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Guglielmo Maria Caporale, Woo-Young Kang

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Bitcoin Price Co-Movements and Culture

Abstract

This paper analyses the cultural drivers (tightness−looseness and individualism−collectivism) of Bitcoin prices co-movements and exchange shutdowns in 34 major countries around the world over the period 20 July 2010 – 5 February 2020. Under the assumption that investors prefer to use local or international Bitcoin exchanges accepting the local currency to trade, we find that Bitcoin prices co-move more in countries with tighter and more collectivistic cultures. However, greater connectivity between international Bitcoin exchanges in the form of financial openness reduces the impact of the cultural variables on the behaviour of investors and on Bitcoin price co-movements. Further, the probability of Bitcoin exchanges shutdowns is higher in tighter and more collectivistic cultures where investors are more risk-averse and thus more likely to exhibit herding behaviour.

JEL-Codes: G150, C360.

Keywords: Bitcoin exchanges, cultural analysis, co-movement.

*Guglielmo Maria Caporale**
Department of Economics and Finance
Brunel University London
United Kingdom – Uxbridge, UB8 3PH
Guglielmo-Maria.Caporale@brunel.ac.uk

Woo-Young Kang
Department of Economics and Finance
Brunel University London
United Kingdom – Uxbridge, UB8 3PH
woo-young.kang@brunel.ac.uk

*corresponding author

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1. Introduction

Cryptocurrency markets have been growing very rapidly in recent years, and they now include 4600 different types of cryptocurrencies (according to coinmarketcap.com, 11 December 2019); Bitcoin is the most popular one and represents about 66.6% of total market capitalisation. The literature on cryptocurrencies is now extensive and has analysed a number of issues such their economic implications (e.g., Böhme et al., 2015; Dwyer, 2015; Harvey, 2016; Raskin and Yermack 2016; Bariviera et al., 2017; Biais et al., 2018; Schilling and Uhlig, 2018), returns and risk (e.g., Balciar et al., 2017; Liu and Tsyvinski, 2018), market efficiency (e.g., Urquhart, 2016; Bariviera, 2017; Nadarajah and Chu, 2017), hedging properties (e.g., Dyhrberg 2016a, 2016b; Baur et al., 2018; Bouri et al., 2017a, 2017b, 2017c), illegal activities (Foley et al., 2018, Li et al., 2018; Gandal et al., 2018; Griffin and Shams, 2018), initial coin offerings (Kostovetsky and Benedetti. 2018; Howell et al., 2018; Lee et al., 2018b; Li and Mann, 2018; Malinova and Park, 2017) and so on. More recently, a few papers have analysed cryptocurrency co-movement (or connectedness). In particular, Corbet et al. (2018) and Lee et al. (2018a) find weak linkages between cryptocurrencies and other traditional assets, which implies that the former may offer diversification benefits to investors, especially in the short run. Ciaian et al. (2017) report that the prices of Bitcoin and other cryptocurrencies are independent of each other. Using a bivariate diagonal BEKK model, Katsiampa (2019) finds that volatility co-movements between Bitcoin and Ether are significant and responsive to major news. Shams (2019) is the first to use a pairwise 'connectivity' measure based on the Manhattan distance between the share of trading volumes of cryptocurrencies across different exchanges to explain their co-movements. However, none of the extant papers investigates the effects of cultural factors on the co-movements between Bitcoin prices across exchanges and on exchange shutdown decisions.

Following an earlier study by Eun et al. (2015), which had shown the importance of such variables to explain stock market co-movements across countries, the present paper examines the cultural drivers of co-movements between Bitcoin prices in 34 major countries around the world over the period 20 July 2010 – 5 February 2020; to our knowledge, it is the first to consider culture as a possible determinant of cryptocurrency dynamics. It is worth explaining at the outset why culture should also be expected to have an impact on investment in cryptocurrency exchanges. Whilst it may seem plausible that it could affect, for instance, regulatory advances, it may not be equally apparent why it could have an impact on the sources of the exchange funds, of criminality and of ethically questionable behaviour. Indeed, in the case of international exchanges, which are characterised by the existence of many companies and funds seeking to profit from arbitrage techniques and the provision of cross-currency markets, national cultural characteristics are not an obvious determinant of international cryptocurrency dynamics on a specific exchange. The fact than an exchange is based, for instance, in the US does not mean that only US citizens trade on that exchange; in fact, a US citizen wanting to trade Bitcoin may decide to stay away from US exchanges for a host of reasons such as tax implications and traceability. In other words, there is no apparent reason to assume that (only) home-based investors will invest in home-based international platforms. However, it should be noted that in fact there exist two types of Bitcoin exchanges, local as well as international. The latter accept a variety of currencies for Bitcoin trading, whilst the former only trade Bitcoins converted into the currency of the country where they are based. Under the assumption that investors have a preference for Bitcoin exchanges (whether local or international) accepting the local currency to trade, it can be argued that culture should affect co-movement between the corresponding Bitcoin prices.

We focus in particular on the cultural dimensions of tightness versus looseness and individualism versus collectivism, which we regard as highly relevant to Bitcoin price co-movements. According to Gelfand et al. (2006), individuals have a more (less) homogeneous behaviour and demonstrate a lower (higher) degree of variation in countries with a tighter (looser) culture, this being an external constraint on individual behaviour. Therefore, tightness should lead to more herding behaviour, and in fact Eun et al. (2015) found that stock prices co-move more in culturally tight countries. We would expect the same to be true of Bitcoin price co-movements.

We also consider the effects on Bitcoin price co-movement of individualism versus collectivism, these being an individual’s internal attributes (Eun et al., 2015). Individualism is the extent to which people are integrated into groups (Hofstede, 1980, 2001); in individualistic cultures people tend to believe that they are above average and less herding behaviour is expected than in collectivistic cultures (Markus and Kitayama, 1991; Heine et al., 1999; Eun et al., 2015). Individualistic agents also tend to have an analytic thinking style and to use logic to explain and predict an object’s behaviour (Choi and Nisbett, 2000; Nisbett et al., 2001; Eun et al., 2015). Accordingly, they may follow a Bitcoin benchmark price which they perceive as reliable because of its large market share, higher transparency, longer history, lower chance of exchange shutdowns, etc. Therefore, individualism should reduce Bitcoin price co-movements.

We expect the underlying culture to affect Bitcoin exchange shutdowns as well. In the cryptocurrency market, the herding behaviour of investors is stronger in the case of negative signals, which suggests heightened risk-aversion in the loss domain (da Gama Silva et al., 2019). Risk-aversion may be higher in tight and collectivistic cultures where herding behaviour is likely to characterise Bitcoin investors. According to Xu (2019), global risk-aversion explains 90 and 40 percent of the stock and bond return conditional co-movements, respectively. Therefore, we expect Bitcoin exchanges to be more likely to shut down in tight and collectivistic cultures characterised by higher risk-aversion.

Our results suggest that, consistently with our prior, Bitcoin prices are more likely to co-move in tighter and collectivistic cultures. In particular, it appears that, in the presence of the higher degree of social stability which is typical of tighter (as opposed to looser) cultures, investor behaviour leads to greater Bitcoin price co-movements within and across countries, similarly to Eun et al.'s (2015) findings on the effects of a tight culture on stock price co-movements. Individualism (as opposed to collectivism), which prioritises personal autonomy, independence, self-fulfilment, and accomplishments over group harmony (e.g., Hofstede, 1980; Oyserman et al., 2002; Triandis, 2001), decreases Bitcoin price co-movements just as it decreases stock price co-movements as previously shown by Eun et al. (2015). Specifically, we find that a one standard deviation increase in *Tight* and *Indiv* generates an 18.6% increase and 3.3% decrease, respectively, in Bitcoin price co-movements. The estimated impact of *Tight* and *Indiv* is stronger and weaker, respectively, than the corresponding one (12.9% and -18.2%, respectively) on stock price co-movements detected by Eun et al. (2015); the latter effect is less pronounced in the case of Bitcoin (as opposed to stock) prices because the analytic thinking style of individualistic investors might make them decide to follow a reliable Bitcoin price benchmark.

In our analysis we use Shams (2019)' connectivity measure, which is a pairwise index calculated in our case on the basis of the daily shares of Bitcoin trading volumes between any non-US and US currencies in their shared international Bitcoin exchanges across countries, and represents the degree of financial openness. We find that greater connectivity between international Bitcoin exchanges reduces the impact of the cultural variables on the behaviour of investors and on Bitcoin price co-movements.

Further, we find that countries with tighter and more collectivist societies are more likely to shut down their Bitcoin exchanges as a result of the higher degree of risk-aversion characterising their investors, who are more likely to exhibit herding behaviour. This interpretation is supported by the additional evidence indicating that an increase in other risk measures, such as the foreign exchange rate risk and the Chicago Board Options Exchange (CBOE) Volatility Index, also makes it more likely that Bitcoin exchanges will be shut down.

