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Does Bitcoin Hedge Industry Credit Risk? A Comparison with Gold

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Abstract: *Credit default swaps are considered indicators of default probability and used to measure credit risk in different sectors of the US industry. This study examines the effectiveness of hedging and safe-haven options for US sectoral credit default swap indices, focusing on whether Bitcoin or gold can serve as effective assets for mitigating credit risk in US industries. The GARCH model with dummy variables and quantile regression are employed to estimate the hedging and safe-haven properties of Bitcoin and gold. The findings indicate that both Bitcoin and gold can be utilized as effective hedging and safe haven assets for US industry credit risk. Furthermore, the study highlights the superior hedging potential and safe-haven properties of Bitcoin compared to gold. Overall, the results suggest that investors and portfolio managers can effectively utilize Bitcoin and gold to protect against credit risk in different US sectors, regardless of market and economic conditions.*

Keywords: Credit default swaps, Bitcoin, gold, hedge, safe haven.

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1. Introduction

Credit default swaps (CDSs) are liquid financial assets that are traded in over-the-counter markets. They are commonly used by market participants to protect against adverse credit events, such as default or debt restructuring. CDSs provide information on the underlying credit risk of a firm, which is updated based on new public information. Industry CDS indices were introduced in the US in 2004 and measure the average level of credit risk exposure for a specific industry. An increase in the CDS spread indicates a higher level of credit risk in the industry, while a lower spread suggests lower credit risk.

Sectoral CDS indices are widely recognized as reliable proxies for credit risk in US industries. In fact, the CDS spread is considered a more accurate indicator of credit risk than credit ratings from agencies such as Standard & Poor's, Fitch and Moody's, which often fail to reflect true market conditions. Academic research has also shown that credit ratings are not optimal predictors of credit probability (Hilscher & Wilson, 2016). On the other hand, the CDS spread not only reflects market conditions more accurately, but also significantly influences the market's perception of credit risk (Longstaff et al., 2005).

The CDS market has experienced significant fluctuations over the past two decades. During its peak, the trading volume of CDSs surged from US Dollar (USD) 180 billion in 1997 to approximately USD 61.2 trillion in 2007. The steady growth of the CDS market was driven by the role of CDSs as hedging and speculation tools for credit risk. However, during the global financial crisis (GFC) and in its aftermath, CDSs played a major role in exacerbating the crisis (Stulz, 2010; Kress, 2011). As a result, the trading volume of CDSs declined to USD 9.4 trillion in 2017 and further dropped to USD 7.8 trillion by the end of March 2019. These significant changes in the CDS market necessitate the exploration of potential hedging options for CDS contracts. This study provides new insights into managing credit risk in different US sectors, particularly during economic downturns and crises.

Against the backdrop of recent economic and financial crises, such as the GFC, the European debt crisis, COVID-19, and the Russia-Ukraine conflict, investors are actively seeking appealing alternative investments that can provide hedging and diversification opportunities. Safe-haven assets are particularly valuable to investors during times of financial crisis. Traditionally, gold has been considered a conventional hedge in normal times and a stabilizer during economic turbulence (Baur & Lucey, 2010; Areal et al., 2015). Multiple studies have found a weak or negative correlation between gold and other asset classes (Ciner, 2001; Hillier et al., 2006). Furthermore, evidence shows that the relationship between gold and other types of assets changes significantly during periods of economic slowdown (Baur & McDermott, 2010; Ciner et al., 2013; Bampinas & Panagiotidis, 2015). Nevertheless, identifying safe-haven assets during crisis periods remains a challenging task. However, many argue that the safe-haven property of gold is diminishing due to overinvestment in gold for hedging purposes (Baur & Glover, 2012).

Cryptocurrencies have been the subject of immense media attention, academic research, and online coverage in recent years. They are considered disruptive financial technologies and have been recognized as one of the most notable financial innovations of the last decade. Consequently, investors and portfolio managers have begun to view cryptocurrencies, such as Bitcoin, as alternative investments. Bitcoin is often referred to as 'digital gold' due to its similarities to gold. In recent times, numerous studies have examined the hedging and safe-haven properties of Bitcoin during crisis periods, such as the European debt crisis of 2010–13 (Luther & Salter, 2017) and the Cypriot banking crisis of 2012/13 (Kristoufek, 2015). These studies have highlighted the weak correlation between Bitcoin and other traditional assets during economic downturns, further supporting the potential use of Bitcoin as a diversification and hedging tool (Brière et al., 2015; Bouri et al., 2017a; Klein et al., 2018; Corbet et al., 2018; Ji et al., 2018; Guesmi et al., 2019; Shahzad et al., 2019; Shahzad et al., 2020).

Due to increased financialization and global market integration, financial markets now have strong linkages and co-movement. There has been a significant increase in the use of different asset classes to take advantage of arbitrage opportunities across markets in recent years. As a result, market participants have started taking different offsetting positions across financial markets to create effective diversification and hedging opportunities. One of the most important interdependencies between financial markets is the joint liquidity dynamics across these markets. Several studies have documented liquidity commonality across markets bracket was missing at the end, it should be: (Pu, 2009; Mancini et al., 2013;

Frino et al., 2014; Benzennou et al., 2020). For example, the underlying markets can experience high or low liquidity due to common liquidity demand, depending on how institutional investors respond to the inflow of new information by buying/selling assets. This leads to simultaneous pressure to buy/sell in the underlying markets as investors look for offsetting positions.

Volatility transmission between markets is another important driver of co-movement. Studies have shown that systematic risk factors, funding costs, common income shocks, and market volatility can significantly impact market liquidity, which is crucial for integration across markets (Xiong, 2001; Brunnermeier & Pedersen, 2008). Particularly during economic crises, higher volatility can lead to the simultaneous withdrawal of liquidity across these markets. Finally, numerous studies have also documented the impact of monetary policy announcements on stock markets (Bomfim, 2003; Rosa, 2011), commodity markets (Kilian & Vega, 2011; Rosa, 2014; Smales & Lucey, 2019), and CDS spreads (Caporin et al., 2017).

Recently, Umar et al. (2019) have proposed using precious metal futures to hedge credit risk in the metal and mining sectors. Building on this, our study suggests using gold and Bitcoin to hedge the credit risk faced by US industries. We use the CDS spread as a proxy for credit risk. Previous research has highlighted the role of gold and Bitcoin as hedging and safe-haven assets against stock volatility (Baur & McDermott, 2010; Shahzad et al., 2020), currency volatility (Reboredo, 2013), commodity prices (Shahzad et al., 2019), oil price volatility (Bouri et al., 2017b; Selmi et al., 2018), and economic policy uncertainty (Wu et al., 2019). Our aim is to determine whether gold and Bitcoin can effectively hedge and act as safe-haven assets for the credit risk of US industries. Additionally, we aim to identify which asset, gold or Bitcoin, is a superior hedger and safe-haven asset.

To test the hedge and safe-haven properties of gold and Bitcoin against industry credit risk, we adopt Baur and Lucey's (2010) framework. We utilize a combination of the GARCH model and quantile regression with dummy variables to represent extreme market outcomes. Our study contributes to the literature by providing insights into the potential use of gold and Bitcoin as hedging and safe-haven assets for industry credit risk. The findings of our study have important implications for investors, portfolio managers, and financial market regulators.

Our findings support the strong hedging and safe-haven potential of both assets in managing the credit risk of sector CDS indices. Furthermore, our study concludes that Bitcoin has superior hedging and safe-haven properties compared to gold for managing the credit risk of US industries.

The rest of the study is organized as follows. Section 2 covers the relevant literature and the process of hypothesis development. Section 3 describes the data and methodology used in the study. Section 4 presents the empirical results and findings. The final section concludes the study, discussing implications, limitations and future research directions.

2. Literature Review

A body of literature shows that CDSs are a reliable proxy for credit risk (Blanco et al., 2005; Das & Hanouna, 2006; Zhu, 2006; Ericsson et al., 2009; Chau et al., 2018; Caglio et al., 2019; Gunay, 2020). Initially, bond spreads were used as a proxy for credit risk, but previous studies have highlighted several reasons why CDSs are a more suitable proxy than bond spreads (Andres et al., 2021). Kapar and Olmo (2011) argue that the low liquidity and limited tradability of bonds make bond spreads inadequate for proxying credit risk. Following this argument, Bessembinder et al. (2008) argue that CDSs have greater liquidity than bonds. Another important aspect emphasized in the literature is that CDSs capture credit risk more accurately compared to bond spreads, which can also be influenced by unrelated factors (Longstaff et al., 2005; Callen et al., 2009).

Additionally, Daniels and Jensen (2005) and Zhu (2006) have shown that price recovery occurs earlier in the CDS market compared to the bond market. Shahzad et al. (2018) suggest that CDSs serve as a basic building block for synthetic credit frameworks and institutional investors, particularly banks, prefer to use CDSs for hedging credit risk. The CDS market has a large number of buyers and sellers who express crucial sentiments about credit events (Shahzad et al., 2018).

Similarly, Carr and Wu (2009) confirm the association between market risk, measured as stock return variance, and credit risk, proxied by default arrival, in their option and CDS pricing model. The findings of the study suggest that CDSs contain overlapping functional information about the credit risk and market risk of the underlying entities. Given these advantages, CDSs are widely acknowledged as a better proxy of credit risk under certain circumstances. Therefore, our study aims to extend the existing literature by exploring new asset classes that can be used as hedge and safe-haven options for credit risk.

The literature has documented the hedging and safe-haven features of gold as an investment asset, especially during periods of economic downturn. Hillier et al. (2006) suggest that precious metals such as gold and silver can be effective diversification and hedging assets for extreme stock volatility. Baur and Lucey (2010) highlight the hedging and safe-haven features of gold against stocks and bonds. Their findings suggest that gold can be viewed as a safe-haven asset for stocks, while the safe-haven property does not hold in bond markets. Similarly, Baur and McDermott (2010) test the safe-haven function of gold in a sample of developed and emerging markets. Their findings suggest that gold has a strong safe-haven function for most developed stock markets, especially during the GFC.

Ciner et al. (2013) use a copula approach to examine the hedging and safe-haven features of five major asset classes: stocks, bonds, dollars, oil, and gold. The findings reveal a strong safe-haven function of gold for all other assets except for oil. He et al. (2018) use Markov-switching CAPM to re-examine gold's hedging and safe-haven properties against stocks. The authors conclude that gold consistently holds hedging potential against stocks although no distinct safe-haven features exist for US and UK stock markets. Madani and Ftiti (2022) inspect gold's hedging and safe-haven potential against currencies and oil prices during extreme market events. Their findings confirm the significant role of gold in reducing portfolio risk, either as a hedge or as a safe haven. More recently, Ming et al. (2023) have retested gold's hedging and safe-haven role for stocks. The findings of the study suggest strong safe-haven properties during downward market movements.

Our study is also related to another strand of the literature that examines hedging and the safe-haven features of cryptocurrencies, particularly Bitcoin. Baur et al. (2015) analyze the correlation between Bitcoin and other traditional asset classes such as stocks, bonds, and commodities. The findings showed an insignificant correlation between Bitcoin and other asset classes during normal periods and economic downturns. Dyhrberg (2016) investigate the hedging properties of Bitcoin against stocks and currencies, confirming its ability to hedge against these assets. They emphasize that including Bitcoin in a portfolio reduces downside risks.

Bouoiyour and Selmi (2015) suggest that Bitcoin's potential as a hedge and safe haven for the US stock market varies over time. Similarly, Bouri et al. (2017a) demonstrate that Bitcoin can serve as a strong safe-haven asset during weekly downturn movements in Asian stocks. Additionally, the hedging and safe-haven functions of Bitcoin vary across different time horizons. Urquhart and Zhang (2019) examine the hedging and safe-haven features of Bitcoin against different currencies. The study reveals that Bitcoin can act as a diversifier, hedge, and safe-haven asset for certain currencies during intraday trading.

