Price, Cultural Dimensions, and the Cross-Section of Expected Stock Returns

Ulrich J. Hammerich [*]

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Abstract

We document a nominal stock price effect that is (like momentum) associated with (national) culture. Using the full spectrum of cultural dimensions proposed by Hofstede et al. and the cross-section of stock returns of 41 countries, we not only show a robust predictive and explanatory power of price in conjunction with several cultural dimensions, but of cultural differences in general. Although momentum and price are related investment strategies, we find a broad (escalating) European high-price effect, but a material low-price effect in Asia as well as the most significant and robust low-price effect for the US (that gets even stronger in recent decades). Most consistent around the world, high-priced stocks show lower return volatility and market betas than low-priced stocks and lower values for skewness of returns. Specifically, we reveal particularly cultural dimensions Individualism and Masculinity to drive the price effect, respectively its opposite poles, and Long Term Orientation and Indulgence to be consequential for the cross-section of expected returns. Additionally, we find the magnitude of country-specific value effects to predict returns on country-level expensive minus cheap (EMC) hedge portfolios. Our findings have far-reaching implications for the validity of financial theory like the EMH, as we are the first to report the most basic stock characteristic, the price, to be consequential for stock returns on international level. Even more impactful for future research should be the relevance of cultural differences for the cross-section of expected stock returns in general, as we are the first to explicitly investigate and document this as a groundbreaking side effect of inevitably culture-based financial decision making.

JEL Classification: G11, G12, G14, G15, G41

Keywords: nominal price effect, cultural finance, behavioral finance, asset pricing, market anomalies

[*] University of Bremen, Department of Finance, Max-von-Laue-Str. 1, 28359 Bremen, Germany.

Contact: *Tel.*: +49 421 218 66727; *E-mail address*: hammerich@uni-bremen.de

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1. Introduction

Major stock characteristics like size and book-to-market equity are (among others) directly dependent on the nominal share price of a stock.[1] Despite the enormous impact of these and many other stock characteristics on finance research in the last decades (e.g., Harvey et al., 2015; Linnainmaa and Roberts, 2018) and their identification and implementation as international asset pricing risk factors (e.g., Fama and French, 1993, 2012, 2015; Carhart, 1997) and investment strategies (e.g., Jacobs and Mueller, 2018), research on an international price effect (i.e., price per se is consequential for future returns of an asset) is virtually non-existent in the finance literature. This is even more astonishing as a very early study of Blume and Husic (1973) already documents an outperformance of low-priced stocks in the US, which was confirmed by later evidence of Hwang and Lu (2008). The conclusion of Kross (1985) that the size effect is mainly a price effect and the evidence of Bhardwaj and Brooks (1992) for a dependency of the January effect on a contemporaneous low-price effect are early examples for the relevance of an overdue study on the character of an international price effect as the (potential) origin or explanatory source of manifold "animals" (anomalies) of the "zoo" (Cochrane, 2011). Later literature for example links (low) nominal price to studies on lottery-type stocks (Kumar, 2009; Birru and Wang, 2016) and uses it (in a logarithmic version) as robust explanatory variable for the MAX effect (Cheon and Lee, 2017).

Furthermore, a possible price effect would challenge the weak form of the efficient market hypothesis (EMH) (Fama, 1970) to an extraordinary extent, as price is the embodiment of (publicly accessible) past information contained in time series and data sheets of securities. Although recently emerging research suggests that there is a (high) price effect (high-priced stocks outperform low-priced stocks) in many Western/European countries and nominal stock

[1] The size or market equity of a firm is defined as its nominal share price times the number of outstanding shares. Book-to-market equity is (usually) calculated as common shareholder's equity divided by market equity (which is, again, dependent on price).

prices are consequential for subsequent returns (e.g., Glas et al., 2017; Singal and Tayal, 2017; Hammerich et al., 2018), a comprehensive international sample that particularly includes Asian countries is still missing. Like momentum (e.g., Jegadeesh and Titman, 1993; Carhart, 1997; Chui et al., 2010) for example, price is a very simple investment style (and thus it is even more puzzling that it appears to be an abnormally profitable and at the same time low-risk investment strategy) that invests in nominally high-priced stocks (top price decile/quintile) and sells low-priced stocks (bottom price decile/quintile) at a given portfolio formation date, whereas holding time frames usually span one month, before the price hedge portfolio is readjusted.[2]

Since our findings suggest diverse country-specific price effects (in several countries) that are not consistently explained by standard finance asset pricing models[3] and a tendency toward a general high-price effect in Europe (see also Glas et al., 2017) as opposed to a low-price effect in Asia, i.e. regional price effect clusters, it seems reasonable to check if cultural differences drive these findings (cp., e.g., Chui et al., 2010, who already managed to link momentum to culture).

In addition, articles on the connection of cultural effects (commonly measured by cultural dimensions), capital market anomalies (and derived investment styles) as well as (and even more) stock returns in general still rarely exist (see, e.g., Karolyi, 2016 for a brief overview of studies exploring the impact of culture for financial decision making and employed cultural datasets, and Nadler and Breuer, 2019 for a structured overview of cultural finance as a research field), although this approach could (like the investigation of the price effect) reveal new connecting factors, especially regarding the (still puzzling) existence and persistence of the "zoo of new

[2] Price as an investment strategy does inherently not suffer materially from frequent portfolio turnovers pushing up transaction costs, as it is (especially in the extremes; like for US stocks quoting above several hundred U.S. dollars or being penny stocks) a rather steady stock characteristic as opposed to momentum for example. A very cheap (expensive) stock usually remains cheap (expensive) for a decent amount of time, if there is no surprising (disturbing) (external) event.

[3] This also means that some (unknown) priced risk that may be associated with investing in nominal price is not only not evenly distributed throughout the world, but (in fact) apparently operates diametrically in specific countries.

factors" (Cochrane, 2011; Harvey et al., 2015) and (forthcoming) capital market anomalies. Chui et al. (2010) laid a cornerstone for a new finance branch "cultural finance" (e.g., Zingales, 2015; Nadler and Breuer, 2019) as they managed to link evidence on international momentum returns to culture, or more specifically to the extent of individualism prevailing in a country. Doing so, they implicitly tested behavioral finance theories on overconfidence and self-attribution bias as these behavioral patterns are positively associated with individualism.

Since momentum shows similar return patterns (low to negative returns in Asian countries, high returns in Western/European countries, cp. e.g., Chui et al., 2010)[4] and price and momentum are clearly overlapping investment styles (almost per definition, since ceteris paribus, intermediate-term winner stocks have to show higher prices than past loser stocks on average, and vice versa, which is also confirmed in unreported descriptive statistics for the vast majority of countries), we also test if two related styles are both driven by (or at least connected to) culture. In this way, we not only execute an "out-of-style" robustness test of the explanatory and predictive power of cultural dimensions for stock market investment styles, but also show that cultural characteristics on their own are consequential for global cross-sectional stock returns in general and remain robust even after controlling for major stock return predictors.

With this paper we make several contributions to the emerging field of cultural finance as well as to the mainstream finance literature debating and exploring the existence, connections and origins of international capital market anomalies: First, we test price in each of the 41 countries in our dataset individually and compare it to the country-specific performance of established investment styles (size, value and momentum). In the process, we implement and execute standard asset pricing tests and cross-sectional regressions, to see if price can be explained by financial risk factors and if it is a robust predictor of stock returns on country level. In a second

[4] The difference to momentum however, is, that price is not only non-existent in Asia, but clearly negative.

step, we use Hofstede's (1980, 2001) cultural dimensions[5] to test our main hypothesis that price is, like momentum (cp. Chui et al., 2010), connected to cultural aspects defining a society and the behavioral patterns of its inhabitants in a long-term, largely time-invariant and general manner.[6] The universal strength of cultural dimensions lies in their stability and quantifiability that behavioral finance is in dire need of to validate their theories. Hofstede and others provide us with such a tool that puts (rather fuzzy) behavioral finance on a comparably firm footing and at the same time remind us that behavioral finance theories and implications (that are often the product of Western minds) should not naively be transferred and applied to all cultural backgrounds (cp., e.g., Hofstede et al., 2010).

The rest of the paper is organized as follows. In the next section, we briefly introduce the concept of nominal stock price and sketch its interdependence with other major stock characteristics, showing its relevance for finance research. Thereafter, we define the six cultural dimensions proposed by Hofstede et al. (2010) and in this way reveal the paramount importance of culture for behavioral finance issues in general. In Section 3, we briefly review literature regarding the price effect and the connection of culture and finance and develop our hypotheses. Following, we introduce our financial and cultural datasets and report basic characteristics and statistics of our country-specific samples. In Section 5, we test the price effect on an international level, report main performance characteristics and compare price portfolio results with established risk factor mimicking portfolios. In Section 6, we move on to standard asset pricing tests and robustness tests of price. Section 7 tests our culture-related sub hypotheses and main hypothesis that price is linked to culture, interprets the results and provides further implications. Section 8 concludes the paper.

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[5] Hofstede (2001) proposes five distinct cultural dimensions: Power Distance, Individualism, Masculinity, Uncertainty Avoidance and Long Term Orientation (a sixth dimension called Indulgence was added later in Hofstede et al., 2010) that together characterize national cultures (see Section 2.2).

[6] "National Culture cannot be changed, but you should understand and respect it." (Geert Hofstede; https://www.hofstede-insights.com/models/national-culture/)

2. Theoretical Foundations

2.1 Nominal Stock Price

The nominal price of a stock (that is, a stocks' actual market price) should not matter at all in fully efficient markets (cp., e.g., Fama, 1970) as it is (as public information) readily obtainable for any investor and therefore should be priced in especially rapidly in case of containing some relevant information for the market. In addition, it is specifically arbitrary (like, e.g., a firm name) as it can be altered easily via stock splits and reverse stock splits[7] (in this way increasing or reducing the number of outstanding shares). Apart from its inherent arbitrariness, the nominal price is (either per definition, correlation or due to market mechanisms) connected to various stock characteristics that have been shown to be eligible for predicting and explaining international stock returns. As an example for how common price really is in the "zoo" of anomalies, we have a look at the definitions of the 97 anomalies that were investigated in the study of McLean and Pontiff (2016). We manage to identify 37 of these 97 anomalies to be directly or indirectly connected with nominal price. Most obviously, virtually all anomalies incorporating returns have to be based more or less on price, since *ceteris paribus* the price of a security is *the* key variable for calculating its returns. The prevalence of price does also not exclude some major anomalies used as risk factors in asset pricing models and as investment styles which is outlined in the following.

Per definition, stock characteristics size (market capitalization of a firm) and value (often measured as book-to-market equity) are directly dependent on price – or more specifically – on the movement of the stock price. The higher the stock price, the higher the firm's market capitalization, as size is calculated as price times number of outstanding shares which leads to a

[7] Another, but less common option for firm managers to manipulate nominal stock prices are face amount changes (e.g., Hammerich et al., 2018).

perfectly proportional relationship between price and size. In the case of value, the relation is less straightforward, since price is present in the denominator (consisting of market capitalization or market equity). Thus, in general, high prices make it more likely to classify a stock as growth stock (having a low book-to-market equity ratio), since then, the value of the denominator increases. The momentum of a stock (past return performance) and price are mutually dependent: an increase in price leads to a higher momentum and a higher momentum leads to a higher price. However, the classification of a stock via price is, especially in the extremes, less volatile than via its (short to intermediate term) momentum, since, e.g., a very high-priced stock stays still very high-priced (in relation to the complete stock universe) even after a 50% price drop, whereas at the same time its momentum would be abysmal. This also cuts back transaction costs to some degree when incorporating a price based investment strategy instead of (or in addition to) a momentum strategy, since portfolio turnover is lower.

In the case of the liquidity of a stock, price is also an influencing factor.[8] This is due to a general market mechanism, namely the indivisibility of shares, leading *ceteris paribus* to a higher stock market turnover for low-priced stocks and a lower turnover for high-priced stocks (cp., e.g., Singal and Tayal, 2017). In turn, a lower liquidity of a stock is also automatically linked to a lower (very) short-term volatility of its nominal price.

Beyond that, many papers point to the relevance of nominal stock prices for investors' decisions (e.g., Gompers and Metrick, 2001; Fernando et al., 2004; Kumar 2009; Fernando et al., 2012; Birru and Wang, 2016; Hammerich et al., 2018). The higher appearance of institutional investors on high-priced stocks shareholder's lists – whereas low-priced stocks are teeming with private investors and noise traders[9] (see, e.g., Kumar, 2009; Fernando et al., 2012) – also suggests to witness lower volatility and lower market sensitivity of high-priced stocks returns as opposed

[8] Price can also be used as a liquidity proxy (Brennan and Subrahmanyam, 1996; Brennan et al., 1998).

