Directional predictability from stock market sector indices to gold: A cross-quantilogram analysis

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Directional predictability from stock market sector indices to gold: A cross-quantilogram analysis

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Abstract

We address the safe haven properties of gold relative to US stock market sector indices using the bivariate cross-quantilogram of Han et al. (2016). Splitting our sample into pre- and post-crisis periods, our results show that the safe haven properties of gold have a changing nature. Before and after the financial crisis, we find only limited quantile dependence and that gold can be considered a safe haven for most of the sectors, except Industrials. On a full sample (1999-2016), there are only three sectors – Healthcare, IT, and Telecommunication services – for which gold can be considered a safe haven.

Keywords: stock market sectors; gold; safe haven; quantile dependence; cross-quantilogram

JEL codes: G01, G10, G11, G15

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1. Introduction

Dependencies across various asset classes are of particular interest for at least two reasons (Ciner et al., 2013): (i) portfolio selection is sensitive to the dependence structure between the considered assets, especially when the dependencies are time-varying, and (ii) if information is transmitted across asset classes, policy decisions are likely to have cross-market influence. This leads us to a large strand of literature focusing on finding the so-called "safe haven" assets, which should provide investors with the full benefits of diversification. Anecdotal evidence and the media usually refer to gold as a safe haven.[1] Baur and Lucey (2010) studied the constant and time-varying relations between US, UK and German stock and bond returns (MSCI indices) and gold returns. They found that gold is not a hedge against bonds; however, it may be used as a hedge for stocks or as a safe haven in extreme stock market conditions but only for a limited time (approximately 15 trading days). Baur and Lucey (2010) and subsequently Baur and McDermott (2010) defined a "hedge" as an uncorrelated or negatively correlated asset on average, whereas a "safe haven" is an uncorrelated or negatively correlated asset in times of market turmoil. A "diversifier" is a positively (but not perfectly) correlated asset.

In this paper, we contribute to the "gold as a safe haven" literature by applying the new methodology proposed by Han et al. (2016), which allows us to measure the directional quantile dependence between gold and stock market returns. As noted by Liu et al. (2016), the conventional approaches may not be appropriate measures of dependence between stock and gold returns when the bivariate normality assumption on the joint distribution does not hold. Such results are unlikely to capture extreme market co-movements accurately.

Our analysis departs from most of the research in this field in two ways: first, we are interested in the quantile dependence among stock market sector indices and gold across the whole range of quantiles, and second, instead of focusing on the contemporaneous relationships, our results are predictive (in the Granger causality sense). From a practical point of view, our main finding is that gold appears to be a safe haven for the Healthcare, IT, and Telecommunication services sectors from a predictive perspective. This result holds when using our full sample (1999-2016), i.e., regardless of whether we include or remove the period of the recent financial crisis. However, during the financial crisis, the directional predictability from other stock market sectors to gold changed – since the crisis, at least from a short-term perspective (up to 10 days), gold acted as a safe haven for all sectors except Industrials. From the same short-term perspective, before the financial crisis, we did not find any quantile dependence, and gold could be considered a safe haven for most of the sectors.

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[1] For an excellent survey on gold as an investment, see O'Connor et al. (2015).

2. Data and methodology

2.1 Data

We study information spillovers in quantiles of the daily continuous returns of the spot prices of the gold and US industry stock market indices (both denominated in US dollars), over the sample period from 1 January 1999 to 2 December 2016. Gold prices and 10 MSCI sector indices were obtained from the Bloomberg database. The sector indices are as follows: Energy (MSCUENR), Materials (MSCUMAT), Industrials (MSCUIND), Consumer discretionary (MSCUCDIS), Consumer staples (MSCUCSTA), Healthcare (MSCUHC), Financials (MSCUFNCL), Information technology (MSCUIT), Telecommunication services (MSCUTEL), and Utilities (MSCUUTI). The data code for the spot gold prices is XAUUSD.

Additionally, our analysis is performed on two subsamples. The first subsample is the period before the financial crisis, and it starts on 1 January 1999 and ends on 1 June 2007. The second subsample is after the crisis period, and it starts on 1 March 2009 and ends on 2 December 2016. The dating of the crisis largely corresponds to the dating employed by Baur (2012), Kontonikas et al. (2013) and Florackis et al. (2014).

2.2 Granger causality in quantiles

To analyze the position of gold as a safe haven, we use the bivariate cross-quantilogram of Han et al. (2016). In a recent contribution, Han et al. (2016) built upon the work of Linton and Whang (2007) by extending the quantilogram, a measure of predictability of different quantiles of the distribution of a stationary time series, into a bi-variate setting. The resulting cross-quantilogram measures the lead/lag dependence between (conditional) quantiles of two time series. More specifically, Han et al. (2016) provided a sample estimate of the measure of lead/lag dependence in quantiles and a corresponding test about directional predictability in quantiles from one series to another. We employ the unconditional quantile version of the approach presented by Han et al. (2016), which was also recently used to study the spillovers between agriculture commodity markets in the US and China by Jiang et al. (2016).

Let us denote the continuous returns as $x_{i,t}$, $i = 1, 2$, and $t = 1, 2, \ldots, T$, where index i represents either returns of gold or a corresponding MSCI sector index. The time series $x_{i,t}$ is assumed to be strictly stationary with the unconditional distribution function $F_i(.)$, the unconditional density function $f_i(.)$ and the corresponding unconditional quantile function as $q_i(\tau_i) = inf\{\upsilon : F_i(\upsilon) \geq \tau_i\}$, for $\tau_i \in (0, 1)$.