Our study is also connected to a growing body of literature that compares the hedging and safe-haven properties of gold and Bitcoin. Shahzad et al. (2020) compare the hedging and safe-haven characteristics of Bitcoin with those of gold. The findings indicate that both assets can be utilized as hedge and safe-haven assets against stocks of G7 countries. However, while the hedging and safe-haven features of gold are evident in all G7 markets, joint features are observed only in the Canadian market for Bitcoin. Chemkha et al. (2021) compare the hedging and safe-haven abilities of gold and Bitcoin against stocks and currencies during the recent COVID-19 pandemic. They find that gold acted as a weak safe-haven during the pandemic, while Bitcoin did not exhibit safe-haven potential during the crisis.

Wen et al. (2022) use the time-varying parameter vector autoregression (TVP-VAR) model to investigate the hedging and safe-haven properties of gold and Bitcoin. The results reveal that gold acted as a safe haven for stocks and oil during the COVID-19 crisis, but the same was not observed for Bitcoin. Choi and Shin (2022) utilize the VAR method to compare the hedging effectiveness of gold and Bitcoin against inflation. The findings clearly demonstrate that gold is a superior hedge against inflation. Rizvi et al. (2022) examine the hedging and safe-haven ability of different asset classes, including gold. Their findings suggest that gold, treasury and cryptocurrencies act as strong safe-haven assets during periods of market turbulence. Based on our review of these three strands of literature, we formulate three research hypotheses, which are described below:

Hypothesis 1: Bitcoin acts as a hedge and safe-haven asset for the credit risk of US industries.

Hypothesis 2: Gold acts as a hedge and safe-haven asset for the credit risk of US industries.

Hypothesis 3: Bitcoin acts as a superior hedge and safe-haven asset for the credit risk of US industries compared to gold.

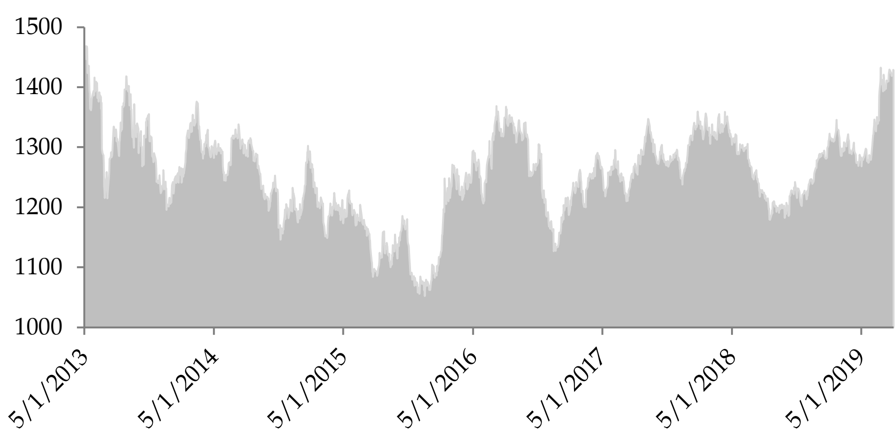
3. Data and Empirical Model

3.1. Data

This study aims to examine the hedging and safe-haven potential of gold and Bitcoin prices against the credit risk of US industries. We selected three variables for our analysis. First, we used sectoral CDS to proxy the credit risk of US industries. As discussed in the literature review section, many researchers consider CDSs to be more suitable proxies for credit risk than other measures, such as bond spread (see Andres et al., 2021). We utilized the five-year CDS indices for 18 US industries, and gold prices quoted as per the London bullion market (USD per metric tonne). The sector CDS data were sourced from Thomson Reuters DataStream. The other two variables used in the study are gold and Bitcoin daily prices.

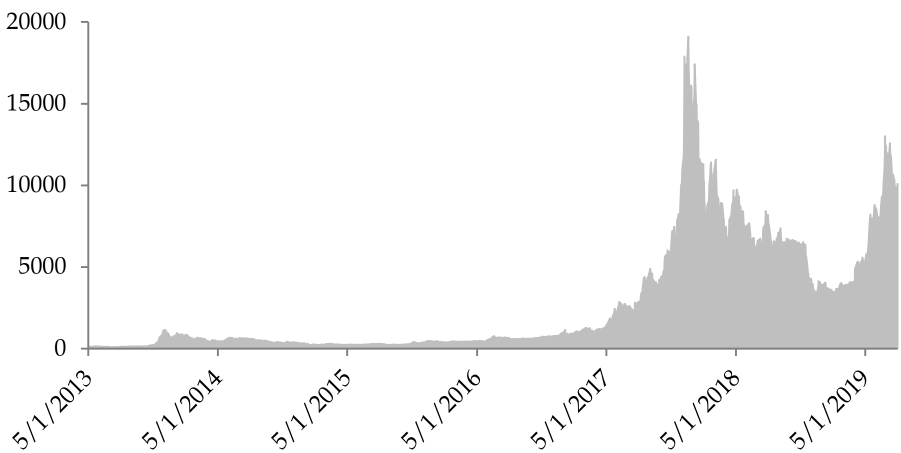
We collected daily closing prices for Bitcoin from https://coinmarketcap.com. The Bitcoin price series constitutes a volume-weighted average of prices from major exchanges denominated in USD. The daily gold prices were also sourced from Thomson Reuters DataStream. The study spans the period from 1 May 2013 to 31 July 2019, and includes 1,631 daily observations.

Figure 1: Time-series plot for Gold prices



The time-series graph for gold illustrates episodes of extensive rise and fall as shown in Figure 1. The downward trend in prices started in May 2013 and reached the lowest level in December 2015. However, the prices had increased to the previous level by the end of our sample period in July 2019. Furthermore, as depicted in Figure 2, the Bitcoin price graph shows an enormous rise in prices starting in February 2017 and reaching an all-time high in December 2017. Moreover, the plot highlights extreme movements in Bitcoin prices. We also report the price evolution of sample CDS indices in Figure 3 (see Appendix). The graphical evidence reveals negative movements between the prices of potential hedgers (gold and Bitcoin) and CDS indices over large time spans.

Figure 2: Time-series plot for Bitcoin prices



We converted the price series into log first-differences and computed continuously compounded returns. Table 1 summarizes the descriptive statistics of returns. The findings reveal that the majority of CDS indices and gold prices reported negative mean returns for the sample period. Six CDS indices, including retail, telecommunications, food and beverages, oil and gas, personal household, and health care, had positive mean returns between 0.01 and 0.05 percent.

As expected, the mean return of the Bitcoin price was the highest at 0.26 percent. Among all the assets, gold had the lowest volatility of 0.8 percent. In the case of sectoral CDS, the spread volatility ranged from 1.48 to 8.30 percent, highlighting concerns regarding the credit risk management of different sectors and the need to explore potential hedgers. Additionally, the skewness, kurtosis, and Jarque–Bera tests showed that all the return series were not normally distributed. Finally, the augmented Dickey-Fuller test rejected the hypothesis of a unit root for all the return series, suggesting that the return series were stationary.

Table 1: Descriptive Statistics of returns

	Abbreviation	Mean	SD	Skewness	Kurtosis	JB-Test	ADF
Banks	USBANCD	-0.0005	0.0244	1.1575	14.4666	9299.576***	-37.948***
Insurance	USINSCD	-0.0007	0.0307	-18.4913	553.7119	20703592***	-35.6156***
Automobiles	USAUTCD	-0.0003	0.0209	1.1052	8.8863	2686.829***	-35.6526***
Chemicals	USCHECD	-0.0001	0.0172	0.9058	8.3189	2145.681***	-37.6057***
Media	USMEDCD	-0.0001	0.0260	-13.7384	398.7826	10696562***	-37.6395***
Retail	USRETCD	0.0005	0.0690	-13.8133	334.7522	7531329***	-23.5042***
Technology	USTECCD	-0.0002	0.0172	0.9243	8.0932	1995.172***	-34.6312***
Telecommunications	USTELCD	0.0004	0.0444	-16.8993	637.2095	27411947***	-20.5911***
Utilities	USUTICD	-0.0010	0.0730	-23.8566	754.6689	38551588***	-21.328***
Basic resources	USBASCD	-0.0002	0.0830	-7.48809	251.019	4195591***	-33.4943***
Construction materials	USCONCD	-0.0002	0.0252	0.0355	8.9122	2375.82***	-37.0563***
Financial services	USFINCD	-0.0001	0.0166	0.7914	7.2332	1388.149***	-24.083***
Food and beverages	USFOOCD	0.0004	0.0163	0.5336	13.47631	7536.06***	-37.8205***
Oil and gas	USOILCD	0.0002	0.0545	-3.7552	129.0092	1082898***	-36.0923***
Personal household	USPERCD	0.00007	0.0538	-20.1063	653.8387	28896434***	-40.3923***
Travel and leisure	USTRACD	-0.0004	0.0172	0.9113	7.7538	1761.606***	-34.5154***
Industrial goods and services	USINDCD	-0.0002	0.0148	1.61475	17.2615	14530.9***	-36.3204***
Healthcare	USHEACD	0.0001	0.0201	-1.89016	52.3873	166729.2***	-38.5304***
Gold	GLD	-0.00001	0.0086	0.0569	7.0937	1139.759***	-42.2257***
Bitcoin	BTC	0.0026	0.0507	0.3983	13.8478	8040.171***	-41.8171***

Note: SD = standard deviation, JB-test = the Jarque-Bera test of normality, ADF test = augmented Dickey-Fuller test of stationarity. *** indicates 1 percent significance level.

Table 2: Correlation Matrix

	USBANCD	USINSCD	USAUTCD	USCHECD	USMEDCD	USRETCD	USTECCD	USTELCD	USUTICD	USBASCD	USCONCD	USFINCD	USFOOCD	USOILCD	USPERCD	USTRACD	USINDCD	USHEACD	GLD	BTC
USBANCD	1																			
USINSCD	0.272054***	1																		
USAUTCD	0.668632***	0.283141***	1																	
USCHECD	0.537577***	0.216273***	0.62237***	1																
USMEDCD	0.331718***	0.189186***	0.418738***	0.329164***	1															
USRETCD	0.124786***	0.065859***	0.144217***	0.125607***	0.074058***	1														
USTECCD	0.596564***	0.285841***	0.728258***	0.602336***	0.399947***	0.157504***	1													
USTELCD	0.273966***	0.114485***	0.31818***	0.223061***	0.176311***	0.06995***	0.318835***	1												
USUTICD	0.093539***	0.048535*	0.098091***	0.09391***	0.04982**	0.027064	0.109441***	0.052386**	1											
USBASCD	0.142881***	0.071446***	0.174153***	0.131605***	0.073644***	0.024803	0.144166***	0.05295**	0.025307	1										
USCONCD	0.483879***	0.192405***	0.597778***	0.476373***	0.325848***	0.112606***	0.5529***	0.241803***	0.087315***	0.190766***	1									
USFINCD	0.697155***	0.348468***	0.767135***	0.608691***	0.459971***	0.156774***	0.716616***	0.315164***	0.111425***	0.1682***	0.574535***	1								
USFOOCD	0.50931***	0.243273***	0.600117***	0.477694***	0.346147***	0.130644***	0.585495***	0.232377***	0.106877***	0.087767***	0.437804***	0.614304***	1							
USOILCD	0.194523***	0.10932***	0.228241***	0.201662***	0.159569***	0.050322**	0.221624***	0.097681***	0.029411	0.057745**	0.237923***	0.248749***	0.183447***	1						
USPERCD	0.174138***	0.060728**	0.196934***	0.134915***	0.10694**	0.053708***	0.168731***	0.084379	0.02358	0.036369	0.147899***	0.165608***	0.149833***	0.071761***	1					
USTRACD	0.636474***	0.265701***	0.7674***	0.616767***	0.400243***	0.137929***	0.702979***	0.286567***	0.114517***	0.123805***	0.555456***	0.719199***	0.584925***	0.214721***	0.159227***					
USINDCD	0.595217***	0.270439***	0.709965***	0.622004***	0.394584***	0.134765***	0.690955***	0.285414***	0.099784***	0.119925***	0.530723***	0.688759***	0.583165***	0.238538***	0.178211***	0.697564***	1			
USHEACD	0.378083***	0.212751***	0.472126***	0.374757***	0.263597***	0.09357***	0.437123***	0.196595***	0.077131***	-0.055027	0.336936***	0.459659***	0.398154***	0.186437***	0.111558***	0.457367***	0.426733***	1		
GLD	0.127194	0.035237	0.063525**	0.034767	0.02921	0.041496*	0.06599***	0.031235	0.057647*	-0.002401	0.025462	0.079505***	0.050243	0.029101*	-0.02835	0.058909**	0.044099*	0.031977	1	
BTC	-0.020004	-0.043284	0.007715	-0.030444	-0.001247	0.025871	0.013471	0.02475	-0.011559	0.005094	-0.013665	0.005314	0.012889	0.038364	0.004433	0.011971	-0.001401	0.043786	0.010001	1