Our research contributes to the fast-growing literature on cryptocurrencies by focusing on behavioural finance issues not previously considered. To the best of our knowledge, this is the first study to investigate how cultural variables such as tightness−looseness and individualism−collectivism affect Bitcoin investor decisions. Specifically, we show that cultural characteristics generate systematic biases in investor behaviour that have an impact on Bitcoin price co-movements and exchange shutdowns under the assumption that investors prefer Bitcoin exchanges, either local or international, accepting the local currency to trade. We contribute to the extant literature that examines how national culture affects investor behaviour, which had previously focused on stocks and corporate decisions only (e.g., Grinblatt and Keloharju, 2001; Stulz and Williamson, 2003; Guiso et al., 2004, 2008; Chui et al., 2010; Li et al., 2011, 2013; Ahern et al., 2015; Cheon and Lee, 2018; Dang et al., 2018).[1] Finally, our finding that higher pairwise Bitcoin exchange connectivity mitigates the biases generated by national cultural characteristics adds a new financial perspective to the literature on trade and capital market openness (e.g., Frankel and Romer, 1999; Stulz, 1999; Karolyi and Stulz, 2003; Rajan and Zingales, 2003; Stulz and Williamson, 2003).

The layout of the paper is as follows. Section 2 reviews the relevant literature providing the background theory on the basis of which we develop our hypotheses about the linkages between Bitcoin price co-movements and culture. Section 3 outlines the methodology. Section 4 describes the data and the construction of the variables. Section 5 presents the empirical analysis on the effects of culture on Bitcoin price co-movements and exchange shutdowns which includes various robustness tests. Section 6 offers some concluding remarks.

2. Literature Review and Hypothesis Development

While numerous studies have analysed stock market co-movements, the extant literature on cryptocurrency co-movements is relatively limited; it includes papers focusing on the dynamic linkages between cryptocurrencies and other types of assets (e.g., Corbet et al., 2018; Lee et al., 2018a) or between different types of cryptocurrencies (e.g., Ciaian et al., 2017; Katsiampa, 2019; Shams, 2019). Investor behaviour has been used to explain stock price co-movements (e.g., Barberis and Shleifer, 2003; Barberis, Shleifer, and Wurgler, 2005; Baker and Wurgler, 2006; Kumar and Lee, 2006); in particular, Eun et al. (2015) argued that culture is an important factor generating correlations in stock selections and trading decisions which cause stock return co-movements. However, the impact of culture on cryptocurrencies co-movements is yet to be investigated.

According to Shams (2019), the types of investors in different cryptocurrency exchanges are heterogeneous because of geographical restrictions and different governance rules. Furthermore, the barriers to capital transfer and frictions to register make these exchanges segregated. These characteristics can differ between local and international cryptocurrency exchanges. As already mentioned, local exchanges trade cryptocurrencies using their local currencies. On the other hand, international exchanges trade them with more currencies and therefore their geographical location does not limit the international currencies they accept. In the present study, we focus on Bitcoin, which has the largest market share among cryptocurrencies. We assume that investors are mostly interested in using Bitcoin exchanges,

[1] Drake et al. (2017) find that co-movement in investor attention is positively associated with excess stock return co-movement; their analysis does not involve cultural considerations but nevertheless shows the importance of considering behavioural finance aspects to explain stock price co-movements.

either local or international ones, where Bitcoin can be traded using the local currency. Our aim is to analyse how their cultural characteristics (i.e., tightness versus looseness, individualism versus collectivism) explain their Bitcoin trading behaviour and co-movements in Bitcoin prices.

The tightness versus looseness distinction focuses on external constraints on human behaviour (Gelfand et al., 2011; Eun et al., 2015). According to Gelfand et al. (2006, 2011) and Harrington and Gelfand (2014), a tight culture is associated with higher conscientiousness and lower levels of openness, as well as a wide array of outcomes at the state level. Compared with loose societies, tight ones have stronger social norms and lower tolerance for deviant behaviour. Therefore, Bitcoin investors in a tight culture are likely to follow similar norms to gather and process information, share common experiences and similar perspectives and conform to the behaviour of others, which will lead to Bitcoin price co-movements. Hence our first hypothesis is the following:

H_1: Bitcoin price co-movements are higher in the case of investors from countries with a tight (as opposed to loose) culture.

Another cultural dimension we consider is individualism versus collectivism, where the former is the extent to which people are integrated into groups; this distinction focuses on the internal attributes of an individual which differentiate his or her behaviour from that of others (e.g., Hofstede, 1980, 2001; Schwartz, 1994; Gelfand et al., 2006; Eun et al., 2015). In particular, an individualistic culture is likely to make people believe that they are above average (Markus and Kitayama, 1991; Heine et al., 1999), which results in overconfidence (Cheon and Lee, 2018) and self-attribution bias and less herding behaviour compared to collectivistic cultures (Chui et al., 2010).

People from individualistic cultures have an analytical thinking style and use logic to explain and predict an object’s behaviour in contrast to those from collectivistic cultures who have holistic thinking styles (Choi and Nisbett, 2000; Nisbett et al., 2001; Eun et al., 2015) and are therefore more likely to be characterised by herding behaviour. However, it would also be possible for investors with an analytic thinking style to follow a reliable Bitcoin benchmark price (such as the price of large domestic Bitcoin exchanges or the US Bitcoin price), which could lead to herding behaviour and Bitcoin price co-movements; consequently, although we expect collectivism to result in Bitcoin price co-movements, its impact could be less pronounced compared to that on stock return co-movements found by Eun et al. (2015). Therefore, our second hypothesis is the following:

H_2: Bitcoin price co-movements are higher in the case of investors from countries with a collectivistic (as opposed to individualistic) culture.

As already mentioned, we use Shams (2019) connectivity measure to analyse co-movement between Bitcoin prices across countries. According to Stulz and Williamson (2003) and Eun et al. (2015), the effects of domestic culture on a country's financial development are mitigated by a higher degree of trade openness. We apply the same type of argument to Bitcoin markets, and therefore expect a higher trading volume between shared international Bitcoin exchanges across countries to reduce the influence of domestic culture on Bitcoin price co-movements. Thus, we formulate our third hypothesis as follows:

H_3: The relationship between culture and Bitcoin price co-movement is weaker in countries with a higher trading volume between shared international Bitcoin exchanges.

Next, we examine the effects of culture on Bitcoin exchange shutdowns across countries. According to da Gama Silva et al. (2019), herding behaviour is more likely to occur in response to negative market news; global risk-aversion explains 90 and 40 percent, respectively, of the conditional return co-movements of stocks and bonds (Xu, 2019). Since, as argued before, tightness and collectivism should result in more herding behaviour, risk-aversion and Bitcoin price co-movements, they should also increase the probability of Bitcoin exchange shutdowns. This leads to our fourth hypothesis, namely:

H_4: Bitcoin exchange shutdowns are more likely in countries with tight and collectivistic cultures than in those with loose and individualistic cultures.

3. Methodology

We use the R^2 from the expanded market model by Morck et al. (2000) and Jin and Myers (2006) to measure Bitcoin price co-movement across countries. The specification is the following:

$$\begin{aligned} r_{i,j,t} = {} & \alpha_{i,j} + \beta_{1,i} r_{m,j,t} + \beta_{2,i}\left[r_{US,t} + EX_{j,t}\right] + \beta_{3,i} r_{m,j,t-1} + \beta_{4,i}\left[r_{US,t-1} + EX_{j,t-1}\right] \\ & + \beta_{5,i} r_{m,j,t-2} + \beta_{6,i}\left[r_{US,t-2} + EX_{j,t-2}\right] + \beta_{7,i} r_{m,j,t+1} + \beta_{8,i}\left[r_{US,t+1} + EX_{j,t+1}\right] \\ & + \beta_{9,i} r_{m,j,t+2} + \beta_{10,i}\left[r_{US,t+2} + EX_{j,t+2}\right] + \varepsilon_{i,j,t} \end{aligned} \tag{1}$$

where $r_{i,j,t}$ is the daily Bitcoin return of exchange *i* of country *j* on day *t*, $r_{m,j,t}$ is the daily Bitcoin market return of country *j* on day *t*, and $r_{US,t} + EX_{j,t}$ is the US market return adjusted for the change in the exchange rate of country *j* vis-à-vis the US dollar, which is the most widely used national currency on exchanges (Hileman and Rauchs, 2017). The daily frequency is more appropriate in the case of Bitcoin returns (given their very high volatility) than the weekly one used in the case of stocks by Morck et al.

(2000), Jin and Myers (2006) and Eun et al. (2015). Following Dimson (1979), we correct for non-synchronous trading by including two lead and lag terms.

The logistic transformation of R^2 is $Tr(R^2)$ as in Morck et al. (2000); both are equally-weighted (i.e., the weight is the same for each exchange). Since the R^2 is bounded within the interval [0,1], the log-transformed R^2, $Tr(R^2)$, can be calculated as follows:

$$\text{Log-transformed } R^2 = Tr\left(R^2\right) = ln\left(\frac{R^2}{1-R^2}\right) \tag{2}$$

As in Eun et al. (2015), we also calculate the variance-weighted versions of R^2 and $Tr(R^2)$ to obtain $VarW\_R^2$ and $Tr(VarW\_R^2)$, respectively.