For an arbitrary pair of $\boldsymbol{\tau} = (\tau_1, \tau_2)$, we are interested in estimating dependence between the event $\{x_{1,t} \leq q_{1,t}(\tau_1)\}$ and $\{x_{2,t} \leq q_{2,t}(\tau_2)\}$ given an integer $k = \pm 1, \pm 2, \ldots$. Now, define a hit function $\psi_a(u) = I[u < 0] - a$. The cross-quantilogram is defined as

$$\rho_{\boldsymbol{\tau}}(k)= \frac{E\left[\psi_{\tau_1}\left(x_{1,t}-q_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(x_{2,t-k}-q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau_1}^2\left(x_{1,t}-q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau_2}^2\left(x_{2,t-k}-q_{2,t-k}(\tau_2)\right)\right]}} \tag{1}$$

The cross-quantilogram in Eq. (1) can be understood as a cross-correlation of quantile-hit processes. In a special case, where the two series are identical, Eq. (1) corresponds to the quantilogram of Lindon and Whang (2007). Now, given the unconditional estimate of quantiles $q^{*}_{i}(\tau_i)$, the sample cross-quantilogram is defined as

$$\rho^*_{\boldsymbol{\tau}}(k)=\frac{\sum_{t=k+1}^{T}\psi_{\tau_1}\left(x_{1,t}-q^*_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(x_{2,t-k}-q^*_{2,t-k}(\tau_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\psi_{\tau_1}^2\left(x_{1,t}-q^*_{1,t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T}\psi_{\tau_2}^2\left(x_{2,t-k}-q^*_{2,t-k}(\tau_2)\right)}} \tag{2}$$

We use Eq. (2) to describe the magnitude of the directional dependence in quantiles of two time series. The value of Eq. (2) is by construction limited to $\rho^{*}_{\boldsymbol{\tau}}(k) \in [-1, 1]$. For example, if we let $x_{1,t}$ be the continuous returns of gold and $x_{2,t}$ the continuous returns of the Energy sector, the value of $\rho^{*}_{\boldsymbol{\tau}}(1) = 0$ implies that if the return on the Energy sector is below (above) a given quantile $q_2(\tau_2)$ at time $t - 1$, it does not help in predicting whether the return on the gold is below (above) a given quantile $q_1(\tau_1)$ at time t. In our setting, the lead/lag parameter k controls the delay in the predictability from one time series to another in terms of days.

The corresponding statistical test is of the form H_0: $\rho_{\boldsymbol{\tau}}(1) = \ldots = \rho_{\boldsymbol{\tau}}(p) = 0$, $H_1 : \exists k, \rho_{\boldsymbol{\tau}}(k) \neq 0$, $k = 1, 2, \ldots, p$, where we are interested in directional predictability from event $\{x_{2,t-k} \leq q_{2,t-k}(\tau_2) : k = 1, 2, \ldots, p\}$ to event $\{x_{1,t} \leq q_{1,t}(\tau_1)\}$. Han et al. (2016) suggested using a Ljung-Box type of test statistics, as given by

$$Q^*_{\boldsymbol{\tau}}(p)=T(T+1)\sum_{k=1}^{p}\frac{\rho^{*2}_{\boldsymbol{\tau}}(k)}{T-k} \tag{3}$$

The critical values are obtained via the stationary bootstrap procedure of Politis and Romano (1994), in which pseudo samples are constructed from blocks of data with random block length. The expected block size is given by Politis and White (2004) and Patton et al. (2009).[2]

In our work, we consider the dependence between all pairs of quantiles given by {0.05, 0.10, …, 0.95}; i.e., we calculate 361 measures of dependence for a given pair of time series and value of p. To counteract the multiple hypothesis problem, we adjust our significance level by employing the Bonferroni correction, which leads to a significance level of 0.05/361 = 0.0001385. Later, we evaluate the dependence across three values of $p \in \{5, 10, 22\}$. The choice of p corresponds to studying whether exceeding a given value for a quantile of one time series leads to exceeding a value for a quantile of the second time series in the next 5, 10, or 22 trading days.

[2] The calculation was performed using the packages of Hayfield and Racine (2008) and Han et al. (2014).

2.3 Heat maps

We present our results in a form of the heat maps only, where the *x*-axis always corresponds to a quantile of the given stock market sector returns and the *y*-axis always corresponds to a quantile of the gold returns. One can easily obtain a good perspective of full quantile dependence among two series because we plot only significant dependencies for a given value of *p*. One plot is thus capable of simultaneously capturing 361 measures of dependence across the whole range of quantiles of the bi-variate distribution of returns as well as the magnitude of the dependency measures (using the color scale). Because we have 10 sectors, the results are provided for three values of the parameter *p* (5, 10, and 22 days) and are divided into three subsamples (full sample, before the crisis, and after the crisis), we deliberately deviate from a conventional form of presenting results in tables—otherwise, we would have tables with 32,490 coefficients and their significance (detailed results are, of course, available upon request).

In this setting, we acknowledge gold as a clear safe haven in two cases:

(1) If there are significant negative coefficients only in the upper left corner of the heat map; i.e., extreme negative stock returns (market turmoil) are followed by future positive gold returns in next days (controlled by the delay parameter *p*).

(2) If the heat map is entirely empty; i.e., no dependence across the whole range of quantiles is found.[3]

3. Results

Figure 1 presents results for a full sample and a lag parameter of 5 days. Gold is a perfect hedge for the Healthcare and Telecommunication services sectors because no significant dependence across all combinations of quantiles was found. There is a similar finding in the IT sector, although there is one significant coefficient around median quantiles. Extreme negative stock returns are associated with extreme negative gold returns for the following sectors: Energy, Materials, Consumer discretionary, Consumer staples, Financials, Utilities, and Industrials. At the same time, extreme negative (i.e., lower quantiles) stock returns are predicting extreme positive (i.e., upper quantiles) gold returns in Energy, Materials, Consumer discretionary, Financials, and Industrials. These results might appear contradictory, but what they show is that the quantile causality from stock market to gold has a changing nature: there are times when extreme negative

[3] Following the definitions proposed by Baur and Lucey (2010) and Baur and McDermott (2010), we do not consider gold to be a safe haven in the case of significant coefficients in the lower right corner, i.e., when extreme positive stock returns are predicting extreme negative gold returns, because this situation cannot be considered market turmoil. Moreover, if some dependence is found in the lower left corner, around the median, or in the upper right corner, this also cannot be considered a hedge or a safe haven because in such a case, some positive dependence among the assets is present.

stock returns are coupled to extreme positive gold returns (safe haven) and times when extreme negative stock returns are followed by extreme negative gold returns.

Of course, these results may be driven by the financial crisis of 2007-2008. The crisis period is not sufficiently long to obtain a required number of observations, particularly for identifying dependence in extreme quantiles. Thus, we decided to apply our procedure to the before- and after-crisis periods. These results are markedly different (see Figures 2-3). On a sample before the crisis, we did not identify any quantile dependence, but after the crisis, for four sectors (Energy, Materials, Consumer discretionary, and Financials), we can observe that extreme negative stock returns are associated with the occurrence of positive gold returns, with negative values of the quantile dependency measure. We interpret this as a safe haven property of the gold. In addition, extreme positive stock returns are associated with extreme positive gold returns in the Industrials sector.