Note: *, **, and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 2 presents the results of the historical correlations among sector CDS indices, Gold and Bitcoin. The results show that Bitcoin is not significantly correlated with any other asset in our sample, which emphasizes the potential use of Bitcoin for portfolio diversification and hedging industry credit risk. In contrast, gold is significantly correlated with a few of the sample sectoral CDS indices. Additionally, the results reveal that most of the sample CDS indices are significantly and positively correlated with each other.

3.2. Dummy Variable GARCH

Following the methods used by Baur and Lucey (2010), Bouri et al. (2017a) and Bouri et al. (2017b), this study utilizes a GARCH model with dummy variables. The maximum likelihood method is used to estimate the following equations:

$$r_t = \alpha + \gamma r_{t-1} + \beta_0 C_{i,t} + \beta_1 D\left(r_{i,q_{90}}\right) C_{i,t} + \beta_2 D\left(r_{i,q_{95}}\right) C_{i,t} + \beta_3 D\left(r_{i,q_{99}}\right) C_{i,t} + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \pi_0 + \pi_1 \epsilon_{t-1}^2 + \pi_2 \sigma_{t-1}^2 \tag{2}$$

In equation (1), r_t represents the return of Bitcoin and gold, and $C_{i,t}$ is the change in sector CDS indices. $D\left(r_{i,q_{90}}\right)$ indicates the dummy variable of the 90 percent quantile, which implies that the change in the respective

CDS index is greater than the 90 percent quantile; the dummy variable takes the value of 1 and 0 otherwise. Similarly, $D(r_{i,q_{95}})$ and $D(r_{i,q_{99}})$ are dummy variables of the 95 and 99 percent quantiles, respectively, following the abovementioned construction method.

In line with Das et al. (2020) and Wu et al. (2019), this study considers Bitcoin or gold a hedge if their contemporaneous relationship with the respective CDS index is positive or 0. The CDS index generally increases when economic conditions are unfavorable and credit risk is on the rise. To test the safe-haven function of Bitcoin and gold, we focus on the extreme upper tail (90, 95 and 99 percent quantiles). This approach helps evaluate the resilience of Bitcoin and gold during periods of exceptionally high credit risk. Therefore, we define Bitcoin/gold as a hedge if $\beta_0 > 0$. Additionally, we stipulate that Bitcoin/gold would serve as a safe-haven asset for the 90, 95 and 99 percent quantiles, where $k = 1, 2, 3$.

However, Baur and Lucey (2010) define underlying assets (gold) as hedges if the estimated contemporaneous coefficient is negative or 0 when modeling the relationship between gold and stocks. To test the safe-haven function of gold during bearish market states (when asset prices decline), they use a lower tail (5, 2.5 and 1 percent quantiles). Consequently, investors can switch from stocks to gold as a means of safeguarding themselves against significant downward movements.

3.3. Quantile Model with Dummy Variables

Following Baur and Lucey (2010), we employ quantiles with dummy variables to test the hedging and safe-haven functions of gold and Bitcoin prices. Suppose that (A) represents the returns of Bitcoin and gold and (B) denotes the changes in the respective CDS indices. Considering (A) as a real random variable with a cumulative distribution function given as FA (a) = P (A > a), the μth quantile of (A) given (B) = b is defined as follows:

$$Q_{\frac{A}{b}}(\mu) = F_{\frac{A}{b}}^{-1}(\mu) = \inf\left\{\mathrm{a}: F_{\frac{a}{b}}(\mathrm{a}) \geq \mu\right\}; \mu \in [0,1] \tag{3}$$

In equation (3), $Q_{\frac{A}{b}}(\mu) = b^{/}\beta_{(\mu)}$, and $\beta(\mu)$ represents the coefficient vector of b at the μth quantile. Hence, the indicator function is given as:

$$\beta^{\wedge}(\mu) = argmin_{\beta} \sum \rho\mu(a_i - b^{/}\beta) \tag{4}$$

where $\rho_\mu(y) = y\,(\mu - \mathrm{I}\,(y < 0))$, I (.). Therefore, we formulate the following model to test the hedge and safe-haven functions of Bitcoin and gold for CDS indices at different quantiles:

$$Q_{A/B}(\mu) = \theta + \beta_{0(\mu)}C_{i,t} + \beta_{1(\mu)}D\left(r_{i,q_{90}}\right)C_{i,t} + \beta_{2(\mu)}D\left(r_{i,q_{95}}\right)C_{i,t} + \beta_{3(\mu)}D\left(r_{i,q_{99}}\right)C_{i,t} + \varepsilon_t \tag{5}$$

In equation (5), $D\left(r_{i,q_{90}}\right)$, $D\left(r_{i,q_{95}}\right)$ and $D\left(r_{i,q_{99}}\right)$ represent the dummy variables that take the value of 1 if the changes in the related CDS index are greater than the respective quantile, and 0 otherwise. The hedge and safe-haven functions of Bitcoin and gold at the μth quantile are determined similarly to the average condition.

4. Empirical Findings and Discussion

4.1. Results of GARCH Model

The results of the conditional GARCH model for Bitcoin prices are shown in Table 3. These results indicate that Bitcoin acts as a strong hedge (with a positive and statistically significant coefficient) for 11 CDS industry indices, including insurance, automobiles, media, retail, telecommunication, basic resources, construction material, food and beverages, oil and gas, travel and leisure, and healthcare. However, Bitcoin is found to be a weak hedge for the utilities sector. Additionally, we observe that Bitcoin is a strong safe-haven asset (with a positive and statistically significant coefficient) for 15 CDS industry indices, excluding banking, insurance, and automobiles, at the extremely low 90 percent quantile. However, at the 95 and 99 percent quantiles, Bitcoin is also identified as a strong safe-haven asset (statistically significant) for the banking, insurance and automobile sectors, on average.

These findings reinforce the role of Bitcoin as both a hedge and safe-haven asset against industry CDS indices and support the idea that cryptocurrencies, particularly Bitcoin, have hedging and safe-haven properties (e.g., Kyriazis, 2020; BenSaïda, 2023). Our results differ from those of Das et al. (2020) and suggest that Bitcoin prices are largely isolated from the real economy. Overall, our findings confirm our first research hypothesis, which states that Bitcoin acts as a hedge and safe-haven asset for credit risk in US industries.

Table 3: GARCH model estimation for Bitcoin

	90Q	95Q	99Q	Hedge
USBANCD	-0.0056***	-0.0143***	0.0249***	-0.0148***
USINSCD	-0.0111***	-0.0113***	0.0140***	0.0008***
USAUTCD	-0.00004***	0.0169***	0.0165***	0.0072***
USCHECD	0.0073***	0.0091***	0.0183***	-0.0201***
USMEDCD	0.0283***	0.0260***	-0.0252***	0.0268***
USRETCD	0.0181***	0.0309***	0.0306***	0.0227***
USTECCD	0.0049***	0.0271***	0.0197***	-0.0344***
USTELCD	0.1212***	0.1081***	0.1209***	0.0235***
USUTICD	0.0047***	0.0054***	-0.0396***	0.0004
USBASCD	0.0008***	0.0007***	-0.0055***	0.0003***
USCONCD	0.0065***	0.0065***	0.0237***	0.0043***
USFINCD	0.1126***	0.1311***	0.0235***	-0.0004***
USFOOCD	0.0735***	0.0882***	0.1213***	0.0015***
USOILCD	0.0389***	0.0392***	0.0007***	0.0089***
USPERCD	0.0124***	0.0128***	0.0362***	-0.0044***
USTRACD	0.0224***	0.0200***	0.0203***	0.0020***
USINDCD	0.0239***	0.0239***	0.0238***	-0.0129***
USHEACD	0.0421***	0.1516***	0.1662***	0.0413***

Note: *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

The results of the conditional GARCH model for gold prices are presented in Table 4. These results demonstrate that gold serves as a strong hedge (with a positive and statistically significant coefficient) for six industry CDS indices, including banking, automobiles, financial services, food, industrial goods and services, and healthcare. However, gold is identified as a weak hedge for the remaining CDS sectoral indices, with the exception of basic resources and personal households. Compared to Bitcoin, the results indicate that gold functions as a strong safe-haven for only three CDS indices at the 90 and 95 percent quantiles. At the 99 percent quantile, gold can be considered a weak safe-haven asset for the majority of CDS indices. These findings differ greatly from the established notion, as supported by a significant body of literature, that positions gold as a superior hedge and safe-haven asset compared to Bitcoin prices (e.g., Conlon et al., 2020; Chemkha et al., 2021; Choi & Shin, 2022; Kayral et al., 2023).

Table 4: GARCH model estimation for Gold

	90Q	95Q	99Q	Hedge
USBANCD	0.0240	0.0182**	0.0099	0.0293***
USINSCD	0.0241	0.0242	0.0032	0.0049
USAUTCD	0.0325***	0.0246	0.0137	0.0270***
USCHECD	0.0271	0.0250***	-0.0182	0.0217
USMEDCD	0.0165	0.0061	-0.0306	0.0077
USRETCD	-0.0016	-0.0024	-0.0069	0.0012
USTECCD	0.0386	0.0287	-0.0064	0.0303
USTELCD	0.0089	0.0053	0.0098	0.0040
USUTICD	0.0056	0.0024	0.0200	0.0057
USBASCD	-0.0051	-0.0055	-0.0040	-0.0027
USCONCD	0.0054	0.0133	-0.0042	0.0078
USFINCD	0.0438***	0.0292	0.0177	0.0361***
USFOOCD	0.0129	0.0047	-0.0168	0.0266***
USOILCD	0.0057	0.0044	0.0086	0.0013
USPERCD	0.0116	0.0139*	0.0132***	-0.0022
USTRACD	0.0295***	0.0203	0.0040	0.0272
USINDCD	0.0298	0.0113	-0.0149	0.0238***
USHEACD	0.0046	-0.0021	-0.0065	0.0148***

Note: *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Overall, our findings indicate that both Bitcoin and gold can serve as hedge and safe-haven assets for the majority of industry CDS indices. This supports our first and second research hypotheses, which suggest that Bitcoin and gold have the potential to hedge against the credit risk of US industries and provide a safe haven. However, our results also show that Bitcoin has a superior capacity for hedging and serving as a safe haven compared to gold. Specifically, Bitcoin performs well as a safe haven for industry credit risk under extreme market conditions, as indicated by the lower and upper quantiles. This confirms our third hypothesis, which argues that Bitcoin has greater potential than gold in terms of hedging and acting as a safe haven.

