.28	16.35	1.92	1.67	1.42	3.37	4.89	4.75	6.17	3.92	1.55	0.63	0.51	2.14	2.91	**4.12**	4.79
0.144	*0.022*	32.58	16.66	35.25	17.68	2.34	1.71	1.80	3.68	5.29	4.69	6.01	4.25	2.05	1.65	0.75	2.90	3.42	3.49	6.03
0.144	*0.032*	36.14	18.85	37.16	19.53	1.99	1.22	1.13	3.08	4.66	4.23	5.39	3.95	1.29	1.23	0.43	2.75	3.37	3.37	6.33
0.144	*0.042*	38.43	20.95	37.60	20.23	2.25	1.16	1.17	2.93	4.49	4.13	5.33	4.01	0.98	1.09	0.43	2.57	2.84	2.98	5.39
0.144	*0.052*	39.15	21.60	37.18	20.28	2.47	1.02	1.21	2.87	4.42	4.08	5.36	4.18	0.92	1.14	0.56	2.36	2.39	2.62	4.57
0.144	*0.062*	39.69	21.79	36.85	20.28	2.49	0.82	1.11	2.76	4.31	3.92	5.26	4.19	0.83	1.12	0.55	2.20	2.10	2.41	4.16
0.144	*0.072*	40.09	21.86	36.66	20.29	2.44	0.66	0.99	2.66	4.20	3.77	5.13	4.14	0.74	1.04	0.46	2.08	1.90	2.29	3.98
0.144	*0.082*	40.38	21.90	36.56	20.30	2.39	0.54	0.89	2.58	4.12	3.66	5.02	4.08	0.65	0.96	0.37	1.98	1.77	2.23	3.90
0.144	*0.092*	40.57	21.92	36.49	20.30	2.35	0.46	0.82	2.53	4.06	3.59	4.95	4.03	0.59	0.90	0.30	1.91	1.67	2.19	3.87
0.144	*0.102*	40.69	21.93	36.45	20.30	2.32	0.41	0.77	2.49	4.02	3.54	4.90	4.00	0.55	0.86	0.25	1.86	1.61	2.17	3.86
0.144	*0.112*	40.77	21.94	36.43	20.30	2.30	0.38	0.74	2.47	3.99	3.50	4.86	3.97	0.52	0.83	0.21	1.83	1.57	2.15	3.85

0.144	*0.122*	40.83	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.97	3.48	4.84	3.95	0.50	0.81	0.19	1.81	1.55	2.14	3.85
0.144	*0.132*	40.86	21.95	36.40	20.30	2.28	0.34	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.79	0.17	1.79	1.53	2.14	3.85
0.144	*0.142*	40.89	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.52	2.14	3.85
0.154	*-0.008*	32.37	17.82	35.10	17.24	1.41	0.14	0.16	1.65	3.01	2.95	4.05	1.50	-0.11	-0.64	-0.29	0.57	-0.16	1.04	3.70
0.154	*0.002*	34.79	18.68	30.89	14.41	2.19	0.91	1.08	2.07	3.32	4.23	5.30	2.53	0.60	-0.44	0.28	1.86	1.90	3.34	2.03
0.154	*0.012*	33.92	18.02	34.39	16.43	1.94	1.69	1.46	3.40	4.92	4.79	6.21	3.97	1.61	0.68	0.53	2.20	2.94	4.12	4.84
0.154	*0.022*	32.61	16.67	35.30	17.73	2.34	1.70	1.79	3.66	5.28	4.67	6.00	4.25	2.03	1.64	0.74	2.90	3.43	3.49	6.06
0.154	*0.032*	36.24	18.92	37.19	19.56	1.99	1.22	1.13	3.07	4.65	4.22	5.38	3.95	1.27	1.22	0.42	2.74	3.36	3.37	6.32
0.154	*0.042*	38.45	20.97	37.59	20.24	2.26	1.16	1.17	2.93	4.48	4.13	5.33	4.01	0.98	1.09	0.44	2.56	2.82	2.97	5.36
0.154	*0.052*	39.16	21.61	37.17	20.28	2.47	1.01	1.21	2.87	4.42	4.08	5.36	4.18	0.92	1.14	0.56	2.36	2.38	2.62	4.56
0.154	*0.062*	39.70	21.79	36.84	20.28	2.49	0.82	1.11	2.76	4.31	3.92	5.26	4.19	0.83	1.12	0.55	2.20	2.10	2.41	4.15
0.154	*0.072*	40.10	21.86	36.66	20.29	2.44	0.65	0.99	2.66	4.20	3.77	5.13	4.14	0.73	1.04	0.46	2.07	1.90	2.29	3.98
0.154	*0.082*	40.38	21.90	36.56	20.30	2.39	0.54	0.89	2.58	4.12	3.66	5.02	4.08	0.65	0.96	0.37	1.98	1.76	2.23	3.90
0.154	*0.092*	40.57	21.92	36.49	20.30	2.35	0.46	0.82	2.53	4.06	3.59	4.95	4.03	0.59	0.90	0.30	1.91	1.67	2.19	3.87
0.154	*0.102*	40.70	21.93	36.45	20.30	2.32	0.41	0.77	2.49	4.02	3.54	4.90	3.99	0.55	0.86	0.25	1.86	1.61	2.16	3.86
0.154	*0.112*	40.78	21.94	36.43	20.30	2.30	0.38	0.74	2.47	3.99	3.50	4.86	3.97	0.52	0.83	0.21	1.83	1.57	2.15	3.85
0.154	*0.122*	40.83	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.97	3.48	4.84	3.95	0.50	0.81	0.19	1.81	1.54	2.14	3.85
0.154	*0.132*	40.86	21.95	36.40	20.30	2.28	0.34	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.79	0.17	1.79	1.53	2.14	3.85
0.154	*0.142*	40.89	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.52	2.14	3.85
0.164	*-0.008*	32.80	17.97	34.65	17.33	1.74	0.33	0.40	1.69	3.03	3.13	4.21	1.65	-0.08	-0.67	-0.40	0.40	-0.32	0.70	3.15
0.164	*0.002*	35.25	18.84	30.88	14.47	2.36	1.06	1.20	2.14	3.37	4.27	5.30	2.48	0.50	-0.47	0.23	1.77	1.85	3.06	2.04
0.164	*0.012*	34.00	18.04	34.49	16.49	1.96	1.71	1.49	3.43	4.95	4.82	6.26	4.02	1.67	0.73	0.56	2.26	2.96	4.11	4.88
0.164	*0.022*	32.64	16.69	35.35	17.77	2.33	1.68	1.77	3.65	5.27	4.66	5.98	4.25	2.01	1.64	0.73	2.89	3.45	3.49	6.10
0.164	*0.032*	36.34	19.00	37.23	19.60	1.99	1.22	1.13	3.06	4.64	4.21	5.37	3.94	1.26	1.21	0.42	2.74	3.35	3.36	6.30
0.164	*0.042*	38.48	21.00	37.59	20.24	2.27	1.15	1.17	2.93	4.48	4.13	5.33	4.02	0.98	1.09	0.44	2.56	2.81	2.96	5.34
0.164	*0.052*	39.18	21.62	37.16	20.28	2.48	1.01	1.21	2.87	4.42	4.07	5.36	4.18	0.91	1.14	0.57	2.35	2.38	2.61	4.54

0.164	*0.062*	39.71	21.79	36.83	20.28	2.49	0.81	1.11	2.76	4.30	3.92	5.25	4.19	0.83	1.12	0.54	2.19	2.09	2.41	4.15
0.164	*0.072*	40.11	21.86	36.66	20.29	2.44	0.65	0.98	2.66	4.20	3.77	5.12	4.14	0.73	1.04	0.45	2.07	1.90	2.29	3.97
0.164	*0.082*	40.39	21.90	36.55	20.30	2.39	0.54	0.89	2.58	4.12	3.66	5.02	4.08	0.65	0.96	0.36	1.98	1.76	2.22	3.90
0.164	*0.092*	40.58	21.92	36.49	20.30	2.35	0.46	0.82	2.53	4.06	3.58	4.95	4.03	0.59	0.90	0.30	1.91	1.67	2.19	3.87
0.164	*0.102*	40.70	21.93	36.45	20.30	2.32	0.41	0.77	2.49	4.02	3.54	4.89	3.99	0.55	0.86	0.25	1.86	1.61	2.16	3.86
0.164	*0.112*	40.78	21.94	36.43	20.30	2.30	0.38	0.74	2.47	3.99	3.50	4.86	3.97	0.52	0.83	0.21	1.83	1.57	2.15	3.85
0.164	*0.122*	40.83	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.97	3.48	4.84	3.95	0.50	0.81	0.19	1.80	1.54	2.14	3.85
0.164	*0.132*	40.86	21.95	36.40	20.30	2.28	0.34	0.71	2.44	3.96	3.47	4.82	3.94	0.49	0.79	0.17	1.79	1.53	2.14	3.85
0.164	*0.142*	40.89	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.52	2.14	3.85
0.174	*-0.008*	33.09	17.96	34.01	17.28	2.09	0.58	0.68	1.75	3.07	3.31	4.38	1.81	-0.05	-0.66	-0.46	0.25	-0.41	0.43	2.78
0.174	*0.002*	35.36	18.86	30.87	14.51	2.46	1.17	1.27	2.19	3.41	4.29	5.27	2.46	0.42	-0.49	0.14	1.65	1.78	2.74	2.04
0.174	*0.012*	34.05	18.04	34.57	16.55	1.98	1.72	1.53	3.46	4.98	4.85	6.29	4.07	1.73	0.78	0.58	2.31	2.97	4.10	4.92
0.174	*0.022*	32.68	16.70	35.39	17.82	2.32	1.66	1.75	3.64	5.26	4.65	5.96	4.24	1.99	1.63	0.72	2.89	3.46	3.49	6.12
0.174	*0.032*	36.44	19.07	37.26	19.63	2.00	1.21	1.12	3.05	4.63	4.21	5.37	3.94	1.25	1.20	0.41	2.74	3.33	3.35	6.29
0.174	*0.042*	38.50	21.03	37.58	20.24	2.27	1.15	1.18	2.93	4.48	4.13	5.33	4.02	0.98	1.09	0.44	2.55	2.80	2.95	5.31
0.174	*0.052*	39.19	21.63	37.15	20.28	2.48	1.00	1.21	2.86	4.41	4.07	5.36	4.18	0.91	1.14	0.57	2.35	2.37	2.60	4.53
0.174	*0.062*	39.72	21.79	36.83	20.28	2.49	0.81	1.10	2.76	4.30	3.91	5.25	4.19	0.83	1.11	0.54	2.19	2.09	2.40	4.14
0.174	*0.072*	40.12	21.86	36.65	20.29	2.44	0.65	0.98	2.65	4.19	3.76	5.12	4.14	0.73	1.04	0.45	2.07	1.89	2.29	3.97
0.174	*0.082*	40.40	21.90	36.55	20.30	2.39	0.53	0.89	2.58	4.11	3.66	5.02	4.08	0.65	0.96	0.36	1.97	1.76	2.22	3.90
0.174	*0.092*	40.58	21.92	36.49	20.30	2.35	0.46	0.82	2.53	4.06	3.58	4.94	4.03	0.59	0.90	0.29	1.91	1.67	2.19	3.87
0.174	*0.102*	40.70	21.93	36.45	20.30	2.32	0.41	0.77	2.49	4.02	3.53	4.89	3.99	0.55	0.86	0.24	1.86	1.61	2.16	3.86
0.174	*0.112*	40.78	21.94	36.43	20.30	2.30	0.38	0.74	2.47	3.99	3.50	4.86	3.97	0.52	0.83	0.21	1.83	1.57	2.15	3.85
0.174	*0.122*	40.83	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.97	3.48	4.84	3.95	0.50	0.81	0.19	1.80	1.54	2.14	3.85
0.174	*0.132*	40.87	21.95	36.40	20.30	2.28	0.34	0.70	2.44	3.96	3.47	4.82	3.94	0.48	0.79	0.17	1.79	1.53	2.14	3.85
0.174	*0.142*	40.89	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.51	2.14	3.85
0.184	*-0.008*	33.22	17.86	33.17	17.09	2.42	0.84	0.97	1.81	3.11	3.47	4.55	1.98	-0.01	-0.62	-0.49	0.12	-0.45	0.27	2.62

0.184	*0.002*	34.97	18.66	30.85	14.53	2.45	1.23	1.26	2.21	3.42	4.26	5.22	2.46	0.37	-0.49	0.04	1.52	1.70	2.41	2.02
0.184	*0.012*	34.08	18.03	34.65	16.60	2.00	1.74	1.56	3.48	5.01	4.88	6.33	4.11	1.79	0.83	0.60	2.36	2.99	4.08	4.95
0.184	*0.022*	32.73	16.72	35.44	17.87	2.31	1.64	1.72	3.62	5.24	4.64	5.94	4.24	1.97	1.62	0.71	2.88	3.47	3.49	6.15
0.184	*0.032*	36.53	19.14	37.30	19.67	2.00	1.21	1.12	3.05	4.62	4.20	5.36	3.94	1.24	1.20	0.41	2.73	3.32	3.34	6.27
0.184	*0.042*	38.52	21.05	37.57	20.25	2.28	1.15	1.18	2.93	4.48	4.13	5.34	4.03	0.97	1.09	0.45	2.55	2.79	2.94	5.29
0.184	*0.052*	39.21	21.63	37.14	20.28	2.48	1.00	1.20	2.86	4.41	4.07	5.36	4.18	0.91	1.15	0.57	2.34	2.36	2.60	4.52
0.184	*0.062*	39.73	21.80	36.82	20.28	2.49	0.80	1.10	2.75	4.30	3.91	5.25	4.19	0.82	1.11	0.54	2.19	2.08	2.40	4.13
0.184	*0.072*	40.13	21.86	36.65	20.29	2.44	0.64	0.98	2.65	4.19	3.76	5.12	4.14	0.73	1.03	0.45	2.07	1.89	2.29	3.97
0.184	*0.082*	40.40	21.90	36.55	20.30	2.39	0.53	0.88	2.58	4.11	3.65	5.02	4.08	0.65	0.96	0.36	1.97	1.76	2.22	3.90
0.184	*0.092*	40.58	21.92	36.49	20.30	2.35	0.46	0.82	2.53	4.06	3.58	4.94	4.03	0.59	0.90	0.29	1.90	1.67	2.19	3.87
0.184	*0.102*	40.70	21.93	36.45	20.30	2.32	0.41	0.77	2.49	4.02	3.53	4.89	3.99	0.54	0.86	0.24	1.86	1.61	2.16	3.86
0.184	*0.112*	40.78	21.94	36.43	20.30	2.30	0.38	0.74	2.47	3.99	3.50	4.86	3.97	0.52	0.83	0.21	1.83	1.57	2.15	3.85
0.184	*0.122*	40.83	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.97	3.48	4.84	3.95	0.50	0.81	0.19	1.80	1.54	2.14	3.85
0.184	*0.132*	40.87	21.95	36.40	20.30	2.28	0.34	0.70	2.44	3.96	3.47	4.82	3.94	0.48	0.79	0.17	1.79	1.53	2.14	3.85
0.184	*0.142*	40.89	21.95	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.51	2.13	3.85
0.194	*-0.008*	33.16	17.67	32.18	16.77	2.65	1.07	1.19	1.86	3.14	3.61	4.72	2.15	0.02	-0.58	-0.51	0.02	-0.45	0.20	2.65
0.194	*0.002*	34.20	18.30	30.81	14.53	2.36	1.22	1.19	2.19	3.40	4.19	5.15	2.47	0.33	-0.49	-0.07	1.39	1.62	2.10	2.00
0.194	***0.012***	34.08	18.01	34.70	16.64	2.02	1.75	1.59	3.51	5.04	**4.90**	**6.35**	4.15	1.84	0.88	0.62	2.42	2.99	4.05	4.98
0.194	*0.022*	32.77	16.74	35.49	17.91	2.29	1.63	1.70	3.61	5.23	4.63	5.93	4.23	1.95	1.61	0.70	2.88	3.48	3.49	6.18
0.194	*0.032*	36.62	19.21	37.33	19.70	2.00	1.21	1.12	3.04	4.61	4.19	5.35	3.93	1.22	1.19	0.41	2.73	3.31	3.33	6.25
0.194	*0.042*	38.54	21.08	37.56	20.25	2.29	1.15	1.18	2.93	4.48	4.13	5.34	4.03	0.97	1.09	0.45	2.54	2.77	2.93	5.27
0.194	*0.052*	39.22	21.64	37.13	20.28	2.48	1.00	1.20	2.86	4.41	4.06	5.36	4.19	0.91	1.15	0.57	2.34	2.35	2.59	4.50
0.194	*0.062*	39.74	21.80	36.82	20.28	2.49	0.80	1.10	2.75	4.29	3.90	5.24	4.19	0.82	1.11	0.54	2.18	2.07	2.40	4.13
0.194	*0.072*	40.13	21.86	36.65	20.29	2.44	0.64	0.98	2.65	4.19	3.76	5.12	4.13	0.72	1.03	0.45	2.06	1.88	2.28	3.96
0.194	*0.082*	40.41	21.90	36.55	20.30	2.39	0.53	0.88	2.58	4.11	3.65	5.01	4.07	0.64	0.96	0.36	1.97	1.75	2.22	3.90
0.194	*0.092*	40.59	21.92	36.49	20.30	2.35	0.46	0.81	2.52	4.05	3.58	4.94	4.03	0.59	0.90	0.29	1.90	1.67	2.18	3.87

0.194	***0.102***	40.71	21.93	36.45	**20.30**	2.32	0.41	0.77	2.49	4.02	3.53	4.89	3.99	0.54	0.85	0.24	1.86	1.61	2.16	3.86
0.194	*0.112*	40.78	21.94	36.43	20.30	2.30	0.38	0.74	2.46	3.99	3.50	4.86	3.97	0.52	0.83	0.21	1.82	1.57	2.15	3.85
0.194	*0.122*	40.83	21.94	36.41	20.30	2.29	0.36	0.72	2.45	3.97	3.48	4.83	3.95	0.50	0.81	0.19	1.80	1.54	2.14	3.85
0.194	*0.132*	40.87	21.95	36.40	20.30	2.28	0.34	0.70	2.44	3.96	3.47	4.82	3.94	0.48	0.79	0.17	1.79	1.53	2.14	3.85
0.194	***0.142***	**40.89**	**21.95**	36.39	20.30	2.27	0.33	0.70	2.43	3.95	3.46	4.81	3.93	0.48	0.78	0.16	1.78	1.51	2.13	3.85

Table B2: Table showing all possible outcomes of the test statistic J_T for the causal relation between futures on crude oil and inflation at various quantiles (on the columns) for all plausible pairs of the polynomial weights (θ_1, θ_2) (on the rows). The pairs yielding the maximum values of J_T at every quantile considered are indicated in bold.