The last step of our analysis is to check for the quantile causality with respect to different values of the parameter *p*. For the 10-day and 22-day calculations, the full sample results become more complex, and several sectors exhibit dependence across different ranges of quantiles (Figures 4-5). However, the most important results still hold. First, there are three sectors – Healthcare, IT, and Telecommunication services – where gold appears to act as a perfect safe haven, even in times of market turmoil. Second, before the financial crisis, we did not find any quantile dependence, and gold was considered a safe haven for most sectors.

4. Conclusion

We study directional predictability from stock market sector indices to gold across the whole range of quantiles of the return distribution. Although we did not examine the crisis period directly due to methodological difficulties (limited number of observations for extreme quantiles), by splitting our full sample into pre- and post-crisis periods, we were able to deductively infer that the safe haven properties of gold were largely challenged during the recent financial crisis. Over the entire sample period, extreme negative stock market returns were followed (up to 5, 10, 22 trading days) by extreme negative gold returns for all sectors except Healthcare, IT, and Telecommunication services, for which gold can be considered a safe haven. Before the financial crisis, gold behaved as a safe haven for most sectors, but in some of them, we identified dependency around the median. After the financial crisis, from a short-term perspective (up to 10 days), gold acted as a safe haven for all sectors except Industrials. This finding implies that during the financial crisis, the directional predictability from stock market sectors to gold changed.

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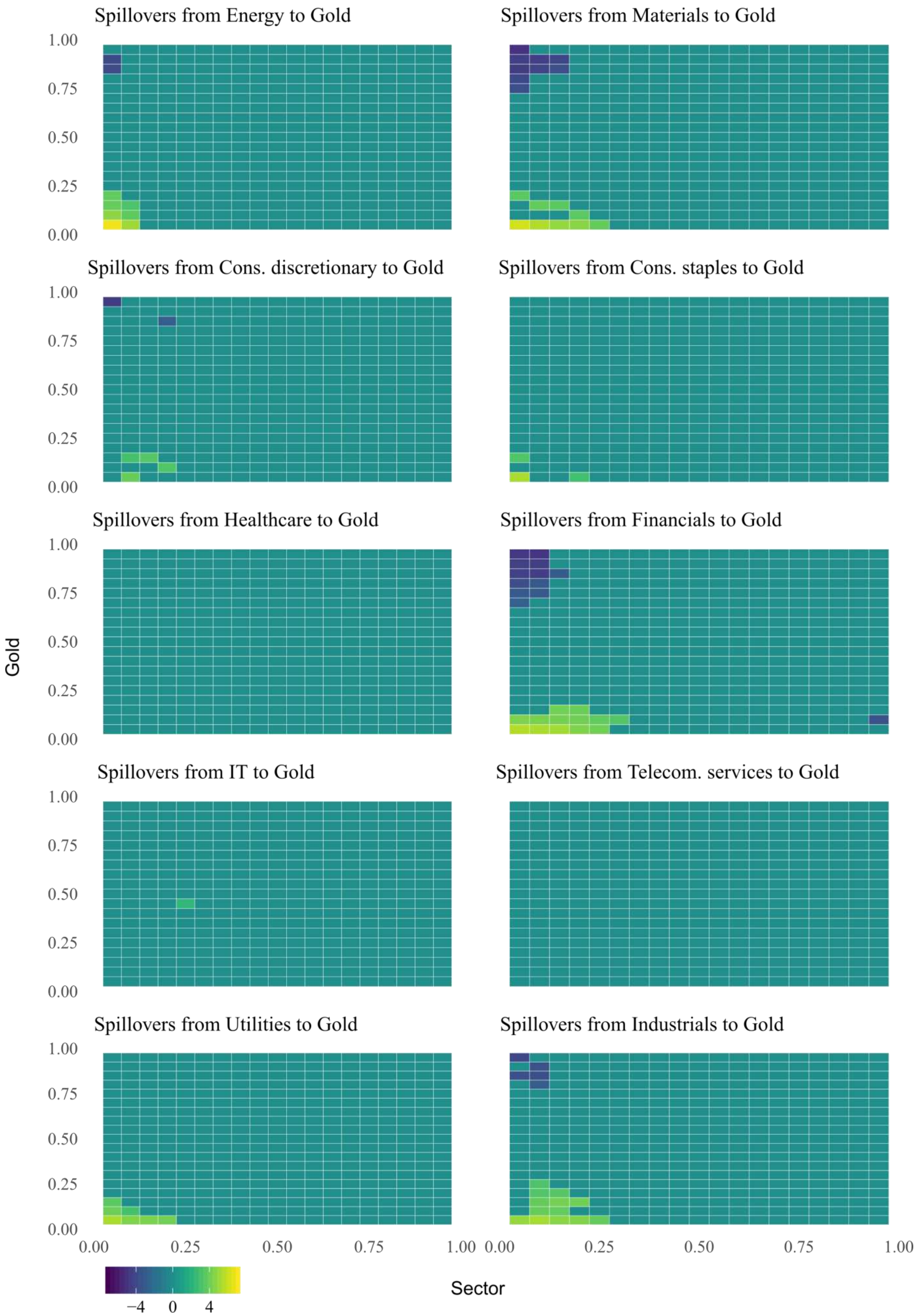

Figure 1: Directional causality in quantiles from stock market sector to gold – full sample using 5-day lags.

Note: x-axis corresponds to a quantile of the sector returns and y-axis to a quantile of the gold returns.