Based on these results, we suggest that investors and portfolio managers who are investing in US industries can utilize both gold and Bitcoin prices to diversify and hedge against downward risks. Additionally, during crisis events such as the GFC, COVID-19 crisis and Russia-Ukraine crisis, both gold and Bitcoin can protect investors from extreme downward movements. In fact, Bitcoin may even serve this purpose better than gold, despite gold being considered the superior hedge and safe-haven asset during meltdown periods.

4.2. Quantile Model Results

The results of the quantile regression with dummy variables are presented in the Appendix. Table 6 (see Appendix) displays the quantile regression results with a dummy variable for Bitcoin. Panels A to R show the results for 18 industry CDS indices and for Bitcoin. We report the regression results for seven quantiles, where the 5, 10 and 25 percent quantiles represent a bearish market state, the 50 percent quantile represents a normal market state, and the 75, 90 and 95 percent quantiles represent bullish market outcomes. Furthermore, when $\beta_0 > 0$, it indicates a hedging function, and when $\sum_{i=1}^{k} \beta i > 0$ (k = 1, 2, 3), it denotes the safe-haven coefficient. Table 5 (Panel B) provides a summary of the hedging potential and safe-haven properties of Bitcoin in the previously described market states.

The results of the quantile regression show that under bearish market conditions, Bitcoin acts as a strong hedge for four sectors, a weak hedge for six sectors, and not a hedge for eight sector CDS indices. Similarly, during normal market conditions, Bitcoin is a strong hedge for five sector CDS indices, a weak hedge for five sectors, and not a hedge for eight sectors. Finally, during bullish market conditions, the digital currency serves as a strong hedge for the credit risk of two industries, a weak hedge for 11 sectors, and not a hedge for five CDS industry indices.

Additionally, the results show that in a bearish market state, Bitcoin is a weak safe-haven asset for 11 sector CDS indices, not a safe-haven asset for six sectors, and a strong safe-haven asset for only one sector. In the normal market, Bitcoin is a weak safe-haven asset for four sectors, not a safe-haven asset for ten sectors, and a strong safe-haven asset for four CDS indices. Furthermore, the results indicate that at higher quantiles, Bitcoin is a weak safe-haven asset for 12 industry CDS indices and a strong safe-haven asset for six industries. Once again, these results confirm the hedging and safe-haven properties of Bitcoin in acting as a hedge and safe haven for financial assets, particularly the credit risk of US industries, under all market states and conditions. These findings support our first study hypothesis.

Table 7 (see Appendix) presents the results of quantile regression for gold and 18 sector CDS indices, including a dummy variable. In addition, Panel A of Table 5 provides a summary of gold's hedging potential and safe-haven properties in various market outcomes. The results indicate that gold is a strong hedge against the credit risk of nine sectors' CDS indices, a weak hedge against the credit risk of eight sectors, and not a hedge for one sector during bearish market conditions. In normal market situations, gold serves as a strong hedge for nine sectors, a weak hedge for six sectors, and not a hedge for three sector CDS indices. Furthermore, the results for the bullish market state show that gold is a strong hedge for four industry CDS indices, a weak hedge for seven industries, and not a hedge for seven indices.

Additionally, the results reveal that under bearish market conditions, gold serves as a weak safe-haven asset for 11 sectors, not a safe-haven asset for six sectors, and a strong safe-haven asset for only one sector CDS index. In normal market conditions, gold has weak safe-haven properties for six sector CDS indices, no safe-haven potential for nine sectors, and strong safe-haven characteristics for three sectors. In the bullish market, gold serves as a weak safe-haven asset for 12 indices, not a safe-haven asset for one index, and a strong safe-haven for five sectors. These results confirm our second study hypothesis. Table 5 provides a summary of the hedge and safe-haven results.

Table 5: Summary of Hedge and Safe-haven Results

Panel A: Gold						
	Hedging potential			**Safe-haven potential**		
Sector CDS	**Bearish market**	**Normal market**	**Bullish market**	**Bearish market**	**Normal market**	**Bullish market**
Banks	SH	WH	SH	NSH	SSH	WSH
Insurance	WH	NH	NH	WSH	WSH	SSH
Automobile	WH	SH	NH	WSH	NSH	WSH
Chemicals	WH	SH	WH	WSH	WSH	WSH
Media	SH	WH	WH	NSH	NSH	WSH
Retail	WH	WH	SH	WSH	NSH	WSH
Technology	SH	SH	NH	WSH	NSH	SSH
Telecommunications	WH	WH	WH	NSH	WSH	WSH
Utilities	SH	WH	WH	WSH	WSH	SSH
Basic resources	SH	SH	NH	WSH	WSH	WSH
Construction materials	SH	SH	NH	WSH	NSH	WSH
Financial services	SH	SH	SH	WSH	NSH	SSH
Food and beverages	WH	SH	SH	NSH	NSH	WSH
Oil and gas	SH	NH	NH	NSH	WSH	WSH
Personal household	NH	NH	NH	WSH	SSH	NSH

Panel A: Gold						
	Hedging potential			Safe-haven potential		
Sector CDS	**Bearish market**	**Normal market**	**Bullish market**	**Bearish market**	**Normal market**	**Bullish market**
Travel and leisure	WH	SH	WH	NSH	NSH	WSH
Industrial goods and services	SH	WH	WH	SSH	SSH	WSH
Healthcare	WH	SH	WH	WSH	NSH	SSH

Panel B: Bitcoin						
	Hedging potential			Safe-haven potential		
Sector CDS	**Bearish market**	**Normal market**	**Bullish market**	**Bearish market**	**Normal market**	**Bullish market**
Banks	NH	NH	NH	WSH	NSH	SSH
Insurance	SH	NH	NH	NSH	NSH	WSH
Automobile	NH	WH	WH	WSH	WSH	WSH
Chemicals	NH	NH	NH	WSH	WSH	WSH
Media	WH	SH	WH	WSH	NSH	WSH
Retail	WH	SH	WH	NSH	SSH	SSH
Technology	NH	NH	WH	WSH	NSH	WSH
Telecommunications	NH	WH	WH	WSH	NSH	WSH
Utilities	WH	WH	WH	NSH	NSH	WSH
Basic resources	NH	WH	SH	WSH	SSH	WSH
Construction materials	NH	NH	WH	WSH	WSH	SSH
Financial services	WH	NH	WH	WSH	NSH	WSH
Food and beverages	SH	SH	SH	NSH	NSH	SSH
Oil and gas	SH	NH	NH	NSH	WSH	WSH
Personal household	NH	NH	NH	WSH	SSH	WSH
Travel and leisure	WH	SH	WH	WSH	NSH	SSH
Industrial goods and services	SH	WH	WH	SSH	SSH	SSH
Healthcare	WH	SH	WH	NSH	NSH	WSH

Note: SH indicates a strong hedge, WH indicates a weak hedge, and NH indicates no hedge. WSH indicates a weak safe-haven, SSH indicates a strong safe-haven, and NSH indicates no safe-haven.

Overall, our quantile regression findings indicate that gold is more effective in hedging credit risk under bearish and normal market conditions, while Bitcoin performs better as a hedge in bullish market outcomes. However, when it comes to safe-haven properties, Bitcoin outperforms gold. In conclusion, our findings support the strong hedging and safe-haven potential of the proposed assets for managing the credit risk of US industries. This aligns with our earlier discussed results and reinforces our third study hypothesis.

5. Conclusion

Increased price volatilities following the GFC have led investors and portfolio managers to seek protection against the credit risk of different sectors. The booms and busts in the CDS market have also highlighted the need for hedging and safe-haven assets for sectoral CDS indices. This study explores whether gold and Bitcoin prices can serve as such assets. Given the strong interlinkages and co-movements among these assets due to financialization and global market integration, it is important for portfolio managers and investors to diversify their portfolios by taking positions across these markets. Building on recent evidence that supports the effectiveness of gold and Bitcoin as hedgers and safe-haven assets for various asset classes, we employ the GARCH model and quantile regression with dummy variables to assess the hedging and safe-haven properties of Bitcoin and gold against industry CDS indices.

The findings of the study strongly support the hypothesis that Bitcoin and gold can effectively hedge and serve as safe-haven assets for the credit risk of US industries. Furthermore, the findings reveal that Bitcoin has superior hedging and safe-haven properties compared to gold. Both our models (GARCH with dummy variable and quantile regression) yield similar results with no significant divergence.

This study has important implications for market participants interested in managing credit risk in US industries. Firstly, portfolio managers and investors can use gold and Bitcoin to protect against credit risk in US industries across different market conditions and economic situations. With a better understanding of the relationship between sectoral US indices, gold and Bitcoin, investors can make more informed decisions regarding diversification and hedging. Second, the evidence presented can guide market participants in making short-term investments in Bitcoin and gold to shield against extreme market outcomes in sectoral CDS indices, especially during periods of high or low credit risk. Lastly, given the high interdependence between different US sector CDS indices as suggested by Shahzad et al. (2017), investors can effectively utilize the proposed potential hedgers to create arbitrage and hedging opportunities for both financial and nonfinancial industries.

Nevertheless, market participants should interpret the findings of this study with caution. The presented results may be limited by the duration of the sample and the econometric technique employed. Therefore, investors and portfolio managers should consider this information alongside other important market insights. Additionally, decision-makers should be mindful that the use of gold and Bitcoin carries certain risks, such as information asymmetry regarding their prices, increased volatility in the digital currency market, and regulatory and theft concerns. Lastly, future research could explore the portfolio benefits of using gold and Bitcoin as potential hedgers and safe-haven assets for CDS indices. Further investigation could also focus on determining the associations between CDS indices and the gold and Bitcoin markets.