		Quantiles																		
θ_1	θ_2	*0.05*	*0.1*	*0.15*	*0.2*	*0.25*	*0.3*	*0.35*	*0.4*	*0.45*	*0.5*	*0.55*	*0.6*	*0.65*	*0.7*	*0.75*	*0.8*	*0.85*	*0.9*	*0.95*
-0.1	*-0.006*	44.66	22.28	35.67	17.11	1.85	0.93	1.10	4.26	6.33	4.80	7.32	4.57	1.17	0.74	-0.07	2.05	2.69	1.53	5.97
-0.1	*-0.004*	43.68	22.03	35.80	17.08	1.93	1.04	1.31	4.42	6.51	4.92	7.53	4.87	1.17	0.80	0.03	2.21	2.91	1.58	5.95
-0.1	*-0.002*	41.72	21.12	35.43	16.68	1.93	1.12	1.47	4.54	6.63	4.99	7.70	5.12	1.22	0.88	0.13	2.41	3.19	1.82	6.16
-0.1	*0*	40.32	20.17	34.80	16.38	2.28	1.37	1.94	4.61	6.66	5.26	8.04	5.45	1.64	1.20	0.18	2.59	3.26	2.33	6.37
-0.1	*0.002*	42.22	20.92	34.41	16.91	4.20	2.49	3.69	4.79	6.73	6.92	9.70	6.91	3.25	2.38	0.56	3.08	3.41	3.56	6.25
-0.1	***0.004***	38.89	20.47	32.28	16.29	5.24	3.17	4.93	4.91	6.76	**8.82**	10.86	8.52	5.07	3.90	1.74	4.40	4.19	5.02	6.44
-0.1	*0.006*	33.45	18.63	30.35	14.24	3.72	2.50	3.27	3.35	5.03	7.23	9.56	7.90	3.19	2.65	1.70	4.20	5.16	4.53	6.08
-0.1	***0.008***	32.03	18.50	30.29	14.59	2.36	2.17	2.51	3.14	4.90	7.50	10.17	8.49	3.10	2.98	2.18	5.22	**6.44**	6.33	6.31
-0.1	*0.01*	34.02	18.71	30.49	14.79	2.33	1.96	2.54	3.07	4.87	7.07	10.01	8.16	3.39	2.47	1.31	4.18	5.04	5.89	7.25
-0.1	*0.012*	35.94	18.62	30.69	14.58	1.78	1.41	2.28	2.89	4.74	6.55	9.64	7.34	3.21	2.20	0.66	3.74	4.19	5.30	6.85
-0.1	*0.014*	38.17	19.07	31.13	14.90	1.59	1.35	2.28	2.94	4.80	6.41	9.45	6.86	3.14	2.11	0.57	3.88	3.71	4.88	7.25
-0.1	*0.016*	40.12	19.84	32.21	15.78	1.84	1.61	2.55	3.19	5.02	6.43	9.35	6.76	3.27	2.32	1.04	4.53	3.81	4.75	8.11
-0.1	*0.018*	39.88	19.81	33.12	16.26	1.71	1.54	2.55	3.21	5.08	6.34	9.22	6.84	3.43	2.65	1.74	5.49	4.34	4.87	9.04
-0.1	*0.02*	38.47	19.29	33.58	16.26	1.31	1.20	2.31	3.03	4.96	6.18	9.04	6.95	3.55	2.88	2.33	6.43	4.88	5.01	9.76
-0.08	*-0.006*	43.73	22.03	35.92	17.15	1.93	1.08	1.34	4.47	6.56	4.99	7.59	4.89	1.17	0.81	0.01	2.17	2.88	1.62	6.00

-0.08	*-0.004*	42.35	21.42	35.84	16.94	1.93	1.18	1.48	4.61	6.71	5.04	7.72	5.09	1.18	0.84	0.09	2.34	3.15	1.82	6.17
-0.08	*-0.002*	40.75	20.44	35.36	16.53	1.96	1.28	1.66	4.67	6.75	5.11	7.89	5.29	1.43	1.06	0.18	2.59	3.42	2.28	6.61
-0.08	*0*	41.30	20.42	35.07	16.85	3.11	1.82	2.66	4.73	6.73	5.91	8.74	6.02	2.42	1.77	0.31	2.82	3.33	2.97	6.62
-0.08	*0.002*	42.69	21.19	34.10	17.05	5.35	3.13	4.71	4.98	6.88	8.24	10.88	8.16	4.64	3.42	1.26	3.93	4.16	4.97	6.72
-0.08	*0.004*	35.92	19.78	31.70	15.63	4.74	2.90	4.29	4.40	6.18	8.25	10.14	8.15	4.76	3.75	2.15	4.76	4.87	5.42	6.55
-0.08	*0.006*	32.58	18.29	29.65	13.27	2.30	1.70	2.20	2.54	4.23	6.59	9.15	7.55	2.27	2.10	1.30	4.04	4.89	4.64	5.81
-0.08	***0.008***	33.01	18.91	30.89	15.29	2.67	2.37	2.70	3.26	5.02	7.58	10.32	8.58	3.38	2.86	2.04	5.02	6.20	**6.54**	7.01
-0.08	*0.01*	35.00	18.75	30.63	14.69	2.22	1.76	2.47	3.01	4.82	6.89	9.90	7.89	3.31	2.29	1.03	3.88	4.67	5.67	7.06
-0.08	*0.012*	36.32	18.53	30.70	14.55	1.64	1.30	2.21	2.85	4.72	6.47	9.57	7.13	3.13	2.10	0.54	3.66	3.97	5.15	6.84
-0.08	*0.014*	38.82	19.28	31.36	15.08	1.64	1.40	2.33	3.00	4.85	6.41	9.41	6.79	3.15	2.11	0.63	3.97	3.65	4.79	7.44
-0.08	*0.016*	40.29	19.92	32.47	15.97	1.86	1.63	2.58	3.23	5.06	6.41	9.31	6.76	3.31	2.40	1.20	4.74	3.91	4.75	8.35
-0.08	*0.018*	39.55	19.68	33.28	16.28	1.60	1.45	2.49	3.17	5.05	6.30	9.17	6.86	3.46	2.72	1.91	5.74	4.49	4.90	9.25
-0.08	*0.02*	38.17	19.18	33.65	16.25	1.23	1.12	2.24	2.98	4.93	6.13	8.99	6.98	3.57	2.92	2.44	6.63	4.99	5.04	9.90
-0.06	*-0.006*	42.74	21.55	36.07	17.09	1.94	1.24	1.51	4.68	6.78	5.11	7.77	5.09	1.15	0.83	0.07	2.29	3.12	1.84	6.18
-0.06	*-0.004*	41.45	20.79	35.86	16.80	1.89	1.31	1.59	4.75	6.85	5.10	7.84	5.22	1.30	0.97	0.16	2.53	3.43	2.21	6.59
-0.06	*-0.002*	40.92	20.24	35.53	16.71	2.32	1.53	2.02	4.77	6.84	5.42	8.24	5.58	1.94	1.42	0.24	2.79	3.55	2.83	7.06
-0.06	*0*	43.09	21.17	35.35	17.36	4.43	2.45	3.68	4.80	6.75	6.98	9.88	7.05	3.59	2.61	0.75	3.40	3.70	3.97	7.02
-0.06	***0.002***	40.73	20.93	33.77	16.99	5.59	**3.21**	**4.98**	**5.00**	6.85	8.80	11.08	8.71	5.45	4.17	1.97	4.71	4.63	5.64	6.99
-0.06	*0.004*	35.54	19.63	31.18	15.01	4.27	2.62	3.61	3.61	5.29	7.56	9.72	7.77	3.75	3.03	1.93	4.27	5.29	4.85	6.30
-0.06	*0.006*	32.76	18.71	30.06	13.96	2.14	1.81	2.16	2.70	4.38	6.92	9.48	7.56	2.33	2.23	1.55	4.42	5.48	5.35	5.62
-0.06	*0.008*	33.62	18.74	30.64	15.05	2.58	2.17	2.59	3.11	4.87	7.34	10.17	8.37	3.26	2.42	1.59	4.39	5.49	6.29	7.32
-0.06	*0.01*	35.57	18.67	30.72	14.63	2.08	1.59	2.40	2.97	4.79	6.74	9.80	7.63	3.24	2.18	0.82	3.70	4.41	5.50	6.88
-0.06	*0.012*	36.86	18.59	30.77	14.59	1.56	1.25	2.19	2.86	4.73	6.42	9.51	6.97	3.08	2.03	0.48	3.65	3.79	5.01	6.94
-0.06	*0.014*	39.38	19.49	31.62	15.29	1.70	1.46	2.40	3.07	4.91	6.40	9.37	6.74	3.17	2.14	0.73	4.10	3.64	4.73	7.65
-0.06	*0.016*	40.30	19.94	32.72	16.11	1.84	1.63	2.59	3.25	5.08	6.38	9.26	6.77	3.34	2.48	1.38	4.97	4.04	4.77	8.60
-0.06	*0.018*	39.19	19.55	33.40	16.28	1.50	1.36	2.43	3.12	5.02	6.25	9.11	6.89	3.49	2.78	2.07	5.98	4.63	4.94	9.45

-0.06	*0.02*	37.91	19.08	33.70	16.25	1.15	1.04	2.18	2.94	4.89	6.09	8.94	7.01	3.60	2.95	2.54	6.82	5.09	5.06	10.03
-0.04	*-0.006*	41.97	20.99	36.19	17.01	1.89	1.37	1.59	4.83	6.94	5.15	7.85	5.19	1.22	0.91	0.13	2.46	3.40	2.17	6.55
-0.04	*-0.004*	41.15	20.35	35.97	16.82	1.98	1.46	1.74	4.85	6.95	5.23	8.02	5.38	1.66	1.23	0.23	2.77	3.69	2.73	7.18
-0.04	*-0.002*	41.85	20.50	35.75	17.15	3.21	1.88	2.70	4.79	6.82	6.07	8.94	6.19	2.76	1.97	0.41	3.10	3.64	3.46	7.39
-0.04	*0*	44.11	21.64	35.63	17.72	5.53	3.04	4.56	4.93	6.82	8.04	10.87	8.23	4.87	3.56	1.46	4.24	4.44	5.29	7.36
-0.04	*0.002*	37.80	20.55	33.32	16.46	5.18	3.06	4.61	4.72	6.51	8.51	10.50	8.37	5.30	4.21	2.43	5.08	4.90	5.67	6.90
-0.04	*0.004*	34.85	19.43	31.07	14.19	3.18	2.17	2.76	2.90	4.55	6.82	9.29	7.36	2.67	2.31	1.47	3.97	4.83	4.10	5.70
-0.04	*0.006*	33.87	19.46	31.28	15.35	2.71	2.36	2.64	3.16	4.86	7.50	10.09	8.10	2.85	2.47	1.85	4.76	5.98	5.93	5.87
-0.04	*0.008*	34.33	18.62	30.56	14.80	2.42	1.92	2.48	3.01	4.78	7.11	10.04	8.15	3.18	2.16	1.24	3.94	4.95	5.94	7.23
-0.04	*0.01*	35.85	18.53	30.74	14.59	1.92	1.44	2.32	2.93	4.76	6.61	9.71	7.38	3.16	2.09	0.65	3.58	4.17	5.33	6.75
-0.04	*0.012*	37.53	18.77	30.91	14.69	1.54	1.26	2.21	2.89	4.76	6.39	9.46	6.85	3.07	2.00	0.48	3.68	3.66	4.88	7.08
-0.04	*0.014*	39.83	19.67	31.90	15.52	1.76	1.53	2.47	3.13	4.96	6.39	9.33	6.72	3.20	2.20	0.86	4.27	3.68	4.70	7.88
-0.04	*0.016*	40.17	19.89	32.94	16.21	1.78	1.59	2.57	3.24	5.08	6.35	9.22	6.79	3.38	2.56	1.57	5.22	4.18	4.81	8.84
-0.04	*0.018*	38.83	19.42	33.51	16.28	1.40	1.28	2.36	3.08	4.99	6.20	9.06	6.92	3.52	2.84	2.21	6.21	4.77	4.98	9.62
-0.04	*0.02*	37.68	19.00	33.75	16.24	1.07	0.96	2.12	2.89	4.86	6.05	8.90	7.03	3.62	2.97	2.62	6.99	5.18	5.09	10.15
-0.02	*-0.006*	41.52	20.48	36.35	17.01	1.87	1.47	1.65	4.93	7.04	5.19	7.94	5.29	1.47	1.10	0.21	2.70	3.70	2.62	7.09
-0.02	*-0.004*	41.24	20.14	36.15	17.01	2.37	1.63	2.08	4.87	6.97	5.57	8.42	5.75	2.25	1.60	0.32	3.04	3.83	3.28	7.71
-0.02	*-0.002*	43.69	21.29	36.23	17.73	4.44	2.31	3.55	4.72	6.68	6.92	9.86	7.13	3.83	2.75	0.88	3.70	4.02	4.39	7.75
-0.02	***0***	42.59	21.39	35.45	17.74	5.86	3.20	4.90	4.98	6.81	8.59	**11.13**	8.86	5.72	4.31	2.10	4.94	4.95	6.10	7.38
-0.02	*0.002*	37.40	20.52	32.59	15.89	4.72	2.70	3.92	3.93	5.63	7.74	9.78	7.71	4.26	3.37	2.11	4.39	5.12	5.07	6.43
-0.02	*0.004*	34.30	19.35	30.63	13.84	2.22	1.68	2.05	2.43	4.05	6.42	8.92	6.72	1.89	1.71	1.12	3.68	4.52	4.28	5.36
-0.02	*0.006*	34.20	19.28	31.31	15.54	2.85	2.41	2.70	3.17	4.88	7.54	10.22	8.28	2.97	2.26	1.73	4.46	5.71	6.20	6.56
-0.02	*0.008*	34.97	18.57	30.66	14.69	2.29	1.73	2.43	2.98	4.77	6.93	9.95	7.90	3.16	2.06	1.00	3.70	4.62	5.69	7.04
-0.02	*0.01*	36.06	18.41	30.73	14.55	1.75	1.31	2.25	2.89	4.74	6.52	9.62	7.17	3.09	2.02	0.52	3.51	3.96	5.16	6.72
-0.02	*0.012*	38.23	19.00	31.11	14.85	1.56	1.30	2.25	2.94	4.81	6.37	9.42	6.77	3.07	2.00	0.51	3.76	3.58	4.78	7.26
-0.02	*0.014*	40.16	19.81	32.19	15.75	1.81	1.58	2.52	3.19	5.01	6.38	9.29	6.71	3.24	2.28	1.02	4.47	3.76	4.70	8.12