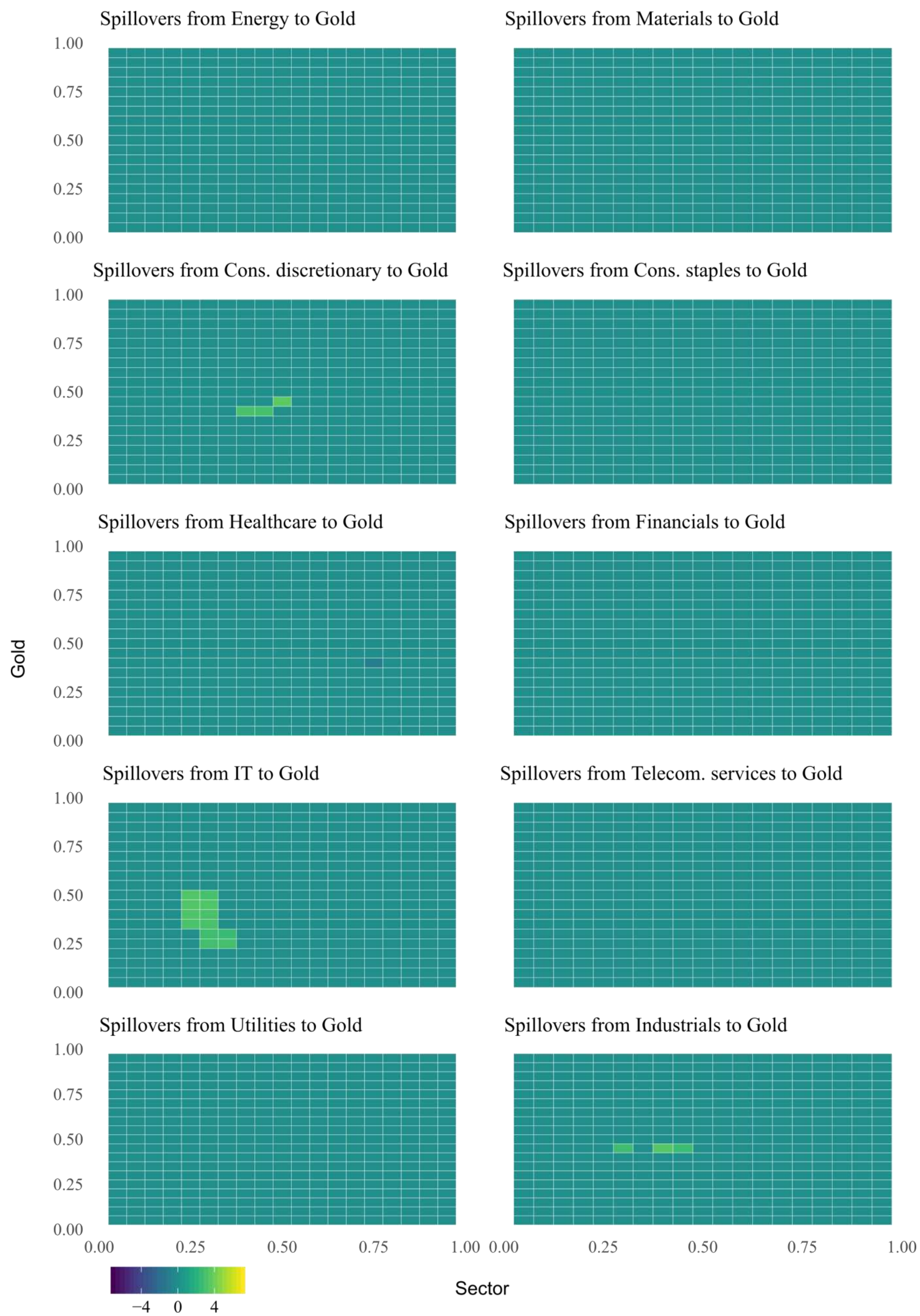

Figure 2: Directional causality in quantiles from stock market sector to gold – before the crisis sample using 5-day lags.

Note: x-axis corresponds to a quantile of the sector returns and y-axis to a quantile of the gold returns.

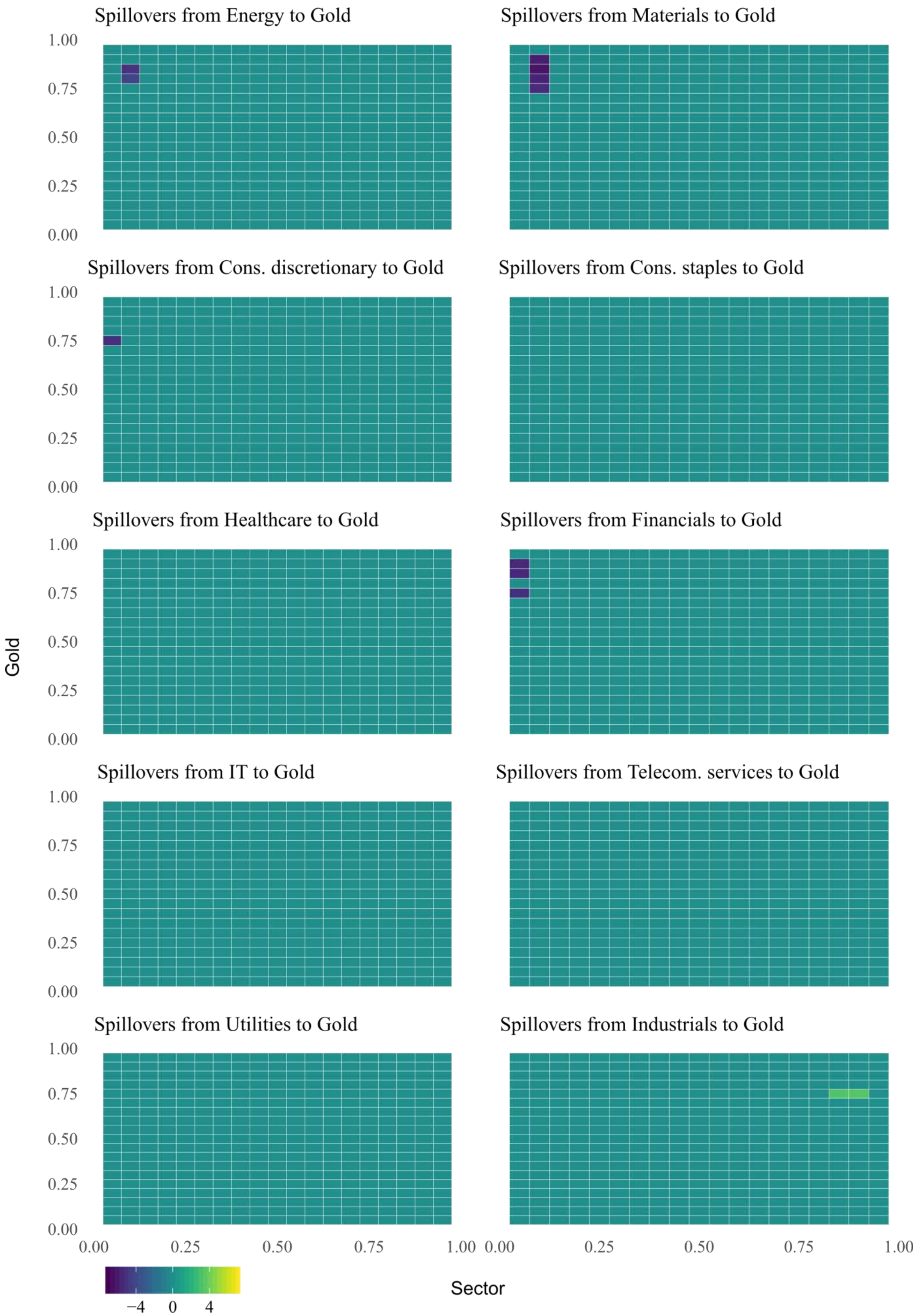

Figure 3: Directional causality in quantiles from stock market sector to gold – after the crisis sample using 5-day lags.