[9] For example, Singal and Tayal (2017) report (for the US market) that low-priced stocks have seven times as many shareholders as high-priced stocks.

to low-priced stocks returns. We will see these hypotheses confirmed not only on the US market (Singal and Tayal 2017) and in Europe (Glas et al., 2017; Hammerich et al., 2018), but worldwide in Section 5.

Furthermore, firm managers are aware of the relevance of stock prices to investors (e.g., Conroy and Harris 1999; Baker et al., 2009). In the US case for example, nominal stock prices remain at about $35 since the Great Depression (Weld et al., 2009), which led to the catering theory of Baker et al. (2009), where managers lower stock prices when they witness investors to overestimate the value of low-priced stocks. Weld et al. (2009) themselves ascribe this constant share price practice to customs and norms as they find neither signaling theories nor optimal trading ranges to account for this issue.

2.2 Cultural Dimensions

Hofstede et al. (2010: 6) define culture as „the collective programming of the mind that distinguishes the members of one group or category of people from others." In a temporal context it resembles "the unwritten book with rules of the social game that is passed on to newcomers [of a society] by its members, nesting itself in their minds." (Hofstede et al., 2010: 26) Unlike the basic layer of human nature which is universal to all humans and inherited, culture is learned. It is a collective phenomenon based on the social environment in which a distinctive group or category of people is raised and socialized. Due to its social nature it is also separate from the top layer, "personality" (whereas culture is the middle layer) which is specific to an individual. Although "personality" is also learned, it is at the same time also partly inherited like the human nature. The core of distinctive cultures is constituted by (largely time-invariant) values, which are emotionally based, general tendencies regarding the preference of certain state of affairs over others, like e.g. the (perceived) morality or immorality of an action. In this way, values determine how people in a country generally think, feel and act (Hofstede et al., 2010).

In his model of national cultures, Hofstede (2001) initially proposes four distinctive cultural dimensions (Power Distance, Individualism, Masculinity and Uncertainty Avoidance) based on a value score database of international IBM employees that was created via extensive surveys for example on work goals between 1967 and 1973. The values of these four dimensions (identified using factor analysis) where initially determined for 40 countries in Hofstede (1980). Based on extensions described in Hofstede (2001) and Hofstede et al. (2010) designed to mimic the initial methodology and to enlarge the covered countries in a consistent manner, data for 76 countries is now available. Later, two additional cultural dimensions (Long Term Orientation and Indulgence), each available for 93 countries, were added based on World Values Survey data. Several replication studies showed the (primary) dimensions to be still valid and to be insensitive to the used methods and datasets (Hofstede et al., 2010). The now six culture dimensions together (but at the same time also for each dimension independently) define the basic nature of distinctive national cultures – or more specifically – the relative differences of countries (rather than individuals) regarding preferences for one state of affairs over another (i.e., e.g., aspects of behavior associated with the distinction individualism versus collectivism). Thus, the values/scores of the dimensions (see Section 4.2) should not be understand as absolute, but rather as relative (to other cultures), since each dimension value is determined in relative terms regarding all of Hofstede's (initially) included countries for each dimension, respectively (Hofstede, 2001).[10]

Power Distance is a dimension dedicated to capture the way a society handles inequalities among people. Scores on this dimension inform about the degree of dependence of subordinates regarding relationships with their bosses. Hofstede et al. (2010: 61) put it that way: "Power distance can (…) be defined as *the extent to which the less powerful members of institutions and*

[10] For more details on, e.g., the construction and calculation of the culture indices (values), the underlying factors/factor analysis, the used survey questions and further implications and correlations, see Hofstede (2001) and Hofstede et al. (2010).

organizations within a country expect and accept that power is distributed unequally. *Institutions* are the basic elements of society, such as the family, the school, and the community; *organizations* are the places where people work." High Power Distance scores of a society show that people generally accept a hierarchical order. On the other side of the scale are societies in which people strive to equalize the distribution of power and – if inequalities of power are (still) present – require justification for this state of affairs.[11]

One of the most impactful and universal dimensions is Individualism (versus Collectivism). It proposes two poles in which members of a society are either clustered in groups (collectivism) or loosely connected (individualism). The two poles of this dimension are defined as follows: "*Individualism* pertains to *societies in which the ties between individuals are loose: everyone is expected to look after him- or herself and his or her immediate family*. *Collectivism* as its opposite pertains to *societies in which people from birth onward are integrated into strong, cohesive in-groups, which throughout people's lifetime continue to protect them in exchange for unquestioning loyalty*." (Hofstede et al., 2010: 92) One striking example of the general differences between collectivist and individualist societies is that in individualist societies, members are expected to have and to share their own (diverse) opinions whereas in collectivist societies members are expected to conform with and stand in for the majority opinion of their (often situation-dependent) (in-)group to which they (feel to) belong.[12] Also, joint-stock companies are regularly in the hands of individual investors in individualistic societies as opposed to collectivistic societies where families, collectives or the government are more likely in charge (Hofstede et al., 2010). Furthermore, there are many meaningful correlations of the degree of Individualism (and even more with Masculinity and Uncertainty

[11] See also Hofstede's website for short summaries of the cultural dimensions: https://www.hofstede-insights.com/models/national-culture/

[12] This could, e.g., contribute to higher market efficiency and lower herding behavior in individualistic societies (see, for example, Eun et al., 2015).

Avoidance) and consumer behavior data (De Mooij, 2004, 2010; Hofstede 2001; De Mooij & Hofstede, 2002; Hofstede et al., 2010).

A third traditional culture dimension, labeled Masculinity versus Femininity (as it is the only dimension that showed consistently different scores among male and female IBM employees), is (like Individualism) also based on work goal items from the original IBM study of Hofstede (2001). "*A society is called* masculine *when emotional gender roles are clearly distinct: men are supposed to be assertive, tough, and focused on material success, whereas women are supposed to be more modest, tender, and concerned with the quality of life.*" On the other hand a "*society is called* feminine *when emotional gender roles overlap: both men and women are supposed to be modest, tender, and concerned with the quality of life.*" (Hofstede et al., 2010: 140) Masculine societies foster competitiveness and strive for career and success that is supposed to be shown by its members (performance society). Feminine societies prefer cooperation and are consensus-orientated (welfare society). The own (good) performance is generally underrated and concealed in those societies, for instance (Hofstede et al., 2010).

Uncertainty Avoidance as the last remaining initial IBM study dimension, deals with a societies' anxiety level due to ambiguous or unknown situations and the extent of an avoidance of these. Uncertainty and anxiety are both diffuse feelings which have no certain probability for an event or an object attached to it (as opposed to risk and fear). Therefore, the higher the Uncertainty Avoidance level of a society is, the more rigid codes of behavior and belief exist and approaches and ideas that are innovative and off-the-wall are regarded with suspicion[13] (e.g., resulting in less new trademarks and higher constraints due to rules for "intrapreneurs" in such societies). However, what these societies lose in invention and (basic) innovation, they make up leeway in implementation of new ideas and processes and developing new products and services (especially due to their higher need for precision and formalization). In the investment sphere, this difference in anxiety tolerance also expresses in, other things being equal, a preference for

[13] Short-term orientated societies are additionally wary of societal change.

precious metals and gems in strong uncertainty-avoidance societies, whereas uncertainty-accepting countries tend to invest more in stocks (De Mooij, 2004; Hofstede et al., 2010).

The first new cultural sphere, Long Term versus Short Term Orientation, deals with the attitudes of a society toward their own past while handling current and coming challenges: "*long-term orientation* stands for *the fostering of virtues oriented toward future rewards—in particular, perseverance and thrift*. Its opposite pole, *short-term orientation*, stands for *the fostering of virtues related to the past and present—in particular, respect for tradition, preservation of "face," and fulfilling social obligations*." (Hofstede et al., 2010: 239) An interesting example for economic implications connected with this dimension is that (as the name suggests) in long-term orientated cultures, long-term profits (10 years in the future) are rated more important than short-term (this year's) profits and vice versa[14] (Hofstede et al., 2010). De Mooij (2004) additionally shows that investing in real estate (i.e., a long-term commitment) is more common in long-term orientated countries, whereas in short-term orientated countries investments in mutual funds are much in demand.

The last and latest culture dimension, first proposed in Hofstede et al. (2010), Indulgence versus Restraint, is highly associated with (expressions of) happiness and optimism in a society and resembles to a certain degree the distinction between a loose and tight society. "*Indulgence* stands for *a tendency to allow relatively free gratification of basic and natural human desires related to enjoying life and having fun*. Its opposite pole, *restraint*, reflects *a conviction that such gratification needs to be curbed and regulated by strict social norms*." (Hofstede et al., 2010: 281)

[14] The US is a prime example for a short-term orientated culture that turns special attention to short-term profits and fast spending of money (reflected in a low savings rate) (Hofstede et al., 2010). This finding gets further underlined due to the common quarterly dividend payout on the US stock market.

3. Literature Review and Hypotheses Development

3.1 Price Effect

Blume and Husic (1973) were the first to investigate a price effect (in the following that is, nominally high-priced stocks outperform low-priced stocks or vice versa) on the NYSE and at the same time drawing connections of stock price to beta, documenting evidence of an inverse relationship of price and returns and a positive (though insignificant) relation of beta and returns in the time frame 1932 to 1966. Contradicting this early US evidence, Seguin and Smoller (1997) report lower risk-adjusted rates of return for portfolios containing low-priced stocks than for portfolios of high-priced stocks for a sample of NASDAQ stocks between 1974 and 1988. By trend, Singal and Tayal (2017) affirm this newer finding (using US stock market data from 1963 to 2015) as they report an outperformance of high-priced stocks when explicitly controlled for size (but no return differences when not controlled for size) and empirically document a negative impact of stock splits (resulting in price deterioration) on subsequent returns. However, Hwang and Lu (2008) find a robust low-price effect (low-priced stocks outperform high-priced stocks) for the US using a similar time frame (1963 to 2006) and the same data sources (CRSP and Compustat) as Singal and Tayal (2017). Besides the US evidence, we find recent papers of Glas et al. (2017) and Hammerich et al. (2018) to report a high-price effect (measured by a high-price minus low-price or expensive minus cheap hedge portfolio) in 9 out of 11 European countries and for Germany since the 1990s. One exception regarding the investigation of an international price effect is Baytas and Cakici (1999) who document a consistent low-price effect for seven industrialized countries (USA, Canada, Japan, UK, Germany, France, Italy), but using only a limited time frame (1983 to 1991).

On a more thorough and diverse international basis (and of course, using a larger time frame and recent data), results on a possible stock price effect have been, to our knowledge, not

yet published, although price is (directly) connected to – or could be partly seen as proxy for – several established stock characteristics used as investment styles and for the construction of common financial risk factors (see Section 2.1) and thus has the potential to shed, e.g., further light on the existence and origin of the internationally robust (with the exception of some Asian countries), but still puzzling momentum effect.

Especially referring to the most consistent empirical findings of the recent papers (Glas et al., 2017; Singal and Tayal, 2017 and Hammerich et al., 2018) which find portfolios consisting of high-priced (expensive) stocks to outperform portfolios of low-priced (cheap) stocks, at the same time showing a clearly lower return volatility, higher risk-adjusted returns, lower market sensitivity and lower, respectively negative values for skewness of returns for expensive portfolios, we derive four sub hypotheses H1a to H1d (all in relation to low-priced portfolios) and one main hypothesis (H1) for our international test of the price effect (see Sections 5 and 6):

H1. Expensive portfolios outperform cheap portfolios.

H1a. Expensive portfolios show lower return volatility.

H1b. Expensive portfolios yield higher risk-adjusted returns.

H1c. Expensive portfolios exhibit lower market sensitivity.

H1d. Expensive portfolios have lower/negative values for skewness of returns.

In the next section, we draw possible cultural prerequisites that are connected with the extent of the fulfillment of H1. Furthermore, we sketch conditions of national cultures that make the contrary hypothesis (cheap portfolios outperform expensive portfolios) more likely.

3.2 Culture-based Market Anomalies: Is Price one of them?

In the finance domain, research on the impact of culture, respectively cultural dimensions of Hofstede (2001) and others (e.g., Schwartz, 1994 and House et al., 2004) on financial decision making is on the rise. Especially investment biases, like the home and foreign bias (e.g. Grinblatt and Keloharju, 2001; Beugelsdijk and Frijns, 2010; Anderson et al., 2011; Aggarwal et al., 2012; Beracha et al., 2014) and behavioral pitfalls like herding (Chang and Lin, 2015) are in the focus of research, mainly from a global perspective. Another strand of literature focuses on the linkage of stock price comovement and culture (Lucey and Zhang, 2010; Eun et al., 2015). Other recent papers applying cultural dimensions in the corporate finance sphere are for example Zheng et al. (2012), Li et al. (2013) and Chui et al. (2016).