-0.02	*0.016*	39.92	19.80	33.13	16.27	1.70	1.53	2.53	3.21	5.07	6.31	9.17	6.81	3.42	2.64	1.75	5.48	4.34	4.85	9.06
-0.02	*0.018*	38.50	19.29	33.60	16.27	1.31	1.19	2.30	3.03	4.95	6.15	9.01	6.94	3.54	2.88	2.34	6.43	4.90	5.01	9.78
-0.02	*0.02*	37.48	18.94	33.81	16.23	1.00	0.89	2.06	2.86	4.84	6.03	8.87	7.06	3.65	2.99	2.69	7.13	5.25	5.11	10.25
0	***-0.006***	41.28	20.09	36.59	17.13	2.00	1.57	1.80	4.98	**7.11**	5.37	8.16	5.52	1.92	1.40	0.31	3.00	3.94	3.13	7.72
0	*-0.004*	42.03	20.40	36.48	17.44	3.19	1.82	2.64	4.76	6.81	6.13	9.01	6.34	3.05	2.13	0.52	3.42	3.95	3.91	8.05
0	*-0.002*	45.14	21.96	37.02	18.28	5.41	2.75	4.22	4.71	6.60	7.67	10.60	8.16	4.93	3.61	1.54	4.46	4.66	5.54	7.98
0	*0*	39.90	21.23	35.21	17.48	5.68	3.20	4.83	4.91	6.69	8.62	10.79	8.70	5.75	4.46	2.44	5.11	4.86	5.77	7.16
0	*0.002*	37.10	20.48	32.29	15.25	3.92	2.44	3.22	3.24	4.86	7.13	9.42	7.28	3.09	2.57	1.64	3.96	4.82	3.85	5.56
0	*0.004*	34.84	19.97	31.31	14.89	2.47	2.02	2.31	2.75	4.38	6.98	9.45	7.08	2.16	1.84	1.38	4.08	5.14	4.96	5.31
0	*0.006*	34.29	18.83	30.87	15.16	2.68	2.16	2.55	3.02	4.75	7.33	10.14	8.22	2.94	1.99	1.46	4.05	5.25	6.17	7.10
0	*0.008*	35.43	18.52	30.77	14.66	2.18	1.59	2.40	2.98	4.78	6.79	9.85	7.66	3.14	2.02	0.82	3.55	4.37	5.49	6.84
0	*0.01*	36.40	18.39	30.73	14.53	1.62	1.24	2.19	2.87	4.73	6.44	9.55	7.00	3.04	1.96	0.44	3.49	3.78	5.02	6.79
0	*0.012*	38.88	19.24	31.35	15.04	1.60	1.37	2.31	3.00	4.85	6.37	9.37	6.71	3.09	2.03	0.59	3.88	3.55	4.71	7.45
0	*0.014*	40.34	19.91	32.47	15.95	1.83	1.62	2.56	3.22	5.05	6.36	9.25	6.72	3.28	2.37	1.20	4.70	3.88	4.72	8.37
0	*0.016*	39.59	19.68	33.29	16.29	1.60	1.45	2.48	3.17	5.05	6.27	9.13	6.84	3.45	2.72	1.92	5.73	4.50	4.90	9.28
0	*0.018*	38.19	19.18	33.67	16.27	1.23	1.11	2.24	2.98	4.92	6.11	8.97	6.97	3.57	2.92	2.45	6.64	5.01	5.04	9.92
0	*0.02*	37.31	18.88	33.87	16.24	0.94	0.82	2.01	2.82	4.82	6.00	8.84	7.09	3.67	3.01	2.76	7.26	5.31	5.13	10.35
0.02	*-0.006*	41.43	20.00	36.93	17.40	2.40	1.65	2.10	4.91	7.03	5.70	8.53	5.92	2.53	1.79	0.43	3.34	4.09	3.68	8.25
0.02	*-0.004*	43.84	21.22	37.22	18.10	4.23	2.05	3.27	4.55	6.53	6.73	9.65	7.14	3.98	2.84	0.99	4.00	4.33	4.78	8.35
0.02	*-0.002*	44.32	21.89	37.13	18.40	5.88	3.01	4.62	4.81	6.62	8.21	10.95	8.85	5.80	4.33	2.08	5.05	5.09	6.31	7.82
0.02	*0*	38.89	21.15	34.57	16.98	5.25	2.92	4.29	4.33	6.03	7.98	9.99	7.93	4.86	3.76	2.27	4.60	4.80	5.09	6.53
0.02	*0.002*	36.31	20.27	31.99	14.56	2.81	1.96	2.37	2.59	4.16	6.42	8.85	6.48	2.01	1.71	1.15	3.41	4.17	3.44	5.07
0.02	*0.004*	35.25	20.02	31.85	15.69	2.86	2.37	2.63	3.02	4.67	7.39	9.92	7.62	2.46	1.87	1.55	4.19	5.45	5.48	5.52
0.02	*0.006*	34.53	18.54	30.67	14.85	2.47	1.89	2.43	2.94	4.69	7.13	10.06	8.09	2.95	1.87	1.21	3.74	4.86	5.93	7.19
0.02	*0.008*	35.74	18.46	30.84	14.65	2.06	1.48	2.36	2.97	4.78	6.67	9.76	7.43	3.10	1.99	0.66	3.45	4.15	5.31	6.68
0.02	*0.01*	36.93	18.50	30.79	14.57	1.54	1.22	2.18	2.87	4.74	6.39	9.49	6.87	3.01	1.92	0.41	3.52	3.64	4.90	6.92

0.02	*0.012*	39.45	19.47	31.62	15.26	1.66	1.44	2.38	3.06	4.90	6.36	9.33	6.68	3.13	2.09	0.71	4.03	3.57	4.67	7.67
0.02	*0.014*	40.36	19.93	32.72	16.11	1.82	1.62	2.58	3.24	5.07	6.34	9.22	6.74	3.32	2.46	1.39	4.95	4.02	4.75	8.62
0.02	*0.016*	39.22	19.55	33.42	16.30	1.50	1.36	2.42	3.12	5.02	6.22	9.08	6.87	3.48	2.78	2.08	5.98	4.65	4.94	9.47
0.02	*0.018*	37.93	19.09	33.72	16.26	1.15	1.03	2.17	2.93	4.89	6.07	8.92	7.00	3.59	2.95	2.55	6.83	5.10	5.07	10.05
0.02	*0.02*	37.15	18.83	33.94	16.25	0.88	0.77	1.96	2.79	4.80	5.98	8.81	7.11	3.69	3.02	2.81	7.37	5.35	5.14	10.43
0.04	*-0.006*	42.50	20.47	37.58	17.94	3.11	1.72	2.53	4.70	6.77	6.12	8.97	6.46	3.26	2.29	0.68	3.77	4.26	4.30	8.55
0.04	*-0.004*	45.33	21.94	38.15	18.65	5.05	2.34	3.75	4.42	6.32	7.21	10.17	7.95	4.86	3.58	1.52	4.59	4.83	5.72	8.52
0.04	***-0.002***	42.12	21.82	36.97	18.35	**5.99**	3.19	4.84	4.92	6.68	8.51	10.93	**8.92**	**6.04**	**4.57**	2.33	5.07	4.85	5.93	7.44
0.04	*0*	39.12	21.26	33.92	16.35	4.53	2.55	3.56	3.54	5.15	7.24	9.34	7.12	3.52	2.74	1.69	3.91	4.57	3.79	5.53
0.04	*0.002*	36.22	20.65	31.99	14.82	2.43	1.83	2.15	2.48	4.05	6.52	8.93	6.31	1.74	1.40	1.03	3.39	4.24	3.94	5.03
0.04	*0.004*	35.12	19.51	31.64	15.68	2.90	2.36	2.64	3.00	4.68	7.39	10.05	7.89	2.57	1.73	1.49	3.97	5.29	5.84	6.14
0.04	*0.006*	34.84	18.39	30.70	14.72	2.31	1.70	2.37	2.93	4.70	6.96	9.97	7.89	2.99	1.84	1.00	3.54	4.56	5.68	7.06
0.04	*0.008*	35.95	18.38	30.84	14.62	1.91	1.37	2.30	2.94	4.76	6.58	9.68	7.23	3.06	1.95	0.53	3.39	3.95	5.16	6.62
0.04	*0.01*	37.61	18.72	30.93	14.67	1.51	1.24	2.20	2.90	4.77	6.36	9.43	6.76	3.01	1.92	0.42	3.58	3.54	4.79	7.08
0.04	*0.012*	39.91	19.66	31.91	15.51	1.73	1.51	2.45	3.13	4.96	6.35	9.28	6.67	3.17	2.16	0.85	4.22	3.63	4.66	7.90
0.04	*0.014*	40.22	19.90	32.95	16.22	1.77	1.58	2.56	3.23	5.08	6.31	9.18	6.76	3.37	2.55	1.58	5.21	4.18	4.80	8.86
0.04	*0.016*	38.86	19.42	33.53	16.30	1.40	1.27	2.35	3.07	4.98	6.18	9.03	6.90	3.51	2.84	2.23	6.22	4.78	4.98	9.64
0.04	*0.018*	37.70	19.01	33.77	16.25	1.07	0.96	2.11	2.89	4.86	6.04	8.88	7.03	3.62	2.98	2.63	7.00	5.19	5.09	10.17
0.04	*0.02*	37.00	18.78	34.02	16.27	0.83	0.71	1.91	2.77	4.78	5.96	8.79	7.12	3.71	3.03	2.86	7.46	5.39	5.15	10.50
0.06	*-0.006*	44.11	21.26	38.41	18.59	3.98	1.81	2.97	4.41	6.39	6.50	9.36	7.07	4.02	2.92	1.10	4.26	4.58	5.06	8.75
0.06	*-0.004*	45.30	22.16	38.53	18.83	5.61	2.66	4.17	4.51	6.34	7.73	10.60	8.59	5.62	4.21	1.92	4.99	5.09	6.32	8.36
0.06	*-0.002*	40.38	21.64	36.63	18.14	5.76	3.16	4.61	4.70	6.37	8.17	10.29	8.25	5.34	4.08	2.29	4.72	4.47	5.02	6.73
0.06	*0*	38.37	21.08	33.56	15.74	3.56	2.27	2.82	2.92	4.46	6.68	8.95	6.55	2.43	1.97	1.38	3.47	4.16	2.99	4.81
0.06	*0.002*	36.13	20.65	32.01	15.34	2.58	2.02	2.31	2.64	4.23	6.91	9.32	6.65	1.87	1.38	1.20	3.62	4.75	4.58	5.07
0.06	*0.004*	34.92	18.97	31.15	15.30	2.73	2.13	2.51	2.91	4.62	7.26	10.05	7.99	2.64	1.63	1.37	3.75	5.03	5.99	6.81
0.06	*0.006*	35.15	18.33	30.81	14.69	2.21	1.57	2.36	2.96	4.74	6.82	9.88	7.68	3.02	1.86	0.82	3.42	4.32	5.46	6.85

0.06	*0.008*	36.16	18.31	30.80	14.57	1.75	1.28	2.24	2.90	4.75	6.49	9.60	7.05	3.01	1.90	0.43	3.37	3.79	5.04	6.66
0.06	*0.01*	38.32	18.98	31.13	14.83	1.53	1.28	2.24	2.95	4.81	6.34	9.38	6.69	3.02	1.94	0.48	3.68	3.49	4.71	7.26
0.06	*0.012*	40.24	19.82	32.20	15.75	1.78	1.57	2.51	3.18	5.00	6.34	9.25	6.67	3.22	2.25	1.02	4.45	3.74	4.67	8.14
0.06	*0.014*	39.97	19.81	33.15	16.28	1.69	1.52	2.52	3.21	5.06	6.28	9.14	6.79	3.41	2.64	1.76	5.48	4.35	4.85	9.09
0.06	*0.016*	38.52	19.29	33.62	16.29	1.31	1.19	2.29	3.02	4.95	6.13	8.99	6.93	3.54	2.89	2.35	6.44	4.91	5.02	9.80
0.06	*0.018*	37.50	18.94	33.82	16.24	1.00	0.89	2.06	2.85	4.83	6.01	8.85	7.06	3.64	3.00	2.70	7.14	5.26	5.11	10.27
0.06	*0.02*	36.86	18.73	34.11	16.29	0.79	0.66	1.87	2.75	4.77	5.94	8.76	7.13	3.72	3.03	2.89	7.52	5.41	5.16	10.56
0.08	*-0.006*	45.32	21.90	39.20	19.02	4.69	2.01	3.34	4.22	6.12	6.82	9.74	7.67	4.70	3.52	1.51	4.62	4.91	5.79	8.89
0.08	*-0.004*	43.91	22.24	38.41	18.90	5.98	2.99	4.60	4.75	6.50	8.23	10.84	8.85	6.03	4.54	2.15	5.06	4.86	6.14	7.87
0.08	*-0.002*	40.28	21.47	35.72	17.42	5.13	2.72	3.90	3.87	5.44	7.36	9.33	7.09	4.02	2.99	1.73	3.96	4.17	3.82	5.65
0.08	*0*	37.85	21.29	33.42	15.49	2.83	1.96	2.31	2.52	4.05	6.41	8.75	6.06	1.77	1.35	1.00	3.07	3.80	3.03	4.67
0.08	*0.002*	36.11	20.32	32.16	15.73	2.79	2.21	2.50	2.77	4.40	7.13	9.64	7.09	2.03	1.34	1.29	3.64	4.98	5.07	5.23
0.08	*0.004*	34.84	18.59	30.84	14.96	2.50	1.88	2.39	2.86	4.60	7.10	10.02	7.97	2.72	1.61	1.20	3.57	4.77	5.89	7.11
0.08	*0.006*	35.50	18.33	30.92	14.70	2.13	1.49	2.36	2.98	4.77	6.72	9.80	7.47	3.03	1.87	0.66	3.33	4.12	5.28	6.65
0.08	*0.008*	36.50	18.33	30.77	14.54	1.61	1.22	2.19	2.88	4.74	6.42	9.52	6.90	2.97	1.87	0.38	3.39	3.64	4.92	6.77
0.08	*0.01*	38.98	19.24	31.38	15.03	1.57	1.35	2.30	3.00	4.85	6.33	9.33	6.65	3.06	1.99	0.57	3.82	3.48	4.65	7.47
0.08	*0.012*	40.42	19.92	32.49	15.96	1.81	1.60	2.55	3.22	5.04	6.33	9.21	6.69	3.26	2.35	1.21	4.69	3.87	4.70	8.39
0.08	*0.014*	39.63	19.69	33.31	16.31	1.60	1.44	2.47	3.16	5.04	6.24	9.09	6.83	3.44	2.72	1.94	5.74	4.51	4.90	9.30
0.08	*0.016*	38.22	19.18	33.69	16.28	1.23	1.11	2.23	2.98	4.91	6.09	8.94	6.96	3.56	2.92	2.46	6.65	5.02	5.05	9.94
0.08	*0.018*	37.32	18.88	33.88	16.25	0.94	0.82	2.01	2.82	4.81	5.99	8.82	7.08	3.67	3.02	2.77	7.27	5.32	5.13	10.37
0.08	*0.02*	36.72	18.68	34.20	16.32	0.74	0.62	1.83	2.73	4.76	5.92	8.73	7.12	3.73	3.03	2.92	7.57	5.43	5.16	10.60
0.1	***-0.006***	**45.79**	22.30	39.69	19.17	5.24	2.28	3.72	4.24	6.07	7.27	10.16	8.17	5.28	4.00	1.73	4.80	5.00	6.18	8.85
0.1	*-0.004*	41.99	22.07	38.24	18.97	5.94	3.16	4.65	4.80	6.48	8.17	10.46	8.38	5.55	4.21	2.14	4.73	4.29	5.11	7.16
0.1	*-0.002*	40.13	21.50	35.30	16.89	4.29	2.48	3.25	3.28	4.80	6.86	8.90	6.43	2.89	2.22	1.52	3.53	4.05	2.87	4.80
0.1	*0*	37.30	21.26	32.91	15.42	2.51	1.79	2.13	2.38	3.93	6.48	8.81	6.02	1.56	1.08	0.94	3.05	3.98	3.64	4.77
0.1	*0.002*	35.91	19.77	31.98	15.74	2.85	2.22	2.53	2.79	4.45	7.16	9.81	7.45	2.18	1.30	1.30	3.55	4.92	5.48	5.75

0.1	*0.004*	34.86	18.36	30.79	14.78	2.31	1.68	2.32	2.87	4.63	6.96	9.97	7.85	2.81	1.64	1.01	3.42	4.52	5.68	7.08
0.1	*0.006*	35.82	18.34	30.97	14.71	2.04	1.42	2.35	2.98	4.78	6.63	9.72	7.28	3.02	1.87	0.54	3.29	3.94	5.14	6.54
0.1	*0.008*	37.04	18.47	30.83	14.57	1.52	1.20	2.18	2.89	4.75	6.36	9.45	6.78	2.96	1.85	0.36	3.43	3.53	4.82	6.92
0.1	*0.01*	39.55	19.48	31.65	15.26	1.64	1.42	2.37	3.06	4.90	6.32	9.28	6.63	3.10	2.06	0.70	4.00	3.52	4.63	7.68
0.1	*0.012*	40.43	19.95	32.75	16.13	1.81	1.61	2.57	3.24	5.06	6.31	9.17	6.71	3.31	2.45	1.40	4.95	4.02	4.74	8.64
0.1	*0.014*	39.26	19.55	33.45	16.32	1.50	1.36	2.41	3.12	5.01	6.20	9.05	6.86	3.48	2.79	2.10	5.99	4.66	4.95	9.49
0.1	*0.016*	37.95	19.09	33.74	16.27	1.15	1.03	2.17	2.93	4.88	6.06	8.90	6.99	3.59	2.96	2.56	6.84	5.12	5.08	10.07
0.1	*0.018*	37.16	18.83	33.95	16.26	0.88	0.77	1.96	2.79	4.80	5.97	8.80	7.10	3.69	3.03	2.82	7.38	5.37	5.15	10.45
0.1	*0.02*	36.58	18.63	34.30	16.35	0.70	0.57	1.78	2.70	4.74	5.89	8.69	7.11	3.72	3.02	2.93	7.59	5.43	5.16	10.62
0.12	***-0.006***	45.18	**22.52**	**39.64**	19.27	5.70	2.61	4.17	4.43	6.19	7.79	10.50	8.45	5.69	4.35	1.91	4.94	4.81	6.18	8.45
0.12	*-0.004*	41.21	21.62	37.42	18.45	5.61	2.91	4.22	4.21	5.75	7.51	9.50	7.24	4.43	3.26	1.78	4.08	3.86	3.94	6.03
0.12	*-0.002*	39.20	21.50	35.01	16.58	3.52	2.24	2.67	2.77	4.24	6.53	8.70	6.06	2.12	1.61	1.22	3.13	3.72	2.49	4.40
0.12	*0*	36.84	20.91	32.43	15.40	2.45	1.78	2.15	2.38	3.96	6.65	9.03	6.18	1.53	0.95	0.99	3.15	4.37	4.24	4.86
0.12	*0.002*	35.59	19.23	31.52	15.44	2.72	2.08	2.46	2.77	4.47	7.11	9.90	7.68	2.33	1.32	1.27	3.48	4.81	5.77	6.47
0.12	*0.004*	34.94	18.22	30.86	14.72	2.19	1.55	2.30	2.90	4.68	6.84	9.90	7.68	2.88	1.69	0.83	3.31	4.29	5.45	6.89
0.12	*0.006*	36.07	18.32	30.94	14.67	1.91	1.34	2.31	2.96	4.78	6.55	9.65	7.11	2.99	1.86	0.44	3.28	3.79	5.03	6.55
0.12	*0.008*	37.72	18.71	30.97	14.67	1.49	1.22	2.19	2.91	4.78	6.33	9.39	6.69	2.97	1.86	0.39	3.52	3.46	4.72	7.09
0.12	*0.01*	40.01	19.68	31.94	15.51	1.71	1.50	2.44	3.12	4.95	6.31	9.24	6.63	3.15	2.15	0.85	4.20	3.61	4.63	7.92
0.12	*0.012*	40.29	19.91	32.98	16.24	1.76	1.58	2.55	3.23	5.07	6.28	9.14	6.74	3.36	2.55	1.59	5.22	4.19	4.80	8.88
0.12	*0.014*	38.89	19.42	33.56	16.31	1.40	1.27	2.35	3.07	4.98	6.15	9.01	6.89	3.51	2.84	2.24	6.23	4.80	4.99	9.67
0.12	*0.016*	37.72	19.01	33.79	16.26	1.07	0.96	2.11	2.89	4.85	6.02	8.87	7.02	3.62	2.98	2.64	7.01	5.20	5.10	10.18
0.12	*0.018*	37.01	18.78	34.03	16.27	0.83	0.71	1.91	2.77	4.78	5.95	8.77	7.12	3.71	3.04	2.87	7.47	5.40	5.16	10.51
0.12	*0.02*	36.45	18.58	34.40	16.38	0.66	0.53	1.74	2.68	4.72	5.86	8.65	7.08	3.71	3.00	2.94	7.60	5.43	5.15	10.64
0.14	***-0.006***	43.38	22.38	39.32	**19.35**	5.73	2.86	4.37	4.62	6.31	7.94	10.39	8.23	5.47	4.19	1.96	4.77	4.33	5.49	7.81
0.14	*-0.004*	40.99	21.44	36.74	17.72	4.84	2.55	3.56	3.53	5.01	6.93	8.80	6.23	3.29	2.38	1.49	3.48	3.71	2.93	5.08
0.14	*-0.002*	38.57	21.58	34.55	16.17	2.85	1.84	2.23	2.37	3.86	6.31	8.55	5.78	1.61	1.09	0.91	2.77	3.56	2.77	4.40