Note: x-axis corresponds to a quantile of the sector returns and y-axis to a quantile of the gold returns.

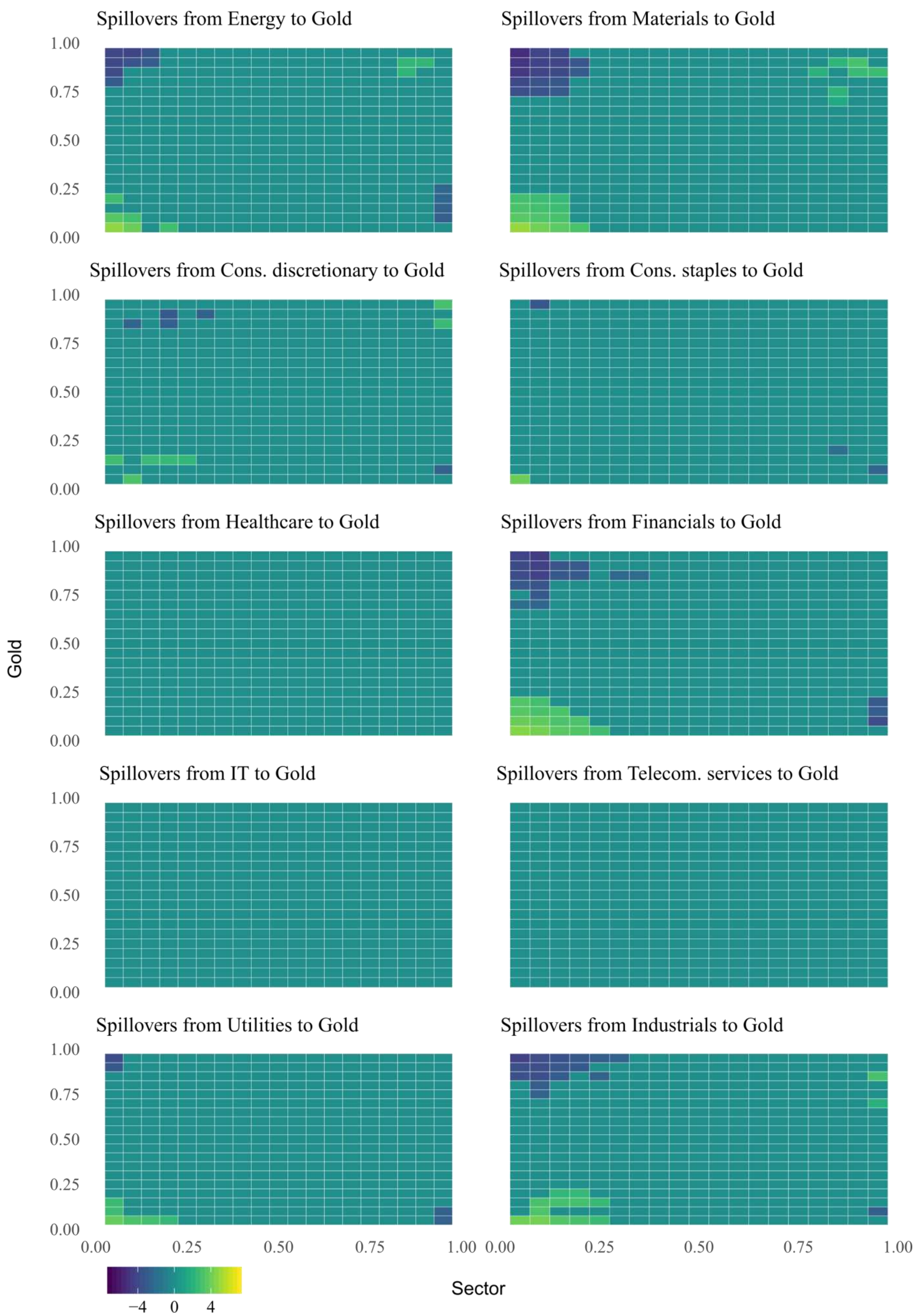

Figure 4: Directional causality in quantiles from stock market sector to gold – full sample using 10-day lags.

Note: x-axis corresponds to a quantile of the sector returns and y-axis to a quantile of the gold returns.