The only prominent paper[15] that connects culture and stock returns (or more specifically, the momentum effect) directly is Chui et al. (2010).[16] They manage to link the strength of the international momentum effect (past winner stocks outperform past loser stocks in an intermediate 3 to 12 month time frame) to one of Hofstede's cultural dimensions (Individualism), in particular and find that the higher the tendency of a society to promote a loosely-knit social framework (i.e. individualism), the stronger is, on average, the momentum effect. As the price and the momentum of a stock are related, we expect a possible international price effect to be

[15] Another (less prominent) paper is Durand et al. (2013): They manage to link culture (i.e., the individualism index of Hofstede (2001)) to the performance of sin stocks and the ratios of substantial/governmental shareholders investing in those stocks. Investors in more collectivistic countries are not deterred from investing in sin stocks (or even inclined to invest) contrary to more individualistic countries, leading to an underperformance of sin stocks in seven Pacific-Basin markets as opposed to a clear outperformance in, e.g., the US. Weigert (2015) and Cheon and Lee (2017) on the other hand, manage to link the presence of the MAX premium and of a crash sensitivity effect (measured by lower tail dependence) to more individualistic countries.

[16] However, Chui et al. (2010) completely concentrate on the momentum effect without investigating the predictive power of cultural dimensions for international (firm-specific) stock returns in general.

especially linked to Individualism. However, since there is no profound theoretical framework depicting which cultural dimensions are connected to (or even consequential for) stock returns (and stock investment styles based on anomalies like momentum), we include all six cultural dimensions of Hofstede and others (Power Distance, Individualism, Masculinity, Uncertainty Avoidance, Long Term Orientation and Indulgence; Hofstede et al., 2010) in this study. Our initial main hypothesis regarding the connection of culture and the price effect therefore is:

H2: Cultural characteristics are consequential for a nominal stock price effect.

Since momentum and price are related investment styles, the cultural explanations of momentum of Chui et al. (2010), especially regarding the (behavior-based) links of individualism and momentum are also (partly) transferable to price. Birru and Wang (2016), show that investors overestimate the skewness of returns of low-priced stocks and therefore their future performance relative to high-priced stocks. Since people in individualistic cultures are more overoptimistic about their abilities and tend to overestimate the precision of their predictions (Heine et al., 1999; Van den Steen, 2004), it is likely that low-priced stocks appear to be more attractive to investors in individualistic cultures (leading to an overvaluation and lower returns of low-priced stocks relative to high-priced stocks). In addition, people in collectivistic countries tend to have high self-monitoring which helps to reduce cognitive biases caused by overconfidence (Biais et al., 2005). This connection (of collectivism) to a high self-monitoring ability is also reflected in the Indulgence dimension (defining the extent to which people try to control their desires and impulses) with low scores (depicting restrained people) in (collectivistic) Asian countries, especially. It seems also reasonable that self-indulgent (presumably action-seeking and rather extrovert) investors prefer low-priced stocks that often have lottery-like characteristics (see, e.g., Kumar, 2009) resulting in an overvaluation. George (2002) shows for example that buying compulsiveness in respect of lottery tickets and scratch cards is positively associated with the

extraversion dimension of personality. Thus, we expect individualistic/self-indulgent (collectivistic/restrained) cultures to trigger a high-price effect (low-price effect):[17]

H2a: *High* (low) values of Individualism are connected to a *high-* (low-)price effect.

H2b: *High* (low) values of Indulgence are linked to a *high-* (low-)price effect.

A possible factor for the prevalence of a low-price effect in "masculine", i.e. competition-orientated cultures could be based upon the existence of more sophisticated (institutional) investors due to higher competitive pressure in masculine countries. Anderson et al. (2011) underline this assumption, as they find (institutional) portfolios (of investors) from countries with higher masculinity levels to display lower levels of home bias and additionally to be more diversified abroad. They also find that investor behavior is impacted directly by culture and not merely indirectly through channels like regulatory and legal framework. Since it is known that institutional investors (who are more sophisticated than (most) private investors) prefer high-priced stocks as opposed to private investors who prefer low-priced stocks (e.g., Kumar, 2009; Fernando et al., 2012), in masculine countries, high-priced stocks tend, under our assumption, to be overbought and yield lower returns relative to more feminine (cooperation-orientated) countries.

H2c: *High* (low) values of Masculinity are related to a *low-* (high-)price effect.

[17] In the following, we construct each hypothesis in a two-way form. In doing so, we refer to Barberis and Shleifer (2003) who (theoretically) propose that naturally, the investment (of a sophisticated investor) in an investment style (e.g. investing in high-priced stocks) is primarily financed by withdrawing funds from the respective twin style (low-priced stocks). In this way, the attractiveness (and therefore the performance) of an investment style has an (indirect) impact on (the performance of) its twin style. However, we mark the expected main effects with italics.

With regard to a possible influence of Long Term Orientation (LTO) and Uncertainty Avoidance (UA) on the price effect we assume that the observed strong association of price and size (cp. Table 4) could be consequential. IPOs for example, are mainly performed by smaller firms with future-orientated business models, offering their stocks at low to moderate share prices (Fernando et al., 2004). In countries with high scores of LTO, i.e. future-orientated cultures, and low scores of UA, that is cultures which are open for new, unorthodox ideas, we expect these young, small, innovative and rather low-priced firms to be more attractive to (IPO) investors compared to more traditional/rigid cultures (countries scoring low on LTO/high on UA). This goes hand in hand with higher demand, an overvaluation and thus lower returns of low-sized, low-priced stocks, contributing to an expected high-price effect in countries with high (low) LTO (UA) and a low-price effect in low-LTO (high-UA) countries. Underlining this argumentation, Costa et al. (2013) document higher (initial) IPO underpricing (i.e., a larger price increase due to high demand when the stock is traded on the secondary market for the first time) for high-LTO, low-UA and high-PD[18] (that is, power is accepted and excepted to be distributed unequally by the less powerful members of society) countries. Thus, we state our last two sub hypotheses as follows:

H2d: *High* (low) values of LTO are connected to a *high*- (low-)price effect.

H2e: *Low* (high) values of UA are linked to a *high*- (low-)price effect.

In ascribing the international price effect(s) to cultural characteristics we have to rely on a certain degree of home bias to be present around the world which is documented by papers like Anderson et al. (2011) for institutional investors. In this way, national investors can drive the price effect in their home country by preferring either low-priced or high-priced stocks, whereas

[18] We develop no hypothesis regarding PD, since we are not able to draw a meaningful connection between PD and a price effect.

the specific preference is expected to be (lastly) determined by their culture (cp. hypotheses construction above). Consequently, the degree of home bias in a country is likely also an indirect determinant/indicator for the prominence of a respective country-specific price effect. However, since the home bias itself is culture-dependent (Anderson et al., 2011), we regard it as sufficient to use cultural dimensions as (fundamental) proxy variables for the prevalence of home bias. As Anderson et al. (2011) find Individualism, Masculinity, Uncertainty Avoidance, and Long Term Orientation (Power Distance and Indulgence were not included in their study) to be significant determinants for the extent of home bias in (institutional) portfolios and funds, we expect these cultural dimensions to be especially consequential for the magnitude and direction of possible price effects in an international sample.

4. Data

In the following, we introduce the used datasets (and the applied data editing methodology) to perform our tests of an international price effect and its expected connection to national culture.

4.1 Financial Time Series

We retrieve the financial data of our international sample from Thomson Reuters Datastream. We select 41 countries to be included in our study (Table 1).[19] The sample starts – for many, especially developed countries – in June 1980 and ends for all countries in April 2017. All stocks listed at the countries' major stock exchange in the respective time frames are included in the (raw) sample.[20] We end up with a total of 31,807 stocks and a maximum sample length of 442 months (stocks from financial sectors are excluded to facilitate comparability of calculations referring to book-to-market ratios especially as this is common practice in asset pricing). We require each country to have at least 30 active stocks in each consecutive month of the sample to attain a sufficient number of stocks for our price portfolios (and risk factors).[21] To mitigate data

[19] Ang et al. (2009) and Fama and French (2012), for example, limit their international sample to (23) developed countries only (with 16 European countries), but including only three Asian countries (Japan, Hong Kong, Singapore). Since our research question relies on cultural diversity in our sample, we choose a more heterogeneous and (regionally) balanced sample which also includes unique and large national cultures like China and India.

[20] We restrict the sample to primary listings traded in local currencies at their home stock exchange. However, we include both dead and active stocks in the raw data, as we implement our own inactive stocks filter, anyway (we do so also due to Datastream's incomplete dead stocks lists).

[21] We cut off (i.e. set "not available") all months which do not fulfill this prerequisite until the month when at least 30 stocks are continuously available through April 2017. Due to this filter, we have to dismiss Ireland and Portugal completely. Apart from these two countries, we cover all countries of Chui et al. (2010) and additionally include Russia and Saudi Arabia.

quality and illiquidity problems (see, e.g., Ince and Porter, 2006), we exclude values in the specific month if the market capitalization of a stock is below the first decile[22] of all stocks in its associated country (every month anew). Second, to account for extreme values due to Datastream's rounding policy for very low-priced stocks, we set, in each month, stock data missing if a stock's unadjusted price is below 1 currency units. Third, we test if a stock is still actively traded/tradable and exclude a stock in a specific month, if it showed monthly returns of zero in the previous four months, respectively. These filters help us to focus more on liquid stocks (without cutting down the sample size too much) and especially ensure that results are not driven by small-sized penny stocks which typically exhibit most data failures (e.g. return outliers).

4.2 Hofstede's Cultural Indexes

The cultural data spans the six cultural dimensions proposed by Geert Hofstede and others (Power Distance, Individualism, Masculinity, Uncertainty Avoidance, Long Term Orientation and Indulgence; see Hofstede et al., 2010). We get the data of the six cultural dimensions for each of the 41 countries in our sample (Table 2) directly from Hofstede's website.[23] Each dimension is labelled in the way that high scores indicate strong fulfillment of that label in a country. For example, a high score (e.g., 80) for Masculinity and Individualism marks a "masculine", individualistic society (as opposed to a feminine, collectivistic society scoring low on these dimensions), whereas a low score (e.g., 20) for Long Term Orientation depicts a normative society that prefers to maintain time-honored traditions as opposed to more

[22] Asness et al. (2013), for example, use a much more rigorous liquidity filter as they only include the very biggest stocks that cumulatively account for 90% of the total market capitalization which results, for the US case, in an inclusion of only the top 17% of all US firms on average. However, since Asness et al. (2013) concentrate on implementable investment strategies and not, like us, on asset pricing, we decide to exclude only the very smallest stocks in each country-specific stock universe (comparably to Chui et al., 2010 who use a 5% cut-off).

[23] https://www.hofstede-insights.com/product/compare-countries/; cp. also Hofstede et al. (2010)

pragmatic, future-orientated societies scoring high on this dimension. The dimensions were initially defined in the way that they are restricted to a value between 0 and 100 (only countries that were added in the extensions after 1980 partly exhibit values above 100; cp., e.g., Hofstede et al., 2010). Furthermore, as outlined in Section 2.2, the values should not be understand as absolute, but rather as relative values, since each value is determined in relative terms regarding all of Hofstede's included countries (initially 40) for each dimension, respectively (Hofstede, 2001). In our sample, the culture dimension values reach from a lowest value of 0 to a maximum of 100 representing high diversity between national cultures as could be expected for an international sample.

Table 1: Summary statistics of international financial data

Our (financial) sample consists of individual stock data from 41 international markets. All data is received from Thomson Reuters Datastream. We only include primary class (common) stocks that are listed in local currency on the major stock exchange in their home country. We exclude stocks from financial sectors, stocks below the first decile of market capitalization in each month within each country, stocks below 1 currency unit and inactive stocks showing zero returns over the prior four months. The table reports the included countries in alphabetical order, the starting year of the respective country-specific samples (earliest date is June 1980), total number of months for each country, the average and total number of stocks in each sample and the average of the monthly median nominal stock prices for each country in local currency. The end date for each country-specific sample is April 2017.

Market	Starting year	Number of months	Number of firms (average)	Number of firms (total)	Nominal price (median)
Argentina	2002	178	51	92	5.1
Australia	1980	442	224	2431	2.7
Austria	1987	358	55	130	66.6
Bangladesh	2008	106	49	73	254.7
Belgium	1985	382	75	178	68.2
Brazil	1998	226	90	206	17.0
Canada	1980	442	454	1630	9.0
Chile	1990	322	110	205	405.4
China	1993	286	567	1157	9.8
Denmark	1987	358	107	228	311.0
Finland	1990	322	83	207	11.6
France	1980	442	440	1373	65.7
Germany	1980	442	353	973	79.3
Greece	1988	346	132	337	4.7
Hong Kong	1983	406	256	1524	2.8
India	1990	322	850	1514	84.4

Table 1: continued.