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Appendix

Figure 3: Price evolution of sample CDS indices

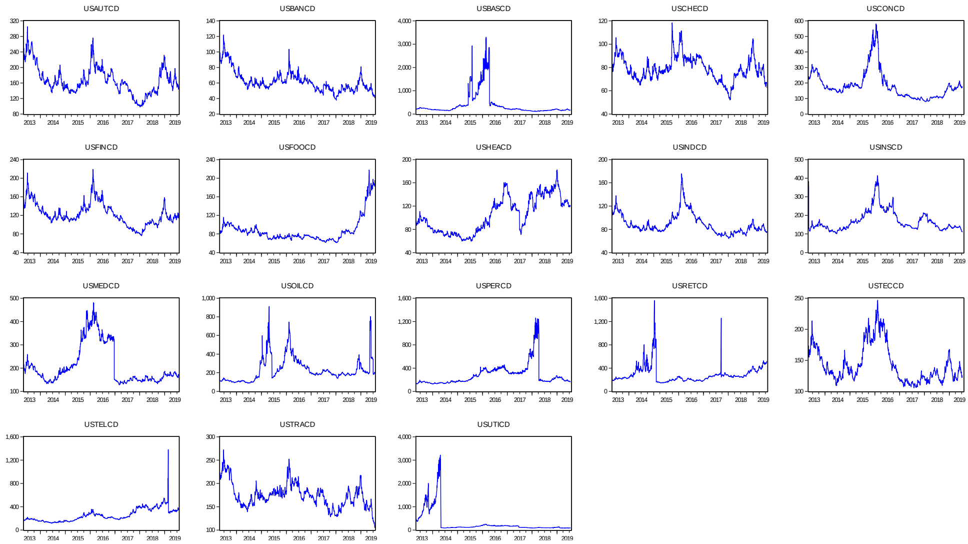

Table 6: Quantile regression model estimation results for Bitcoin

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel A: Banks			
λ	-0.07606***	-0.0506***	-0.015***	0.00194***	0.02031***	0.05054***	0.07783***
	(0.004)	(0.00363)	(0.00136)	(0.00073)	(0.00131)	(0.00318)	(0.00455)
β0	-0.20681	-0.3144*	0.00748	-0.06383*	-0.12524**	-0.02186	0.12954
	(0.19984)	(0.18516)	(0.07745)	(0.03661)	(0.05587)	(0.15351)	(0.28694)
$\sum_{i=0}^{1} \beta i$	0.4671	0.57255	0.09594	0.17084	0.35225**	0.94905**	0.59594
	(1.83199)	(0.51329)	(0.15155)	(0.12693)	(0.15143)	(0.45131)	(1.74732)
$\sum_{i=0}^{2} \beta i$	-1.39615	-0.65956	-0.23673	-0.12167	-0.11095	-0.22375	-0.33001
	(1.89308)	(0.93414)	(0.17659)	(0.15908)	(0.20484)	(0.55455)	(1.71558)
$\sum_{i=0}^{3} \beta i$	0.56077	-0.09382	-0.02795	-0.07495	0.03255	-0.6323	-0.46728
	(0.73544)	(1.07627)	(0.13702)	(0.11348)	(0.30049)	(0.43589)	(1.4566)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel B: Insurance			
λ	-0.0747***	-0.04812***	-0.01498***	0.00204***	0.0215	0.05099***	0.07709***
	(0.00451)	(0.00367)	(0.00137)	(0.0007)	(0.00135)	(0.00322)	(0.00509)
β0	-0.01279	0.08852	0.02035***	-0.03736	-0.12419	-0.09296	-0.06532
	(0.13576)	(0.3267)	(0.00348)	(0.0855)	(0.1163)	(0.27825)	(0.44002)
$\sum_{i=0}^{1} \beta i$	-0.24854	0.39091	-0.01866	0.09671	0.3467	1.36059	2.19116
	(1.52902)	(0.68871)	(0.23091)	(0.20517)	(0.48678)	(0.90248)	(1.85136)
$\sum_{i=0}^{2} \beta i$	0.27684	-0.72504	-0.18807	-0.11634	-0.24592	-0.8709	-2.23252
	(1.97728)	(0.73164)	(0.26826)	(0.20774)	(0.47246)	(0.93969)	(-1.2425)
$\sum_{i=0}^{3} \beta i$	-0.40684	-0.01931	0.14783	-0.06509	0.11746	-0.24949	-0.03872
	(1.52744)	(0.56359)	(0.16669)	(0.1471)	(0.20508)	(0.47715)	(-0.0881)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel C: Automobiles			
λ	-0.07581***	-0.05015***	-0.01463***	0.00247***	0.02184***	0.05139***	0.07957***
	(0.00504)	(0.00377)	(0.0014)	(0.00071)	(0.00139)	(0.00331)	(0.00467)
β0	-0.1671	-0.15357	0.11152	0.04266	0.02488	0.06676	0.25234
	(0.20635)	(0.20242)	(0.08554)	(0.04943)	(0.08314)	(0.22191)	(0.33647)
$\sum_{i=0}^{1} \beta i$	-0.31124	0.39837	-0.00978	-0.07393	0.13755	0.27987	-0.07725
	(0.97292)	(0.64129)	(0.22183)	(0.16003)	(0.39828)	(0.43352)	(1.11852)
$\sum_{i=0}^{2} \beta i$	0.5147	0.05451	-0.13545	0.01361	-0.11937	0.00773	-0.14419
	(1.24998)	(0.81475)	(0.23546)	(0.18826)	(0.41062)	(0.38915)	(1.09067)
$\sum_{i=0}^{3} \beta i$	-1.09288	-0.23734	0.11787	0.11291	0.04549	-0.21949	0.01545
	(1.28559)	(1.11939)	(0.14667)	(0.14605)	(0.19502)	(0.20373)	(0.42452)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel D: Chemicals				
λ	-0.07441***	-0.05085***	-0.01466***	0.00208***	0.02169***	0.05143***	0.07969***
	(0.0041)	(0.00407)	(0.00138)	(0.00071)	(0.00142)	(0.00348)	(0.00479)
β0	-0.13246	-0.3248	-0.075	-0.02813	-0.09726	-0.1092	0.17498
	(0.32725)	(0.22475)	(0.09649)	(0.05654)	(0.06678)	(0.25153)	(0.35707)
$\sum_{i=0}^{1} \beta i$	0.72898	0.25495	-0.0228	-0.00123	-0.0295	0.52934	0.7508
	(0.98182)	(0.58006)	(0.35173)	(0.15728)	(0.22026)	(0.86854)	(1.64732)
$\sum_{i=0}^{2} \beta i$	-2.45993**	-1.21418	-0.25103	-0.15379	0.01064	-0.58183	-0.78764
	(0.98184)	(1.0536)	(0.39307)	(0.17661)	(0.25292)	(1.13275)	(1.58352)
$\sum_{i=0}^{3} \beta i$	2.29724***	1.53586	0.49556**	0.19822	0.07636	0.20639	-0.40652***
	(0.43956)	(0.95885)	(0.22834)	(0.12805)	(0.17067)	(0.92313)	(0.12206)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel E: Media				
λ	-0.07557***	-0.04763***	-0.01494***	0.00222***	0.0222***	0.05222***	0.07887***
	(0.00478)	(0.00346)	(0.00131)	(0.0007)	(0.00133)	(0.00354)	(0.00512)
β0	-0.07386	0.01971	0.03535	0.03146**	-0.02527	0.01539	0.05147
	(0.28624)	(0.08354)	(0.13495)	(0.01342)	(0.14745)	(0.39057)	(0.56644)
$\sum_{i=0}^{1} \beta i$	-1.10357	-0.76212	-0.22224	-0.01444	-0.23191	-0.15138	0.03392
	(0.91016)	(0.957850)	(0.27017)	(0.14814)	(0.33346)	(0.99959)	(0.73988)
$\sum_{i=0}^{2} \beta i$	1.20986	1.13966	0.14077	0.06234	0.31574	0.22637	0.04931
	(0.92786)	(1.19431)	(0.26886)	(0.17865)	(0.29596)	(0.90429)	(0.69081)
$\sum_{i=0}^{3} \beta i$	0.07339	-0.31808	-0.09915	-0.10752	-0.11221	-0.37927	-0.64722
	(0.47009)	(0.779)	(0.18106)	(0.12406)	(0.09115)	(0.25709)	(0.63132)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel F: Retail				
λ	-0.07568***	-0.04958***	-0.01501***	0.00227***	0.02172***	0.05141***	0.0779***
	(0.0046)	(0.00369)	(0.00145)	(0.00069)	(0.0013)	(0.0033)	(0.00477)
β0	0.00935	-0.0089	0.02497	0.02297***	-0.00118	0.01855	0.03615
	(0.23894)	(0.16875)	(0.08853)	(0.00212)	(0.03111)	(0.23781)	(0.34262)
$\sum_{i=0}^{1} \beta i$	0.20867	0.36765	-0.10369	-0.15884	-0.14161	0.00501	-0.20521
	(1.21824)	(0.49475)	(0.15718)	(0.10094)	(0.20447)	(0.35325)	(0.91861)
$\sum_{i=0}^{2} \beta i$	-0.19733	-0.23737	0.18468	0.24345**	0.24864	0.28804	1.10485
	(1.18117)	(0.48939)	(0.15426)	(0.12293)	(0.23671)	(0.52017)	(0.9995)
$\sum_{i=0}^{3} \beta i$	-0.3001**	-0.45611**	-0.12224	-0.07814	-0.08654	-0.20305	-0.69779
	(0.11901)	(0.21296)	(0.14774)	(0.0778)	(0.20755)	(0.47849)	(0.64975)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel G: Technology				
λ	-0.07829***	-0.05287***	-0.01523***	0.00199***	0.02198***	0.05253***	0.07895***
	(0.00503)	(0.00405)	(0.00141)	(0.00074)	(0.00137)	(0.00306)	(0.00519)
β_0	-0.4938*	-0.47952**	0.07025	-0.02993	0.02329	0.21426	0.29986
	(0.29157)	(0.21895)	(0.1076)	(0.05503)	(0.10159)	(0.23791)	(0.24379)
$\sum_{i=0}^{1} \beta i$	0.36695	0.76227	-0.05718	-0.02413	0.3407	0.26783	0.51721
	(1.18759)	(0.51695)	(0.28655)	(0.20533)	(0.38398)	(0.63129)	(0.46985)
$\sum_{i=0}^{2} \beta i$	0.20816	0.27197	0.04285	0.08372	-0.49583	0.1782	-0.23615
	(2.02857)	(0.7147)	(0.26588)	(0.20911)	(0.37573)	(1.16475)	(0.26394)
$\sum_{i=0}^{3} \beta i$	0.3495	-0.25006	0.03287	-0.00794	0.09348	-0.6425	-0.81341
	(1.74886)	(0.60327)	(0.10542)	(0.1016)	(0.19389)	(1.03131)	(0.31871)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel H: Telecommunication				
λ	-0.07468***	-0.04743***	-0.01501***	0.00217***	0.02212***	0.05122***	0.07826***
	(0.00497)	(0.00402)	(0.00152)	(0.0008)	(0.00145)	(0.00339)	(0.00584)
β_0	-0.03108	-0.01162	0.01152	0.02378	0.03803	0.0588	0.0781
	(0.66994)	(0.54323)	(0.20805)	(0.10945)	(0.19873)	(0.46512)	(0.78534)
$\sum_{i=0}^{1} \beta i$	0.36765	0.20992	-0.11612	-0.04167	-0.11994	-0.03974	0.0948
	(1.33257)	(0.69305)	(0.33529)	(0.16802)	(0.27045)	(0.84442)	(1.70919)
$\sum_{i=0}^{2} \beta i$	-1.45638	-1.1538**	-0.19417	-0.07656	0.23576	0.21096	-0.12417
	(1.37559)	(0.35847)	(0.2773)	(0.17553)	(0.32612)	(0.74853)	(1.55897)
$\sum_{i=0}^{3} \beta i$	1.26953	1.04065	0.30713	0.21461	-0.06519	0.1669	0.16188
	(1.32482)	(0.85094)	(0.29609)	(0.13999)	(0.29882)	(0.48516)	(0.7597)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel I: Utilities				
λ	-0.0727***	-0.04584***	-0.01503***	0.00202***	0.02193***	0.05137***	0.078***
	(0.00332)	(0.00385)	(0.00131)	(0.00073)	(0.00132)	(0.00321)	(0.00474)
β_0	-0.02733	0.00117	0.00609	0.00044	0.00868	0.01537	0.03188
	(0.06009)	(0.21816)	(0.03772)	(0.02778)	(0.05026)	(0.1223)	(0.02906)
$\sum_{i=0}^{1} \beta i$	-2.41857	-0.48779	-0.3374	-0.00396	0.01713	0.37747	0.20169
	(1.85003)	(0.62716)	(0.34146)	(0.12874)	(0.1553)	(0.48771)	(0.14297)
$\sum_{i=0}^{2} \beta i$	2.23901	0.64563	0.49758	0.05405	0.08566	0.14826	0.37413
	(1.85785)	(0.72634)	(0.34741)	(0.13336)	(0.20418)	(0.5098)	(0.57482)
$\sum_{i=0}^{3} \beta i$	-0.73021***	-0.98352*	-0.61594**	-0.0908	-0.13504	-0.67673***	-0.71418