We examine the relationship between culture and Bitcoin price co-movement within and across countries using a similar set of variables to Morek et al. (2000), Jin and Myers (2006) and Eun et al. (2015). The model includes the cultural variables, $Tight_j$ and $Indiv_j$, which are the main variables of interest, and also country-specific variables for government bureaucracy ($Govbur_j$), religion ($Religion_j$), income ($ln(GDP_j)$ and GDP_gvol_j), foreign exchange risk ($Fxrisk_j$), liquidity (Liq_j), active mobile phone users per 100 population ($Mobile_j$) and percentage of individuals using the internet ($Internet\_users_j$). Finally, we include the global hash rate of blockchain $ln(Hash\_rate_j)$. Note that we take the natural logarithm (*ln*) of the *GDP* and *Hash_rate* variables to deal with the scaling issue. The estimated ordinary least squares (OLS) regression is the following:

$$\begin{aligned} R_j^2 = {} & \alpha + \beta_1 Tight_j + \beta_2 Indiv_j + \beta_3 Govbur_j + \beta_4 Religion_j + \beta_5 ln\left(GDP_j\right) + \beta_6 GDP\_gvol_j \\ & + \beta_7 Fxrisk_j + \beta_8 Liq_j + \beta_9 Mobile_j + \beta_{10} Internet\_users_j + \beta_{11} ln\left(Hash\_rate_j\right) + \varepsilon_j \end{aligned} \tag{3}$$

where the variables are defined as specified above and j is the country subscript. R_j^2 (the goodness-of-fit from equation (1)) is our co-movement measure, with four variants: equally-weighted R^2 (R_j^2), transformed equally-weighted R^2 ($Tr(R_j^2)$), variance-weighted R^2 ($VarW\_R_j^2$), or transformed variance-weighted R^2 ($Tr(VarW\_R_j^2)$).

We then examine the effects of the cultural variables on Bitcoin exchange shutdowns or inactivity; specifically, we estimate regression (4) with a *Shutdown* binary variable, where again j is the country subscript. We add the *VIX*, a global risk benchmark, which is more appropriate to predict Bitcoin exchange shutdowns compared to the foreign exchange rate risk (*Fxrisk*) and stock market liquidity (*Liq*), which are country-specific variables more suitable to analyse Bitcoin price co-movements in the context of regression (4); to check the robustness of the results we also run an instrumental variable (IV) regression (see Section 5.3).

$$Shutdown_j = \alpha + \beta_1 Tight_j + \beta_2 Indiv_j + \beta_3 Govbur_j + \beta_4 Religion_j + \beta_5 ln\left(GDP_j\right)$$

$$+\beta_6 GDP\_gvol_j + \beta_7 Mobile + \beta_8 Internet\_user_j + \beta_9 Fxrisk_j + \beta_{10} Liq_j$$
$$+ \beta_{11} VIX_j + \beta_{12} ln\left(Hash\_rate_j\right) + \varepsilon_j \qquad (4)$$

To avoid hindsight bias in both regressions (3) and (4), we use country-specific control variables lagged one year (*Govbur*, *Religion*, *ln*(*GDP*), *GDP_gvol*, *Mobile* and *Internet_users*) or six months (*Fxrisk* , *Liq* and *VIX*).

4. Data

The data on weekly Bitcoin prices and trading volumes are obtained from https://data.bitcoinity.org which fetches all global data directly from exchanges through their Application Programming Interface (API) and therefore is a reliable cryptocurrency data source as pointed out by Alexander and Dakos (2020). The sample period goes from 20 July 2010 to 5 February 2020.

Equally-weighted R^2 (R^2), transformed equally-weighted R^2 ($Tr(R^2)$), variance-weighted R^2 ($VarW\_ R^2$) and transformed variance-weighted R^2 ($Tr(VarW\_ R^2)$) are our four Bitcoin co-movement measures. The mean and the median of R^2 and $VarW\_ R^2$ are around 0.80 and 0.70 respectively, which indicates higher co-movements in Bitcoin prices compared to stock prices for which the corresponding value is 0.30 in Eun et al. (2015)'s study. All four co-movement measures are clustered towards high values.

Tight and *Indiv* are the cultural variables as in Eun et al. (2015). *Tight* is the country-specific tightness-looseness score from the Gelfand et al.'s (2011) data set. A tight (loose) culture characterises a country with strong (weak) social norms and low (high) tolerance for deviant behaviour (Gelfand et al., 2011; Eun et al., 2015). *Indiv* is the country-specific individualism-collectivism score obtained from the Hofstede's (2001) data set. It is based on the extent to which people are integrated into groups and focus on their internal attributes to differentiate themselves from others (Hofstede, 1980, 2001; Eun et al., 2015).

We then add country-specific control variables and blockchain property. *Govbur* is an inefficient government bureaucracy index for each country collected from the Global Competitiveness Reports, with a higher value indicating more inefficiency in government bureaucracy. According to Weber (1946), bureaucracy is a social organization formed to manage effectively large populations by following uniform rules and procedures by means of a hierarchical system (Schiller, M). The *Religion* variable is collected from the Central Intelligence Agency (CIA) World Factbook; it is a binary variable equal to one if a country's main religion is hierarchical (e.g., Catholic, Greek Orthodox, and Muslim) and zero otherwise. Hierarchical religions provide strict and vertical bonds of authority which may help instill order and structure (La Porta et al., 1997) affecting the trading behaviour of Bitcoin investors. The economic control variables are *ln*(*GDP*) and *ln*(*GDP_gvol*), which stand for the natural logarithms of Gross Domestic Product (GDP) and GDP growth volatility, respectively, in each country; the source is the World Bank database. We also include two financial markets control variables. *Fxrisk* is the foreign exchange rate risk measured by the realized volatility of the daily foreign exchange rates of each country vis-à-vis the USD; it is calculated for all countries except the US, which is the benchmark country. *Liq* is a stock market liquidity measure calculated using the following FHT method due to Fong et al. (2017):

$$FHT \equiv S \equiv 2\sigma N^{-1}\left(\frac{1+z}{2}\right) \tag{5}$$

where

$$z \equiv Zeros \equiv \frac{ZRD}{TD + NTD} \tag{6}$$

ZRD is the number of zero return days, TD is the number of trading days and NTD is the number of no-trade days in a given month. Further, S is the percentage transaction cost, $N^{-1}()$ is the inverse of the cumulative normal distribution function and σ is the standard deviation of the daily stock return over a month. The proportion of mobile phone (*Mobile*) and internet users (*Internet_users*) in a country are the information technology (IT) control variables. *Mobile* is the number of active mobile phone users per country; the source is the World Bank database. *Internet_users* is the percentage of total population using the internet in each country collected from the Global Competitiveness Reports. *ln*(*Hash_rate*) and *ln*(*Num_trans*) are the natural logarithms of the block chain's hash rate and the average number of transactions per block both in daily frequencies collected from https://data.bitcoinity.org. *Connectivity* is the measure used by Shams (2019) to calculate the pairwise connectivity between two different cryptocurrency exchanges on the basis of their trading volumes. In our context we calculate it as a pairwise index whose value is between zero and one, where one indicates that the share of daily volume between Bitcoins in any non-US (trading Bitcoins using non-US currency) and US (the benchmark country for comparison) countries' international exchanges is identical, zero indicates that there is no overlap between the exchanges, and a value in between indicates the extent of their partial overlap. As shown in equation (7) below, we calculate *Connectivity* as a pairwise index that has a negative relationship with the Manhattan distance in the daily shares of Bitcoin trading volume between any non-US country's currency *i* and US currency *j* across their international exchanges. Since *Connectivity* is a pairwise index which uses the US currency as a benchmark, it is calculated for all countries except the US.

$$Connectivity_{i,j,t} = 1 - \frac{1}{2}\sum_{k=1}^{K}\left|p_{i,k,t} - p_{j,k,t}\right| \tag{7}$$

where $p_{i,k,t}$ is the share of trading volume of Bitcoin in currency *i* in day *t* on their shared international exchange *k*, and $V_{i,k,t}$ is the volume of Bitcoin in currency *i* in day *t* on the shared international exchange *k*.

$$p_{i,k,t} = \frac{V_{i,k,t}}{\sum_{n=1}^{K} V_{i,n,t}} \tag{8}$$

VIX is the Chicago Board Options Exchange index of implied volatility from options on the S&P 500 collected from Bloomberg. *Shutdown* is a binary variable equal to one if a Bitcoin exchange officially shuts down in the countries we consider (i.e., China (Okcoin), Hong Kong (Gatecoin), New Zealand (Anxbtc), Norway (Bitcoinsnorway), Singapore (Itbit), Sweden (Mtgox), Switzerland (Anxbtc) and Thailand (Mtgox)), and zero otherwise. We then winsorize our price co-movement measures and control variables at the 1st and 99th percentiles.