Market	Starting year	Number of months	Number of firms (average)	Number of firms (total)	Nominal price (median)
Indonesia	1991	310	205	426	1172.8
Israel	1992	298	219	388	10.8
Italy	1983	406	116	403	6.2
Japan	1980	442	1769	3258	730.5
Malaysia	1985	382	293	902	2.9
Mexico	1991	310	79	168	19.4
Netherlands	1980	442	106	244	28.3
New Zealand	1992	298	55	188	2.8
Norway	1982	418	107	408	67.6
Pakistan	1993	286	132	193	51.5
Philippines	1992	298	79	190	6.7
Poland	1995	262	198	535	14.1
Russia	2004	154	118	251	78.5
Saudi Arabia	2005	142	79	118	38.9
Singapore	1982	418	67	647	2.3
South Africa	1980	442	156	596	13.6
South Korea	1985	382	545	896	12816.4
Spain	1987	358	89	229	12.5
Sweden	1986	370	201	791	69.5
Switzerland	1980	442	131	274	746.1
Taiwan	1989	334	498	940	27.7
Thailand	1989	334	293	665	27.6
Turkey	1988	346	163	319	6.4
UK	1980	442	1087	3452	118.1
US	1980	442	1240	3068	25.9

Table 2: Statistics of cultural indexes

This table reports the values of Hofstede's six cultural dimensions for each country in our dataset in alphabetical order. Culture dimension scores are standardized in the way that they lay within the interval [0, 100]. We receive the data directly from Hofstede's website. The value on the Indulgence dimension is not available (NA) for Israel.

Market	Power Distance	Individualism	Masculinity	Uncertainty Avoidance	Long Term Orientation	Indulgence
Argentina	49	46	56	86	20	62
Australia	36	90	61	51	21	71
Austria	11	55	79	70	60	63
Bangladesh	80	20	55	60	47	20
Belgium	65	75	54	94	82	57
Brazil	69	38	49	76	44	59
Canada	39	80	52	48	36	68
Chile	63	23	28	86	31	68
China	80	20	66	30	87	24
Denmark	18	74	16	23	35	70
Finland	33	63	26	59	38	57
France	68	71	43	86	63	48
Germany	35	67	66	65	83	40
Greece	60	35	57	100	45	50
Hong Kong	68	25	57	29	61	17
India	77	48	56	40	51	26
Indonesia	78	14	46	48	62	38
Israel	13	54	47	81	38	NA
Italy	50	76	70	75	61	30
Japan	54	46	95	92	88	42
Malaysia	100	26	50	36	41	57
Mexico	81	30	69	82	24	97
Netherlands	38	80	14	53	67	68
New Zealand	22	79	58	49	33	75
Norway	31	69	8	50	35	55
Pakistan	55	14	50	70	50	0
Philippines	94	32	64	44	27	42
Poland	68	60	64	93	38	29
Russia	93	39	36	95	81	20
Saudi Arabia	95	25	60	80	36	52
Singapore	74	20	48	8	72	46
South Africa	49	65	63	49	34	63
South Korea	60	18	39	85	100	29
Spain	57	51	42	86	48	44
Sweden	31	71	5	29	53	78
Switzerland	34	68	70	58	74	66
Taiwan	58	17	45	69	93	49
Thailand	64	20	34	64	32	45
Turkey	66	37	45	85	46	49
UK	35	89	66	35	51	69
US	40	91	62	46	26	68

5. International Performance of Price Portfolios

In this section, we test our hypotheses regarding an international price effect (see Section 3.1). We report main performance statistics of international price portfolios – Expensive Minus Cheap (EMC) – for each country and show returns of three common risk factor mimicking portfolios, Small Minus Big (SMB), High Minus Low (HML) and Winner Minus Loser (WML) for comparison (we construct these portfolios following Fama and French, 1993 and Carhart, 1997).[24] In each month and for each country, we sort stocks by unadjusted price and assign the top 20% stocks to the Expensive (E) portfolio and the bottom 20% to the Cheap (C) portfolio. The two portfolios are equal weighted and rebalanced each month to form the EMC hedge portfolio. We use quintile breakpoints instead of, for example, decile breakpoints to ensure a sufficient number of stocks in each portfolio, especially in those countries with lower numbers of stocks and at the beginning of the sample. The returns are measured in local currencies to keep the assumed link of nominal stock prices and subsequent returns engaged.[25]

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[24] We define SMB and HML in the tradition of Fama and French (1993): we form six value-weighted intersection portfolios (present month's median market capitalization is used to get the small and big portfolio, S and B). Top 30%, middle 40% and bottom 30% of stocks ranked by book-to-market ratio (common shareholder's equity divided by market value, with values lagged six months and negative values excluded) are used to get a high (H), middle (M) and low (L) portfolio. The intersection portfolios are (initially) formed and rearranged (once) each year in June (i.e., using previous year's book-to-market ratios), whereas returns are calculated monthly. SMB is built via the difference of the average monthly returns of the three small portfolios (SL, SM, SH) and the three big portfolios (BL, BM, BH); HML incorporates the difference of the average monthly returns of the two high portfolios (SH, BH) and the two low portfolios (SL, BL). WML is the equal-weighted winner-minus-loser portfolio. Following Carhart (1997), each month t, stocks are ranked by cumulative returns from month t-12 to month t-2. Stocks in the top 30% build the winner portfolio (W) and stocks in the bottom 30% the loser portfolio (L). WML is the difference of average monthly returns of these portfolios, rearranged monthly.

[25] Anyway, other studies on international stock returns show virtually identical results for returns measured in local currencies and U.S. dollars (e.g., Ang et al., 2009; Chui et al., 2010).

Several first conclusions concerning the international price effect can be derived from Table 3:[26] First, it is not an internationally uniform investment style like value (see HML column) as EMC portfolios show (drastically) differing returns in many countries (this also holds for size; see SMB column). The momentum mimicking portfolio WML also shows, like HML, consistent positive returns, except in some Asian/Eastern countries. Examining the raw returns, we find a consistent low-price effect in Asian/Middle East countries (where at the same time, the momentum effect is remarkably weaker compared to nearly the rest of the world or even non-existent/insignificant with a few exceptions like India, Bangladesh[27] and Israel, showing the linkage of momentum and price) and a tendency toward a high-price effect for Europe (cp. also Glas et al., 2017), although the results are mainly not significant. Also striking, we find (with a t-statistic of -3.56) the most robust (low-)price effect (see also Table 4 and 5) in the US (that is getting even stronger in the newer half of our sample), which is not corresponding to the evidence of Singal and Tayal (2017)[28], but confirming the older US evidence of Blume and Husic (1973), Baytas and Cakici (1999) and Hwang and Lu (2008).

On the other hand, regarding return volatilities, our international sample shows significantly lower values for the expensive (E) portfolios compared to cheap (C) portfolios (see F-test column showing the p-values) in all countries (except Italy, Israel and South Africa),

[26] When we use a 5% market capitalization cut-off (like e.g. Ang et al., 2009 and Chui et al., 2010) instead of a 10% cut-off, performance statistics do not change in the big picture.

[27] The positive outlier for momentum in India is also documented by Ansari and Khan (2012) and Chui et al. (2010) who also document a strong momentum effect for Bangladesh and Hong Kong.

[28] Note however, that there are several differences in the research design and the used data regarding our study and Singal and Tayal (2017). For example, Singal and Tayal (2017) control for size via orthogonalization (i.e. they use residual prices) when calculating returns of price (decile) portfolios. When they do not control for size, returns of high-price and low-price portfolios are nearly identical. Also, their time frame spans the years 1963 to 2015 and includes the entire US stock universe, whereas we concentrate on NYSE stocks only. Nevertheless, Hwang and Lu (2008) confirm our results using the same data sources and nearly the same time frame (1963 to 2006) as Singal and Tayal (2017).

providing strong support of H1a. Connected to that, the Sharpe ratio equality test of Wright et al. (2014) indicates higher Sharpe ratios (in the following, we use this common term defining risk/return ratios) for the E-portfolio in most countries outside of Asia and the Middle East (column SR-test). Skewness of return values of the EMC portfolios are again quite consistent and show negative values for all but three countries and a few clear (negative) outliers. More specifically, only three countries (Norway, Bangladesh and South Africa) show higher values for skewness of returns for E-portfolios than for C-portfolios (not reported), confirming H1d.

The Euro conversion in several European countries in 1999 (except Denmark, Norway, Poland, Sweden, Switzerland and the UK) does not seem to have a (systematic) impact on the price effect: In France, Greece and Italy a price effect stays virtually non-existent in both periods (before and after 1999) and in the Netherlands the observed high-price effect remains unchanged. On the other hand, in Austria and Spain the effect reverses from a low-price to a high-price effect. Germany experiences an especially rapid inversion toward a high-price effect with a turning point around the mid-1990s, i.e. before the Euro conversion (here Hammerich et al., 2018 argue that this inversion could be amplified or even triggered due to law amendments regarding face amounts of shares in the 1990s). In Belgium, the returns of high-price portfolios increase over time (high-price effect strengthens) and Finland shows no price effect before 1999 and a clear (statistically significant) high-price effect after.

However, in Switzerland (no Euro), the respective high-price effect appears not before 1999 and is statistically significant since then (like in Finland), whereas Denmark also shows a clear inversion from a low-price to a (highly statistically significant) high-price effect, despite not being affected by a currency conversion. Poland shows a weak high-price effect in both periods and in Norway it stays unchanged (or gets slightly stronger), but insignificant. For Sweden and the UK our data indicates an intensification of the high-price effect toward statistically significant levels like in Belgium. An obvious main factor for these inversions from a low-price to a high-price effect or step-ups of the latter is the amplification of the momentum effect (and to a lower

degree the inversion of the size effect) which can be witnessed especially in several European markets of our dataset in the course of the last decades that drives up the high-price effect due to its inherent linkage. However there are also some countries (especially in Asia and the US) that contradict or attenuate this correlation and deter from concluding that price is a simple outflow or by-product of the momentum effect. We examine this in the next section.

Table 3: Performance statistics of EMC hedge portfolios and risk factor portfolios

Within each country and for each month, we rank all stocks by nominal, unadjusted price. Stocks in the top 20% are assigned to the expensive (E) portfolio and those in the bottom 20% to the cheap (C) portfolio. The portfolios are equal-weighted and (re)formed at the end of each month. The zero-cost "price" portfolio expensive-minus-cheap (EMC) is the hedge portfolio. EMC returns are calculated at the end of each month as the difference of monthly returns of the E and C portfolio, formed at the end of the prior month, respectively. Column "Return" reports the average monthly returns of the EMC hedge portfolio for each country in each (region-specific) panel. Countries in Panel F are assigned to category miscellaneous (Misc.). The other columns report t-statistics of a t-test with the null hypothesis that monthly mean returns are equal to zero (T-stat.), standard deviations of monthly returns (SD), p-values of an one-sided F-test with the null that the ratio of variances is equal to 1 (small p-values indicate that variances of C portfolios are larger than variances of E portfolios), the ratio of Return and SD (Sharpe) with negative values not reported (n/a), p-values of a Wright et al. (2014) Sharpe ratio equality test (small p-values indicate that Sharpe ratios of E portfolios are larger than Sharpe ratios of C portfolios) and skewness of returns of the EMC portfolios (Skew). The three columns on the right give average monthly returns of common risk factor portfolios mimicking the size (SMB), value (HML) and momentum (WML) effect for the purpose of comparison (see fn. 24). The longest time frame of a country-specific dataset is June 1980 to April 2017 (442 months, cp. Table 1).