0.14	*0*	36.74	20.53	32.43	15.61	2.57	1.91	2.27	2.46	4.09	6.78	9.30	6.55	1.63	0.92	1.05	3.19	4.59	4.72	5.00
0.14	*0.002*	35.33	18.80	31.11	15.10	2.52	1.88	2.36	2.76	4.49	7.02	9.94	7.79	2.48	1.36	1.18	3.42	4.67	5.82	6.96
0.14	*0.004*	35.16	18.18	30.97	14.73	2.14	1.48	2.32	2.96	4.73	6.74	9.82	7.50	2.93	1.74	0.68	3.23	4.10	5.26	6.67
0.14	*0.006*	36.29	18.29	30.87	14.60	1.75	1.27	2.25	2.93	4.77	6.47	9.57	6.96	2.96	1.83	0.37	3.28	3.66	4.94	6.63
0.14	*0.008*	38.44	18.99	31.17	14.83	1.51	1.27	2.24	2.96	4.81	6.30	9.33	6.63	2.99	1.90	0.46	3.64	3.43	4.65	7.28
0.14	*0.01*	40.34	19.84	32.24	15.76	1.77	1.56	2.50	3.18	5.00	6.30	9.20	6.64	3.20	2.25	1.03	4.44	3.72	4.65	8.17
0.14	*0.012*	40.02	19.82	33.17	16.30	1.69	1.52	2.52	3.20	5.05	6.25	9.10	6.77	3.40	2.64	1.78	5.48	4.36	4.85	9.11
0.14	*0.014*	38.55	19.30	33.64	16.31	1.31	1.19	2.29	3.02	4.94	6.11	8.96	6.92	3.53	2.89	2.37	6.45	4.92	5.02	9.82
0.14	*0.016*	37.52	18.94	33.83	16.25	1.00	0.89	2.05	2.85	4.83	6.00	8.84	7.05	3.64	3.00	2.71	7.15	5.27	5.12	10.29
0.14	*0.018*	36.87	18.73	34.12	16.30	0.79	0.66	1.87	2.75	4.77	5.93	8.75	7.13	3.72	3.04	2.90	7.53	5.42	5.17	10.57
0.14	*0.02*	36.32	18.53	34.49	16.40	0.62	0.48	1.69	2.66	4.70	5.83	8.61	7.04	3.69	2.97	2.93	7.59	5.42	5.14	10.64
0.16	*-0.006*	42.40	21.97	38.70	19.15	5.66	2.85	4.26	4.34	5.89	7.54	9.63	7.32	4.59	3.44	1.78	4.18	3.76	4.26	6.77
0.16	*-0.004*	40.30	21.50	36.66	17.61	4.22	2.46	3.10	3.11	4.54	6.64	8.57	5.92	2.57	1.98	1.45	3.33	3.68	2.38	4.45
0.16	*-0.002*	37.80	21.29	33.56	15.61	2.36	1.50	1.93	2.12	3.66	6.23	8.52	5.65	1.32	0.77	0.80	2.67	3.71	3.37	4.54
0.16	*0*	36.56	20.05	32.35	15.73	2.69	2.01	2.38	2.55	4.21	6.87	9.52	6.98	1.83	0.96	1.11	3.20	4.61	5.15	5.42
0.16	*0.002*	35.16	18.50	30.96	14.88	2.33	1.69	2.29	2.78	4.54	6.93	9.94	7.77	2.62	1.44	1.03	3.33	4.49	5.69	7.08
0.16	*0.004*	35.54	18.24	31.07	14.76	2.10	1.44	2.35	3.00	4.78	6.66	9.76	7.33	2.96	1.78	0.56	3.19	3.93	5.12	6.51
0.16	*0.006*	36.63	18.33	30.82	14.55	1.61	1.21	2.20	2.90	4.76	6.39	9.49	6.82	2.93	1.81	0.33	3.32	3.54	4.85	6.76
0.16	*0.008*	39.11	19.26	31.42	15.04	1.55	1.34	2.29	3.01	4.85	6.29	9.28	6.60	3.04	1.96	0.56	3.79	3.44	4.61	7.48
0.16	*0.01*	40.51	19.94	32.52	15.97	1.80	1.60	2.54	3.21	5.03	6.29	9.16	6.66	3.25	2.35	1.22	4.69	3.87	4.69	8.42
0.16	*0.012*	39.67	19.70	33.34	16.33	1.59	1.44	2.46	3.16	5.03	6.21	9.06	6.81	3.44	2.72	1.95	5.75	4.52	4.90	9.32
0.16	*0.014*	38.24	19.19	33.71	16.29	1.23	1.11	2.22	2.97	4.91	6.07	8.92	6.95	3.56	2.93	2.47	6.66	5.04	5.06	9.96
0.16	*0.016*	37.34	18.89	33.89	16.25	0.94	0.82	2.00	2.82	4.81	5.98	8.81	7.08	3.66	3.02	2.78	7.28	5.33	5.14	10.38
0.16	*0.018*	36.73	18.68	34.21	16.33	0.75	0.62	1.83	2.73	4.75	5.91	8.72	7.12	3.72	3.03	2.92	7.57	5.44	5.17	10.61
0.16	*0.02*	36.19	18.47	34.58	16.43	0.57	0.43	1.64	2.63	4.68	5.79	8.56	7.00	3.67	2.94	2.92	7.57	5.40	5.12	10.64
0.18	*-0.006*	41.73	21.52	37.84	18.38	5.15	2.49	3.74	3.70	5.15	6.96	8.79	6.21	3.54	2.52	1.43	3.44	3.43	3.13	5.69

0.18	*-0.004*	39.20	21.36	36.12	17.19	3.53	2.10	2.56	2.59	4.00	6.36	8.41	5.70	1.94	1.42	1.13	2.88	3.46	2.25	4.18
0.18	*-0.002*	37.30	20.94	32.83	15.29	2.16	1.40	1.87	2.06	3.65	6.28	8.67	5.71	1.19	0.61	0.79	2.74	4.04	3.96	4.68
0.18	*0*	36.20	19.53	31.93	15.56	2.67	1.98	2.39	2.61	4.30	6.91	9.69	7.33	2.04	1.05	1.16	3.24	4.60	5.52	6.12
0.18	*0.002*	35.03	18.28	30.97	14.78	2.18	1.55	2.26	2.83	4.61	6.83	9.89	7.67	2.73	1.52	0.86	3.23	4.28	5.47	6.95
0.18	*0.004*	35.93	18.30	31.09	14.77	2.04	1.40	2.35	3.01	4.81	6.60	9.69	7.18	2.97	1.80	0.46	3.19	3.79	5.02	6.46
0.18	*0.006*	37.17	18.48	30.86	14.58	1.51	1.19	2.18	2.90	4.76	6.34	9.42	6.71	2.92	1.81	0.33	3.38	3.45	4.75	6.92
0.18	*0.008*	39.67	19.50	31.69	15.27	1.62	1.42	2.36	3.07	4.90	6.28	9.23	6.59	3.09	2.04	0.70	3.98	3.50	4.60	7.71
0.18	*0.01*	40.51	19.97	32.78	16.14	1.80	1.60	2.56	3.23	5.06	6.27	9.13	6.69	3.30	2.46	1.41	4.95	4.03	4.74	8.67
0.18	*0.012*	39.30	19.56	33.47	16.33	1.50	1.36	2.40	3.11	5.00	6.17	9.02	6.84	3.47	2.79	2.11	6.00	4.67	4.95	9.51
0.18	*0.014*	37.97	19.09	33.76	16.28	1.15	1.03	2.16	2.93	4.88	6.04	8.88	6.99	3.59	2.96	2.57	6.85	5.13	5.08	10.09
0.18	*0.016*	37.18	18.84	33.96	16.26	0.89	0.76	1.95	2.79	4.79	5.96	8.79	7.10	3.69	3.03	2.83	7.39	5.38	5.15	10.46
0.18	*0.018*	36.59	18.63	34.30	16.35	0.71	0.57	1.78	2.70	4.74	5.89	8.68	7.11	3.72	3.02	2.94	7.60	5.44	5.16	10.64
0.18	*0.02*	36.07	18.42	34.67	16.45	0.53	0.39	1.59	2.60	4.65	5.75	8.50	6.94	3.64	2.91	2.91	7.53	5.38	5.10	10.62
0.2	*-0.006*	41.08	21.50	37.76	18.12	4.59	2.37	3.31	3.28	4.70	6.66	8.40	5.72	2.90	2.18	1.46	3.35	3.49	2.51	4.86
0.2	*-0.004*	38.62	21.28	35.35	16.47	2.75	1.56	2.05	2.14	3.61	6.08	8.23	5.46	1.44	0.90	0.82	2.50	3.36	2.57	4.18
0.2	*-0.002*	37.15	20.63	32.70	15.40	2.26	1.52	1.99	2.14	3.78	6.40	8.93	6.04	1.28	0.61	0.85	2.83	4.28	4.43	4.82
0.2	*0*	35.85	19.08	31.45	15.25	2.53	1.86	2.34	2.65	4.37	6.90	9.80	7.55	2.24	1.14	1.14	3.26	4.56	5.71	6.74
0.2	*0.002*	34.99	18.13	31.03	14.76	2.11	1.47	2.26	2.90	4.68	6.74	9.83	7.52	2.82	1.60	0.70	3.15	4.08	5.26	6.72
0.2	*0.004*	36.23	18.32	31.03	14.71	1.92	1.34	2.32	2.99	4.80	6.53	9.62	7.03	2.95	1.80	0.38	3.20	3.67	4.94	6.51
0.2	*0.006*	37.85	18.73	31.00	14.68	1.48	1.22	2.19	2.92	4.78	6.30	9.35	6.63	2.94	1.83	0.37	3.48	3.39	4.67	7.10
0.2	*0.008*	40.13	19.71	31.98	15.52	1.69	1.49	2.43	3.12	4.95	6.28	9.19	6.59	3.14	2.14	0.86	4.20	3.59	4.61	7.95
0.2	*0.01*	40.36	19.92	33.00	16.26	1.76	1.58	2.55	3.22	5.06	6.25	9.10	6.72	3.35	2.55	1.61	5.22	4.20	4.80	8.91
0.2	*0.012*	38.93	19.43	33.58	16.33	1.40	1.27	2.34	3.06	4.97	6.13	8.98	6.88	3.50	2.85	2.25	6.24	4.81	5.00	9.69
0.2	*0.014*	37.74	19.02	33.80	16.27	1.08	0.96	2.10	2.89	4.85	6.01	8.85	7.02	3.61	2.99	2.65	7.02	5.22	5.11	10.20
0.2	*0.016*	37.03	18.79	34.04	16.28	0.84	0.71	1.91	2.77	4.78	5.94	8.76	7.12	3.70	3.04	2.87	7.47	5.41	5.16	10.53
0.2	***0.018***	36.46	18.58	34.40	16.38	0.66	0.53	1.74	2.68	4.72	5.86	8.64	7.08	3.71	3.00	**2.94**	**7.61**	5.44	5.16	10.65

0.2	*0.02*	35.95	18.37	34.75	16.46	0.48	0.34	1.53	2.58	4.63	5.70	8.45	6.88	3.60	2.87	2.88	7.48	5.35	5.07	10.59
0.22	*-0.006*	39.81	21.24	37.47	17.96	4.08	2.23	2.91	2.86	4.23	6.42	8.23	5.55	2.36	1.86	1.39	3.20	3.47	2.17	4.31
0.22	*-0.004*	38.06	21.05	34.21	15.66	2.15	1.14	1.70	1.85	3.39	5.91	8.17	5.28	1.10	0.55	0.65	2.37	3.46	3.15	4.34
0.22	*-0.002*	36.99	20.27	32.70	15.64	2.47	1.72	2.17	2.30	3.96	6.57	9.22	6.53	1.51	0.71	0.96	2.91	4.36	4.86	5.16
0.22	*0*	35.60	18.75	31.19	15.01	2.36	1.71	2.28	2.69	4.44	6.86	9.85	7.64	2.42	1.25	1.05	3.24	4.46	5.69	7.03
0.22	*0.002*	35.19	18.11	31.12	14.79	2.09	1.43	2.30	2.97	4.75	6.67	9.77	7.37	2.88	1.68	0.58	3.11	3.92	5.10	6.52
0.22	*0.004*	36.46	18.30	30.93	14.62	1.76	1.27	2.26	2.96	4.79	6.45	9.54	6.88	2.92	1.79	0.33	3.22	3.55	4.87	6.62
0.22	*0.006*	38.58	19.01	31.21	14.84	1.49	1.27	2.23	2.96	4.81	6.27	9.29	6.58	2.97	1.88	0.44	3.61	3.38	4.61	7.30
0.22	*0.008*	40.45	19.87	32.28	15.77	1.75	1.55	2.49	3.17	4.99	6.27	9.16	6.61	3.19	2.25	1.04	4.44	3.72	4.65	8.20
0.22	*0.01*	40.08	19.83	33.20	16.32	1.69	1.52	2.51	3.20	5.05	6.22	9.06	6.75	3.39	2.65	1.79	5.49	4.37	4.85	9.14
0.22	*0.012*	38.58	19.30	33.67	16.32	1.31	1.19	2.28	3.02	4.94	6.09	8.94	6.91	3.53	2.90	2.38	6.47	4.94	5.03	9.84
0.22	*0.014*	37.54	18.95	33.85	16.26	1.01	0.89	2.05	2.85	4.83	5.99	8.82	7.05	3.64	3.01	2.72	7.16	5.29	5.13	10.30
0.22	*0.016*	36.88	18.74	34.12	16.30	0.79	0.66	1.87	2.75	4.77	5.92	8.74	7.12	3.72	3.04	2.91	7.54	5.43	5.17	10.58
0.22	***0.018***	36.33	18.53	34.49	16.41	0.62	0.48	1.69	2.66	4.70	5.82	8.60	7.04	3.69	2.98	2.94	7.60	5.43	5.14	**10.65**
0.22	*0.02*	35.83	18.31	34.82	16.47	0.43	0.29	1.48	2.55	4.60	5.66	8.39	6.81	3.56	2.83	2.85	7.42	5.32	5.04	10.56
0.24	*-0.006*	38.82	20.94	36.74	17.33	3.36	1.76	2.36	2.33	3.72	6.15	8.08	5.39	1.79	1.30	1.06	2.72	3.31	2.14	4.06
0.24	*-0.004*	37.58	20.77	33.28	15.15	1.87	0.99	1.58	1.76	3.36	5.91	8.31	5.30	0.93	0.38	0.61	2.43	3.77	3.74	4.53
0.24	*-0.002*	36.65	19.81	32.36	15.62	2.58	1.82	2.28	2.44	4.12	6.69	9.47	6.97	1.77	0.83	1.06	3.02	4.41	5.27	5.78
0.24	*0*	35.38	18.49	31.14	14.88	2.20	1.58	2.24	2.75	4.53	6.79	9.86	7.62	2.57	1.36	0.90	3.17	4.29	5.51	7.00
0.24	*0.002*	35.62	18.20	31.19	14.82	2.09	1.42	2.35	3.03	4.80	6.63	9.72	7.23	2.92	1.73	0.48	3.10	3.78	5.00	6.42
0.24	*0.004*	36.78	18.35	30.86	14.57	1.61	1.21	2.21	2.92	4.77	6.37	9.46	6.75	2.90	1.77	0.30	3.27	3.45	4.79	6.77
0.24	*0.006*	39.24	19.29	31.46	15.05	1.54	1.34	2.29	3.01	4.85	6.26	9.23	6.56	3.02	1.95	0.56	3.78	3.41	4.58	7.51
0.24	*0.008*	40.61	19.97	32.56	15.99	1.79	1.59	2.53	3.21	5.03	6.26	9.12	6.63	3.25	2.35	1.23	4.69	3.87	4.69	8.45
0.24	*0.01*	39.72	19.71	33.36	16.35	1.59	1.44	2.46	3.16	5.02	6.19	9.03	6.79	3.43	2.73	1.97	5.76	4.53	4.91	9.35
0.24	*0.012*	38.27	19.19	33.73	16.31	1.23	1.11	2.22	2.97	4.90	6.06	8.90	6.95	3.56	2.94	2.49	6.67	5.05	5.06	9.98
0.24	*0.014*	37.36	18.89	33.90	16.26	0.94	0.82	2.00	2.82	4.81	5.97	8.80	7.08	3.66	3.03	2.79	7.29	5.34	5.15	10.40

0.24	*0.016*	36.74	18.69	34.21	16.33	0.75	0.62	1.82	2.72	4.75	5.90	8.71	7.12	3.72	3.04	2.93	7.58	5.45	5.17	10.62
0.24	*0.018*	36.20	18.48	34.58	16.43	0.58	0.44	1.64	2.63	4.68	5.79	8.55	7.00	3.67	2.95	2.93	7.57	5.41	5.12	10.65
0.24	*0.02*	35.72	18.26	34.89	16.48	0.38	0.24	1.42	2.52	4.57	5.61	8.33	6.74	3.52	2.78	2.82	7.35	5.29	5.00	10.52

Table B3: Table showing all possible outcomes of the test statistic J_T for the causal relation between futures on corn and inflation at various quantiles (on the columns) for all plausible pairs of the polynomial weights (θ_1, θ_2) (on the rows). The pairs yielding the maximum values of J_T at every quantile considered are indicated in bold.