Panel A of Table 1 reports some summary statistics for the variables included in the model. It can be seen that the Bitcoin co-movement measures R^2, $VarW\_R^2$, $Tr(R^2)$ and $Tr(VarW\_R^2)$ tend to be clustered in the high value region and therefore have a left-skewed distribution. The two log-transformed measures $Tr(R^2)$ and $Tr(VarW\_R^2)$ are more volatile (with a Std. of 0.49 and 0.40, respectively) than the corresponding non log-transformed measures R^2 (Std. = 0.10) and $VarW\_R^2$ (Std. = 0.08), respectively. We also find that the countries in our sample tend to be relatively tight (*Tight*) and individualistic (*Indiv*), and to have relatively inefficient government bureaucracy (*Govbur*) and hierarchical religion (*Religion*), as indicated by the skewed distribution of each of these variables.

Most countries in our sample also have relatively high economic growth (*ln*(*GDP*)) and low volatility (*ln*(*GDP_gvol*)). This is plausible since most of them (26 out of 34) are OECD (Organization for Economic Co-operation and Development) members. On the other hand, the foreign exchange rate risk (*Fxrisk*) and liquidity (*Liq*) measures are rather low. Countries with a large number of mobile phone users per 100 population (*Mobile*) are relatively few and therefore the distribution of this variable is right-skewed. Individuals tend to use at least one mobile phone as indicated by the fact that the *Mobile* mean value is 123.33, which is greater than 100. On the contrary, the distribution of *Internet_users* shows that the majority of countries have a percentage of internet users higher than 75% of the population (mean = 75.91), similarly to mobile phone subscribers using at least one mobile phone per person on average in our sample countries. The hashrate (*ln*(*Hash_rate*)) and the number of transactions (*ln*(*Num_trans*)) per day of blockchain are relatively high in most cases, as shown by their left-skewed distributions. In other words, the speed at which a computer is completing an operation in the Bitcoin code (*ln*(*Hash_rate*)) and the number of transactions happening each day (*ln*(*Num_trans*)) are generally high. We also find that the pairwise connectivity between Bitcoins in non-US and US exchanges is generally high (mean = 0.79, median = 0.77), while there are a few non-US Bitcoin exchanges with high connectivity as indicated by the positively skewed distribution of *Connectivity*. The *VIX* has mainly low values and a positively skewed distribution. The *Shutdown* binary variable also has a positively skewed distribution with a mean value of 0.17. In other words, Bitcoin exchange shutdowns or inactivity are a rare occurrence.

Panel B shows the 34 countries and the corresponding Bitcoin exchange quotes (XBT) included in our sample. Panel C displays the Bitcoin exchanges, which include both local and international ones, with the corresponding exchange quotes used for trading. The local Bitcoin exchanges tend to appear only once in each corresponding exchange quote while the international ones appear multiple times across different exchange quotes.[2] Table 2 reports the correlation coefficients between the variables and suggests that there is no multicollinearity between the regressors.

[Insert Table 1 Here]

[Insert Table 2 Here]

Figure 1 shows the distribution of the cultural variables *Tight* and *Indiv* for the countries characterised by both. It can be seen that they tend to have a negative relationship. This is plausible since tightness (looseness), as an external constraint, requires more (less) homogeneous behaviour which increases the collectivistic (individualistic) internal attributes of an individual. We also find that Asian countries tend to exhibit less individualism (more collectivism) compared to the Western countries.

[Insert Figure 1 Here]

5. Empirical Results

5.1. Cultural effects on Bitcoin price co-movements

Table 3 presents the results from the regressions with our two main co-movement measures, namely R^2 and $Tr(R^2)$, as the dependent variables. *Tight* has a positive effect on the co-movement of Bitcoin prices. According to Harrington and Gelfand (2014), this variable is associated with a higher level of conscientiousness, social stability, incarceration rates, discrimination and inequality, and lower openness, homeliness, social disorganization, drug or alcohol use, creativity and happiness, in comparison to looseness. Our results indicate that Bitcoin co-movement increases with tightness, i.e., it is higher in the

[2] The API data source https://data.bitcoinity.org does not include all the Bitcoin prices from the local exchanges in the world, possibly because of the fact that they are not standardised.

case of countries with a higher level of conscientiousness and social stability, which is consistent with the findings of Eun et al. (2015) concerning stock co-movements. This supports our first hypothesis; Figure 2.1 also shows a positive relationship between the equally weighted R^2 measure and tightness. On the other hand, Figure 2.2 shows a negative relationship between *Indiv* and Bitcoin price co-movements. Collectivism leads to higher Bitcoin price co-movements, according to our second hypothesis, which is also supported by our empirical results (see Figure 2.2). We find that a one standard deviation increase in *Tight* and *Indiv* in equation (2) and (3) in Panel B is associated with an 18.6% increase and 3.3% decrease in Bitcoin price co-movements, respectively.[3] Therefore this impact is stronger and weaker, respectively, compared to their corresponding one on stock price co-movements measured by $Tr(R^2)$ in Eun et al. (2015), namely 12.9% and -18.2%; as argued before, the negative effect of *Indiv* is mitigated by the analytic thinking characteristic that makes investors more likely to follow a reliable Bitcoin benchmark price than in the case of stock prices.

The country-specific government bureaucracy variable *Govbur* has a significant, either positive or negative, effect on Bitcoin price co-movements. Investors dislike excessively complicated and hierarchical administrative procedures in domestic Bitcoin trading that make them more inclined to use international Bitcoin exchanges and follow their more reliable Bitcoin prices as a benchmark, which leads to greater co-movements. However, in such a setup they are also less likely to exhibit herding behaviour, which will decrease Bitcoin price co-movements. Therefore the net effect of this variable is ambiguous a priori.

Hierarchical religions (*Religion*) significantly influence Bitcoin price co-movements. In our sample, these are the Catholic, Greek Orthodox, and Muslim ones, which are likely to promote order and structure in a country by providing strict and vertical bonds of authority (La Porta et al., 1997). Therefore, if a country's main religion is hierarchical, herd behaviour of Bitcoin investors following shared information and benchmarks is more likely, especially in the domestic exchanges, and this increases Bitcoin price co-movements. On the other hand, if the strict orthodoxy of the hierarchical religion discourages speculative investments, there will be less interest in Bitcoin trading and analysis, which reduces shared information and Bitcoin price co-movements.

Concerning the effect of the economic control variables, we find that wealthier (*ln(GDP)*) countries exhibit higher Bitcoin price co-movements; these countries can afford to invest to improve the Bitcoin trading related infrastructure, transparency, cyber protection, legal structure, etc., Bitcoin investors preferring the resulting safer environment and lower uncertainty in comparison to low-income

[3] For a one standard deviation increase in *Tight* (2.00) and *Indiv* (22.89), there is an increase of 0.26 (=2.00 × 0.13) and -0.04578 (=22.89 × (-0.002)) in the value of $Tr(R^2)$, which is equivalent to a 18.6% (=100 × 0.26/1.4) increase and 3.27% (=100 × (-0.04578)/1.4) decrease, respectively, from the mean value of $Tr(R^2)$ (1.4).

countries. Therefore, Bitcoin prices in wealthier countries tend to be used as benchmarks by investors, which increases co-movement. This is in contrast to the negative correlation between stock price co-movement and per capita income (GDP) found by Morck et al. (2000) and Eun et al. (2015). GDP growth volatility (*ln(GDP_gvol)*) also has a significant effect on Bitcoin price co-movements: higher volatility increases uncertainty for Bitcoin investors, who perceive domestic Bitcoin prices as less reliable, which reduces Bitcoin price co-movements within a country. However, if investors consider overseas Bitcoin prices as more reliable Bitcoin price co-movements between countries will increase. The net effect on co-movement will depend on which of these two effects is stronger.

The foreign exchange rate risk (*Fxrisk*) has a significant, negative effect on Bitcoin price co-movements, as one would expect. We also find a significant impact of stock market liquidity (*Liq*). If higher stock market liquidity is considered a positive signal implying that Bitcoin market liquidity will also increase, the Bitcoin price of that country is more likely to become a benchmark that investors will follow, which will increase co-movements. On the other hand, if stock and Bitcoin investments are considered substitutes, higher stock market liquidity could be seen as an indication that liquidity in a given Bitcoin exchange will decrease, and therefore its Bitcoin price is less likely to become a benchmark and co-movement will fall.