	EMC							SMB	HML	WML
	Return	T-stat.	SD	F-Test	Sharpe	SR-Test	Skew	Return		
Panel A: The Americas										
North										
Canada	-0.05%	-0.22	4.99%	0.00	n/a	0.00	-0.26	0.45%	0.16%	1.42%
US	-0.78%	-3.56	4.55%	0.00	n/a	0.61	-2.22	0.35%	0.19%	0.26%
Middle & South										
Argentina	0.22%	0.42	6.71%	0.00	0.03	0.00	-2.06	0.68%	1.24%	0.34%
Brazil	0.16%	0.29	8.26%	0.00	0.02	0.00	-1.77	0.34%	0.86%	1.27%
Chile	-1.30%	-1.70	13.47%	0.00	n/a	0.00	-14.27	-0.38%	1.68%	0.46%
Mexico	-0.06%	-0.20	5.35%	0.04	n/a	0.37	-0.82	-0.31%	0.55%	1.24%
Panel B: Europe										
Austria	0.32%	0.98	6.07%	0.00	0.05	0.05	-1.36	-0.02%	1.19%	1.10%
Belgium	0.70%	2.92	4.63%	0.00	0.15	0.00	-0.60	-0.21%	0.41%	1.37%
Denmark	0.44%	1.82	4.50%	0.00	0.10	0.00	-0.33	-0.51%	0.43%	1.21%
Finland	0.50%	1.60	5.52%	0.00	0.09	0.00	-0.89	-0.03%	0.60%	1.02%
France	-0.05%	-0.27	4.12%	0.00	n/a	0.00	-0.75	0.00%	0.36%	1.23%
Germany	0.20%	0.98	4.34%	0.00	0.05	0.00	-0.91	-0.31%	0.70%	1.33%
Greece	-0.08%	-0.19	7.51%	0.00	n/a	0.12	-1.25	0.34%	0.36%	0.69%
Italy	-0.01%	-0.06	3.93%	0.08	0.00	0.41	0.14	-0.50%	0.59%	0.95%
Netherlands	0.57%	2.41	4.94%	0.00	0.12	0.00	-0.77	-0.08%	0.34%	1.31%
Norway	0.38%	1.18	6.47%	0.00	0.06	0.00	-0.58	-0.04%	0.25%	1.29%
Poland	0.16%	0.47	5.38%	0.00	0.03	0.14	-0.55	0.76%	0.57%	1.54%
Spain	0.06%	0.22	5.23%	0.00	0.01	0.06	-0.38	-0.18%	0.64%	0.95%
Sweden	0.77%	2.34	6.21%	0.00	0.12	0.00	-0.92	-0.13%	0.05%	1.24%
Switzerland	0.31%	1.66	3.92%	0.00	0.08	0.00	-0.49	-0.24%	0.32%	1.17%
UK	0.56%	2.85	4.05%	0.00	0.14	0.00	-1.02	0.14%	0.45%	1.54%

Table 3: continued.

	EMC							SMB	HML	WML
	Return	T-stat.	SD	F-Test	Sharpe	SR-Test	Skew	Return		
Panel C: Asia										
Bangladesh	0.84%	0.83	9.82%	0.00	0.09	0.06	-0.17	0.96%	-0.16%	1.39%
China	-1.21%	-2.71	7.39%	0.00	n/a	0.97	-1.20	0.61%	0.17%	0.00%
Hong Kong	0.37%	1.41	5.19%	0.00	0.07	0.00	-0.39	-0.45%	1.03%	0.78%
India	-0.61%	-1.28	8.39%	0.00	n/a	0.11	-0.95	0.70%	0.53%	1.64%
Indonesia	-1.08%	-1.52	12.32%	0.00	n/a	0.01	-4.32	0.43%	1.05%	-0.04%
Japan	-0.83%	-2.93	5.91%	0.00	n/a	0.98	-0.56	0.17%	0.59%	0.15%
Malaysia	-0.26%	-0.80	6.33%	0.00	n/a	0.11	-1.73	0.26%	0.39%	0.80%
Pakistan	-0.27%	-0.47	9.42%	0.00	n/a	0.00	-1.68	0.10%	1.00%	0.73%
Philippines	-1.27%	-2.49	8.65%	0.00	n/a	0.84	-1.45	0.19%	0.43%	0.49%
Singapore	-0.11%	-0.42	5.24%	0.00	n/a	0.26	-0.81	-0.01%	0.84%	0.74%
South Korea	-1.07%	-1.93	10.67%	0.00	n/a	0.73	-1.93	0.26%	1.35%	0.23%
Taiwan	-0.24%	-0.55	8.01%	0.01	n/a	0.60	-0.46	-0.08%	-0.05%	0.26%
Thailand	-0.77%	-1.45	9.58%	0.00	n/a	0.15	-3.47	0.22%	0.73%	0.41%
Panel D: Middle East										
Israel	-0.36%	-1.38	4.42%	0.19	n/a	0.89	-1.46	-0.06%	1.70%	1.58%
Saudi Arabia	-0.17%	-0.35	5.48%	0.00	n/a	0.62	-1.41	-0.32%	0.50%	0.07%
Turkey	-0.43%	-0.50	15.67%	0.00	n/a	0.00	-8.30	-0.69%	1.02%	-0.43%
Panel E: Oceania										
Australia	0.19%	1.18	3.40%	0.00	0.06	0.04	0.28	-0.05%	0.44%	1.36%
New Zealand	0.12%	0.50	4.17%	0.00	0.03	0.09	-0.07	-0.16%	0.96%	1.37%
Panel F: Misc.										
Russia	0.51%	0.94	6.41%	0.00	0.08	0.03	-0.91	-0.19%	1.00%	0.54%
South Africa	0.06%	0.25	5.09%	0.90	0.01	0.57	0.25	-0.12%	0.56%	1.47%

6. Common Financial Risk Factors

6.1 4-Factor Model

To investigate if common financial risk factors can explain EMC portfolio returns on country level and to test H1c, we implement a Carhart (1997) 4-factor[29] model. Table 4 shows the regression results: we regress EMC returns (for each country $j = 1, 2, \dots, 41$) on a market proxy MKT, i.e. monthly value-weighted excess returns (using short term deposit rates in local currency if available), and corresponding hedge portfolios mimicking the size (SMB), value (HML) and momentum (WML) effect:

$$rEMC_{jt} = \alpha_j + b_j MKT_{jt} + s_j SMB_{jt} + h_j HML_{jt} + w_j WML_{jt} + \varepsilon_{jt} \quad t = 1, 2, \dots, T \qquad (1)$$

We (still) find significant (mainly negative) alpha values in nine countries (US, Argentina, Mexico, France, Germany, China, the Philippines, South Korea and New Zealand) and a barely significant value in the UK. The (absolute) peak value is reported for the US, which shows a whopping 4-factor alpha t-statistic of -4.12 (with an abnormal mean return of about 5% p.a. for a cheap minus expensive hedge portfolio) and thus even more significant abnormal returns than raw returns. For Asia and the Middle East, we report mainly negative alpha values. The market beta values (coefficients of MKT) are virtually worldwide negative and show mainly significant t-

[29] A traditional 4-factor model enables us to explicitly investigate the (presumed) relevance of momentum when explaining price hedge portfolio returns as opposed to, e.g., the 5-factor model of Fama and French (2015) that leaves out the momentum factor in exchange for added investment and profitability factors. In this way, we also circumvent likely data availability and quality issues especially regarding economically less developed countries that we would face, if we constructed RMW and CMA on local (country) level (like our other factors).

statistics, which clearly confirms H1c[30] (that expensive portfolios show lower market sensitivity than cheap portfolios) and is also in line with the evidence in Table 3 that expensive (E) portfolios exhibit lower return volatility than cheap (C) portfolios. The mainly significantly negative coefficients for SMB and HML (and more precisely, unreported descriptive statistics) also indicate that around the world, on average,[31] expensive stocks are bigger stocks with lower book-to-market ratios (i.e. growth stocks) than cheap stocks. We find average momentum values however, measured by prior one year returns, to be clearly higher for expensive portfolios relative to cheap portfolios on most international markets. Hence, on the one hand, EMC portfolios (and expensive portfolios) generally exhibit a strong connection to a low market beta and the momentum effect (positive WML factors), whereas on the other hand, EMC portfolios (and expensive portfolios) are inversely linked to the size effect (negative SMB factors) and the value effect (negative HML factors). The opposite holds for cheap portfolios (on average). Effectively, this means that nearly worldwide, EMC portfolios offer solid hedge potential against systemic (market) risk and common size and value (risk) factors.

However, though common risk factors cannot thoroughly explain EMC returns and thus the price effect on specific international stock markets, EMC returns can be explained by a 4-factor model in most countries (but not nearly as much as would be expected, if the price effect was no anomaly), confirming the obvious (construction-inherent) mutual links of price with common characteristics (a follow-up study for example shows international EMC returns to explain WML returns; t-statistic >13). Then again, values for adjusted R^2 drastically differ between countries with a highest value for Chile (0.93) and a lowest value for Russia (0.04), showing a limited international efficacy of common financial risk factors when explaining EMC portfolio returns (also reflected in partly positive, but partly negatively significant alphas).

[30] Negative loadings of the country-specific EMC hedge portfolios on the market beta factor consistently go hand in hand with high(er) betas for cheap portfolios and with low(er) betas for expensive portfolios (not reported).

[31] For example, it is possible that specific low-priced, small-sized stocks also load negatively on SMB.

Table 4: 4-factor regression outcomes with EMC hedge portfolio returns as dependent variable

This table shows Carhart (1997) 4-factor regression results. We regress monthly country-specific EMC portfolio returns on four known asset-pricing risk factors. Each panel depicts a different world region (except Panel F that includes miscellaneous countries that do not fit the other categories) to facilitate comparability of the outcomes and show assumed regional dependency. MKT is the market proxy, that is, monthly value-weighted excess returns, calculated, as every other factor of the performed 4-factor regressions, for each country-specific stock universe. We use, when available, local short-term deposit rates (1M to 3M) in local currency as risk free rates (or if not available - respectively when covering only short time frames - local short-term treasury bills and equivalents) to calculate excess returns. The three columns in the middle of the table report the factor loadings/coefficients of common risk factor portfolios mimicking the size (SMB), value (HML) and momentum (WML) effect (see fn. 24). "Alpha" labels the coefficients of the regression constant. Adj. R^2 gives the value of the adjusted R^2 for each regression and T displays the available number of months for each regression with maximum (country-dependent) time frame coverage from June 1981 to April 2017 (430 months; we need an extra 12 months to calculate WML returns which reduces the effective time frame by one year). The t-statistics of each regression coefficient are reported on the right of each coefficient in italics and parentheses.

	Alpha		MKT		SMB		HML		WML		Adj. R^2	T
Panel A: The Americas												
North												
Canada	0.16%	*(0.85)*	-0.42	*(-9.97)*	-0.87	*(-14.79)*	-0.14	*(-2.96)*	0.25	*(6.32)*	0.44	430
US	-0.41%	*(-4.12)*	-0.20	*(-8.05)*	-0.92	*(-23.93)*	-0.41	*(-8.75)*	0.54	*(20.31)*	0.81	430
Middle & South												
Argentina	1.10%	*(2.39)*	-0.24	*(-4.41)*	-0.61	*(-6.92)*	-0.22	*(-3.37)*	0.25	*(2.77)*	0.30	166
Brazil	0.06%	*(0.14)*	-0.19	*(-2.01)*	-0.44	*(-3.40)*	-0.27	*(-3.27)*	0.42	*(4.21)*	0.41	114
Chile	0.40%	*(1.19)*	-0.36	*(-4.03)*	-0.32	*(-3.41)*	-0.93	*(-14.45)*	0.54	*(8.41)*	0.93	210
Mexico	-0.70%	*(-2.74)*	0.07	*(1.42)*	-0.61	*(-8.52)*	-0.31	*(-6.07)*	0.38	*(7.55)*	0.41	270
Panel B: Europe												
Austria	-0.02%	*(-0.05)*	-0.03	*(-0.39)*	-0.14	*(-1.67)*	-0.19	*(-2.79)*	0.44	*(7.18)*	0.14	310
Belgium	0.24%	*(0.94)*	-0.26	*(-4.29)*	-0.42	*(-5.73)*	-0.19	*(-3.17)*	0.42	*(7.09)*	0.27	315
Denmark	-0.19%	*(-0.88)*	-0.20	*(-3.97)*	-0.34	*(-5.61)*	-0.02	*(-0.40)*	0.50	*(9.24)*	0.29	346
Finland	0.41%	*(1.37)*	-0.25	*(-5.19)*	-0.43	*(-5.64)*	-0.09	*(-1.75)*	0.35	*(5.81)*	0.21	310
France	-0.37%	*(-2.24)*	-0.25	*(-7.68)*	-0.45	*(-9.09)*	-0.24	*(-5.66)*	0.45	*(11.56)*	0.42	430
Germany	-0.36%	*(-2.37)*	-0.31	*(-9.52)*	-0.60	*(-11.99)*	-0.15	*(-3.69)*	0.50	*(13.30)*	0.57	430
Greece	0.05%	*(0.18)*	-0.20	*(-5.59)*	-0.67	*(-15.35)*	-0.25	*(-5.36)*	0.23	*(5.40)*	0.48	334
Italy	0.10%	*(0.56)*	-0.04	*(-1.12)*	-0.22	*(-3.85)*	-0.41	*(-10.14)*	0.04	*(1.11)*	0.22	394
Netherlands	0.08%	*(0.35)*	-0.11	*(-2.41)*	-0.31	*(-6.28)*	-0.03	*(-0.79)*	0.43	*(8.27)*	0.25	430
Norway	0.03%	*(0.11)*	-0.43	*(-9.92)*	-0.69	*(-11.89)*	-0.22	*(-4.50)*	0.35	*(7.79)*	0.45	375
Poland	0.07%	*(0.22)*	-0.05	*(-1.28)*	-0.40	*(-7.09)*	-0.23	*(-4.50)*	0.36	*(6.45)*	0.30	250
Spain	-0.02%	*(-0.06)*	-0.22	*(-4.48)*	-0.69	*(-10.84)*	-0.23	*(-3.75)*	0.29	*(5.32)*	0.39	300
Sweden	0.23%	*(0.95)*	-0.12	*(-2.89)*	-0.82	*(-14.41)*	-0.03	*(-0.71)*	0.45	*(10.56)*	0.56	336
Switzerland	-0.06%	*(-0.34)*	-0.22	*(-5.54)*	-0.45	*(-8.14)*	-0.06	*(-1.21)*	0.39	*(9.18)*	0.30	430
UK	0.28%	*(1.94)*	-0.16	*(-5.35)*	-0.61	*(-18.24)*	-0.37	*(-7.07)*	0.40	*(10.91)*	0.59	430

Table 4: continued.