		Quantiles																		
θ_1	θ_2	*0.05*	*0.1*	*0.15*	*0.2*	*0.25*	*0.3*	*0.35*	*0.4*	*0.45*	*0.5*	*0.55*	*0.6*	*0.65*	*0.7*	*0.75*	*0.8*	*0.85*	*0.9*	*0.95*
-0.07	*-0.18*	48.63	25.79	42.37	19.37	2.23	-0.16	-0.28	0.57	1.75	1.91	3.38	1.10	0.02	-0.34	0.07	1.13	3.02	3.94	8.33
-0.07	*-0.15*	48.71	25.76	42.63	19.52	2.22	-0.17	-0.29	0.55	1.72	1.83	3.25	1.00	-0.06	-0.36	-0.01	0.98	2.78	3.55	7.67
-0.07	*-0.12*	47.76	25.11	42.17	19.18	2.13	-0.15	-0.30	0.62	1.81	1.87	3.26	1.00	-0.14	-0.41	-0.16	0.76	2.44	3.06	7.14
-0.07	*-0.09*	47.19	24.60	41.46	18.71	2.11	-0.08	-0.26	0.78	1.99	1.99	3.35	1.00	-0.27	-0.42	-0.34	0.55	1.96	2.39	6.57
-0.07	*-0.06*	49.78	25.87	41.86	19.09	2.40	0.10	-0.07	1.06	2.28	2.17	3.41	0.98	-0.46	-0.36	-0.52	0.52	1.38	1.61	5.77
-0.07	*-0.03*	56.77	28.10	43.48	19.91	3.17	0.12	0.28	1.56	2.85	2.53	3.63	1.30	-0.33	-0.52	-0.74	0.79	1.19	1.88	5.46
-0.07	***0***	49.44	23.90	38.40	17.28	3.16	0.93	1.38	**3.78**	**5.50**	4.95	6.05	3.91	0.77	-0.28	-0.49	2.05	2.00	4.44	9.15
-0.07	*0.03*	51.59	23.46	39.00	18.20	1.38	0.26	1.10	2.34	4.29	5.13	6.84	4.92	0.97	0.42	0.40	2.05	1.94	1.79	6.32
-0.07	*0.06*	61.51	28.04	48.26	22.97	2.00	0.35	0.92	2.79	4.95	5.21	7.19	4.61	0.88	0.09	-0.02	2.41	2.41	2.29	6.72
-0.07	*0.09*	64.98	30.74	52.01	25.12	2.21	0.07	0.34	2.50	4.64	4.17	6.09	3.58	0.39	-0.34	-0.36	2.04	2.18	2.16	6.28
-0.07	*0.12*	65.33	31.16	52.45	25.41	2.26	0.03	0.26	2.44	4.58	4.00	5.90	3.41	0.30	-0.41	-0.41	1.96	2.12	2.10	6.19
-0.04	*-0.18*	48.82	25.87	42.52	19.47	2.24	-0.17	-0.29	0.55	1.72	1.87	3.33	1.07	0.00	-0.34	0.06	1.09	2.96	3.84	8.13
-0.04	*-0.15*	48.57	25.66	42.59	19.49	2.21	-0.18	-0.30	0.54	1.71	1.81	3.22	0.99	-0.09	-0.37	-0.03	0.93	2.70	3.43	7.49
-0.04	*-0.12*	47.36	24.86	41.94	19.03	2.10	-0.16	-0.31	0.63	1.83	1.88	3.27	1.00	-0.16	-0.41	-0.20	0.70	2.32	2.90	6.99
-0.04	*-0.09*	47.40	24.70	41.44	18.71	2.12	-0.06	-0.25	0.81	2.03	2.01	3.37	1.00	-0.32	-0.40	-0.36	0.53	1.82	2.18	6.39
-0.04	*-0.06*	50.97	26.40	42.18	19.36	2.51	0.15	-0.01	1.14	2.36	2.23	3.45	1.01	-0.49	-0.34	-0.53	0.60	1.30	1.51	5.61
-0.04	*-0.03*	58.45	28.54	43.46	19.82	3.39	0.14	0.40	1.72	3.04	2.65	3.73	1.43	-0.24	-0.53	-0.74	1.00	1.26	2.10	5.50

-0.04	***0***	47.28	22.91	37.56	16.60	2.47	0.53	0.82	3.21	5.05	4.56	5.87	3.94	0.77	-0.28	-0.52	2.05	2.18	4.12	**9.96**
-0.04	*0.03*	51.87	23.60	39.18	18.29	1.40	0.27	1.12	2.36	4.31	5.16	6.88	4.94	0.98	0.43	0.40	2.07	1.94	1.79	6.34
-0.04	*0.06*	61.70	28.16	48.45	23.08	2.01	0.34	0.90	2.78	4.94	5.17	7.15	4.57	0.86	0.07	-0.03	2.40	2.40	2.29	6.71
-0.04	*0.09*	65.00	30.76	52.03	25.14	2.22	0.07	0.33	2.49	4.63	4.16	6.08	3.57	0.38	-0.34	-0.36	2.04	2.18	2.15	6.27
-0.04	*0.12*	65.34	31.16	52.46	25.41	2.26	0.03	0.26	2.44	4.57	4.00	5.90	3.41	0.30	-0.41	-0.41	1.96	2.12	2.10	6.19
-0.01	*-0.18*	48.93	25.91	42.63	19.55	2.26	-0.18	-0.29	0.53	1.70	1.83	3.28	1.03	-0.03	-0.34	0.05	1.05	2.89	3.73	7.92
-0.01	*-0.15*	48.29	25.49	42.47	19.41	2.18	-0.19	-0.32	0.54	1.72	1.80	3.21	0.98	-0.11	-0.38	-0.07	0.87	2.61	3.30	7.33
-0.01	*-0.12*	47.01	24.65	41.72	18.88	2.06	-0.16	-0.32	0.65	1.86	1.89	3.28	1.01	-0.19	-0.41	-0.24	0.63	2.20	2.74	6.86
-0.01	*-0.09*	47.89	24.97	41.56	18.80	2.16	-0.02	-0.23	0.85	2.07	2.04	3.40	0.99	-0.37	-0.37	-0.37	0.55	1.69	1.98	6.22
-0.01	*-0.06*	52.28	26.90	42.45	19.58	2.64	0.21	0.06	1.23	2.46	2.30	3.50	1.06	-0.50	-0.36	-0.52	0.71	1.28	1.52	5.51
-0.01	*-0.03*	59.59	28.78	43.17	19.57	3.57	0.16	0.51	1.91	3.26	2.82	3.86	1.62	-0.09	-0.44	-0.71	1.30	1.39	2.38	5.59
-0.01	*0*	52.52	25.30	39.02	17.45	2.31	0.49	0.55	2.71	4.63	4.41	5.98	4.17	0.73	-0.14	-0.24	2.29	2.87	3.94	9.67
-0.01	*0.03*	52.13	23.73	39.35	18.38	1.43	0.28	1.13	2.37	4.33	5.20	6.92	4.96	0.99	0.44	0.40	2.08	1.95	1.79	6.37
-0.01	*0.06*	61.88	28.28	48.63	23.18	2.02	0.33	0.88	2.77	4.93	5.13	7.11	4.53	0.84	0.05	-0.05	2.39	2.40	2.29	6.70
-0.01	*0.09*	65.02	30.78	52.06	25.15	2.22	0.07	0.33	2.49	4.63	4.15	6.07	3.56	0.38	-0.35	-0.36	2.03	2.18	2.15	6.27
-0.01	*0.12*	65.34	31.16	52.46	25.41	2.26	0.03	0.26	2.44	4.57	4.00	5.90	3.40	0.30	-0.41	-0.41	1.96	2.12	2.10	6.19
0.02	*-0.18*	48.92	25.90	42.68	19.58	2.26	-0.19	-0.30	0.51	1.67	1.80	3.23	1.00	-0.05	-0.35	0.03	1.01	2.82	3.61	7.72
0.02	*-0.15*	47.88	25.25	42.28	19.27	2.14	-0.19	-0.33	0.55	1.73	1.80	3.21	0.99	-0.13	-0.38	-0.11	0.80	2.51	3.16	7.19
0.02	*-0.12*	46.81	24.52	41.58	18.78	2.03	-0.14	-0.33	0.68	1.89	1.91	3.31	1.01	-0.24	-0.40	-0.26	0.59	2.08	2.56	6.72
0.02	*-0.09*	48.69	25.39	41.80	19.00	2.23	0.04	-0.19	0.91	2.14	2.09	3.45	1.01	-0.41	-0.33	-0.37	0.61	1.59	1.81	6.06
0.02	*-0.06*	53.61	27.29	42.56	19.67	2.80	0.26	0.14	1.34	2.58	2.39	3.57	1.11	-0.51	-0.42	-0.51	0.81	1.30	1.58	5.49
0.02	*-0.03*	59.65	28.57	42.46	19.13	3.66	0.22	0.64	2.15	3.53	3.09	4.08	1.91	0.13	-0.22	-0.62	1.73	1.62	2.78	5.77
0.02	*0*	50.57	24.38	38.01	16.78	1.93	0.18	0.31	2.12	3.90	4.34	5.67	4.11	0.72	-0.33	-0.41	1.74	2.36	3.57	8.89
0.02	*0.03*	52.38	23.85	39.53	18.47	1.45	0.29	1.15	2.39	4.35	5.23	6.96	4.98	1.00	0.45	0.40	2.10	1.96	1.79	6.39
0.02	*0.06*	62.06	28.39	48.81	23.27	2.03	0.32	0.85	2.77	4.93	5.10	7.07	4.49	0.83	0.03	-0.06	2.38	2.40	2.29	6.68
0.02	*0.09*	65.04	30.81	52.08	25.17	2.22	0.07	0.33	2.49	4.63	4.14	6.06	3.55	0.37	-0.35	-0.37	2.03	2.17	2.15	6.27

0.02	*0.12*	65.34	31.16	52.46	25.42	2.26	0.03	0.26	2.44	4.57	3.99	5.90	3.40	0.30	-0.41	-0.41	1.96	2.12	2.10	6.19
0.05	*-0.18*	48.77	25.81	42.65	19.56	2.24	-0.20	-0.32	0.50	1.66	1.77	3.20	0.98	-0.08	-0.36	0.01	0.96	2.75	3.49	7.53
0.05	*-0.15*	47.39	24.98	42.05	19.11	2.09	-0.20	-0.35	0.56	1.75	1.81	3.22	1.00	-0.15	-0.38	-0.15	0.74	2.41	3.02	7.07
0.05	*-0.12*	46.83	24.53	41.55	18.75	2.02	-0.12	-0.34	0.72	1.93	1.93	3.33	1.01	-0.29	-0.39	-0.28	0.57	1.97	2.38	6.58
0.05	*-0.09*	49.74	25.92	42.12	19.26	2.32	0.11	-0.13	1.00	2.22	2.16	3.52	1.05	-0.43	-0.28	-0.36	0.72	1.53	1.71	5.94
0.05	*-0.06*	54.85	27.54	42.45	19.59	2.99	0.29	0.23	1.45	2.70	2.48	3.66	1.15	-0.51	-0.53	-0.49	0.88	1.34	1.64	5.56
0.05	*-0.03*	58.28	27.77	41.22	18.47	3.66	0.32	0.78	2.40	3.82	3.50	4.44	2.33	0.43	0.09	-0.46	2.22	1.94	3.33	6.14
0.05	*0*	46.77	22.82	36.42	16.29	2.18	0.53	0.83	2.81	4.50	4.83	5.81	3.90	0.74	-0.48	-0.55	1.22	1.65	3.21	7.94
0.05	*0.03*	52.61	23.96	39.70	18.56	1.47	0.31	1.16	2.40	4.37	5.25	6.99	4.99	1.01	0.45	0.40	2.12	1.96	1.79	6.42
0.05	*0.06*	62.23	28.50	48.98	23.37	2.04	0.31	0.83	2.76	4.92	5.06	7.04	4.46	0.81	0.02	-0.07	2.37	2.39	2.29	6.67
0.05	*0.09*	65.06	30.83	52.11	25.18	2.22	0.06	0.32	2.48	4.62	4.14	6.05	3.54	0.37	-0.35	-0.37	2.03	2.17	2.15	6.26
0.05	*0.12*	65.34	31.17	52.46	25.42	2.26	0.03	0.26	2.44	4.57	3.99	5.90	3.40	0.30	-0.41	-0.41	1.96	2.12	2.10	6.19
0.08	*-0.18*	48.46	25.63	42.55	19.48	2.21	-0.21	-0.33	0.49	1.66	1.76	3.18	0.97	-0.10	-0.36	-0.02	0.90	2.67	3.37	7.37
0.08	*-0.15*	46.93	24.72	41.83	18.96	2.04	-0.20	-0.37	0.58	1.78	1.83	3.24	1.01	-0.17	-0.38	-0.18	0.67	2.30	2.88	6.96
0.08	*-0.12*	47.14	24.69	41.65	18.82	2.02	-0.08	-0.33	0.76	1.98	1.96	3.37	1.01	-0.34	-0.37	-0.28	0.59	1.86	2.21	6.44
0.08	*-0.09*	50.96	26.46	42.42	19.53	2.43	0.20	-0.05	1.09	2.33	2.25	3.59	1.10	-0.43	-0.25	-0.33	0.87	1.54	1.72	5.88
0.08	*-0.06*	55.89	27.63	42.11	19.34	3.18	0.31	0.32	1.55	2.81	2.56	3.76	1.20	-0.47	-0.60	-0.45	0.99	1.44	1.73	5.65
0.08	*-0.03*	55.71	26.47	39.57	17.67	3.56	0.45	0.91	2.64	4.07	3.99	4.90	2.80	0.75	0.44	-0.33	2.55	2.23	3.87	6.74
0.08	*0*	43.96	21.08	37.39	16.41	1.63	0.43	0.82	3.04	4.87	5.02	6.11	3.95	0.58	-0.58	-0.39	1.50	1.47	2.50	6.74
0.08	*0.03*	52.84	24.06	39.88	18.65	1.49	0.32	1.18	2.42	4.40	5.28	7.03	5.01	1.02	0.46	0.39	2.13	1.97	1.79	6.44
0.08	*0.06*	62.39	28.60	49.15	23.46	2.04	0.30	0.81	2.75	4.91	5.02	7.00	4.42	0.79	0.00	-0.09	2.36	2.39	2.29	6.65
0.08	*0.09*	65.08	30.85	52.13	25.20	2.22	0.06	0.32	2.48	4.62	4.13	6.05	3.54	0.36	-0.36	-0.37	2.02	2.17	2.15	6.26
0.08	*0.12*	65.34	31.17	52.47	25.42	2.26	0.03	0.26	2.44	4.57	3.99	5.90	3.40	0.30	-0.41	-0.41	1.95	2.11	2.10	6.19
0.11	*-0.18*	48.00	25.39	42.37	19.35	2.17	-0.22	-0.35	0.50	1.67	1.76	3.17	0.98	-0.11	-0.36	-0.06	0.84	2.58	3.25	7.25
0.11	*-0.15*	46.60	24.54	41.69	18.85	1.99	-0.18	-0.38	0.61	1.81	1.85	3.26	1.02	-0.21	-0.38	-0.21	0.63	2.20	2.73	6.85
0.11	*-0.12*	47.75	25.02	41.89	18.99	2.06	-0.02	-0.30	0.82	2.04	2.01	3.43	1.02	-0.37	-0.33	-0.27	0.67	1.78	2.06	6.33