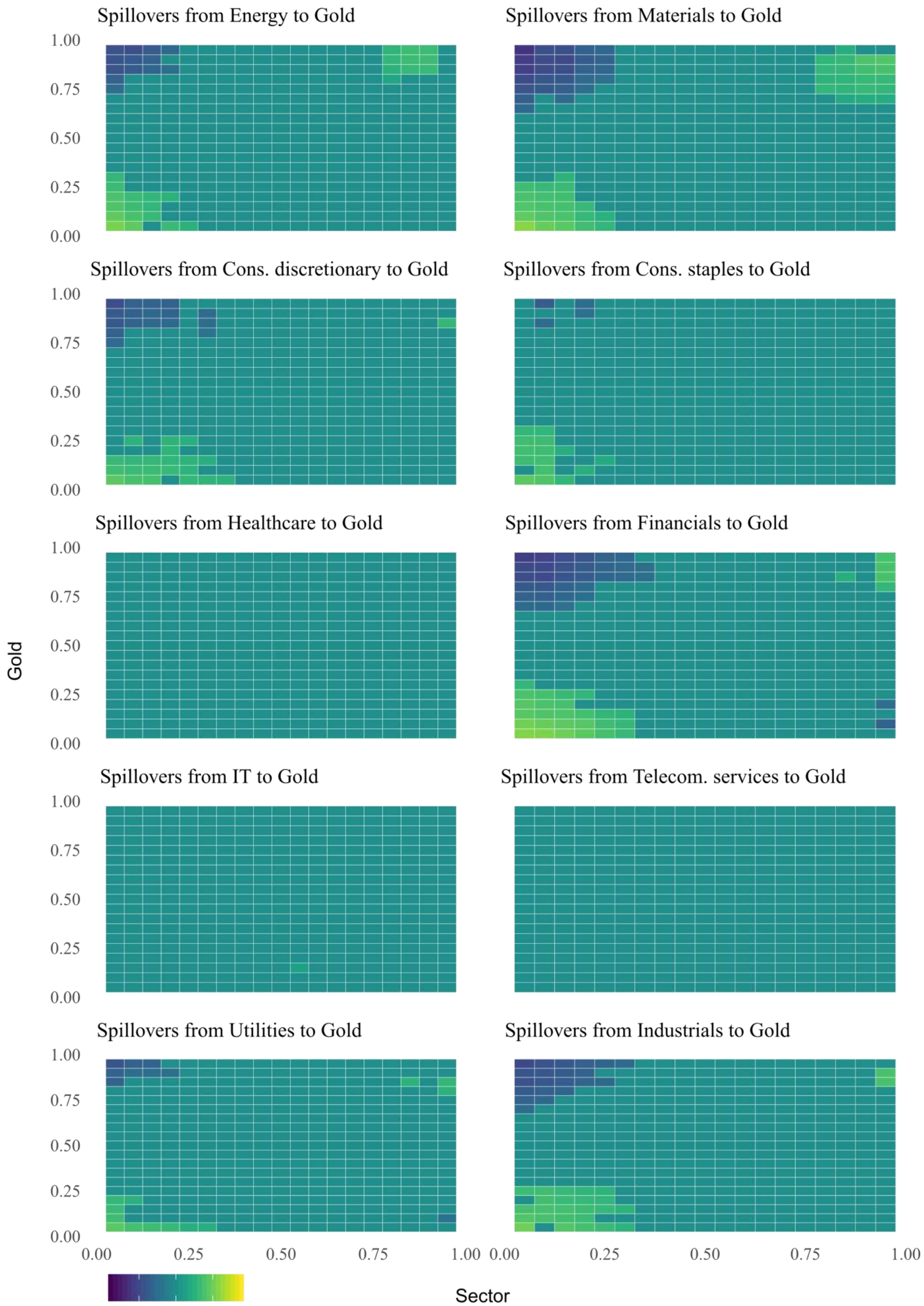

Figure 5: Directional causality in quantiles from stock market sector to gold – full sample using 22-day lags.

Note: x-axis corresponds to a quantile of the sector returns and y-axis to a quantile of the gold returns.

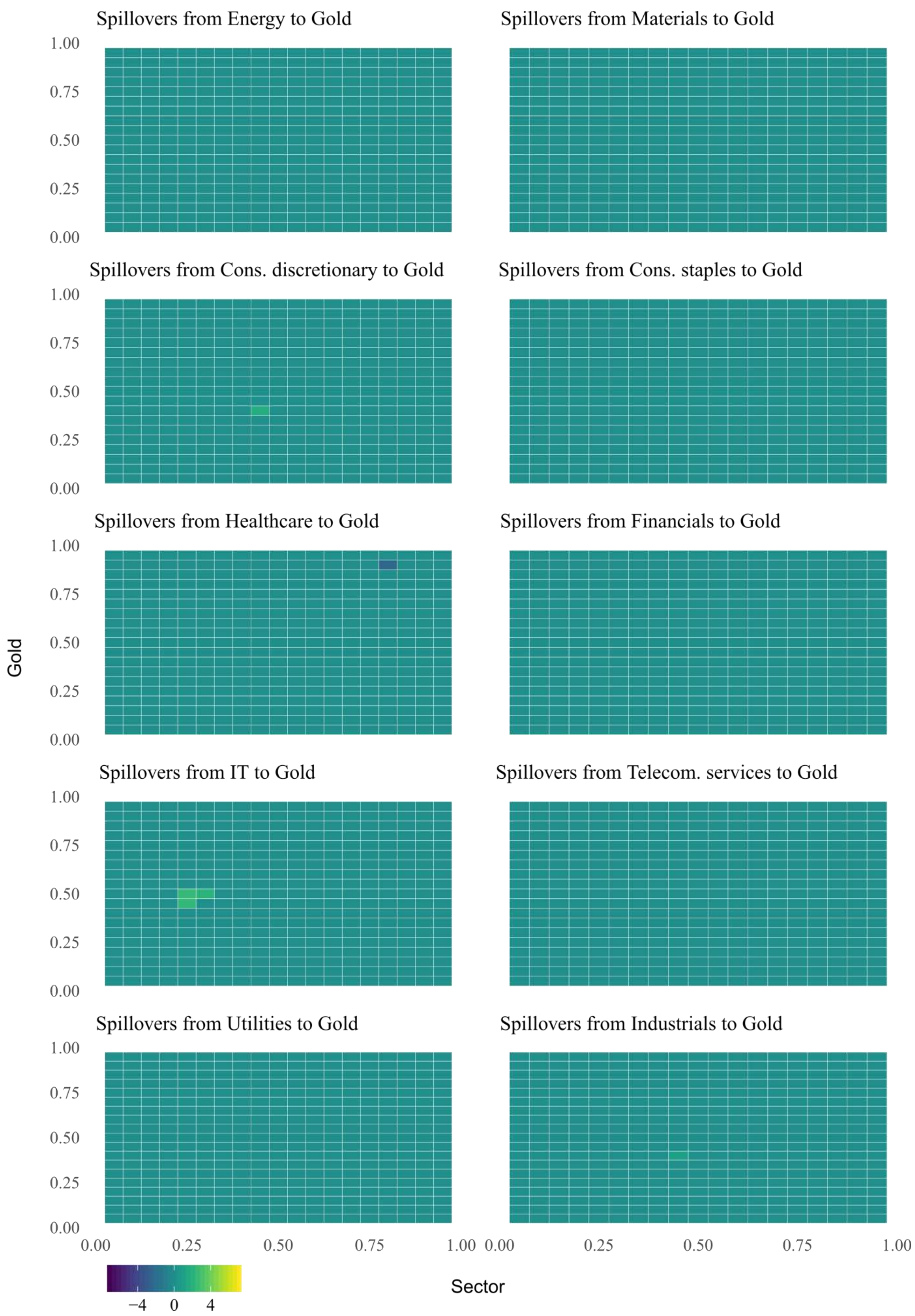

Figure 6: Directional causality in quantiles from stock market sector to gold – before the crisis sample using 10-day lags.