Both IT control variables, the proportion of mobile phone (*Mobile*) and internet users (*Internet_users*), two different access modes to the internet, have significant effects on Bitcoin price co-movements. *Internet_users* refers to the proportion of people using internet for any purpose irrespective of the device and network used.[4] In general, adolescents have more mobile phones than adults and girls tend to own mobile phones more than boys (Madell and Muncer, 2004). However, females are known to account for only 4 to 6 percent of blockchain investors (Bowles, 2018) who also trade Bitcoin, possibly because of their risk-averse characteristics. Therefore, younger males are most likely to trade Bitcoins using mobile phones. In most studies, females are found to be more risk-averse than males (e.g., Bajtelsmit and Bernasek, 1996; Byrnes et al., 1999; Weber et al., 2002; Felton et al., 2003; Eckel and Grossman, 2008; Croson and Gneezy, 2009; Brooks et al., 2019) and younger individuals exhibit more risk-seeking behaviour in the loss domain than older ones (e.g., Mikels and Reed, 2009; O'Brien and Hess, 2020). Furthermore, herding behaviour is more common in risk-averse investors than in risk-loving ones (da Gama Silva et al., 2019). Therefore, investors using mobile phones to trade Bitcoins are less likely to herd and pursue safer trading strategies since they are likely to be young males with risk-loving behaviour, and as a result Bitcoin price co-movement will decrease. On the other hand, internet non-users are more likely not to own mobile phones than internet users (Bowles, 2018). Therefore, Bitcoin investors

[4] Although *Internet_users* includes *Mobile* by definition, these two variables do not have a multicollinearity problem since their correlation is only 1% as shown in Table 2.

(either risk-averse or risk-loving) are more likely to be accessing the internet through a variety of devices than to be mobile phone owners. Consequently, the *Internet_users* variable can have either a positive or a negative effect on Bitcoin price co-movements depending on which type of Bitcoin traders using the internet dominate in each country.

The hash rate (*ln(Hash_rate)*) and the blockchain control variables also affect Bitcoin price co-movements. Hash rate is the number of hashes per second the network of a blockchain is performing, which reflects the difficulty of mining new coins. Therefore, as this increases, the electricity and computing power costs for new cryptocurrency mining increase as well (Shams, 2019). As Bitcoins become easier to mine with higher hash rates, their availability becomes greater. The impact on Bitcoin price co-movements depends on the percentage of Bitcoin investors exhibiting herding behaviour: if it is large (small), an increased hash rate will result in higher (lower) Bitcoin price co-movements. The estimated coefficient for *ln(Hash_rate)* is consistently positive in Table 3, but has mixed signs elsewhere.

[Insert Table 3 Here]

[Insert Figure 2 Here]

5.2. Culture, connectivity, and Bitcoin price co-movements

We analyse the cultural (*Tight* and *Indiv*) effects on Bitcoin price co-movements by considering the overlapping international Bitcoin exchanges across countries. As already mentioned, we use a connectivity measure (*Connectivity*) based on Shams (2019)'s pairwise index which we calculate for the share of trading volumes of Bitcoins in currencies of country i (non-US) and j (US) across their shared international exchanges.

It can be seen from Table 4 that stronger connectivity between international Bitcoin exchanges across countries leads to higher Bitcoin price co-movements. Also, the estimated coefficients on *Tight* and *Indiv* are significant and their signs are consistent with those reported in Table 4 and support our first and second hypotheses. However, stronger connectivity between international Bitcoin exchanges (*Connectivity*) mitigates the cultural effects of *Tight* and *Indiv* on Bitcoin price co-movements as indicated by the coefficients on the interaction terms, *Tight* × *Connectivity* and *Indiv* × *Connectivity*. This supports our third hypothesis since it implies that openness reduces the potential biases associated with a country's national culture (Stulz and Williamson, 2003 and Eun et al., 2015).

[Insert Table 4 Here]

5.3. Cultural effects on the Bitcoin exchange shutdowns

Next, we analyse cultural effects on Bitcoin exchange shutdowns. We assume that a higher degree of risk-aversion increases the probability of Bitcoin exchange shutdowns. Table 5 reports some evidence on the determinants of Bitcoin exchange shutdowns. We find that countries with tighter and more collectivistic cultures are more likely to shut down their Bitcoin exchanges, since investors in these countries are more likely to exhibit herd behaviour and are more risk-averse. This confirms our fourth hypothesis.

Inefficient government bureaucracy (*Govbur*) and hierarchical religion (*Religion*) reduce the probability of Bitcoin exchange shutdowns. The former may decrease domestic Bitcoin trading and herding behaviour, and consequently risk and exchange shutdowns. As for the latter, hierarchical religions (*Religion*), such as the Catholic, Greek Orthodox, and Muslim ones, view monetary greed as a negative feature, which discourages people from making speculative Bitcoin investments and again reduces risk and shutdowns.

Wealthier (*ln(GDP)*) countries have more Bitcoin exchange shutdowns despite their better Bitcoin trading environment, possibly because of the speculative activities of wealthy investors. Similarly, countries with higher growth volatility (*ln(GDP_gvol)*) are more likely to shut down Bitcoin exchanges, presumably because higher uncertainty encourages the speculative activities of risk-loving investors (Shaw, 1996).

A higher foreign exchange rate risk (*Fxrisk*) also increases the probability of Bitcoin exchange shutdowns as a result of higher Bitcoin price differences across countries and higher risk. By contrast, higher stock market liquidity (*Liq*) reduces the probability of Bitcoin exchange shutdowns by making the stock market relatively more attractive and decreasing Bitcoin trading with the associated risk.

A higher percentage of mobile phone users (*Mobile*) increases the probability of Bitcoin exchange shutdowns. As previously mentioned, Bitcoin traders using mobile phones tend to be young males whose risk-loving behaviour increases the risks of Bitcoin trading and results in more exchange shutdowns. However, the increase in cryptocurrency investors who are internet users and are more risk-averse (Klumov, 2020) could reduce Bitcoin exchange shutdowns.

A higher *VIX* increases the probability of Bitcoin exchange shutdowns, whilst an increase in the hash rate (*ln(Hash_rate)*) reduces it as Bitcoin investors benefit from less costly mining regardless of their trading behaviour. To check robustness, we use the number of transactions (*ln(Num_trans)*) as an instrument: as this increases, the required electricity and computing power costs for Bitcoin mining also increase, which leads to more mining difficulties and a slower hash rate. In Table 5, we report the estimated coefficients, as well as P-values and a Hausman-Wu test for the validity of the chosen instrument; as can be seen, the IV regression confirms the robustness of the previous estimation results.

[Insert Table 5 Here]

5.4. Robustness tests

As a further robustness check, we use alternative measures of Bitcoin price synchronicity. Specifically, we repeat our cultural analysis of Bitcoin price co-movements with fixed effects using the same four co-movement measures in turn as the dependent variable. The results are reported in Table 6 and are consistent with our earlier findings implying that the cultural variables *Tight* and *Indiv* have, respectively, a significantly positive and negative effect on Bitcoin price co-movements.

[Insert Table 6 Here]

Table 7 displays the IV estimation results for the same regressions using the number of transactions (*ln(Num_trans)*) as the instrument. Consistently with the results reported in Table 6, we find a more sizeable impact of the cultural variables *Tight* and *Indiv* and of other regressors on the log transformed measures of R^2 ($Tr(R_j^2)$), and variance-weighted R^2 ($Tr(VarW\_R_j^2)$) compared to the corresponding non-log transformed measures R_j^2 and $VarW\_R_j^2$, respectively.

[Insert Table 7 Here]

6. Conclusions

This paper examines the importance of cultural factors as determinants of the degree of co-movement between Bitcoin exchanges in 34 major countries around the world. The approach taken is an extension of the market model of Morck et al. (2000) and Jin and Myers (2006); both OLS and IV regressions are run and various robustness tests are carried out. This is the first study to analyse how national cultural characteristics, such as tightness/looseness and individualism/collectivism, influence Bitcoin investor decisions, following Eun et al. (2015), who had used the same cultural variables to explain stock price co-movements across countries. The basic assumption is that investors prefer to use Bitcoin exchanges, either local or international, accepting the local currency to trade.

We find that Bitcoin prices in tighter and more collectivistic societies are more likely to co-move. However, greater connectivity between international Bitcoin exchanges in the form of financial openness reduces the impact of the cultural variables on the behaviour of investors and on Bitcoin price co-movements. Further, the probability of Bitcoin exchanges shutdowns is higher in tighter and more collectivistic cultures where investors are more risk-averse and thus more likely to exhibit herding behaviour.

Our analysis documents the importance of cultural variables as determinants of Bitcoin price co-movement and exchange shutdown decisions and casts doubt on the reliability of the findings of previous studies (e.g., Katsiampa, 2019; Shams, 2019), which are likely to have been affected by omitted variable bias. In addition, our findings have important implications for Bitcoin investors, who are well advised to take into account the behavioural effects factors of national cultural characteristics on Bitcoin price co-movements and exchange shutdowns for making optimal portfolio decisions.

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Table 1. Summary statistics

The following table shows the summary statistics of our variables. R^2 is our measure of Bitcoin price co-movements across countries using an expanded version of the market model by Morck et al. (2000) and Jin and Myers (2006). In Panel A, we show the data for our Bitcoin, culture and control variables. We report their mean, median, 25th percentile (25th per), 75th percentile (75th per), standard deviation (Std.) and total number of observations (N) for each series. We winsorize the price co-movement measures and control variables at the 1st and 99th percentiles. In Panel B, we show the countries and their corresponding bitcoin exchange quotes. Panel C shows the bitcoin exchanges and their corresponding exchange quotes used in our data set.