0.11	*-0.09*	52.17	26.92	42.59	19.70	2.55	0.29	0.05	1.20	2.44	2.36	3.67	1.16	-0.45	-0.25	-0.28	1.01	1.59	1.78	5.89
0.11	*-0.06*	56.71	27.60	41.66	18.98	3.36	0.29	0.37	1.61	2.89	2.62	3.85	1.27	-0.39	-0.54	-0.37	1.21	1.61	1.91	5.71
0.11	***-0.03***	52.85	25.07	37.99	16.93	3.43	0.59	1.00	2.80	4.22	4.37	5.31	3.16	0.91	**0.67**	-0.29	2.56	2.40	4.23	7.49
0.11	*0*	43.87	21.09	38.24	16.76	1.30	0.27	0.70	2.94	4.84	5.13	6.45	4.16	0.87	-0.30	0.09	2.27	2.54	2.06	6.12
0.11	*0.03*	53.06	24.16	40.06	18.74	1.51	0.33	1.19	2.44	4.42	5.31	7.07	5.02	1.03	0.46	0.39	2.15	1.98	1.80	6.47
0.11	*0.06*	62.54	28.71	49.31	23.55	2.05	0.29	0.78	2.74	4.90	4.98	6.96	4.38	0.77	-0.01	-0.10	2.35	2.38	2.29	6.64
0.11	*0.09*	65.10	30.86	52.15	25.21	2.23	0.06	0.31	2.48	4.62	4.12	6.04	3.53	0.36	-0.36	-0.37	2.02	2.17	2.14	6.25
0.11	*0.12*	65.35	31.17	52.47	25.42	2.26	0.02	0.26	2.44	4.57	3.99	5.89	3.40	0.30	-0.41	-0.41	1.95	2.11	2.10	6.19
0.14	*-0.18*	47.46	25.10	42.14	19.19	2.11	-0.22	-0.37	0.51	1.68	1.77	3.18	1.00	-0.13	-0.36	-0.10	0.78	2.49	3.13	7.14
0.14	*-0.15*	46.49	24.48	41.67	18.82	1.96	-0.16	-0.39	0.65	1.86	1.87	3.29	1.02	-0.26	-0.38	-0.22	0.61	2.10	2.57	6.74
0.14	*-0.12*	48.65	25.49	42.22	19.25	2.12	0.06	-0.25	0.90	2.13	2.08	3.52	1.07	-0.38	-0.27	-0.24	0.80	1.73	1.96	6.26
0.14	*-0.09*	53.19	27.19	42.50	19.70	2.69	0.37	0.14	1.32	2.57	2.47	3.76	1.21	-0.47	-0.30	-0.23	1.12	1.66	1.83	5.99
0.14	*-0.06*	57.29	27.47	41.19	18.56	3.48	0.22	0.36	1.63	2.93	2.65	3.90	1.36	-0.30	-0.38	-0.31	1.48	1.77	2.12	5.69
0.14	*-0.03*	50.28	23.81	36.74	16.33	3.27	0.63	0.99	2.78	4.18	4.46	5.46	3.23	0.86	0.62	-0.30	2.37	2.56	4.44	8.16
0.14	*0*	43.72	21.02	37.63	16.46	0.98	0.12	0.63	2.74	4.64	5.06	6.55	4.14	1.07	-0.11	0.29	2.54	3.25	2.17	6.04
0.14	*0.03*	53.28	24.25	40.25	18.83	1.52	0.34	1.20	2.46	4.45	5.34	7.11	5.04	1.04	0.46	0.38	2.17	2.00	1.81	6.49
0.14	*0.06*	62.69	28.81	49.46	23.64	2.06	0.28	0.76	2.73	4.89	4.95	6.92	4.34	0.75	-0.03	-0.11	2.34	2.37	2.29	6.63
0.14	*0.09*	65.11	30.88	52.17	25.22	2.23	0.06	0.31	2.48	4.61	4.11	6.03	3.52	0.36	-0.36	-0.37	2.01	2.16	2.14	6.25
0.14	*0.12*	65.35	31.17	52.47	25.42	2.26	0.02	0.25	2.44	4.57	3.99	5.89	3.40	0.30	-0.41	-0.41	1.95	2.11	2.10	6.19
0.17	*-0.18*	46.93	24.82	41.93	19.04	2.05	-0.22	-0.39	0.53	1.71	1.78	3.20	1.02	-0.15	-0.35	-0.13	0.72	2.39	3.01	7.06
0.17	*-0.15*	46.66	24.58	41.78	18.88	1.94	-0.12	-0.38	0.69	1.91	1.90	3.33	1.02	-0.31	-0.37	-0.21	0.63	2.01	2.42	6.64
0.17	*-0.12*	49.77	26.02	42.57	19.53	2.21	0.16	-0.17	1.00	2.24	2.19	3.64	1.15	-0.36	-0.20	-0.19	0.98	1.76	1.97	6.25
0.17	*-0.09*	53.80	27.19	42.07	19.48	2.83	0.45	0.25	1.43	2.70	2.57	3.87	1.27	-0.46	-0.35	-0.14	1.21	1.79	1.90	6.15
0.17	*-0.06*	57.46	27.23	40.70	18.08	3.50	0.13	0.30	1.63	2.95	2.61	3.87	1.44	-0.25	-0.24	-0.31	1.65	1.78	2.25	5.59
0.17	***-0.03***	47.62	22.50	35.59	15.78	3.06	0.56	0.87	2.61	3.96	4.29	5.36	3.04	0.71	0.39	-0.27	2.21	2.80	**4.59**	8.57
0.17	*0*	43.66	20.74	36.92	16.10	0.79	-0.04	0.54	2.50	4.38	4.88	6.46	3.93	1.12	0.03	0.35	2.58	3.53	2.52	6.22

0.17	*0.03*	53.50	24.34	40.44	18.93	1.54	0.35	1.21	2.48	4.48	5.37	7.15	5.05	1.05	0.47	0.38	2.18	2.01	1.82	6.52
0.17	*0.06*	62.83	28.91	49.61	23.72	2.06	0.27	0.74	2.72	4.88	4.91	6.88	4.31	0.74	-0.05	-0.13	2.32	2.37	2.28	6.61
0.17	*0.09*	65.13	30.90	52.18	25.23	2.23	0.06	0.31	2.47	4.61	4.11	6.02	3.51	0.35	-0.36	-0.38	2.01	2.16	2.14	6.25
0.17	*0.12*	65.35	31.18	52.47	25.42	2.26	0.02	0.25	2.44	4.57	3.99	5.89	3.40	0.29	-0.41	-0.41	1.95	2.11	2.10	6.19
0.2	*-0.18*	46.52	24.61	41.80	18.93	1.99	-0.20	-0.40	0.56	1.75	1.81	3.22	1.03	-0.18	-0.35	-0.16	0.67	2.30	2.88	6.97
0.2	*-0.15*	47.14	24.85	42.02	19.03	1.95	-0.06	-0.36	0.75	1.97	1.95	3.39	1.02	-0.35	-0.34	-0.20	0.71	1.94	2.29	6.57
0.2	*-0.12*	50.93	26.50	42.81	19.75	2.32	0.27	-0.06	1.12	2.37	2.33	3.77	1.25	-0.33	-0.14	-0.13	1.19	1.85	2.06	6.31
0.2	*-0.09*	53.96	26.95	41.35	19.05	2.96	0.51	0.33	1.53	2.80	2.66	4.01	1.35	-0.41	-0.34	0.00	1.36	2.02	2.05	6.30
0.2	*-0.06*	57.09	26.85	40.20	17.58	3.45	0.03	0.20	1.61	2.96	2.52	3.73	1.45	-0.28	-0.21	-0.37	1.64	1.67	2.29	5.52
0.2	*-0.03*	45.64	21.56	34.93	15.64	3.02	0.53	0.82	2.52	3.81	4.12	5.18	2.73	0.49	0.21	-0.21	2.04	2.85	4.26	8.65
0.2	*0*	43.96	20.52	36.40	15.91	0.74	-0.12	0.49	2.33	4.17	4.73	6.35	3.76	1.11	0.16	0.41	2.61	3.69	2.85	6.44
0.2	*0.03*	53.71	24.42	40.64	19.03	1.55	0.36	1.22	2.50	4.51	5.39	7.18	5.06	1.06	0.47	0.37	2.20	2.03	1.83	6.54
0.2	*0.06*	62.97	29.00	49.75	23.80	2.07	0.26	0.72	2.71	4.87	4.87	6.85	4.27	0.72	-0.06	-0.14	2.31	2.36	2.28	6.60
0.2	*0.09*	65.14	30.91	52.20	25.24	2.23	0.05	0.30	2.47	4.61	4.10	6.01	3.51	0.35	-0.37	-0.38	2.01	2.16	2.14	6.24
0.2	*0.12*	65.35	31.18	52.48	25.43	2.26	0.02	0.25	2.44	4.57	3.99	5.89	3.40	0.29	-0.41	-0.41	1.95	2.11	2.09	6.19
0.23	*-0.18*	46.34	24.53	41.79	18.90	1.94	-0.18	-0.41	0.59	1.79	1.83	3.25	1.03	-0.22	-0.34	-0.17	0.65	2.22	2.75	6.89
0.23	*-0.15*	47.92	25.26	42.36	19.27	1.98	0.02	-0.32	0.83	2.06	2.03	3.48	1.07	-0.36	-0.29	-0.17	0.84	1.91	2.20	6.53
0.23	*-0.12*	51.96	26.81	42.81	19.83	2.44	0.38	0.05	1.24	2.50	2.47	3.90	1.36	-0.31	-0.11	-0.04	1.37	1.97	2.16	6.44
0.23	*-0.09*	53.89	26.56	40.57	18.53	3.08	0.52	0.37	1.56	2.85	2.71	4.13	1.42	-0.36	-0.27	0.12	1.53	2.21	2.16	6.43
0.23	*-0.06*	56.14	26.35	39.74	17.13	3.33	-0.05	0.11	1.57	2.94	2.43	3.58	1.42	-0.34	-0.26	-0.44	1.45	1.55	2.33	5.60
0.23	*-0.03*	44.65	21.17	35.04	16.06	3.18	0.68	0.87	2.57	3.77	3.90	4.87	2.28	0.23	-0.10	-0.44	1.49	2.38	3.24	8.08
0.23	*0*	44.58	20.44	36.17	15.88	0.77	-0.13	0.48	2.21	4.03	4.61	6.25	3.66	1.09	0.27	0.49	2.64	3.79	3.09	6.61
0.23	*0.03*	53.93	24.51	40.84	19.13	1.57	0.37	1.23	2.52	4.53	5.42	7.22	5.08	1.07	0.46	0.37	2.22	2.04	1.85	6.56
0.23	*0.06*	63.10	29.09	49.89	23.87	2.08	0.25	0.70	2.70	4.86	4.84	6.81	4.24	0.70	-0.08	-0.15	2.30	2.36	2.28	6.58
0.23	*0.09*	65.15	30.93	52.22	25.25	2.23	0.05	0.30	2.47	4.61	4.09	6.01	3.50	0.35	-0.37	-0.38	2.01	2.16	2.13	6.24
0.23	*0.12*	65.35	31.18	52.48	25.43	2.26	0.02	0.25	2.44	4.57	3.99	5.89	3.40	0.29	-0.41	-0.41	1.95	2.11	2.09	6.19

0.26	*-0.18*	46.46	24.61	41.92	18.96	1.91	-0.14	-0.41	0.64	1.84	1.87	3.29	1.03	-0.27	-0.34	-0.16	0.67	2.15	2.62	6.81
0.26	*-0.15*	48.94	25.75	42.73	19.55	2.05	0.12	-0.25	0.94	2.18	2.14	3.61	1.15	-0.33	-0.20	-0.12	1.05	1.93	2.19	6.55
0.26	*-0.12*	52.63	26.87	42.47	19.68	2.56	0.48	0.17	1.35	2.63	2.60	4.04	1.47	-0.29	-0.09	0.07	1.52	2.14	2.26	6.62
0.26	*-0.09*	53.69	26.07	39.82	17.98	3.17	0.45	0.35	1.53	2.82	2.70	4.19	1.47	-0.36	-0.20	0.11	1.63	2.20	2.10	6.50
0.26	*-0.06*	54.59	25.69	39.30	16.71	3.12	-0.13	0.01	1.48	2.83	2.43	3.52	1.41	-0.36	-0.27	-0.57	1.14	1.46	2.42	5.88
0.26	*-0.03*	44.15	21.17	35.63	16.70	3.59	0.99	1.15	2.75	3.85	3.92	4.77	2.43	0.48	-0.22	-0.66	0.98	1.78	2.27	6.97
0.26	***0***	45.29	20.46	36.14	15.94	0.83	-0.10	0.50	2.14	3.93	4.53	6.16	3.60	1.06	0.36	0.55	2.67	**3.82**	3.23	6.69
0.26	*0.03*	54.14	24.59	41.05	19.23	1.59	0.38	1.24	2.54	4.56	5.45	7.25	5.09	1.07	0.46	0.36	2.24	2.06	1.86	6.59
0.26	*0.06*	63.22	29.18	50.02	23.95	2.08	0.24	0.68	2.69	4.85	4.81	6.77	4.20	0.69	-0.09	-0.16	2.29	2.35	2.27	6.57
0.26	*0.09*	65.16	30.94	52.23	25.26	2.24	0.05	0.30	2.47	4.60	4.09	6.00	3.50	0.34	-0.37	-0.38	2.00	2.15	2.13	6.24
0.26	*0.12*	65.35	31.18	52.48	25.43	2.26	0.02	0.25	2.44	4.57	3.99	5.89	3.40	0.29	-0.41	-0.41	1.95	2.11	2.09	6.18
0.29	*-0.18*	46.90	24.86	42.19	19.12	1.90	-0.08	-0.39	0.69	1.91	1.91	3.34	1.03	-0.31	-0.33	-0.14	0.74	2.09	2.50	6.76
0.29	*-0.15*	50.05	26.23	43.03	19.80	2.14	0.24	-0.14	1.06	2.32	2.29	3.78	1.28	-0.27	-0.11	-0.04	1.29	2.03	2.28	6.63
0.29	*-0.12*	52.76	26.63	41.73	19.27	2.68	0.59	0.29	1.46	2.76	2.73	4.21	1.59	-0.24	-0.05	0.24	1.68	2.39	2.40	6.79
0.29	*-0.09*	53.21	25.42	39.01	17.34	3.19	0.31	0.27	1.46	2.75	2.66	4.18	1.49	-0.38	-0.16	-0.07	1.66	1.96	1.86	6.45
0.29	*-0.06*	52.37	24.76	38.60	16.22	2.81	-0.17	-0.11	1.34	2.66	2.47	3.57	1.44	-0.36	-0.28	-0.68	0.93	1.54	2.65	6.34
0.29	***-0.03***	42.41	20.55	35.93	17.10	**3.82**	1.21	1.45	2.95	4.02	4.09	4.91	2.97	0.92	-0.27	-0.77	0.53	1.16	1.46	5.72
0.29	*0*	45.88	20.52	36.19	16.03	0.89	-0.07	0.52	2.09	3.86	4.48	6.10	3.59	1.04	0.42	0.59	2.68	3.80	3.30	6.70
0.29	*0.03*	54.37	24.68	41.27	19.33	1.60	0.39	1.24	2.57	4.59	5.47	7.29	5.10	1.08	0.46	0.35	2.26	2.08	1.88	6.61
0.29	*0.06*	63.33	29.27	50.14	24.02	2.09	0.23	0.66	2.68	4.84	4.77	6.74	4.17	0.67	-0.10	-0.17	2.28	2.34	2.27	6.55
0.29	*0.09*	65.18	30.96	52.25	25.27	2.24	0.05	0.30	2.47	4.60	4.08	5.99	3.49	0.34	-0.37	-0.38	2.00	2.15	2.13	6.23
0.29	*0.12*	65.36	31.18	52.48	25.43	2.26	0.02	0.25	2.44	4.57	3.99	5.89	3.40	0.29	-0.41	-0.41	1.95	2.11	2.09	6.18
0.32	*-0.18*	47.65	25.26	42.56	19.36	1.93	0.00	-0.35	0.77	2.00	1.98	3.43	1.06	-0.34	-0.29	-0.11	0.87	2.07	2.41	6.75
0.32	*-0.15*	51.07	26.56	43.12	19.93	2.25	0.36	-0.02	1.19	2.47	2.46	3.96	1.43	-0.21	-0.02	0.06	1.53	2.18	2.42	6.77
0.32	*-0.12*	52.39	26.15	40.73	18.68	2.79	0.68	0.40	1.55	2.85	2.84	4.36	1.69	-0.20	-0.01	0.40	1.79	2.62	2.50	6.93
0.32	*-0.09*	52.62	24.73	38.28	16.73	3.19	0.14	0.17	1.40	2.71	2.59	4.10	1.48	-0.40	-0.16	-0.34	1.62	1.64	1.58	6.28

0.32	*-0.06*	49.81	23.63	37.53	15.60	2.49	-0.14	-0.17	1.25	2.53	2.50	3.69	1.54	-0.33	-0.29	-0.66	0.96	1.89	3.13	6.82
0.32	***-0.03***	39.26	19.09	36.09	17.33	3.54	**1.23**	**1.50**	3.10	4.22	4.22	5.09	3.21	**1.13**	-0.39	-0.92	0.11	0.64	0.77	4.54
0.32	***0***	46.27	20.56	36.26	16.13	0.93	-0.05	0.55	2.05	3.80	4.46	6.06	3.62	1.03	0.46	**0.61**	**2.68**	3.75	3.33	6.65
0.32	***0.03***	54.59	24.77	41.49	19.44	1.62	0.39	1.25	2.59	4.62	**5.49**	**7.32**	**5.11**	1.09	0.46	0.34	2.28	2.10	1.90	6.63
0.32	*0.06*	63.45	29.35	50.26	24.09	2.09	0.23	0.64	2.67	4.83	4.74	6.70	4.14	0.65	-0.12	-0.18	2.27	2.33	2.27	6.54
0.32	*0.09*	65.19	30.97	52.26	25.28	2.24	0.05	0.29	2.47	4.60	4.08	5.99	3.49	0.34	-0.38	-0.39	2.00	2.15	2.13	6.23
0.32	***0.12***	**65.36**	**31.19**	**52.48**	**25.43**	2.26	0.02	0.25	2.44	4.57	3.99	5.89	3.39	0.29	-0.41	-0.41	1.95	2.11	2.09	6.18

C Unrestricted Quantile-MIDAS

C.1 Gold

Figure C1: Test statistic J_T with respect to various quantiles. The red dashed line marks the aggregated critical value at $\alpha = 0.01$ and the associated standard normal critical value of 2.57.