	(0.21046)	(0.58644)	(0.28962)	(0.09764)	(0.16078)	(0.23067)	(0.5893)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel J: Basic resources				
λ	-0.07513***	-0.05029***	-0.01565***	0.00213***	0.02238***	0.05226***	0.07991***
	(0.00473)	(0.00404)	(0.00147)	(0.0007)	(0.00132)	(0.00313)	(0.00459)
β0	-0.03879	-0.02358	-0.00237	0.00048	0.01209***	0.02921***	-0.06762
	(0.26817)	(0.23218)	(0.08321)	(0.00171)	(0.00324)	(0.00768)	(0.17549)
$\sum_{i=0}^{1} \beta i$	-0.1105	0.03485	0.04019	-0.09669	-0.21978	-0.5998	0.0796
	(0.85956)	(0.73447)	(0.18729)	(0.06357)	(0.17773)	(0.52128)	(0.89196)
$\sum_{i=0}^{2} \beta i$	0.55514	0.27754	0.05919	0.22244***	0.23937	0.71495	0.01121
	(1.008)	(0.67654)	(0.20361)	(0.08412)	(0.21005)	(0.55748)	(0.86552)
$\sum_{i=0}^{3} \beta i$	-0.34291	-0.24594***	-0.08211	-0.13215*	-0.04749	-0.18431	-0.08546
	(0.63916)	(0.0927)	(0.13689)	(0.05975)	(0.12181)	(0.22204)	(0.09612)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel K: Construction materials				
λ	-0.07778***	-0.05133***	-0.01574***	0.00207	0.02281***	0.05215***	0.07997
	(0.00474)	(0.00383)	(0.00146)	(0.00073)	(0.00132)	(0.00326)	(0.00475)0
β0	-0.47131***	-0.29967**	-0.04522	-0.00608	0.07084	0.11146	0.21321
	(0.18118)	(0.12602)	(0.05151)	(0.03553)	(0.0631)	(0.16271)	(0.25558)
$\sum_{i=0}^{1} \beta i$	-0.39137	-0.12725	0.0747	-0.10796	-0.38733***	-0.18593	-0.3537
	(1.17165)	(0.88309)	(0.12269)	(0.12089)	(0.13678)	(0.55074)	(0.82603)
$\sum_{i=0}^{2} \beta i$	0.9385	0.70425	-0.02183	0.11619	0.33162**	0.10054	0.1494
	(1.14775)	(0.89393)	(0.15201)	(0.13956)	(0.14013)	(0.5688)	(0.89505)
$\sum_{i=0}^{3} \beta i$	-1.07505	-0.02283	0.08033	0.13984	0.08087	0.34877	0.03977
	(2.16238)	(0.3016)	(0.12593)	(0.14786)	(0.22764)	(0.42198)	(0.47332)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel L: Financial services				
λ	-0.07506***	-0.04752***	-0.0154***	0.00199	0.02201***	0.05148***	0.07869***
	(0.00477)	(0.00388)	(0.00143)	(0.00068)	(0.00145)	(0.00342)	(0.00463)
β0	-0.03645	-0.05027	0.03741	-0.00601	0.0558	0.19053	0.40674
	(0.25767)	(0.29205)	(0.10128)	(0.05526)	(0.09983)	(0.19684)	(0.43777)
$\sum_{i=0}^{1} \beta i$	-0.22837	0.84154	0.19382	-0.01252	0.23807	0.37297	-0.20613
	(2.09636)	(0.88432)	(0.14807)	(0.18741)	(0.40085)	(0.66419)	(0.93345)
$\sum_{i=0}^{2} \beta i$	0.27949	-1.26301	-0.26913	0.20342	-0.10261	0.26011	0.50291
	(2.12134)	(0.8098)	(0.25584)	(0.24347)	(0.45071)	(0.94033)	(1.29557)
$\sum_{i=0}^{3} \beta i$	-1.41501	-0.29059	-0.25485	-0.16291	-0.23325	-1.09096	-0.88202
	(1.69811)	(0.49153)	(0.26904)	(0.2315)	(0.26832)	(0.74212)	(1.04766)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel M: Food and beverages			
λ	-0.01387***	-0.00943***	-0.00424***	0.00005	0.00447***	0.00947***	0.01289***
	(0.00101)	(0.00039)	(0.0003)	(0.00018)	(0.00026)	(0.00048)	(0.00065)
β0	0.02762	0.0492	0.0618**	0.06034***	0.07076***	0.04946***	0.02946
	(0.08277)	(0.03205)	(0.02971)	(0.01482)	(0.02532)	(0.01332)	(0.06873)
$\sum_{i=0}^{1}\beta i$	-0.00468	0.03263	-0.02511	-0.03588	0.07739	0.13505	0.1071
	(0.31384)	(0.07039)	(0.07058)	(0.0533)	(0.06411)	(0.13375)	(0.16598)
$\sum_{i=0}^{2}\beta i$	-0.01524	-0.03865	-0.0018	0.02587	-0.07419	-0.18215	-0.15558
	(0.3908)	(0.08973)	(0.06778)	(0.05806)	(0.0691)	(0.13863)	(0.1543)
$\sum_{i=0}^{3}\beta i$	-0.34972	-0.04889	-0.05581	-0.10701**	-0.1164***	0.38371	0.36022***
	(0.26151)	(0.48958)	(0.04891)	(0.05318)	(0.04062)	(0.58947)	(0.08421)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel N: Oil and gas			
λ	-0.01378***	-0.00946***	-0.00431***	0	0.00444***	0.00915***	0.01298***
	(0.00098)	(0.00039)	(0.00028)	(0.00018)	(0.00027)	(0.00043)	(0.00068)
β0	0.0144	0.01076	0.00987**	-0.00327	0.00185	-0.00001	-0.01774
	(0.02813)	(0.00711)	(0.00387)	(0.01268)	(0.01137)	(0.02822)	(0.01392)
$\sum_{i=0}^{1}\beta i$	-0.12026	-0.04696	-0.00868	0.02593	0.06116	0.07558**	0.20933
	(0.09632)	(0.07999)	(0.04445)	(0.02255)	(0.06949)	(0.037)	(0.17057)
$\sum_{i=0}^{2}\beta i$	0.14228	0.0483	-0.00585	-0.02469	-0.06136	-0.04689	-0.19797
	(0.17637)	(0.08237)	(0.04611)	(0.02289)	(0.07392)	(0.04378)	(0.17357)
$\sum_{i=0}^{3}\beta i$	-0.0248	-0.01188	0.01207	0.01249	0.00538	-0.03043	-0.00048
	(0.1605)	(0.0349)	(0.03096)	(0.01876)	(0.02941)	(0.04336)	(0.21494)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel O: Personal household			
λ	-0.01348***	-0.00944***	-0.00446***	0	0.00449***	0.00946***	0.01343***
	(0.00107)	(0.0004)	(0.00031)	(0.0002)	(0.00032)	(0.00046)	(0.00061)
β0	-0.01019	-0.00786	-0.00498	-0.0024	0.0002	-0.00731	-0.02221
	(0.08506)	(0.03183)	(0.02442)	(0.01586)	(0.02568)	(0.01133)	(0.06904)
$\sum_{i=0}^{1}\beta i$	-0.12104	-0.01317	-0.01386	-0.01599	-0.04574	0.05087	-0.00566
	(0.10296)	(0.12349)	(0.04907)	(0.02772)	(0.06375)	(0.05291)	(0.09924)
$\sum_{i=0}^{2}\beta i$	0.17356	0.02987	0.03934	0.03836*	0.06259	-0.04237	0.0084
	(0.08232)	(0.11787)	(0.04464)	(0.02281)	(0.06123)	(0.0546)	(0.09696)
$\sum_{i=0}^{3}\beta i$	-0.02417	-0.00621	-0.02966	-0.00683	-0.02068	-0.01699	-0.01703
	(0.53391)	(0.01536)	(0.03538)	(0.01112)	(0.02588)	(0.0242)	(0.06948)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel P: Travel and leisure				
λ	-0.01437***	-0.00947***	-0.00444***	0	0.0044***	0.00892***	0.01268***
	(0.00095)	(0.00042)	(0.00027)	(0.00018)	(0.00028)	(0.0005)	(0.00058)
β0	0.07013	0.02388	0.03818	0.02808*	0.02898	0.00407	-0.00845
	(0.07589)	(0.03178)	(0.02365)	(0.01594)	(0.02265)	(0.03672)	(0.05624)
$\sum_{i=0}^{1} \beta i$	0.14211	0.12107	0.06418	0.03087	0.05745	0.07559	0.10937
	(0.11256)	(0.08666)	(0.06701)	(0.03713)	(0.06242)	(0.12382)	(0.19927)
$\sum_{i=0}^{2} \beta i$	-0.07591	-0.08965	-0.05827	-0.01212	0.02252*	0.12503	0.04848
	(0.10018)	(0.0777)	(0.0703)	(0.03862)	(0.08268)	(0.13044)	(0.41438)
$\sum_{i=0}^{3} \beta i$	-0.54025***	-0.33984	-0.0501	-0.05241	-0.12592	-0.20072	0.12717
	(0.0798)	(0.55489)	(0.04094)	(0.03725)	(0.06859)	(0.44844)	(0.36804)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel Q: Industrial goods and services				
λ	-0.01402***	-0.00933***	-0.0046***	-0.00004	0.00439***	0.00904***	0.01279***
	(0.00094)	(0.00036)	(0.0003)	(0.00019)	(0.00027)	(0.00048)	(0.00065)
β0	0.07427	0.07663*	0.0417	0.02119	0.02916	0.01207	-0.01368
	(0.0873)	(0.03909)	(0.03004)	(0.0211)	(0.02789)	(0.04792)	(`0.07512)
$1aZ$	0.36987	0.19171***	0.15325***	0.07395*	0.15709	0.07685	-0.04041
	(0.28869)	(0.06123)	(0.04838)	(0.04205)	(0.0969)	(0.09247)	(0.14211)
$\sum_{i=0}^{2} \beta i$	-0.32602	-0.23926	-0.13647**	-0.04939	-0.06473	0.14247*	0.28278
	(0.3064)	(0.11276)	(0.06268)	(0.04593)	(0.09575)	(0.0857)	(0.40251)
$\sum_{i=0}^{3} \beta i$	-0.5055***	-0.18191	-0.08163	-0.05275	-0.13673***	-0.28629	-0.19789
	(0.16273)	(0.39492)	(0.05993)	(0.05737)	(0.03978)	(0.20042)	(0.7165)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel R: Healthcare				
λ	-0.01401***	-0.00967***	-0.0043***	0.00002	0.00452***	0.00958***	0.01359***
	(0.00094)	(0.00036)	(0.00028)	(0.00019)	(0.00031)	(0.00045)	(0.00063)
β0	0.06617	-0.01128	0.02047	0.0189*	0.02556	0.03044	0.03758
	(0.068)	(0.03857)	(0.02033)	(0.0108)	(0.02113)	(0.03316)	(0.04409)
$\sum_{i=0}^{1} \beta i$	0.12765	0.12034	0.04083	0.02477	0.04556	0.06364	0.01272
	(0.09745)	(0.05253)	(0.06308)	(0.03321)	(0.05036)	(0.09071)	(0.17008)
$\sum_{i=0}^{2} \beta i$	-0.11813**	-0.06452**	-0.06374	-0.04124	-0.0953*	-0.14876*	-0.1156
	(0.052)	(0.06917)	(0.05947)	(0.0363)	(0.05201)	(0.08968)	(0.16746)
$\sum_{i=0}^{3} \beta i$	-0.54432	-0.06418	-0.04567	-0.009	0.04002	0.0426	0.43959***
	(0.77408)	(0.06715)	(0.08057)	(0.02861)	(0.07859)	(0.57415)	(0.05111)