Note: x-axis corresponds to a quantile of the sector returns and y-axis to a quantile of the gold returns.

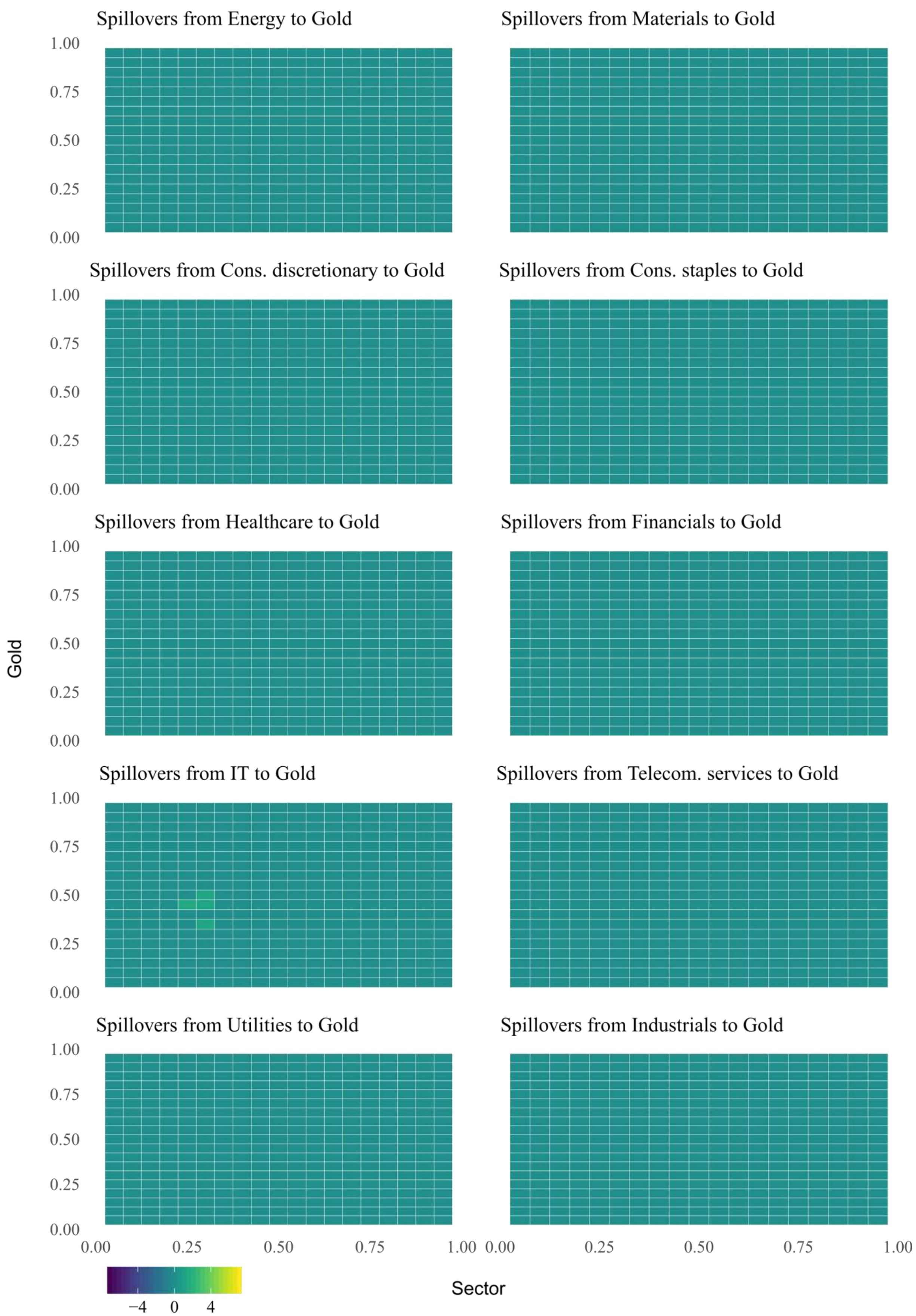

Figure 7: Directional causality in quantiles from stock market sector to gold – before the crisis sample using 22-day lags.

Note: x-axis corresponds to a quantile of the sector returns and y-axis to a quantile of the gold returns.