Panel A. Bitcoin, culture and control variables						
	Mean	Median	25th per	75th per	Std.	N
R^2	0.79	0.81	0.80	0.81	0.10	85297
$VarW\_R^2$	0.707	0.713	0.71	0.72	0.08	85297
$Tr(R^2)$	1.40	1.48	1.38	1.48	0.49	85297
$Tr(VarW\_R^2)$	0.90	0.91	0.88	0.95	0.40	85297
Tight	5.97	6.00	4.40	6.90	2.00	55698
Indiv	56.32	60.00	38.00	75.00	22.89	84249
Govbur	13.10	13.30	10.50	15.60	4.19	75619
Religion	0.69	1.00	0.00	1.00	0.46	85297
ln(GDP)	10.52	10.69	10.20	10.92	0.83	85296
ln(GDP_gvol)	0.16	0.09	0.04	0.20	0.18	60612
Fxrisk (%)	0.014	0.009	0.004	0.018	0.015	81986
Liq (%)	0.69	0.61	0.45	0.84	0.34	85293
Mobile	123.33	119.34	109.37	134.94	24.76	84470
Interner_user	75.91	80.72	68.00	87.48	16.18	83375
ln(Hash_rate)	37.01	38.12	31.26	41.22	5.35	85297
ln(Num_trans)	11.44	11.70	10.88	12.42	1.24	85297
Connectivity	0.79	0.77	0.75	0.82	0.04	81665
VIX	16.25	14.85	12.86	18.03	5.19	85297
Shutdown	0.14	0	0	0	0.35	85297

Panel B. Countries	
Country	Exchange quote
Australia	AUD/XBT
Austria	EUR/XBT
Belgium	EUR/XBT
Brazil	BRL/XBT
Canada	CAD/XBT
China	CNY/XBT
Denmark	DKK/XBT
Finland	EUR/XBT
France	EUR/XBT
Germany	EUR/XBT
Greece	EUR/XBT
Hong Kong	HKD/XBT
Indonesia	IDR/XBT
Ireland	EUR/XBT

Israel	ILS/XBT
Italy	EUR/XBT
Japan	JPY/XBT
Luxembourg	EUR/XBT
Mexico	MXN/XBT
Netherlands	EUR/XBT
New Zealand	NZD/XBT
Norway	NOK/XBT
Poland	PLN/XBT
Portugal	EUR/XBT
Republic of Korea	KRW/XBT
Russian Federation	RUB/XBT
Singapore	SGD/XBT
Spain	EUR/XBT
Sweden	SEK/XBT
Switzerland	CHF/XBT
Thailand	THB/XBT
Ukraine	UAH/XBT
United Kingdom	GBP/XBT
United States of America	USD/XBT

Panel C. Bitcoin exchanges

Exchange quote	Bitcoin exchanges
AUD/XBT	Anxbtc, Bitmarket, Btcmarkets, Mtgox
BRL/XBT	Mercadobitcoin
CAD/XBT	Anxbtc, Bitmarket, Cavirtex, Coinbase, Kraken, Mtgox, Quadrigacx
CHF/XBT	Anxbtc, Bitmarket, Mtgox
CNY/XBT	Btcchina, Huobi, Lakebtc, Mtgox, Okcoin, Rmbtb
DKK/XBT	Mtgox
EUR/XBT	Anxbtc, Bit-x, Bitbay, Bitcoin24, Bitcoincentral, Bitcoinde, Bitcurex, Bitmarket, Bitmarketpl, Bitstamp, Btce, Cex.io, Clevercoin, Coinbase, Exmo, Gatecoin, Hitbtc, Itbit, Justcoin, Kraken, Mtgox, Paymium, Therocktrading
GBP/XBT	Anxbtc, Bit-x, Bitmarket, Britcoin, Coinbase, Coinfloor, Kraken, Mtgox
HKD/XBT	Anxbtc, Gatecoin, Mtgox
IDR/XBT	Bitcoin.co.id
ILS/XBT	Bit2c, Bitmarket
JPY/XBT	Anxbtc, Bitflyer, Kraken, Mtgox

KRW/XBT	Bithumb, Korbit, Kraken
MXN/XBT	Bitso
NOK/XBT	Bitcoinsnorway, Justcoin, Mtgox
NZD/XBT	Anxbtc, Mtgox
PLN/XBT	Bitbay, Bitcurex, Bitmarket, Bitmarketpl, Bitomat, Mtgox
RUB/XBT	Bitmarket, Exmo, Mtgox
SEK/XBT	Mtgox
SGD/XBT	Anxbtc, Itbit, Mtgox
THB/XBT	Mtgox
UAH/XBT	Exmo
USD/XBT	Anxbtc, Bit-x, Bitbay, Bitcoin24, Bitcurex, Bitfinex, Bitfloor, Bitmarket, Bitstamp, Btce, Campbx, Cex.io, Coinbase, Coinsetter, Exmo, Gatecoin, Gemini, Hitbtc, Icbit, Itbit, Justcoin, Kraken, Lakebtc, Mtgox, Okcoin, Therocktrading, Tradehill

Table 2. Variable correlations

The following table presents the Pearson's correlation matrix for the variables in our sample. [a] stands for significance at the 1% level, [b] at the 5% significance level and [c] at the 10% level.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)	(m)
Tight (a)	1[a]												
Indiv (b)	-0.36[a]	1[a]											
Govbur (c)	-0.36[a]	0.09[a]	1[a]										
Religion (d)	-0.3[a]	0.14[a]	0.26[a]	1[a]									
ln(GDP) (e)	0.24[a]	0.52[a]	0.07[a]	-0.1[a]	1[a]								
ln(GDP_gvol) (f)	0.06[a]	0.08[a]	0.05[a]	0.1[a]	0.12[a]	1[a]							
Fxrisk (%) (g)	-0.08[a]	0.12[a]	0.08[a]	0.08[a]	0.01[c]	0.06[a]	1[a]						
Liq (%) (h)	-0.06[a]	-0.16[a]	0.16[a]	0.06[a]	-0.15[a]	0.06[a]	0.15[a]	1[a]					
Mobile (i)	0.19[a]	-0.23[a]	-0.08[a]	-0.13[a]	0.04[a]	0.11[a]	-0.04[a]	0.08[a]	1[a]				
Interner_user (j)	0.18[a]	0.53[a]	-0.09[a]	-0.14[a]	0.76[a]	0.02[a]	-0.04[a]	-0.21[a]	0.01[a]	1[a]			
ln(Hash_rate) (k)	-0.01[c]	-0.05[a]	-0.11[a]	0.05[a]	0.09[a]	-0.25[a]	-0.32[a]	-0.25[a]	-0.01[a]	0.17[a]	1[a]		
Connectivity (l)	-0.02[a]	0.08[a]	0.12[a]	0.14[a]	0.19[a]	-0.04[a]	-0.16[a]	0.08[a]	-0.11[a]	0.19[a]	0.35[a]	1[a]	
VIX (m)	0.01	0.03[a]	0.07[a]	-0.02[a]	0.05[a]	0.04[a]	0.27[a]	0.46[a]	-0.01[b]	-0.07[a]	-0.43[a]	-0.1[a]	1[a]

Table 3. Cultural effects on the co-movements in Bitcoin prices

The following table shows the regressions using equally-weighted R^2 (R_j^2) (Panel A) and transformed equally-weighted R^2 ($Tr(R_j^2)$) (Panel B) as dependent variables to analyse the cultural effects on Bitcoin's co-movements. The standard errors are in brackets. We report the adjusted R^2 and F-statistics as for our goodness-of-fit measures. N is the total number of observations reflecting missing values in our regressions. *** stands for significance at the 1% level, ** at the 5% level and * at the 10% level.