	Alpha		MKT		SMB		HML		WML		Adj. R^2	T
Panel C: Asia												
Bangladesh	0.27%	*(0.46)*	-0.35	*(-4.71)*	-0.16	*(-1.41)*	-0.80	*(-8.51)*	0.37	*(3.82)*	0.70	88
China	-0.95%	*(-2.85)*	-0.23	*(-7.00)*	0.08	*(1.29)*	-0.16	*(-2.90)*	1.03	*(12.50)*	0.47	274
Hong Kong	0.22%	*(1.09)*	-0.08	*(-2.99)*	-0.59	*(-15.76)*	-0.23	*(-6.08)*	-0.04	*(-1.00)*	0.41	376
India	0.04%	*(0.12)*	-0.02	*(-0.31)*	-0.74	*(-13.60)*	-0.66	*(-13.91)*	0.55	*(8.24)*	0.70	202
Indonesia	-0.33%	*(-0.79)*	-0.45	*(-7.40)*	-0.55	*(-10.40)*	-0.12	*(-2.64)*	0.89	*(15.46)*	0.74	262
Japan	-0.31%	*(-1.41)*	-0.24	*(-5.56)*	-0.59	*(-9.34)*	-0.69	*(-8.51)*	0.52	*(9.06)*	0.42	430
Malaysia	-0.06%	*(-0.27)*	-0.33	*(-9.20)*	-0.28	*(-6.00)*	-0.46	*(-8.18)*	0.33	*(7.14)*	0.51	370
Pakistan	0.64%	*(1.36)*	-0.46	*(-6.05)*	-0.43	*(-4.46)*	-0.45	*(-5.60)*	0.66	*(8.13)*	0.51	175
Philippines	-1.08%	*(-2.25)*	-0.28	*(-3.52)*	-0.41	*(-5.04)*	-0.17	*(-2.69)*	0.20	*(3.51)*	0.14	286
Singapore	0.21%	*(0.81)*	-0.19	*(-3.83)*	-0.47	*(-6.41)*	-0.15	*(-2.70)*	-0.03	*(-0.68)*	0.18	267
South Korea	-0.85%	*(-2.36)*	-0.15	*(-3.26)*	-0.57	*(-9.85)*	0.11	*(1.78)*	0.91	*(16.77)*	0.64	303
Taiwan	-0.40%	*(-1.54)*	0.09	*(2.43)*	-0.12	*(-2.18)*	-0.87	*(-20.00)*	0.47	*(9.45)*	0.66	322
Thailand	0.22%	*(0.59)*	-0.84	*(-12.83)*	-1.07	*(-12.06)*	-0.57	*(-8.63)*	0.57	*(8.47)*	0.67	248
Panel D: Middle East												
Israel	-0.46%	*(-1.83)*	0.11	*(2.06)*	-0.17	*(-3.72)*	0.04	*(1.11)*	0.02	*(0.65)*	0.12	269
Saudi Arabia	-0.05%	*(-0.16)*	-0.15	*(-3.28)*	-0.30	*(-4.66)*	-0.52	*(-5.89)*	0.58	*(7.90)*	0.51	130
Turkey	-0.06%	*(-0.14)*	-0.05	*(-1.42)*	-0.29	*(-3.97)*	-0.20	*(-3.13)*	1.15	*(30.48)*	0.80	256
Panel E: Oceania												
Australia	0.33%	*(1.72)*	-0.18	*(-4.25)*	-0.60	*(-10.04)*	-0.07	*(-1.34)*	0.10	*(2.28)*	0.33	241
New Zealand	-0.54%	*(-2.16)*	0.06	*(0.95)*	-0.29	*(-4.37)*	0.05	*(1.04)*	0.39	*(5.98)*	0.18	286
Panel F: Misc.												
Russia	0.65%	*(1.20)*	-0.03	*(-0.42)*	-0.21	*(-2.21)*	-0.18	*(-1.53)*	0.09	*(1.38)*	0.04	142
South Africa	-0.01%	*(-0.03)*	0.18	*(4.69)*	-0.47	*(-9.67)*	-0.21	*(-4.92)*	0.01	*(0.28)*	0.28	430

6.2 Fama-MacBeth Cross-Sectional Regressions

As robustness check of price's (country-specific) predictive power, Table 5 shows Fama-MacBeth (1973) rolling cross-sectional regressions results for all 41 countries. We regress next-month country-specific firm-level stock returns (r_{it+1}) on a constant, the natural logarithm of price (LN(Price)), size (LN(Size)), book-to-market ratio (LN(BTM)), prior one year return momentum (MOM) and prior three year standard deviation of returns (VOL):

$$r_{it+1} = \alpha_t + p_t LN(Price)_{it} + s_t LN(Size)_{it} + b_t LN(BTM)_{it} + m_t MOM_{it} + v_t VOL_{it} + \varepsilon_t \qquad (2)$$

where ε_t is a time-variant error term.

Although robust t-statistics (see used AR(1)-adjusted standard errors $\sigma(\bar{x})$ with ρ as first-order autocorrelation and $\sigma(x)$ as standard deviation of the respective regression coefficient x with $x \in \{\alpha, p, s, b, m, v\}$ and T as the number of months in Eq.(3) and e.g., Cochrane, 2009: 223) of our price variable are mainly insignificant, we still find significant values (at 5% confidence level) for seven countries (Australia, Belgium, Brazil, Israel, Poland, Switzerland and the most significant value for the US).[32]

[32] Note however that even an internationally very robust and consistent investment style like volatility (see, e.g., Ang et al., 2009) shows only four significant t-statistics in our regression setup. We choose total volatility instead of e.g., idiosyncratic volatility as predictor in our regressions, since these two volatility measures are very highly correlated (Ang et al., 2009). In addition, total volatility is interpretable and implementable in a more straightforward way since it is not dependent on (and sensitive to) the choice of an underlying asset pricing factor model (generating the residuals) and enables us to directly control for the low (total) volatility levels consistently found for expensive portfolios around the world (see Table 3).

$$\sigma(\bar{x}) = \frac{\sigma(x)}{\sqrt{T}} \sqrt{\frac{1+\rho}{1-\rho}} \qquad (3)$$

If these results were due to chance, on average only two significant values could be expected. Without VOL as predictor, we find t-statistics for Argentina, Hong Kong and Spain to increase above 2 (and for China to decrease below -2) whereas values for Australia and Belgium reach nearly 4, which makes these country-specific price effects very likely not a coincidence. On a regional basis our results reveal a tendency for positive values in Europe (also present if we leave out VOL) and regarding the economically most important Asian countries (China and Japan), a slight tendency for negative values in Asia. Most striking however, is once again the price effect for our US sample, as here we report the highest (absolute) t-statistic of -2.71 for our logarithmic price variable which is consistent with the findings of the preceding sections.

Table 5: Fama-MacBeth cross-sectional regression results

This table reports outcomes of rolling cross-sectional regressions: Following Eq.(2), in each month and within each country, we regress next-month firm returns (countries are clustered in regions in the table, except Panel F) on a constant; LN(Price), that is the current natural logarithm of nominal price of each firm (in country-specific major currency unit; with the prominent exception of the UK); LN(Size), that is the log market capitalization (in millions of country-specific major currency unit) of each firm at the present month; LN(BTM) (logarithm of six months lagged book-to-market ratio of each firm, updated in June each year); MOM, which is the one-year return momentum (return of each firm measured from t-12 to t-2) and VOL (prior 3-year firm-specific return standard deviation). The AR(1)-adjusted t-statistics (derived from a t-test with the null that the mean of the coefficients equals zero with an additional term when calculating standard errors that accounts for common first-order serial correlation of the coefficients, see, e.g., Cochrane, 2009 and Eq.(3)) of the respective coefficients are written on the right in italics and in parentheses. "Adj. R^2" reports the values of the average cross-sectional adjusted R^2's. The maximum effective time frame coverage of our country-specific regressions is July 1983 to April 2017 (405 months; we need an extra 36 months to calculate return volatility which reduces the effective time frame by three years and skip another month due to the prior calculation of our lagged predictors).

	Constant		LN(Price)		LN(Size)		LN(BTM)		MOM		VOL		Adj. R^2
Panel A: The Americas													
North													
Canada	0.0173	*(4.24)*	-0.0006	*(-0.56)*	-0.0008	*(-1.55)*	0.0014	*(1.68)*	0.0067	*(2.85)*	-0.0158	*(-0.97)*	0.051
US	0.0257	*(6.59)*	-0.0022	*(-2.71)*	-0.0008	*(-2.97)*	0.0005	*(1.20)*	0.0031	*(1.50)*	-0.0191	*(-1.03)*	0.048
Middle & South													
Argentina	0.0447	*(3.55)*	0.0028	*(1.58)*	-0.0024	*(-1.71)*	0.0056	*(1.78)*	-0.0064	*(-0.94)*	-0.0441	*(-1.36)*	0.059
Brazil	0.0303	*(3.32)*	0.0023	*(2.04)*	-0.0017	*(-1.99)*	0.0045	*(2.62)*	0.0039	*(0.77)*	-0.0595	*(-2.72)*	0.047
Chile	0.0237	*(2.08)*	-0.0012	*(-1.23)*	0.0002	*(0.18)*	0.0051	*(2.68)*	0.0006	*(0.10)*	-0.0337	*(-0.99)*	0.064
Mexico	0.0067	*(0.91)*	0.0006	*(0.35)*	0.0006	*(0.65)*	0.0058	*(3.61)*	0.0021	*(0.42)*	-0.0060	*(-0.15)*	0.069
Panel B: Europe													
Austria	0.0055	*(0.89)*	0.0007	*(0.54)*	0.0007	*(0.86)*	0.0029	*(2.28)*	0.0140	*(2.77)*	-0.0415	*(-1.41)*	0.088
Belgium	0.0054	*(1.40)*	0.0013	*(2.28)*	-0.0000	*(-0.05)*	0.0030	*(3.34)*	0.0136	*(3.77)*	-0.0366	*(-1.35)*	0.065
Denmark	0.0053	*(0.87)*	-0.0002	*(-0.38)*	0.0008	*(1.28)*	0.0028	*(1.97)*	0.0117	*(3.65)*	-0.0245	*(-1.11)*	0.050
Finland	0.0116	*(1.69)*	0.0013	*(1.17)*	-0.0007	*(-0.81)*	0.0002	*(0.18)*	0.0119	*(2.96)*	-0.0125	*(-0.35)*	0.086
France	0.0144	*(3.41)*	0.0005	*(0.90)*	-0.0006	*(-1.05)*	0.0016	*(1.84)*	0.0094	*(4.04)*	-0.0150	*(-1.11)*	0.047
Germany	0.0113	*(2.86)*	-0.0001	*(-0.11)*	0.0000	*(0.02)*	0.0011	*(1.55)*	0.0102	*(4.28)*	-0.0202	*(-1.03)*	0.049
Greece	0.0209	*(1.85)*	0.0013	*(0.82)*	-0.0014	*(-0.97)*	0.0028	*(1.90)*	0.0035	*(0.69)*	-0.0590	*(-2.48)*	0.088
Italy	0.0064	*(1.43)*	-0.0004	*(-0.54)*	0.0006	*(1.20)*	0.0015	*(1.60)*	0.0078	*(1.75)*	-0.0381	*(-1.31)*	0.063
Netherlands	0.0094	*(2.04)*	0.0009	*(1.11)*	-0.0002	*(-0.37)*	0.0022	*(2.30)*	0.0122	*(3.64)*	-0.0236	*(-0.65)*	0.077
Norway	0.0129	*(1.76)*	0.0005	*(0.40)*	-0.0006	*(-0.64)*	0.0040	*(2.06)*	0.0069	*(1.85)*	0.0159	*(0.71)*	0.068
Poland	0.0093	*(0.81)*	0.0029	*(2.05)*	-0.0037	*(-3.43)*	0.0022	*(1.24)*	0.0041	*(0.80)*	0.0763	*(1.55)*	0.052
Spain	0.0103	*(1.95)*	0.0011	*(1.27)*	0.0000	*(0.01)*	0.0015	*(1.63)*	0.0096	*(1.77)*	-0.0471	*(-1.65)*	0.094
Sweden	0.0070	*(0.87)*	0.0020	*(1.63)*	-0.0007	*(-1.11)*	-0.0001	*(-0.12)*	0.0087	*(2.32)*	-0.0106	*(-0.39)*	0.068
Switzerland	0.0013	*(0.32)*	0.0008	*(2.09)*	0.0002	*(0.59)*	0.0020	*(2.74)*	0.0130	*(4.35)*	-0.0105	*(-0.29)*	0.061
UK	0.0140	*(3.23)*	-0.0002	*(-0.37)*	-0.0004	*(-0.85)*	0.0021	*(3.14)*	0.0097	*(5.73)*	-0.0091	*(-0.76)*	0.033

Table 5: continued.