Note: *, ** and *** denote statistical significance at the 1, 5 and 10 percent levels, respectively. The standard errors are indicated in parentheses.

Table 7: Quantile regression model estimation results for gold

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Panel A: Banks							
λ	0.01322***	0.00923***	0.00429***	0.00003	0.00446***	0.0093***	0.01257
	(0.00088)	(0.00043	(0.00029)	(0.00018)	(0.00026)	(0.00045)	(0.00061)
β0	0.12438***	0.0672**	0.04894**	0.04626	0.05805***	0.03717	0.00722
	(0.0454)	(0.02647)	(0.01732)	(0.01083)	(0.01445)	(0.02483)	(0.03768)
$\sum_{i=0}^{1}\beta i$	-0.02284	0.01711	-0.01173	0.05882***	0.08175***	0.1306	0.09297
	(0.11052	(0.08578)	(0.04908)	(0.04479)	(0.02718)	(0.07979)	(0.06263)
$\sum_{i=0}^{2}\beta i$	-0.05121	-0.04302	-0.00965	-0.07839	-0.09199	-0.02803	0.045
	(0.13679)	(0.09066)	(0.0465)	(0.0452)	(0.04513)	(0.11619)	(0.08773)
$\sum_{i=0}^{3}\beta i$	-0.45912	-0.00766	-0.01159	-0.01986*	-0.0629	0.01557	-0.00701
	(0.74581)	(0.04761)	(0.02053)	(0.01543)	(0.04773)	(0.09472)	(0.22501)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Panel B: Insurance							
λ	0.01346***	0.00931***	0.0045***	-0.00002	0.00425***	0.00891***	0.01253***
	(0.00087)	(0.00038)	(0.00029)	(0.00019)	(0.00029)	(0.00044)	(0.00079)
β0	0.11796	0.05912	-0.00306	-0.00041	0.00411	-0.02962	-0.01374
	(0.09167)	(0.0613)	(0.02342)	(0.00782)	(0.02488)	(0.03623)	(0.04215)
$\sum_{i=0}^{1}\beta i$	-0.21016	0.01403	0.04841	0.03166	0.14712**	0.18563***	0.09915
	(0.28114)	(0.08843)	(0.05767)	(0.04631)	(0.05847)	(0.06512)	(0.08967)
$\sum_{i=0}^{2}\beta i$	0.12847	-0.05972	0.03529	0.01222	-0.0603	-0.0288	0.1124
	(0.27079)	(0.08172)	(0.05768)	(0.05203)	(0.06104)	(0.0794)	(0.40834)
$\sum_{i=0}^{3}\beta i$	0.49474***	-0.00588	-0.10408	-0.03972	-0.06217	-0.06008	0.09836
	(0.07707)	(0.65079)	(0.07649)	(0.02869)	(0.0622)	(0.06472)	(0.40416)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Panel C: Automobiles							
λ	0.01414***	-0.00958***	0.00443***	-0.00004	0.00427***	0.00888**	0.01253***
	(0.00095)	(0.0004)	(0.00031)	(0.00019)	(0.00028)	(0.00046)	(0.00065)
β0	0.06008	0.01842	0.0168	0.02685**	0.00583	-0.01144	-0.04147
	(0.05357)	(0.02939)	(0.02009)	(0.01315)	(0.01916)	(0.03167)	(0.0387)
$\sum_{i=0}^{1}\beta i$	-0.09416	0.0209	0.06336	0.02674	0.07487	0.14464	0.17451**
	(0.19039)	(0.05668)	(0.05539)	(0.02555)	(0.06563)	(0.08941)	(0.05903)
$\sum_{i=0}^{2}\beta i$	0.19829	0.04215	-0.04611	-0.0195	0.00148	-0.01547	0.01701
	(0.17642)	(0.05304)	(0.05798)	(0.03606)	(0.065)	(0.09633)	(0.28671)
$\sum_{i=0}^{3}\beta i$	-0.47192	-0.08606	-0.03829	-0.01819	-0.08542	-0.11415**	0.12989
	(0.0249)	(0.43222)	(0.03103)	(0.03532)	(0.04127)	(0.05677)	(0.56075)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel D: Chemicals			
λ	0.01392***	-0.00948***	0.00449***	-0.00001	0.00449***	0.00928***	0.01285***
	(0.00103)	(0.00036)	(0.00031)	(0.00018)	(0.00027)	(0.00044)	(0.00066)
β0	0.03468	0.01709	0.00689	0.03272**	0.04173*	-0.01246	-0.05911
	(0.0771)	(0.02976)	(0.02068)	(0.01497)	(0.02373)	(0.03951)	(0.0595)
$\sum_{i=0}^{1} \beta i$	0.11896	0.02796	0.06906	0.00728	0.0206	0.11329*	0.08616
	(0.0982)	(0.10188)	(0.0444)	(0.04151)	(0.09453)	(0.06017)	(0.10681)
$\sum_{i=0}^{2} \beta i$	0.19017***	-0.12905	-0.0369	0.01222	-0.03226	-0.10092	0.02918
	(0.02457)	(0.17082)	(0.06819)	(0.04084)	(0.09965)	(0.07781)	(0.15953)
$\sum_{i=0}^{3} \beta i$	-0.4851	0.08919	-0.04647	-0.07603**	-0.03036	0.12264	0.027
	(0.88144)	(0.14227)	(0.06319)	(0.02985)	(0.05596)	(0.21991)	(0.51033)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel E: Media			
λ	0.01321***	-0.00937***	0.00434***	0	0.00427***	0.00893***	0.01266***
	(0.00101)	(0.00037)	(0.00029)	(0.00018)	(0.0003)	(0.00047)	(0.00062)
β0	0.11237**	0.03478	0.01999	0	0.00052	0.00023	-0.01705
	(0.05702)	(0.05035)	(0.0273)	(0.02169)	(0.03273)	(0.04509)	(0.05346)
$\sum_{i=0}^{1} \beta i$	-0.00816	-0.01572	-0.01675	0.05954	0.09348	0.08752	0.08226
	(0.12271)	(0.08814)	(0.04578)	(0.05634)	(0.04891)	(0.0983)	(0.11475)
$\sum_{i=0}^{2} \beta i$	-0.0336	0.06283	0.05758	-0.02344	-0.01379	0.13967	0.33614
	(0.14589)	(0.07749)	(0.03783)	(0.05558)	(0.04941)	(0.17032)	(0.25413)
$\sum_{i=0}^{3} \beta i$	-0.4418***	-0.15303	-0.08415***	-0.06097	-0.08643**	-0.19404	-0.40216
	(0.11785)	(0.4395)	(0.02346)	(0.04101)	(0.04019)	(0.1494)	(0.57866)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel F: Retail			
λ	0.01379***	-0.00923***	0.00428***	0	0.00446***	0.00944***	0.01286***
	(0.00104)	(0.0035)	(0.00029)	(0.00018)	(0.00028)	(0.00043)	(0.00062)
β0	0.0178	0.00861	0.01189	0.00468	0.00301***	0.00607***	0.00818***
	(0.02434)	(0.02072)	(0.02108)	(0.01434)	(0.00085)	(0.00133)	(0.00193)
$\sum_{i=0}^{1} \beta i$	0.00685	-0.06216	-0.05109	0.01419	-0.00279	0.03981	0.05618
	(0.07912)	(0.04747)	(0.06346)	(0.02711)	(0.0354)	(0.09563)	(0.14512)
$\sum_{i=0}^{2} \beta i$	-0.10646	0.03359	0.03849	-0.00836	0.04152	-0.02789	0.04086
	(0.0849)	(0.06488)	(0.06445)	(0.02435)	(0.03741)	(0.11454)	(0.14596)
$\sum_{i=0}^{3} \beta i$	0.08912*	0.01898	-0.00028	-0.01795	-0.04783**	-0.03244	0.12538***
	(0.05332)	(0.05067)	(0.02793)	(0.01499)	(0.01995)	(0.06471)	(0.02224)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Panel G: Technology							
λ	0.01388***	0.00909***	0.00452***	-0.00007	0.00433***	0.00884	0.01278***
	(0.0009)	(0.00041)	(0.00028)	(0.00018)	(0.00028)	(0.00047)	(0.00073)
β0	0.0809	0.08909**	0.03924	0.02846*	0.02175	-0.04022	-0.00859
	(0.06649)	(0.03599)	(0.02649)	(0.01587)	(0.0228)	(0.03668)	(0.04151)
$\sum_{i=0}^{1}\beta i$	0.06985	0.02632	0.10667	0.05716	0.10524*	0.14466***	0.00971
	(0.14382	(0.094)	(0.05452)	(0.03789)	(0.06304)	(0.0502)	(0.09046)
$\sum_{i=0}^{2}\beta i$	-0.12056	-0.08661	-0.06406	-0.01469	-0.03325	0.00079	0.11039
	(0.12489)	(0.10567)	(0.0655)	(0.04843)	(0.05742)	(0.07353)	(0.0761)
$\sum_{i=0}^{3}\beta i$	0.39724***	-0.03853	-0.08711*	-0.07642	-0.0992***	-0.134	0.28163***
	(0.0634)	(0.51426)	(0.05045)	(0.05179)	(0.02602)	(0.60845)	(0.0391)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Panel H: Telecommunication							
λ	-0.01379***	0.00939***	0.00444***	0.00001	0.00427***	0.00937***	0.0128***
	(0.00113)	(0.0004)	(0.0003)	(0.00018)	(0.0003)	(0.00054)	(0.00075)
β0	0.02955	0.00504	0.00062	0.01114	0.00399	0.00763	0.01008
	(0.15163)	(0.05168)	(0.01984)	(0.01939)	(0.04195)	(0.0734)	(0.103)
$\sum_{i=0}^{1}\beta i$	-0.06039	0.01252	0.01455	0.01786	0.09903	0.08513	0.0554
	(0.19399)	(0.10428)	(0.03486)	(0.04307)	(0.07866)	(0.12765)	(0.12806)
$\sum_{i=0}^{2}\beta i$	0.0336	-0.01686	-0.01192	-0.0187	-0.04451	-0.07166	0.0134
	(0.1116)	(0.10152)	(0.04194)	(0.0418)	(0.06468)	(0.1295)	(0.06833)
$\sum_{i=0}^{3}\beta i$	-0.34513	-0.00353	-0.01781	0.00271	-0.05225**	0.02951	0.25245
	(0.79069)	(0.10591)	(0.07681)	(0.02838)	(0.02211)	(0.11932)	(0.64797)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Panel I: Utilities							
λ	-0.0133***	0.00897***	-0.0042***	0.00001	0.00438***	0.00891***	0.01263***
	(0.00098)	(0.0004)	(0.00028)	(0.00017)	(0.00029)	(0.00048)	(0.00068)
β0	0.04501	0.02618***	0.01539	0.0062	0.00361	0.00549	0.00703
	(0.07662)	(0.00018)	(0.0301)	(0.00401)	(0.01091)	(0.0181)	(0.02588)
$\sum_{i=0}^{1}\beta i$	0.01995	-0.0052	-0.0321	0.05325	0.09189	0.14925	0.28378**
	(0.09334)	(0.05752)	(0.04641)	(0.04355)	(0.04314)	(0.09218)	(0.15003)
$\sum_{i=0}^{2}\beta i$	-0.15182	-0.10941	-0.04994	-0.07574	-0.10328**	-0.13959	-0.22889
	(0.0558)	(0.06655)	(0.04118)	(0.0469)	(0.05188)	(0.11395)	(0.15076)
$\sum_{i=0}^{3}\beta i$	0.0951	0.10404	0.07052**	0.02223	0.05131	0.0273	0.1399
	(0.08383)	(0.06467)	(0.03069)	(0.02635)	(0.03265)	(0.07565)	(0.27966)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel J: Basic resources				
λ	0.01354***	0.00934***	0.00433***	0.00003	0.00444***	0.00929***	0.01264***
	(0.00098)	(0.00037)	(0.00028)	(0.00017)	(0.00028)	(0.00047)	(0.00068)
β0	-0.00011	0.0023***	0.00517***	0.00393***	-0.00293	-0.01815	-0.02324
	(0.00407)	(0.00091)	(0.00069)	(0.00105)	(0.01485)	(0.02234)	(0.01642)
$\sum_{i=0}^{1} \beta i$	-0.06738	-0.02308	-0.01011	0.02176	0.00941	0.01357	0.0961*
	(0.0828)	(0.12339)	(0.04585)	(0.03213)	(0.04534)	(0.10794)	(0.05657)
$\sum_{i=0}^{2} \beta i$	0.00393	-0.03944	-0.00552	-0.04304	0.00156	0.04562	-0.02552
	(0.14166)	(0.13921)	(0.04852)	(0.0369)	(0.04934)	(0.10378)	(0.12247)
$\sum_{i=0}^{3} \beta i$	0.07114	0.06195	0.00342	0.01337	-0.01498	-0.02732	-0.04682
	(0.11948)	(0.06631)	(0.01925)	(0.02084)	(0.0274)	(0.01976)	(0.2266)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel K: Construction materials				
λ	0.01418***	0.00922***	0.00412***	0.00001	0.00438***	0.00929***	0.01295***
	(0.00094)	(0.00046)	(0.00029)	(0.00018)	(0.00028)	(0.00046)	(0.0007)
β0	0.04994	0.01253*	0.0188	0.00789	0.00739	-0.00413	-0.0186
	(0.04196)	(0.0222)	(0.01627)	(0.00941)	(0.01528)	(0.02574)	(0.02424)
$\sum_{i=0}^{1} \beta i$	0.03863	-0.01561	-0.07121*	-0.01519	0.04001	0.06641	-0.0032
	(0.06968)	(0.05852)	(0.03716)	(0.02969)	(0.04443)	(0.05044)	(0.0646)
$\sum_{i=0}^{2} \beta i$	-0.02845	-0.00725	0.01057	0.0325	-0.00667	-0.03057	0.04297
	(0.18873)	(0.05114)	(0.05099)	(0.03165)	(0.04367)	(0.06513)	(0.15344)
$\sum_{i=0}^{3} \beta i$	-0.55536	0.00466	0.02789	-0.03093	-0.03985*	-0.02474	0.18746
	(0.82902)	(0.01529)	(0.04272)	(0.05282)	(0.02368)	(0.30271)	(0.146)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
			Panel L: Financial services				
λ	0.01326***	0.00911***	0.00437***	-0.00001	0.00454***	0.00899***	0.01276***
	(0.00095)	(0.00041)	(0.00027)	(0.00019)	(0.00028)	(0.00047)	(0.00068)
β0	0.12917**	0.09112***	0.04613*	0.03342**	0.03796*	0.00911	0.01736
	(0.06107)	(0.03798)	(0.02634)	(0.01638)	(0.02128)	(0.04025)	(0.06076)
$\sum_{i=0}^{1} \beta i$	-0.01522	-0.04009	0.09601	0.0301	0.07234	0.12992	0.13291
	(0.27962)	(0.09714)	(0.06106)	(0.02731)	(0.07488)	(0.11015)	(0.20531)
$\sum_{i=0}^{2} \beta i$	-0.12822	-0.06923	-0.09661	-0.02161	-0.03372	-0.0726	-0.0738
	(0.27914)	(0.09702)	(0.0724)	(0.02832)	(0.0839)	(0.10165)	(0.20274)
$\sum_{i=0}^{3} \beta i$	0.39068***	0.06238	-0.05324	-0.02157	-0.03592	0.35599***	0.36559***
	(0.09736)	(0.62731)	(0.05345)	(0.0291)	(0.37617)	(0.07277)	(0.06357)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Panel M: Food and beverages							
λ	0.01387***	0.00943***	0.00424***	0.00005	0.00447***	0.00947***	0.01289***
	(0.00101)	(0.00039)	(0.0003)	(0.00018)	(0.00026)	(0.00048)	(0.00065)
β0	0.02762	0.0492	0.0618	0.06034***	0.07076***	0.04946***	0.02946
	(0.08277)	(0.03205)	(0.02971)	(0.01482)	(0.02532)	(0.01332)	(0.06873)
$\sum_{i=0}^{1}\beta i$	-0.00468	0.03263	-0.02511	-0.03588	0.07739	0.13505	0.1071
	(0.31384)	(0.07039)	(0.07058)	(0.0533)	(0.06411)	(0.13375)	(0.16598)
$\sum_{i=0}^{2}\beta i$	-0.01524	-0.03865	-0.0018	0.02587	-0.07419	-0.18215	-0.15558
	(0.3908)	(0.08973)	(0.06778)	(0.05806)	(0.0691)	(0.13863)	(0.1543)
$\sum_{i=0}^{3}\beta i$	-0.34972	-0.04889	-0.05581	-0.10701**	-0.1164***	0.38371	0.36022***
	(0.26151)	(0.48958)	(0.04891)	(0.05318)	(0.04062)	(0.58947)	(0.08421)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Panel N: Oil and gas							
λ	-0.01378***	-0.00946***	-0.00431***	0	0.00444***	0.00915***	0.01298***
	(0.00098)	(0.00039)	(0.00028)	(0.00018)	(0.00027)	(0.00043)	(0.00068)
β0	0.0144	0.01076	0.00987**	-0.00327	0.00185	-0.00001	-0.01774
	(0.02813)	(0.00711)	(0.00387)	(0.01268)	(0.01137)	(0.02822)	(0.01392)
$\sum_{i=0}^{1}\beta i$	-0.12026	-0.04696	-0.00868	0.02593	0.06116	0.07558	0.20933
	(0.09632)	(0.07999)	(0.04445)	(0.02255)	(0.06949)	(0.037)	(0.17057)
$\sum_{i=0}^{2}\beta i$	0.14228	0.0483	-0.00585	-0.02469	-0.06136	-0.04689	-0.19797
	(0.17637)	(0.08237)	(0.04611)	(0.02289)	(0.07392)	(0.04378)	(0.17357)
$\sum_{i=0}^{3}\beta i$	-0.0248	-0.01188	0.01207	0.01249	0.00538	-0.03043	-0.00048
	(0.1605)	(0.0349)	(0.03096)	(0.01876)	(0.02941)	(0.04336)	(0.21494)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
Panel O: Personal household							
λ	-0.01348***	-0.00944	-0.00446	0	0.00449***	0.00946***	0.01343***
	(0.00107)	(0.0004)	(0.00031)	(0.0002)	(0.00032)	(0.00046)	(0.00061)
β0	-0.01019	-0.00786	-0.00498	-0.0024	0.0002	-0.00731	-0.02221
	(0.08506)	(0.03183)	(0.02442)	(0.01586)	(0.02568)	(0.01133)	(0.06904)
$\sum_{i=0}^{1}\beta i$	-0.12104	-0.01317	-0.01386	-0.01599	-0.04574	0.05087	-0.00566
	(0.10296)	(0.12349)	(0.04907)	(0.02772)	(0.06375)	(0.05291)	(0.09924)
$\sum_{i=0}^{2}\beta i$	0.17356**	0.02987	0.03934	0.03836*	0.06259	-0.04237	0.0084
	(0.08232)	(0.11787)	(0.04464)	(0.02281)	(0.06123)	(0.0546)	(0.09696)
$\sum_{i=0}^{3}\beta i$	-0.02417	-0.00621	-0.02966	-0.00683	-0.02068	-0.01699	-0.01703
	(0.53391)	(0.01536)	(0.03538)	(0.01112)	(0.02588)	(0.0242)	(0.06948)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel P: Travel and leisure			
λ	-0.01437***	-0.00947***	-0.00444	0	0.0044***	0.00892***	0.01268***
	(0.00095)	(0.00042)	(0.00027)	(0.00018)	(0.00028)	(0.0005)	(0.00058)
β0	0.07013	0.02388	0.03818	0.02808*	0.02898	0.00407	-0.00845
	(0.07589)	(0.03178)	(0.02365)	(0.01594)	(0.02265)	(0.03672)	(0.05624)
$\sum_{i=0}^{1} \beta i$	0.14211	0.12107	0.06418	0.03087	0.05745	0.07559	0.10937
	(0.11256)	(0.08666)	(0.06701)	(0.03713)	(0.06242)	(0.12382)	(0.19927)
$\sum_{i=0}^{2} \beta i$	-0.07591	-0.08965	-0.05827	-0.01212	0.02252	0.12503	0.04848
	(0.10018)	(0.0777)	(0.0703)	(0.03862)	(0.08268)	(0.13044)	(0.41438)
$\sum_{i=0}^{3} \beta i$	-0.54025***	-0.33984	-0.0501	-0.05241	-0.12592*	-0.20072	0.12717
	(0.0798)	(0.55489)	(0.04094)	(0.03725)	(0.06859)	(0.44844)	(0.36804)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel Q: Industrial goods and services			
λ	-0.01402***	-0.00933***	-0.0046***	-0.00004	0.00439***	0.00904***	0.01279***
	(0.00094)	(0.00036)	(0.0003)	(0.000019)	(0.000270)	(0.00048)	(0.00065)
			0.0417				
β0	0.07427	0.07663*	(0.03004)	0.02119	0.02916	0.01207	-0.01368
	(0.0873)	(0.03909)		(0.00211)	(0.02789)	(0.04792)	(0.07512)
$\sum_{i=0}^{1} \beta i$	0.36987	0.19171***	0.15325***	0.07395*	0.15709	0.07685	-0.04041
	(0.28869)	(0.06123)	(0.04838)	(0.04205)	(0.0969)	(0.09247)	(0.14211)
$\sum_{i=0}^{2} \beta i$	-0.32602	-0.23926**	-0.13647**	-0.04939	-0.06473	0.14247*	0.28278
	(0.3064)	(0.11276)	(0.06268)	(0.04593)	(0.09575)	(0.0857)	(0.40251)
$\sum_{i=0}^{3} \beta i$	-0.5055***	-0.18191	-0.08163	-0.05275	-0.13673***	-0.28629	-0.19789
	(0.16273)	(0.39492)	(0.05993)	(0.05737)	(0.03978)	(0.20042)	(0.7165)