Panel A. Cultural effects on R_j^2				
	(1)	(2)	(3)	(4)
Intercept		0.144*** (0.015)	0.676*** (0.011)	-0.4*** (0.016)
Tight		0.026*** (0)		0.029*** (0)
Indiv			-0.0004*** (0)	-0.001*** (0)
Govbur	-0.002*** (0)	0.007*** (0)	-0.001*** (0)	0.008*** (0)
Religion	-0.008*** (0.001)	0.047*** (0.001)	-0.003** (0.001)	0.072*** (0.001)
ln(GDP)	0.02*** (0.001)	0.033*** (0.002)	0.03*** (0.001)	0.09*** (0.002)
ln(GDP_gvol)	0.018*** (0.002)	-0.022*** (0.003)	0.019*** (0.002)	-0.026*** (0.003)
Fxrisk	-0.878*** (0.032)	-0.757*** (0.04)	-0.851*** (0.032)	-0.527*** (0.036)
Liq	0.007*** (0.001)	-0.007*** (0.002)	0.006*** (0.001)	-0.01*** (0.001)
Mobile	-0.001*** (0)	-0.001*** (0)	-0.001*** (0)	-0.002*** (0)
Internet_user	-0.0003*** (0)	0.002*** (0)	-0.0003*** (0)	0.001*** (0)
ln(Hashrate)	0.0005*** (0)	0.0001 (0)	0.0004*** (0)	0.001*** (0)
Adjusted R^2	0.07	0.36	0.08	0.47
F-statistics	473***	1984***	469.9***	2877***
N	57798	35840	57433	35475

Panel B. Cultural effects on $Tr(R_j^2)$				
	(1)	(2)	(3)	(4)
Intercept		-1.257^{***}	1.543^{***}	-3.967^{***}
		(0.073)	(0.054)	(0.075)
Tight		0.13^{***}		0.141^{***}
		(0.001)		(0.001)
Indiv			-0.002^{***}	-0.004^{***}
			(0)	(0)
Govbur	-0.011^{***}	0.031^{***}	-0.01^{***}	0.039^{***}
	(0)	(0.001)	(0.001)	(0.001)
Religion	-0.077^{***}	0.197^{***}	-0.05^{***}	0.333^{***}
	(0.005)	(0.006)	(0.005)	(0.007)
ln(GDP)	0.06^{***}	0.1^{***}	0.105^{***}	0.39^{***}
	(0.006)	(0.008)	(0.006)	(0.008)
ln(GDP_gvol)	0.156^{***}	-0.036^{**}	0.162^{***}	-0.063^{***}
	(0.012)	(0.015)	(0.012)	(0.014)
Fxrisk	-4.641^{***}	-3.546^{***}	-4.523^{***}	-2.401^{***}
	(0.163)	(0.191)	(0.163)	(0.175)
Liq	0.077^{***}	0.019^{***}	0.074^{***}	0
	(0.006)	(0.007)	(0.006)	(0.007)
Mobile	-0.007^{***}	-0.005^{***}	-0.007^{***}	-0.007^{***}
	(0)	(0)	(0)	(0)
Internet_user	-0.002^{***}	0.011^{***}	-0.002^{***}	0.0079^{***}
	(0)	(0)	(0)	(0)
ln(Hashrate)	0.001^{*}	0.0004	0.0007	0.0029^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.09	0.35	0.1	0.47
F-statistics	648.7^{***}	1935^{***}	616.9^{***}	2821^{***}
N	57798	35840	57433	35475

Table 4. Culture, connectivity, and co-movements in Bitcoin prices

The following table shows the regressions using equally-weighted R^2 (R_j^2) (regressions (1) and (2)) and transformed equally-weighted R^2 ($Tr(R_j^2)$) (regressions (3) and (4)) as dependent variables to analyze the culture and trading volume connectivity effects on Bitcoin's co-movements. The standard errors are in brackets. We report the adjusted R^2 and *F*-statistics as for our goodness-of-fit measures. *N* is the total number of observations reflecting missing values in our regressions. *** stands for significance at the 1% level, ** at the 5% level and * at the 10% level.

	(1)	(2)	(3)	(4)
Intercept	0.68*** (0.017)	0.819*** (0.012)	1.503*** (0.082)	2.255*** (0.059)
Tight	0.022*** (0)		0.11*** (0.001)	
Tight × Connectivity	-0.191*** (0.007)		-0.786*** (0.034)	
Indiv		-0.0002*** (0)		-0.001*** (0)
Indiv × Connectivity		0.002*** (0)		0.004 (0.002)
Connectivity	0.666*** (0.015)	0.571*** (0.011)	3.658*** (0.073)	2.945*** (0.055)
Govbur	0.006*** (0)	-0.002*** (0)	0.028*** (0.001)	-0.012*** (0)
Religion	0.011*** (0.002)	-0.011*** (0.001)	0.012* (0.007)	-0.093*** (0.005)
ln(GDP)	0.008*** (0.002)	0.022*** (0.001)	-0.023*** (0.008)	0.068*** (0.006)
ln(GDP_gvol)	-0.015*** (0.003)	0.017*** (0.002)	-0.004 (0.015)	0.153*** (0.012)
Fxrisk	-0.641*** (0.039)	-0.704*** (0.031)	-2.965*** (0.185)	-3.753*** (0.16)
Liq	-0.023*** (0.002)	-0.011*** (0.001)	-0.072*** (0.007)	-0.017*** (0.006)
Mobile	-0.001*** (0)	-0.001*** (0)	-0.005*** (0)	-0.006*** (0)
Internet_user	0.002*** (0)	-0.0004*** (0)	0.011*** (0)	-0.002*** (0)

ln(Hashrate)	-0.002*** (0)	-0.002*** (0)	-0.013*** (0.001)	-0.009*** (0.001)
Adjusted R^2	0.39	0.11	0.40	0.14
F-statistics	1948***	652.6***	1963***	794.1***
N	35828	57421	35828	57421

Table 5. Cultural effects on the Bitcoin exchange shutdowns

The following table reports the results from regressions to analyze the impact of the cultural variables on Bitcoin shutdowns where the dependent variable is *Shutdown*. We show our linear probability regression (model (1)) and replicate this using the instrumental variable (IV) regression (model (2)) as for our robustness test. We use the *F*-statistic, χ^2 and R^2 as for our goodness-of-fit measures. We report the p-values for the instrument relevance (using Wald test) and exogeneity (using Wu-Hausman test) tests. *N* is the total number of observations reflecting missing values in our regressions. *** stands for significance at the 1% level, ** at the 5% level and * at the 10% level.

	(1)	(2)
Intercept	-2.216***	-2.185***
	(0.045)	(0.05)
Tight	0.003***	0.004***
	(0.001)	(0.001)
Indiv	-0.006***	-0.006***
	(0)	(0)
Govbur	-0.025***	-0.025***
	(0)	(0)
Religion	-0.025***	-0.026***
	(0.004)	(0.004)
ln(GDP)	0.361***	0.359***
	(0.005)	(0.005)
ln(GDP_gvol)	-0.231***	-0.233***
	(0.008)	(0.008)
Fxrisk	1.55***	1.531***
	(0.105)	(0.106)
Liq	-0.239***	-0.239***
	(0.004)	(0.004)
Mobile	0.0005***	0.0005***
	(0)	(0)
Internet_user	-0.004***	-0.004***
	(0)	(0)
VIX	0.005***	0.004***
	(0)	(0)
ln(Hashrate)	-0.009***	-0.009***
	(0)	(0)
F-statistic	3749***	
χ^2		3733***

Adjusted R^2	0.56	0.56
Instrument Relevance (P-value): *ln(Hashrate)*		0
Wu-Hausman (P-value)		0.17
N	38197	38197

Table 6. Cultural effects on the co-movements in Bitcoin prices – with different R^2 measures

The following table shows the regressions with year fixed effects using (1) equally-weighted R^2 (R_j^2), (2) transformed equally-weighted R^2 ($Tr(R_j^2)$), (3) variance-weighted R^2 ($VarW\_R_j^2$) and (4) transformed variance-weighted R^2 ($Tr(VarW\_R_j^2)$) as dependent variables to analyze the cultural effects on Bitcoin's co-movements. The standard errors are in brackets. We report the adjusted R^2 and F-statistics as for our goodness-of-fit measures. N is the total number of observations reflecting missing values in our regressions. *** stands for significance at the 1% level, ** at the 5% level and * at the 10% level.

	(1)	(2)	(3)	(4)
Intercept	-0.235*** (0.022)	-3.106*** (0.103)	0.318*** (0.019)	-0.255*** (0.087)
Tight	0.029*** (0)	0.143*** (0.001)	0.029*** (0)	0.131*** (0.001)
Indiv	-0.001*** (0)	-0.003*** (0)	-0.0001*** (0)	-0.0005*** (0)
Govbur	0.008*** (0)	0.038*** (0.001)	0.007*** (0)	0.031*** (0)
Religion	0.067*** (0.001)	0.305*** (0.007)	0.024*** (0.001)	0.088*** (0.005)
ln(GDP)	0.089*** (0.002)	0.378*** (0.008)	0.03*** (0.001)	0.088*** (0.007)
ln(GDP_gvol)	0.011*** (0.003)	0.129*** (0.015)	-0.017*** (0.003)	-0.062*** (0.012)
Fxrisk	-0.666*** (0.037)	-3.111*** (0.176)	-0.599*** (0.033)	-2.594*** (0.147)
Liq	-0.024*** (0.001)	-0.057*** (0.007)	-0.044*** (0.001)	-0.199*** (0.006)
Mobile	-0.002*** (0)	-0.008*** (0)	-0.001*** (0)	-0.007*** (0)
Internet_user	0.001*** (0)	0.008*** (0)	0.001*** (0)	0.006*** (0)
ln(Hashrate)	-0.001** (0.001)	-0.006** (0.003)	-0.001*** (0)	-0.006*** (0.002)
Year Fixed Effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.49	0.49	0.43	0.42
F-statistics	1904***	1867***	1493***	1424***
N	35475	35475	35475	35475

Table 7. Cultural effects on the co-movements in Bitcoin prices – IV regressions
The following table shows the instrumental variable (IV) regressions using (1) equally-weighted R^2 (R_j^2), (2) transformed equally-weighted R^2 ($Tr(R_j^2)$), (3) variance-weighted R^2 ($VarW\_R_j^2$) and (4) transformed variance-weighted R^2 ($Tr(VarW\_R_j^2)$) as dependent variables to analyze the cultural effects on Bitcoin's co-movements. The standard errors are in brackets. We report the adjusted R^2 and χ^2 values as for our goodness-of-fit measures. We report the p-values for the instrument relevance (using Wald test) and exogeneity (using Wu-Hausman test) tests. *N* is the total number of observations reflecting missing values in our regressions. *** stands for significance at the 1% level, ** at the 5% level and * at the 10% level.