	Constant		LN(Price)		LN(Size)		LN(BTM)		MOM		VOL		Adj. R^2
Panel C: Asia													
Bangladesh	0.0076	*(0.18)*	0.0029	*(0.65)*	-0.0004	*(-0.17)*	-0.0008	*(-0.21)*	0.0068	*(0.80)*	-0.0955	*(-1.13)*	0.171
China	0.0668	*(3.64)*	-0.0060	*(-1.63)*	-0.0050	*(-3.27)*	-0.0034	*(-1.25)*	0.0058	*(1.27)*	-0.0178	*(-0.94)*	0.074
Hong Kong	0.0258	*(2.68)*	0.0005	*(0.41)*	-0.0007	*(-0.67)*	0.0049	*(3.64)*	0.0041	*(1.32)*	-0.0469	*(-2.08)*	0.064
India	0.0328	*(2.77)*	0.0011	*(1.08)*	-0.0025	*(-2.77)*	0.0016	*(1.06)*	0.0083	*(2.95)*	0.0190	*(1.18)*	0.062
Indonesia	0.0436	*(1.41)*	0.0026	*(0.95)*	-0.0030	*(-1.99)*	0.0040	*(1.82)*	-0.0043	*(-1.25)*	-0.0057	*(-0.37)*	0.046
Japan	0.0256	*(2.75)*	-0.0017	*(-1.37)*	-0.0005	*(-0.82)*	0.0027	*(4.18)*	-0.0009	*(-0.37)*	-0.0061	*(-0.37)*	0.080
Malaysia	0.0245	*(2.80)*	0.0013	*(0.64)*	-0.0020	*(-1.70)*	0.0034	*(2.63)*	0.0079	*(2.20)*	-0.0251	*(-1.18)*	0.078
Pakistan	0.0287	*(2.50)*	0.0014	*(0.73)*	-0.0013	*(-1.16)*	0.0044	*(2.20)*	0.0058	*(1.74)*	-0.0057	*(-0.24)*	0.083
Philippines	0.0324	*(2.31)*	0.0016	*(1.30)*	-0.0027	*(-1.56)*	0.0009	*(0.46)*	-0.0018	*(-0.25)*	0.0083	*(0.32)*	0.045
Singapore	0.0189	*(2.19)*	-0.0005	*(-0.29)*	-0.0007	*(-0.57)*	0.0011	*(0.81)*	0.0150	*(3.39)*	-0.0712	*(-1.77)*	0.087
South Korea	0.0375	*(1.28)*	0.0001	*(0.05)*	-0.0019	*(-1.54)*	0.0039	*(2.66)*	-0.0022	*(-0.92)*	-0.0327	*(-1.70)*	0.094
Taiwan	0.0154	*(1.06)*	-0.0025	*(-0.66)*	-0.0002	*(-0.21)*	-0.0012	*(-0.43)*	0.0050	*(1.09)*	-0.0190	*(-0.64)*	0.102
Thailand	0.0129	*(1.19)*	0.0002	*(0.08)*	0.0001	*(0.06)*	0.0055	*(3.08)*	-0.0009	*(-0.27)*	-0.0102	*(-0.43)*	0.067
Panel D: Middle East													
Israel	0.0136	*(0.93)*	-0.0025	*(-2.15)*	-0.0001	*(-0.07)*	0.0094	*(1.68)*	0.0137	*(2.00)*	0.0364	*(0.46)*	0.060
Saudi Arabia	0.0158	*(0.93)*	0.0029	*(0.95)*	-0.0008	*(-0.61)*	0.0071	*(2.21)*	-0.0013	*(-0.17)*	-0.1485	*(-2.05)*	0.130
Turkey	0.0488	*(3.32)*	-0.0038	*(-0.85)*	-0.0032	*(-2.06)*	0.0025	*(0.70)*	-0.0026	*(-0.55)*	0.0245	*(0.69)*	0.045
Panel E: Oceania													
Australia	0.0193	*(4.54)*	0.0021	*(2.41)*	-0.0011	*(-2.04)*	0.0026	*(2.41)*	0.0100	*(4.07)*	-0.0538	*(-1.60)*	0.070
New Zealand	0.0112	*(1.84)*	0.0004	*(0.27)*	0.0001	*(0.19)*	0.0039	*(2.48)*	0.0172	*(3.84)*	-0.0250	*(-0.44)*	0.061
Panel F: Misc.													
Russia	0.0120	*(0.79)*	0.0010	*(0.95)*	-0.0013	*(-1.04)*	-0.0010	*(-0.40)*	-0.0070	*(-1.05)*	0.0005	*(0.01)*	0.036
South Africa	0.0165	*(2.22)*	-0.0007	*(-0.92)*	0.0004	*(0.52)*	0.0027	*(2.75)*	0.0074	*(2.07)*	-0.0225	*(-0.65)*	0.080

7. Culture, Price and Stock Returns

The previous sections point to a large diversity of the existence, magnitude, direction and robustness of the price effect across the tested countries that is not consistently explained by standard finance models. In this section, we test our main hypothesis H2 (and our respective culture dimension related sub hypotheses from Section 3.2), that price is connected with culture, since cultural characteristics and differences are known to be comparably stable over time and are also major macro-social drivers that influence attitudes, values, beliefs, behaviors, practices and actions of a whole population (e.g., Hofstede et al., 2010) having a permanent impact on investment decisions and the efficacy of associated investment styles (see, e.g., Chui et al., 2010).

7.1 World Regions and Common Cultural Characteristics

At first, Table 6 presents the values of Hofstede's six cultural dimensions for all countries in our dataset sorted by world region.[33] We calculate the means and standard deviations of the six cultural dimensions for each world region (except for those countries sorted in the category miscellaneous) to give a quick impression of the main differences and commonalities among the regions, as this helps to interpret our main results regarding the culture dimensions and the connection to the price effect (Sections 7.2 to 7.4). Most striking is the difference in the dimension Individualism between Asian and Western developed countries. High values on this scale depict individualistic countries, whereas countries ranked low on this index are collectivistic. Other remarkable patterns are that many Asian, respectively less developed countries show high

[33] For example, what (all) American countries have in common is that they experienced substantial immigration especially from European countries. On the other hand, the American cultures where influenced far longer by natives than the European cultures. Maybe this is reflected by the very similar, consistently low values for Long Term Orientation (indicating more traditional societies) as opposed to the clearly higher LTO values found in Europe.

Power Distance values as opposed to developed countries (e.g., all English-speaking countries) and that Asian cultures are generally going hand in hand with restrained societies (see, e.g., Hofstede et al., 2010).

Table 6: Culture indexes and commonalities among world regions

In this table, we structure Hofstede's culture dimension values (presented in Table 2) for each country by region-specific clusters (Panel A to E; Panel F contains miscellaneous countries). We report average values (row "Mean") for each world region alongside standard deviations (row "Standard Dev.") in italics to facilitate comparability between regional clusters.

Market	Power Distance	Individualism	Masculinity	Uncertainty Avoidance	Long Term Orientation	Indulgence
Panel A: The Americas						
North						
Canada	39	80	52	48	36	68
US	40	91	62	46	26	68
Mean	*39.5*	*85.5*	*57.0*	*47.0*	*31.0*	*68.0*
Standard Dev.	*0.7*	*7.8*	*7.1*	*1.4*	*7.1*	*0.0*
Middle & South						
Argentina	49	46	56	86	20	62
Brazil	69	38	49	76	44	59
Chile	63	23	28	86	31	68
Mexico	81	30	69	82	24	97
Mean	*65.5*	*34.3*	*50.5*	*82.5*	*29.8*	*71.5*
Standard Dev.	*13.3*	*9.9*	*17.1*	*4.7*	*10.5*	*17.4*
Panel B: Europe						
Austria	11	55	79	70	60	63
Belgium	65	75	54	94	82	57
Denmark	18	74	16	23	35	70
Finland	33	63	26	59	38	57
France	68	71	43	86	63	48
Germany	35	67	66	65	83	40
Greece	60	35	57	100	45	50
Italy	50	76	70	75	61	30
Netherlands	38	80	14	53	67	68
Norway	31	69	8	50	35	55
Poland	68	60	64	93	38	29
Spain	57	51	42	86	48	44
Sweden	31	71	5	29	53	78
Switzerland	34	68	70	58	74	66
UK	35	89	66	35	51	69
Mean	*42.3*	*66.9*	*45.3*	*65.1*	*55.5*	*54.9*
Standard Dev.	*18.0*	*13.0*	*25.4*	*24.3*	*16.2*	*14.7*

Table 6: continued.

Market	Power Distance	Individualism	Masculinity	Uncertainty Avoidance	Long Term Orientation	Indulgence
Panel C: Asia						
Bangladesh	80	20	55	60	47	20
China	80	20	66	30	87	24
Hong Kong	68	25	57	29	61	17
India	77	48	56	40	51	26
Indonesia	78	14	46	48	62	38
Japan	54	46	95	92	88	42
Malaysia	100	26	50	36	41	57
Pakistan	55	14	50	70	50	0
Philippines	94	32	64	44	27	42
Singapore	74	20	48	8	72	46
South Korea	60	18	39	85	100	29
Taiwan	58	17	45	69	93	49
Thailand	64	20	34	64	32	45
Mean	*72.5*	*24.6*	*54.2*	*51.9*	*62.4*	*33.5*
Standard Dev.	*14.4*	*11.1*	*15.2*	*24.0*	*23.9*	*15.8*
Panel D: Middle East						
Israel	13	54	47	81	38	NA
Saudi Arabia	95	25	60	80	36	52
Turkey	66	37	45	85	46	49
Mean	*58.0*	*38.7*	*50.7*	*82.0*	*40.0*	*50.5*
Standard Dev.	*41.6*	*14.6*	*8.1*	*2.6*	*5.3*	*2.1*
Panel E: Oceania						
Australia	36	90	61	51	21	71
New Zealand	22	79	58	49	33	75
Mean	*29.0*	*84.5*	*59.5*	*50.0*	*27.0*	*73.0*
Standard Dev.	*9.9*	*7.8*	*2.1*	*1.4*	*8.5*	*2.8*
Panel F: Misc.						
Russia	93	39	36	95	81	20
South Africa	49	65	63	49	34	63

7.2 Double Sorts on Cultural Dimensions and Price

As a first straightforward, nonparametric test of our hypotheses regarding the connection of the price effect and the proposed cultural dimensions (cp. Section 3.2), we perform independent double sorts (see Table 7). We use our country-specific price quintile portfolios (E and C) of Section 5 and generate equal-weighted returns of these portfolios in each month across all active (that is yielding non-NA returns) countries that at the same time have to be constituents of one of our three portfolios given each cultural dimension (we add results on the Power Distance dimension for the sake of completeness): Every country is either sorted in the Low (bottom 30%), High (top 30%) or Middle (neither top, nor bottom; i.e. middle 40%) category in respect to its value on any of the six cultural dimensions, respectively. Given these portfolios, we form 3 x 2 (6) intersection portfolios regarding each cultural dimension (Panels A to F in Table 7). We additionally construct hedge portfolios based on every portfolio sorted into the Expensive and Cheap category (E minus C) and High and Low category (portfolios with High value on cultural dimension minus portfolios with low value on cultural dimension), respectively. At last we add – also to check if our results are consistent – the hedge portfolio (or simply put the return spread) of the hedge portfolios (see bottom right corner in each Panel of Table 7).