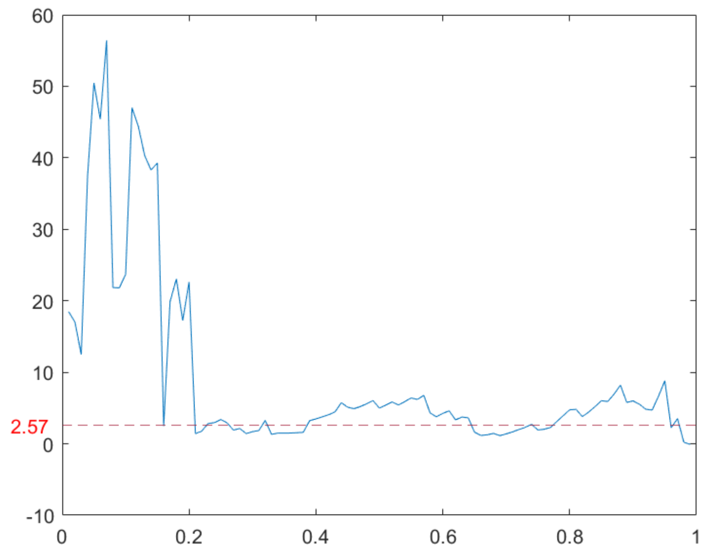


Figure C2: Unrestricted Quantile MIDAS Conditional Quantiles and actual data

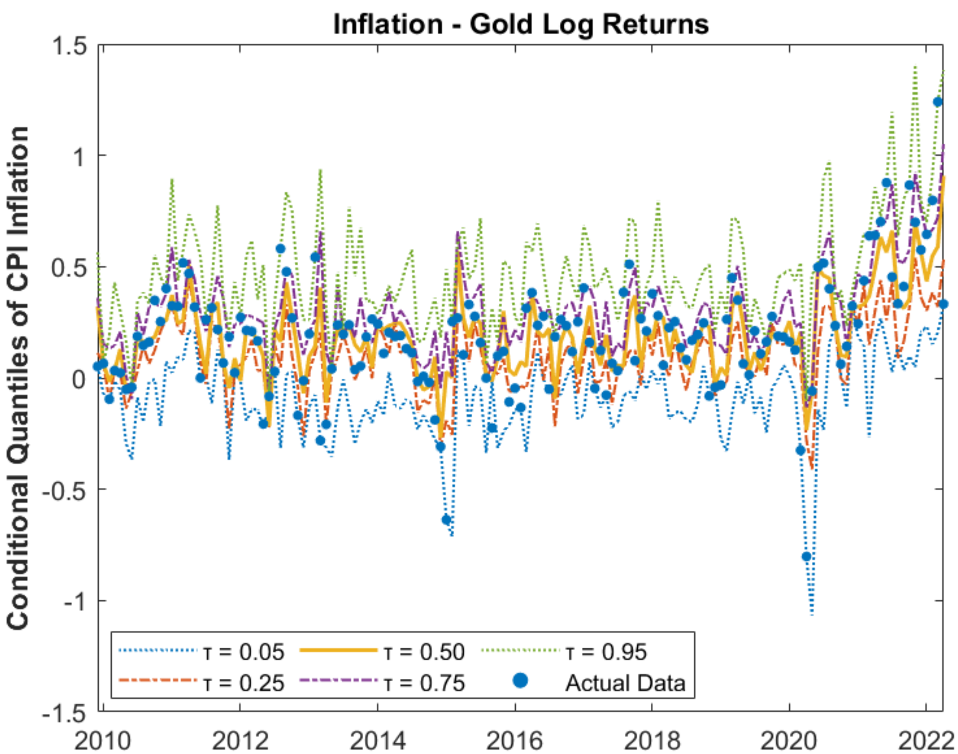


Table C1: Table showing Unrestricted Quantile-MIDAS Estimation Results

	Quantiles				
y_t: **Inflation**	*0.05*	*0.25*	*0.50*	*0.75*	*0.95*
β_0: intercept	-0.164	-0.002	0.009***	0.108***	0.256***
	[1.000]	[0.122]	[0.000]	[0.000]	[0.000]
$\beta_1 : y_t - 1$	0.642	0.638***	0.617***	0.528	0.515
	[1.000]	[0.000]	[0.000]	[0.999]	[1.000]
$\beta_2 : y_t - 2$	-0.436	0.031***	0.203***	0.301	0.686
	[1.000]	[0.000]	[0.000]	[0.999]	[1.000]
$\beta_3 : \|y_t - 1\|$	0.107	-0.141***	-0.341	-0.195***	-0.229
	[1.000]	[0.000]	[0.999]	[0.000]	[1.000]
$\beta_4 : \|y_t - 2\|$	0.178	-0.018***	0.314	0.271***	0.024
	[1.000]	[0.000]	[1.000]	[0.000]	[1.000]
$\beta_5 : m = 1$	0.809	1.826***	1.179	2.025	-3.077
	[1.000]	[0.000]	[1.000]	[0.999]	[0.999]
$\beta_5 : m = 2$	1.622	-1.202 .	-0.137	-1.727	-2.131
	[1.000]	[0.015]	[0.999]	[0.999]	[1.000]
$\beta_5 : m = 3$	-0.472	-0.117	-0.371	-0.091	-3.281
	[1.000]	[0.438]	[0.999]	[1.000]	[0.999]
$\beta_5 : m = 4$	-4.838	-6.040***	-4.346	-3.219	1.272
	[1.000]	[0.000]	[0.999]	[0.999]	[1.000]
$\beta_5 : m = 5$	-2.458	0.876***	1.956	-1.403	0.496
	[1.000]	[0.000]	[0.999]	[1.000]	[1.000]
$\beta_5 : m = 6$	2.578	4.535***	2.283	0.044	1.735
	[1.000]	[0.000]	[0.999]	[1.000]	[0.999]
$\beta_5 : m = 7$	1.723	1.042***	1.759	4.036	4.778
	[1.000]	[0.000]	[0.999]	[0.999]	[0.999]
$\beta_5 : m = 8$	-0.344	-2.520***	-0.121	-0.265	3.354
	[1.000]	[0.000]	[1.000]	[1.000]	[1.000]
$\beta_5 : m = 9$	2.569	-1.160***	0.949	-2.274	-3.894
	[1.000]	[0.000]	[0.999]	[0.999]	[0.999]
$\beta_5 : m = 10$	5.150	3.365***	1.806	2.184	-1.364
	[0.999]	[0.000]	[0.999]	[0.999]	1.000]
$\beta_5 : m = 11$	3.441	0.695***	1.889	4.540	10.083
	[1.000]	[0.000]	[0.999]	[0.999]	[0.999]
$\beta_5 : m = 12$	-1.960	2.019***	0.841	-0.974	4.531
	[1.000]	[0.000]	[0.999]	[0.999]	[0.999]
$\beta_5 : m = 13$	2.903	-0.065	0.474	-0.118	0.277
	[1.000]	[0.640]	[0.999]	[1.000]	[1.000]
$\beta_5 : m = 14$	-4.065	1.542***	-1.341	-0.487	-0.546
	[1.000]	[0.000]	[0.999]	[1.000]	[1.000]
$\beta_5 : m = 15$	-3.869	1.781***	-0.017	-0.593	-1.061
	[1.000]	[0.000]	[1.000]	[1.000]	[1.000]
$\beta_5 : m = 16$	-1.072	-0.887 .	1.336	2.308	6.461
	[1.000]	[0.041]	[0.999]	[0.999]	[0.999]
$\beta_5 : m = 17$	-1.849	-2.288***	-1.511	1.875	2.561
	[1.000]	[0.000]	[0.999]	[0.999]	[0.999]
$\beta_5 : m = 18$	-0.044	1.969***	-1.407	-1.588	-0.393
	[1.000]	[0.000]	[0.999]	[0.999]	[1.000]
$\beta_5 : m = 19$	3.731	-1.159***	-1.142	-0.848	-0.884
	[0.999]	[0.000]	[0.999]	[0.999]	[1.000]
$\beta_5 : m = 20$	3.986	0.213 .	-2.249	-2.578	-2.974
	[0.997]	[0.042]	[0.999]	[0.999]	[0.999]
$\beta_5 : m = 21$	2.729	2.572***	2.228	1.223	-2.078
	[0.999]	[0.000]	[0.999]	[0.999]	[0.999]
Pseudo R Squared	0.29	0.27	0.30	0.31	0.38
Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'					

C.2 Crude Oil

Figure C3: Unrestricted Quantile MIDAS Conditional Quantiles and actual data

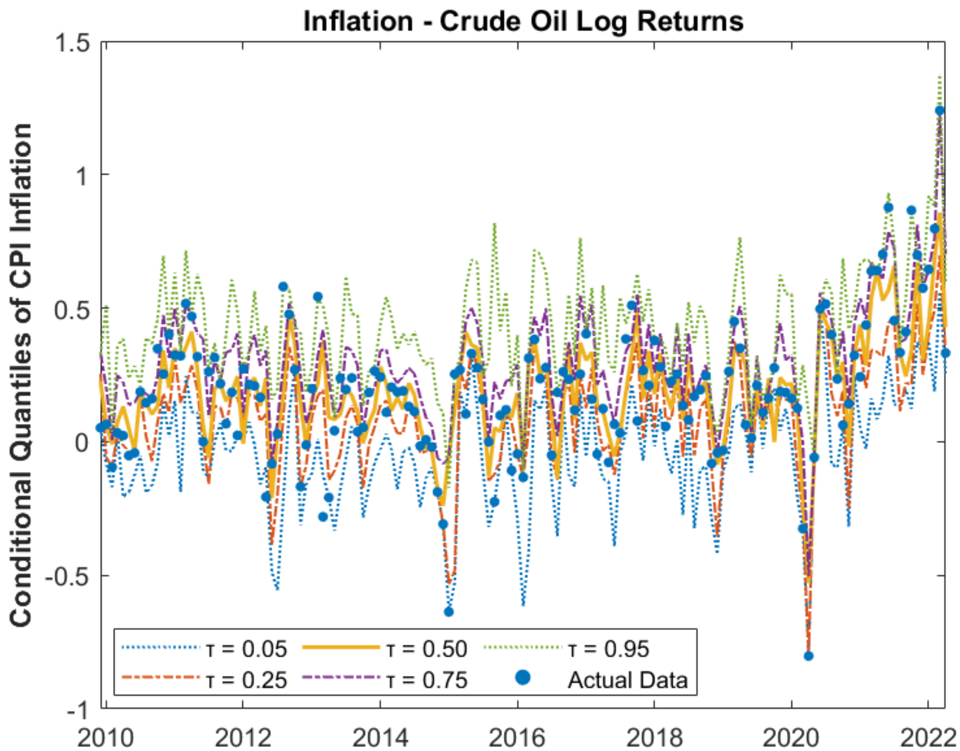


Figure C4: Test statistic J_T with respect to various quantiles. The red dashed line marks the aggregated critical value at $\alpha = 0.01$ and the associated standard normal critical value of 2.57.

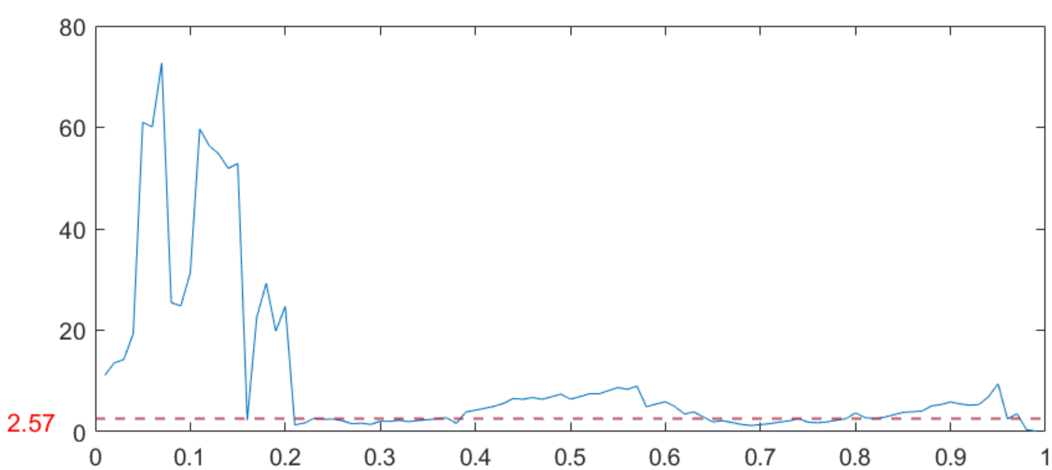


Table C2: Table showing Unrestricted Quantile-MIDAS Estimation Results

	Quantiles				
y_t: **Inflation**	*0.05*	*0.25*	*0.50*	*0.75*	*0.95*
β_0: intercept	-0.126*** [0.000]	-0.008*** [0.000]	0.036*** [0.000]	0.139*** [0.000]	0.321 [1.000]
$\beta_1 : y_t - 1$	0.362 [1.000]	0.446*** [0.000]	0.245*** [0.000]	0.213*** [0.000]	0.258 [1.000]
$\beta_2 : y_t - 2$	-0.039 [1.000]	0.194*** [0.000]	0.442*** [0.000]	0.472*** [0.000]	0.241 [1.000]
$beta_3 : \|y_t - 1\|$	0.124 [1.000]	-0.041*** [0.000]	-0.066*** [0.000]	0.146*** [0.000]	0.327 [1.000]
$\beta_4 : \|y_t - 2\|$	-0.155 [1.000]	-0.152*** [0.000]	0.056*** [1.000]	-0.178*** [0.000]	-0.404 [1.000]
$\beta_5 : m = 1$	2.621 [0.999]	1.865*** [0.000]	1.276*** [0.000]	1.610 [0.999]	0.275 [0.999]
$\beta_5 : m = 2$	0.865 [0.999]	0.117*** [0.000]	1.229*** [0.000]	0.467 [0.999]	-0.257 [1.000]
$\beta_5 : m = 3$	2.573 [0.999]	1.512*** [0.000]	0.017 [0.884]	0.482 . [0.078]	1.009 [0.999]
$\beta_5 : m = 4$	0.299 [1.000]	-0.265** [0.001]	0.061 [0.656]	-1.221 [0.999]	-2.029 [1.000]
$\beta_5 : m = 5$	0.186 [1.000]	1.174*** [0.000]	1.207*** [0.000]	2.176 [0.999]	2.610 [1.000]
$\beta_5 : m = 6$	2.906 [0.999]	0.518*** [0.000]	-0.590*** [0.000]	0.779*** [0.000]	0.517 [0.999]
$\beta_5 : m = 7$	-0.249 [1.000]	0.869*** [0.000]	0.476*** [0.000]	-0.012 [0.271]	0.579 [0.999]
$\beta_5 : m = 8$	1.069 [1.000]	2.037*** [0.000]	1.031*** [0.000]	0.357 [1.000]	0.689 [1.000]
$\beta_5 : m = 9$	1.425 [1.000]	1.461*** [0.000]	1.890*** [0.000]	2.228*** [0.000]	2.429 [0.999]
$\beta_5 : m = 10$	3.074 [0.999]	2.561*** [0.000]	0.210 . [0.074]	0.799 [0.999]	2.517 1.000]
$\beta_5 : m = 11$	2.270 [1.000]	1.841*** [0.000]	1.803*** [0.000]	1.689 [0.999]	2.656 [0.999]
$\beta_5 : m = 12$	-1.349 [0.999]	0.689*** [0.000]	1.401*** [0.000]	1.363 [0.999]	-0.092 [0.999]
$\beta_5 : m = 13$	0.463 [1.000]	1.821*** [0.640]	1.239*** [0.000]	0.934 [0.999]	2.476 [1.000]
$\beta_5 : m = 14$	0.475 [1.000]	1.189*** [0.000]	1.333*** [0.000]	0.884*** [0.000]	0.797 [1.000]
$\beta_5 : m = 15$	3.389 [0.999]	3.467*** [0.000]	1.587*** [0.000]	1.178 [0.999]	-1.214 [1.000]
$\beta_5 : m = 16$	2.518 [1.000]	1.962*** [0.041]	2.373*** [0.000]	2.059*** [0.000]	2.059 [0.999]
$\beta_5 : m = 17$	-0.269 [1.000]	1.360*** [0.000]	1.001*** [0.000]	1.631 [0.999]	1.170 [0.999]
$\beta_5 : m = 18$	0.384 [1.000]	-1.302*** [0.000]	-1.423*** [0.000]	0.064 [0.999]	2.517 [1.000]
$\beta_5 : m = 19$	0.259 [1.000]	1.065*** [0.000]	1.056*** [0.000]	0.894 [0.999]	3.929 [1.000]
$\beta_5 : m = 20$	2.484 [1.000]	2.786*** [0.042]	2.586*** [0.000]	2.849 [0.999]	2.101 [0.999]
$\beta_5 : m = 21$	1.935 [0.999]	0.005 [0.776]	0.269 [0.156]	1.615 [0.999]	3.822 [0.999]
Pseudo R Squared	0.46	0.40	0.36	0.42	0.50
Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'					

C.3 Corn

Figure C5: Unrestricted Quantile MIDAS Conditional Quantiles and actual data

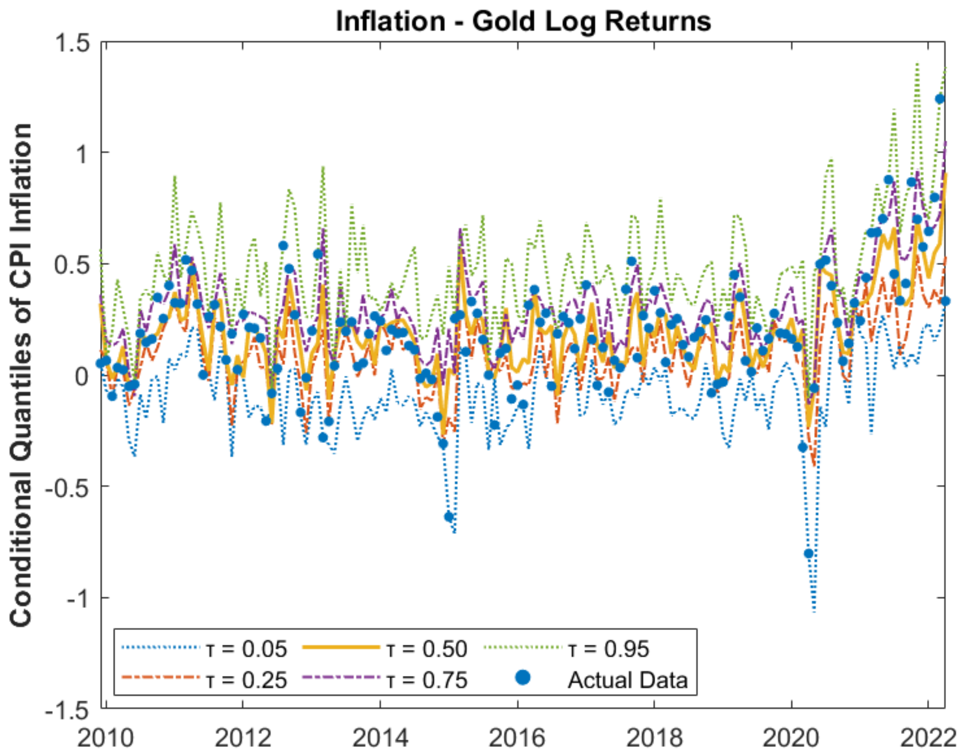


Figure C6: Test statistic J_T with respect to various quantiles. The red dashed line marks the aggregated critical value at $\alpha = 0.01$ and the associated standard normal critical value of 2.57.