	(1)	(2)	(3)	(4)
Intercept	-0.408*** (0.017)	-3.932*** (0.082)	0.223*** (0.015)	-0.653*** (0.068)
Tight	0.029*** (0)	0.141*** (0.001)	0.028*** (0)	0.131*** (0.001)
Indiv	-0.001*** (0)	-0.004*** (0)	-0.0001*** (0)	-0.001*** (0)
Govbur	0.008*** (0)	0.04*** (0.001)	0.007*** (0)	0.031*** (0)
Religion	0.072*** (0.001)	0.332*** (0.007)	0.025*** (0.001)	0.092*** (0.005)
ln(GDP)	0.091*** (0.002)	0.387*** (0.008)	0.031*** (0.002)	0.091*** (0.007)
ln(GDP_gvol)	-0.026*** (0.003)	-0.065*** (0.014)	-0.039*** (0.003)	-0.158*** (0.012)
Fxrisk	-0.521*** (0.037)	-2.432*** (0.177)	-0.464*** (0.033)	-1.982*** (0.148)
Liq	-0.01*** (0.001)	-0.001 (0.007)	-0.031*** (0.001)	-0.142*** (0.006)
Mobile	-0.002*** (0)	-0.007*** (0)	-0.001*** (0)	-0.007*** (0)
Internet_user	0.001*** (0)	0.008*** (0)	0.001*** (0)	0.006*** (0)
ln(Hashrate)	0.001*** (0)	0.002*** (0.001)	-0.001*** (0)	-0.005*** (0.001)
Adjusted R^2	0.47	0.47	0.41	0.4
χ^2	2877***	2820***	2271***	2168***
Instrument Relevance (P-value):	0	0	0	0

ln(Hashrate)				
Wu-Hausman (P-value)	0.3	0.3	0.5	0.1
N	35475	35475	35475	35475

Figure 1. Tightness and individualism

The following figure plots the tightness and individualism scores available for both of our sample countries simultaneously.

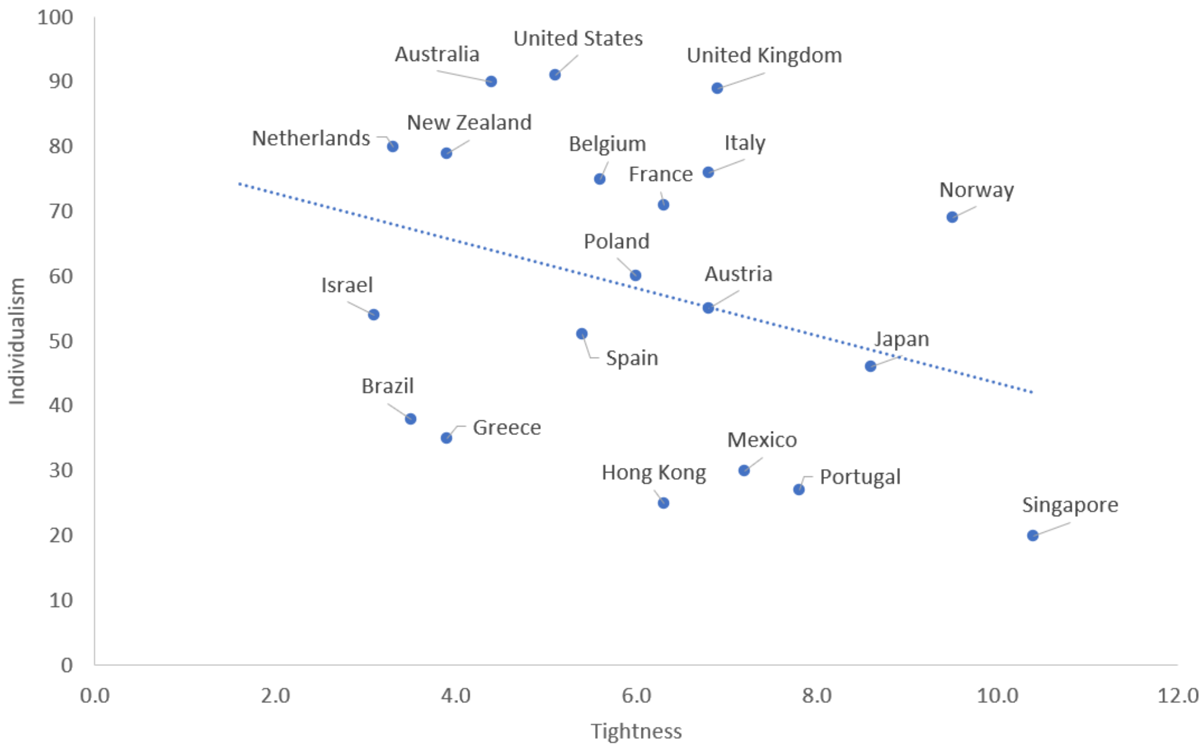

Figure 2. Culture and R^2

The following figures plot the R^2 of the sample countries against our four cultural variables: tightness (Figure 2.1) and individualism (Figure 2.2). The R^2 measure for each country is the average of the equal-weighted R^2 of Bitcoin returns in a country estimated from our model in equation (1).

Figure 2.1. Tightness and R^2

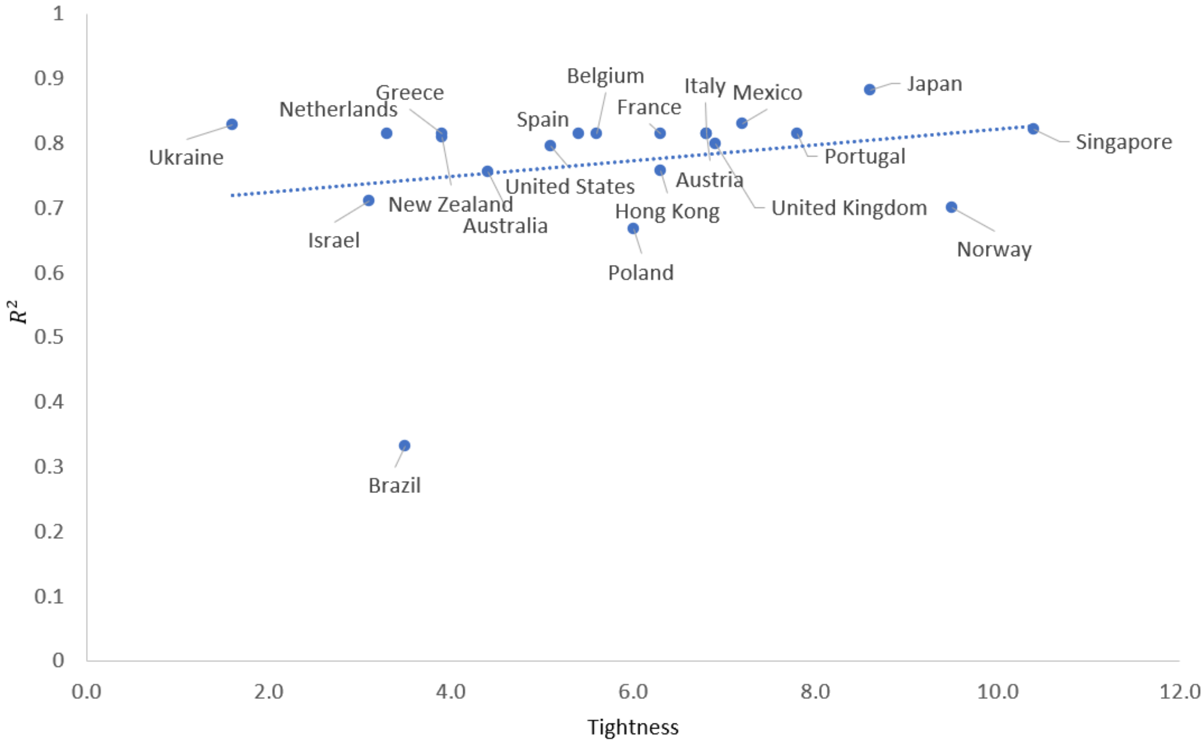

Figure 2.2. Individualism and R^2