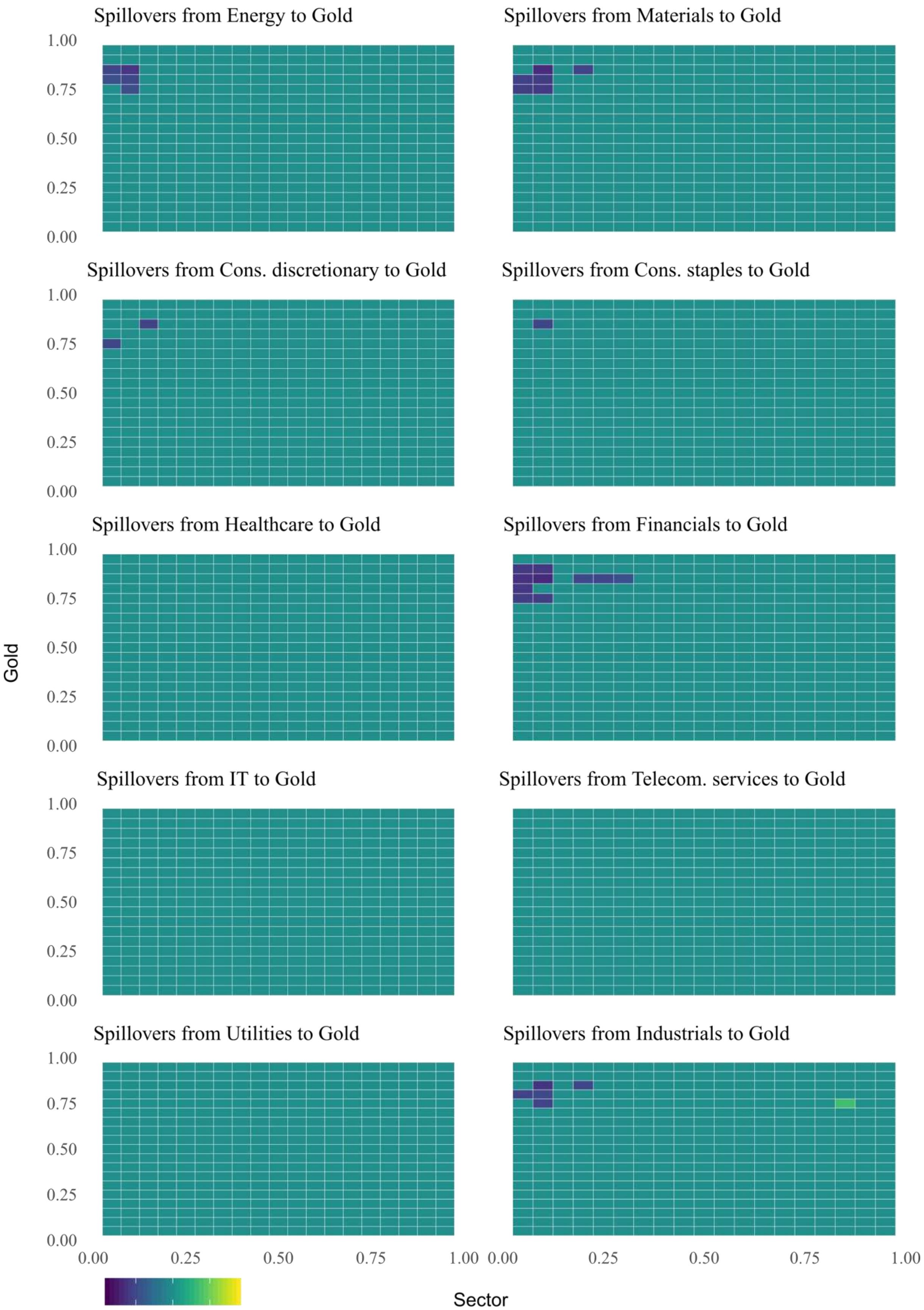

Figure 8: Directional causality in quantiles from stock market sector to gold – after the crisis sample using 10-day lags.

Note: x-axis corresponds to a quantile of the sector returns and y-axis to a quantile of the gold returns.

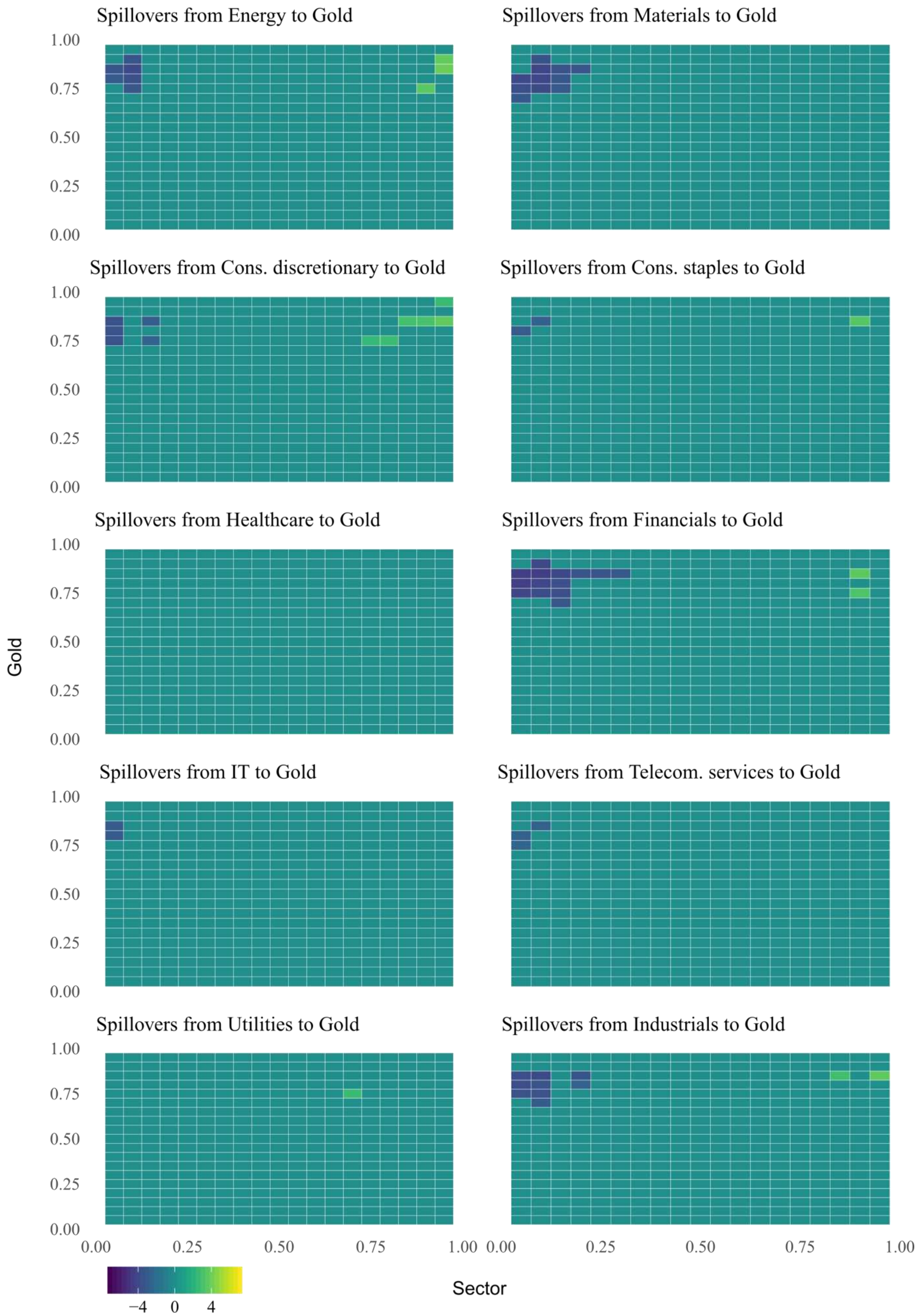

Figure 9: Directional causality in quantiles from stock market sector to gold – after the crisis sample using 22-day lags.

Note: x-axis corresponds to a quantile of the sector returns and y-axis to a quantile of the gold returns.