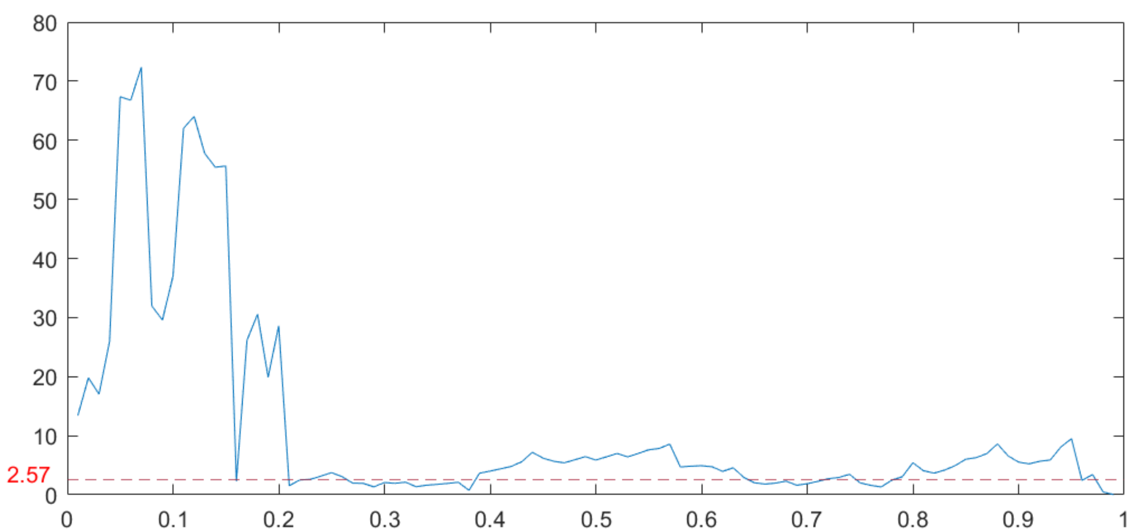


Table C3: Table showing Unrestricted Quantile-MIDAS Estimation Results

	Quantiles				
y_t: **Inflation**	*0.05*	*0.25*	*0.50*	*0.75*	*0.95*
β_0: intercept	-0.176 [0.983]	0.013 [1.000]	0.035 [0.999]	0.157 [0.643]	0.285 [0.253]
$\beta_1 : y_t - 1$	0.420 [1.000]	0.586 [1.000]	0.552 [1.000]	0.591 [1.000]	0.337 [1.000]
$\beta_2 : y_t - 2$	-0.007 [1.000]	-0.036 [1.000]	0.365 [1.000]	0.248 [1.000]	0.225 [1.000]
$beta_3 : \|y_t - 1\|$	0.016 [1.000]	-0.166 [1.000]	-0.155 [0.998]	-0.222 [1.000]	0.037 [1.000]
$\beta_4 : \|y_t - 2\|$	0.076 [1.000]	-0.092 [1.000]	0.005 [0.999]	0.174 [1.000]	0.196 [0.987]
$\beta_5 : m = 1$	-0.036 [1.000]	-0.011 [1.000]	-0.025 [0.999]	-0.025 [1.000]	-0.058 [0.929]
$\beta_5 : m = 2$	-0.012 [0.999]	-0.009 [1.000]	-0.018 [0.999]	-0.029 [1.000]	-0.071 [1.000]
$\beta_5 : m = 3$	0.069 [0.999]	0.018 [1.000]	0.033 [1.000]	0.021 [1.000]	0.022 [1.000]
$\beta_5 : m = 4$	0.141 [0.999]	0.114 [1.000]	0.080 [1.000]	0.035 [1.000]	0.045 [1.000]
$\beta_5 : m = 5$	0.008 [1.000]	0.025 [1.000]	0.036 [1.000]	0.008 [1.000]	0.030 [1.000]
$\beta_5 : m = 6$	0.029 [0.999]	-0.008 [1.000]	0.003 [0.990]	-0.027 [0.999]	0.052 [1.000]
$\beta_5 : m = 7$	0.073 [1.000]	0.043 [1.000]	0.027 [1.000]	-0.007 [1.000]	0.039 [1.000]
$\beta_5 : m = 8$	0.091 [1.000]	0.075 [1.000]	0.044 [1.000]	-0.012 [0.999]	0.046 [1.000]
$\beta_5 : m = 9$	0.032 [1.000]	0.038 [1.000]	-0.002 [0.998]	-0.041 [1.000]	-0.035 [1.000]
$\beta_5 : m = 10$	0.054 [0.999]	0.086 [1.000]	0.042 [1.000]	-0.013 [1.000]	0.020 [1.000]
$\beta_5 : m = 11$	0.064 [1.000]	0.118 [1.000]	0.039 [1.000]	0.009 [1.000]	0.044 [1.000]
$\beta_5 : m = 12$	0.092 [0.999]	0.133 [1.000]	0.031 [1.000]	-0.031 [1.000]	-0.005 [1.000]
$\beta_5 : m = 13$	0.077 [0.999]	0.127 [1.000]	0.007 [1.000]	-0.049 [1.000]	-0.014 [1.000]
$\beta_5 : m = 14$	-0.036 [1.000]	0.111 [1.000]	0.016 [1.000]	-0.054 [1.000]	-0.029 [1.000]
$\beta_5 : m = 15$	-0.034 [0.999]	0.102 [1.000]	0.016 [1.000]	-0.078 [1.000]	-0.037 [1.000]
$\beta_5 : m = 16$	-0.033 [1.000]	0.068 [1.000]	0.022 [1.000]	-0.076 [1.000]	0.018 [1.000]
$\beta_5 : m = 17$	0.051 [1.000]	0.099 [1.000]	0.054 [1.000]	-0.054 [1.000]	0.017 [1.000]
$\beta_5 : m = 18$	-0.009 [1.000]	0.080 [1.000]	0.055 [1.000]	-0.036 [1.000]	0.056 [1.000]
$\beta_5 : m = 19$	0.039 [1.000]	0.094 [1.000]	0.055 [1.000]	0.006 [1.000]	0.087 [1.000]
$\beta_5 : m = 20$	0.059 [1.000]	0.080 [1.000]	0.033 [1.000]	-0.005 [0.999]	0.109 [1.000]
$\beta_5 : m = 21$	0.082 [0.999]	0.078 [1.000]	0.037 [1.000]	0.025 [1.000]	0.075 [1.000]
Pseudo R Squared	0.38	0.40	0.28	0.33	0.48
Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'					

D Nowcasting: Full Selection of Quantiles

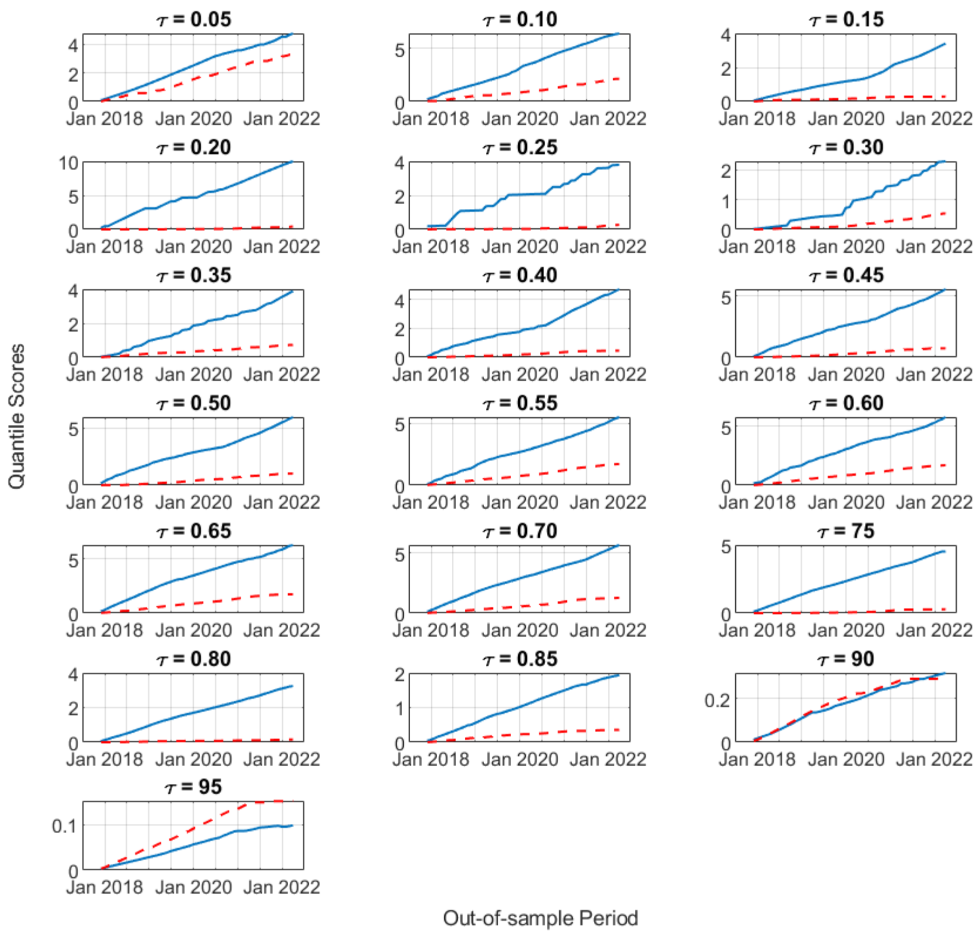
D.1 Nowcasting at Quantiles: Causality from Gold

Table D1: Table showing quantile scores for different quantiles (on the columns) and for three different models (on the rows). , and indicate that ratios are significantly different from 1 at 1%, 5% and 10%, according to the Diebold-Mariano test. The model in italic is our benchmark model.

τ	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
QAR(2)	*1.971*	*3.342*	*4.219*	*4.743*	*4.911*	*4.888*	*4.746*	*5.501*	*4.196*	*3.819*
QMIDAS	0.954***	0.964***	0.985***	0.960***	0.985***	0.991***	0.985***	0.980***	0.975***	0.971***
QAVG	0.968***	0.988***	0.999***	0.998***	0.999***	0.998***	0.997***	0.998***	0.997***	0.995***

τ	*0.55*	*0.60*	*0.65*	*0.70*	*0.75*	*0.80*	*0.85*	*0.90*	*0.95*
QAR(2)	*3.389*	*2.928*	*2.453*	*1.969*	*1.495*	*1.051*	*0.650*	*0.313*	*0.085*
QMIDAS	0.969***	0.963**	0.952***	0.946***	0.943***	0.942***	0.944***	0.981***	0.978***
QAVG	0.990***	0.989***	0.987***	0.988**	0.996***	0.997***	0.989***	0.982***	0.966***

Figure D1: Quantile Scores of QMDIDAS (solid blue line) vs QAVG model (dashed red line) over the out-of-sample period.



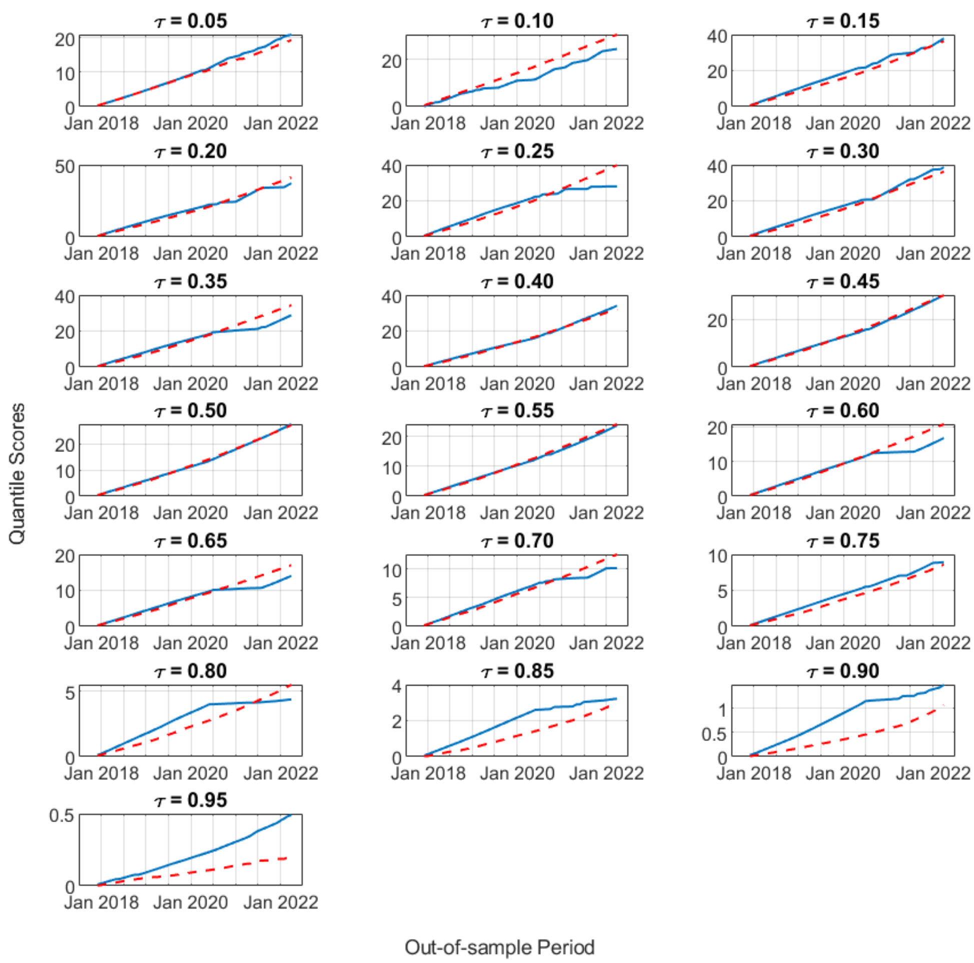
D.2 Nowcasting at Quantiles: Causality from Crude Oil

Table D2: Table showing quantile scores for different quantiles (on the columns) and for three different models (on the rows). , and indicate that ratios are significantly different from 1 at 1%, 5% and 10%, according to the Diebold-Mariano test. The model in italic is our benchmark model.

τ	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
QAR(2)	*1.971*	*3.342*	*4.219*	*4.743*	*4.911*	*4.888*	*4.746*	*5.501*	*4.196*	*3.819*
QMIDAS	0.799***	0.861***	0.831***	0.852***	0.892***	0.851***	0.885***	0.857***	0.864***	0.864***
QAVG	0.815***	0.827***	0.838***	0.836***	0.847***	0.860***	0.863***	0.865***	0.864***	0.866***

τ	*0.55*	*0.60*	*0.65*	*0.70*	*0.75*	*0.80*	*0.85*	*0.90*	*0.95*
QAR(2)	*3.389*	*2.928*	*2.453*	*1.969*	*1.495*	*1.051*	*0.650*	*0.313*	*0.085*
QMIDAS	0.868***	0.892**	0.892***	0.903***	0.887***	0.921***	0.907***	0.910***	0.891***
QAVG	0.866***	0.866***	0.869***	0.878**	0.891***	0.901***	0.913***	0.936***	0.955***

Figure D2: Quantile Scores of QMDIDAS (solid blue line) vs QAVG model (dashed red line) over the out-of-sample period.



D.3 Nowcasting at Quantiles: Causality from Corn

Table D3: Table showing quantile scores for different quantiles (on the columns) and for three different models (on the rows). , and indicate that ratios are significantly different from 1 at 1%, 5% and 10%, according to the Diebold-Mariano test. The model in italic is our benchmark model.

τ	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
QAR(2)	*1.971*	*3.342*	*4.219*	*4.743*	*4.911*	*4.888*	*4.746*	*5.501*	*4.196*	*3.819*
QMIDAS	0.961***	0.960***	0.953***	0.965***	0.973***	0.982***	0.988***	0.947***	0.993***	0.992***
QAVG	0.903***	0.923***	0.934***	0.948***	0.961***	0.972***	0.983***	0.990***	0.995***	0.996***

τ	*0.55*	*0.60*	*0.65*	*0.70*	*0.75*	*0.80*	*0.85*	*0.90*	*0.95*
QAR(2)	*3.389*	*2.928*	*2.453*	*1.969*	*1.495*	*1.051*	*0.650*	*0.313*	*0.085*
QMIDAS	0.994***	0.995**	0.992***	0.983***	0.978***	0.979***	0.972***	0.981***	0.943***
QAVG	0.998***	0.999***	0.999***	0.999**	0.999***	0.996***	0.988***	0.986***	0.987***

Figure D3: Quantile Scores of QMDIDAS (solid blue line) vs QAVG model (dashed red line) over the out-of-sample period.