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
				Panel R: Healthcare			
λ	-0.01401***	-0.00967***	-0.0043***	0.00002	0.00452***	0.00958***	0.01359***
	(0.00094)	(0.00036)	(0.00028)	(0.00019)	(0.00031)	(0.00045)	(0.00063)
β0	0.06617	-0.01128	0.02047	0.0189*	0.02556	0.03044	0.03758
	(0.068)	(0.03857)	(0.02033)	(0.0108)	(0.02113)	(0.03316)	(0.04409)
$\sum_{i=0}^{1} \beta i$	0.12765	0.12034**	0.04083	0.02477	0.04556	0.06364	0.01272
	(0.09745)	(0.05253)	(0.06308)	(0.03321)	(0.05036)	(0.09071)	(0.17008)
$\sum_{i=0}^{2} \beta i$	-0.11813**	-0.06452	(0.05947)	-0.04124	-0.0953*	-0.14876*	-0.1156
	(0.052)	(0.06917)		(0.0363)	(0.05201)	(0.08968)	(0.16746)
$\sum_{i=0}^{3} \beta i$	-0.54432	-0.06418	-0.04567	-0.009	0.04002	0.0426	0.43959***
	(0.77408)	(0.06715)	(0.08057)	(0.02861)	(0.07859)	(0.57415)	(0.05111)

Note: *, ** and *** denote statistical significance at the 1, 5 and 10 percent levels, respectively. The standard errors are indicated in parentheses.