Not surprisingly, we find the most consistent results regarding our hypothesis of the link of Individualism and Price (H2a). Panel B of Table 7 shows that E-portfolios from collectivistic countries (low Individualism score) significantly underperform C-Portfolios from those countries (low-price effect). The respective (E minus C) hedge portfolio shows a significantly negative average return of -0.44% per month with a t-statistic of -2.54. On the other hand, E-portfolios from individualistic countries (high Individualism score) outperform C-portfolios (average monthly return of 0.22%, t-statistic 1.93) which results in an average monthly return spread of 0.69% (t-statistic of 3.73), showing clear evidence for a high-price effect in (more) individualistic countries and thereby underlining the results of Chui et al. (2010) regarding a concurrent

momentum effect associated with an (increasingly) individualistic culture. In respect to Uncertainty Avoidance (Panel D) and Indulgence (Panel F), we find (only) one side of our hypotheses (H2e and H2b) confirmed: C-portfolios perform better than E-portfolios (low-price effect) in countries with high scores on Uncertainty Avoidance and low values for Indulgence. However, the displayed t-statistics are highly significant with (absolute) values around 3 and the hedge portfolio return spread in Panel F shows like for Individualism a highly significant value (average monthly return of 0.58% with a t-statistic of 3.73). Panel C additionally underpins hypothesis H2c as we find that masculine cultures tend to result in a low-price effect. For H2d (connection of Long Term Orientation and Price), we find mixed, respectively all in all no evidence, since results on the one hand confirm our hypothesis, but on the other hand contradict it (however both on insignificant levels, see Panel E). Interestingly, for Power Distance (Panel A) we find some significant evidence that low values are connected to a high-price effect and high values correlate with a low-price effect. Possible explanations for this finding are difficult and would be ad hoc, since we initially abstained from hypothesizing due to the lack of a well-founded relationship between the properties of this cultural dimension and a possible price effect. However, as we show in the next sections, when controlled for the other cultural dimensions and additional control variables, the connection between Power Distance and Price turns out to be not robust.

In general, we find high-price (E) portfolios to have (clearly) higher t-statistics than low-price portfolios despite several cases in which C-portfolios yield significantly higher mean returns. This is once again due to one of our main findings in Section 5 that E-portfolios' returns are less volatile than C-portfolios' returns.

7.3 Fama-MacBeth EMC Hedge Portfolio Regressions

In this section we step up and examine possible international determinants of the price effect by performing Fama-MacBeth (1973) regressions. We choose a lag structure for our regression equation (Eq. 4), that is, we regress one month ahead Expensive minus Cheap (EMC) hedge portfolio returns of our j ($j = 1, 2, \dots, 41$) countries ($rEMC_{jt+1}$) on the six cultural dimensions of Hofstede et al. (2010), common financial risk factors and a national wealth proxy. This enables us to additionally test the predictive power (and not only the explanatory power, since we already investigated that in Section 6) of SMB, HML and WML in a meaningful way:

$$rEMC_{jt+1} = \alpha + DIM_j d + RISKCON_{jt} c + gGDPpc_j + \varepsilon_{jt} \quad (4)$$

where α is the regression constant, DIM_j is a vector of the six (time-invariant) cultural dimensions Power Distance (PD), Individualism (INDIV), Masculinity (MASC), Uncertainty Avoidance (UA), Long Term Orientation (LTO) and Indulgence (INDUL) and $RISKCON_{jt}$ is a vector of three (time-varying) financial risk factor control variables, that is the factor-mimicking portfolios for the size (SMB), value (HML) and momentum effect (WML). $GDPpc_j$ is the value of the GDP per capita (in U.S. dollars) for each country j in 1980[34] and ε_{jt} is a time-varying error

[34] We use the (time-invariant) GDP per capita value of 1980 instead of a time series of yearly GDP per capita data due to three reasons: First, we would have a nonstationarity problem in our regressions when using time series data, since GDP per capita values are clearly increasing worldwide over time. Second, we do not want to mitigate this problem via a stationary GDP per capita growth variable since this would only be a second-rank proxy of national wealth that is reliably connected to the values of Long Term Orientation, only (Hofstede et al. 2010). Third, Hofstede et al. (2010) also apply comparable data as national wealth proxy since they find many correlations between their cultural dimensions and national wealth being strongest when using GNI per capita values at the time of the IBM study, i.e. around 1970 (and thus the same time the data for the construction of the initial four cultural dimensions was collected). For example, Hofstede et al. (2010) find that GNI per capita explains 71% of the

term. We calculate the t-statistics using the same procedure as depicted in Section 6.2 and Eq. (3) (first-order autocorrelation robust t-statistics).

Table 8 reports the results of these EMC Fama-Macbeth regressions. We find Panel A (Model 1 to 6) to show consistent evidence regarding our double sorts (Table 7) on cultural dimensions and price portfolios and confirm all our hypotheses (H2a, H2b, H2c, H2e) apart from H2d regarding the connection of LTO and a price effect. All cultural dimensions apart from LTO can predict (and explain) EMC returns on their own on significant levels (with the clearly strongest single predictor being INDIV, which once again underlines the evidence of Chui et al., 2010). MASC proves to be the most robust cultural predictor of EMC returns, since it stays significant in virtually all performed regressions. The factor-mimicking portfolio for the value effect (HML) is another strong predictor of one-month ahead EMC returns in our global sample and is significant throughout all regression configurations: the stronger the value effect, that is, the higher the HML return in the preceding month, the lower (on average) are subsequent EMC returns (i.e., weaker high-price effect and stronger low-price effect). SMB returns affect EMC returns in the same direction (weak size effect associated with strong high-price effect in the next month and vice versa) and WML returns in the opposite direction (strong momentum effect leads to strong high-price effect and vice versa). However, for SMB and WML the effects are not significant[35] (see Panel B). These results are consistent with our evidence in Section 6.1 where we

differences in Individualism scores for the initial fifty countries of the IBM study and that the GNI per capita of 1970 is an important predictor for Power Distance values (poorer countries are associated with higher PD values and vice versa). We use the country-specific GDP per capita values of 1980 since this is the earliest date in our dataset received from the IMF website (http://www.imf.org/external/pubs/ft/weo/2017/01/weodata/index.aspx) and our main datasets also start in 1980. Additionally, the first book of Hofstede on his four initial cultural dimensions was also published in that year (Hofstede 1980), so we limit the possibility of some kind of forward looking bias. We get data for all 41 countries except for Russia.

[35] When we regress one-month ahead WML returns on EMC returns though, we get a significant t-statistic (2.12). Consequently, EMC returns are a significant predictor of WML returns on cross-country level, but not vice versa.

find EMC returns to load negatively on SMB and HML, but positively on WML and coherent with the inherent connections of price, size, value and momentum outlined in Section 2.1.

However, also the GDP per capita of 1980 is capable of predicting the magnitude of EMC returns on significant levels alone (Panel C) and is an important control variable when it comes to our cultural dimensions, since it affects the coefficients of our cultural variables (and to a lesser extent that of the risk factor controls), leaving the cultural connections of the price effect engaged though when looking at our most comprehensive models (Panel D in Table 8).

We find the documented cultural connections of the price effect to hold also – or being even clearer pronounced – on global firm-specific levels, where the "cultural price effect" is very robust and persistent in presence of financial control variables and GDP per capita. In the next, final section, we investigate this important remaining issue profoundly and also show a direct connection of global stock returns and cultural dimensions irrespective of a price effect.

Table 7: Price profits and cultural dimensions

In this table, we present outcomes of (independent) double sorts on (country-level) top and bottom quintile price portfolios (see columns Expensive and Cheap) and three categories regarding the (country-specific) values on any cultural dimension (bottom 30%: Low, middle 40%: Medium and top 30%: High), respectively. We display the respective results for each cultural dimension and structure them by using panels (Panel A to F). Country-average monthly returns of the intersection portfolios across all (active) countries in our sample (test period is from June 1981 to April 2017) are presented in the upper line of each segment alongside t-statistics (below in italics and parentheses). In the right column and the bottom row of every panel, we report the statistics for the hedge portfolios (E minus C; High minus Low). In the bottom right segment we give statistics for the hedge portfolio return spread.

Panel A: Power Distance and Price	Price Portfolios		
Index on Power Distance	Expensive (E)	Cheap (C)	E minus C
Low	1.19%	0.90%	0.29%
	(6.87)	*(3.99)*	*(2.53)*
Medium	1.55%	1.92%	-0.37%
	(8.37)	*(7.98)*	*(-2.71)*
High	1.56%	1.82%	-0.26%
	(6.93)	*(6.12)*	*(-1.82)*
High minus Low	0.37%	0.92%	-0.55%
	(2.41)	*(4.05)*	*(-3.39)*

Panel B: Individualism and Price	Price Portfolios		
Index on Individualism	Expensive (E)	Cheap (C)	E minus C
Low	1.26%	1.70%	-0.44%
	(5.66)	*(5.38)*	*(-2.54)*
Medium	1.65%	1.88%	-0.22%
	(8.02)	*(7.75)*	*(-1.69)*
High	1.20%	0.99%	0.22%
	(7.08)	*(4.28)*	*(1.93)*
High minus Low	-0.07%	-0.77%	0.69%
	(-0.43)	*(-2.94)*	*(3.73)*

Panel C: Masculinity and Price	Price Portfolios		
Index on Masculinity	Expensive (E)	Cheap (C)	E minus C
Low	1.72%	1.76%	-0.04%
	(8.59)	*(6.57)*	*(-0.28)*
Medium	1.39%	1.39%	0.00%
	(6.97)	*(4.95)*	*(0.01)*
High	1.14%	1.30%	-0.16%
	(6.49)	*(6.20)*	*(-1.72)*
High minus Low	-0.58%	-0.46%	-0.12%
	(-4.20)	*(-2.65)*	*(-0.85)*

Panel D: Uncertainty Avoidance and Price	Price Portfolios		
Index on Uncertainty Avoidance	Expensive (E)	Cheap (C)	E minus C
Low	1.40%	1.50%	-0.10%
	(7.34)	*(6.00)*	*(-0.91)*
Medium	1.23%	1.12%	0.11%
	(6.78)	*(4.84)*	*(0.97)*
High	1.63%	2.04%	-0.41%
	(8.28)	*(7.95)*	*(-2.73)*
High minus Low	0.23%	0.54%	-0.31%
	(1.49)	*(2.49)*	*(-1.92)*

Panel E: Long Term Orientation and Price	Price Portfolios		
Index on Long Term Orientation	Expensive (E)	Cheap (C)	E minus C
Low	1.35%	1.48%	-0.13%
	(7.95)	*(6.62)*	*(-1.05)*
Medium	1.81%	1.81%	-0.01%
	(8.37)	*(6.48)*	*(-0.05)*
High	1.16%	1.31%	-0.15%
	(6.16)	*(5.37)*	*(-1.37)*
High minus Low	-0.19%	-0.17%	-0.02%
	(-1.59)	*(-1.00)*	*(-0.15)*

Panel F: Indulgence and Price	Price Portfolios		
Index on Indulgence	Expensive (E)	Cheap (C)	E minus C
Low	1.33%	1.80%	-0.47%
	(6.88)	*(7.07)*	*(-3.40)*
Medium	1.65%	1.68%	-0.03%
	(7.77)	*(6.06)*	*(-0.20)*
High	1.26%	1.15%	0.11%
	(7.71)	*(5.38)*	*(0.99)*
High minus Low	-0.07%	-0.65%	0.58%
	(-0.60)	*(-3.43)*	*(3.73)*

Table 8: Determinants and predictors of cross-country EMC returns: Fama-MacBeth regressions results

We regress, each month, one-month ahead country-specific EMC (Expensive minus Cheap) hedge portfolio returns on a constant, the six cultural dimensions of Hofstede et al., the (previous month) returns of three (country-level) factor-mimicking portfolios for the size (SMB), value (HML) and momentum effect (WML) and a national wealth proxy (GDP per capita of 1980: GDPpc). The regressions start in June 1981 and end in April 2017. We divide the results in four panels (Panel A to D) and up to seven tested models, depending on the included determinants and predictors. Panel D incorporates all variables. The top line of each row gives mean values of the coefficients across all performed regressions, the bottom line reports first-order autocorrelation robust t-statistics (in italics and parentheses; cp. Sect. 6.2 and Eq. (3)). Right down at the bottom, we display average values for adjusted R-squares.

	Panel A: Cultural Dimensions							*Panel B: Common Risk Factors*				*Panel C: Develop-ment*	*Panel D: Comprehen-sive*		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)		(1)	(2)	(3)
Constant	0.00445 *(2.35)*	-0.00715 *(-2.89)*	0.00316 *(1.47)*	0.00217 *(1.17)*	0.00153 *(0.74)*	-0.00683 *(-2.78)*	0.00531 *(0.63)*	-0.00075 *(-0.66)*	-0.00013 *(-0.12)*	-0.00113 *(-0.97)*	-0.00033 *(-0.29)*	-0.00477 *(-2.44)*	0.00986 *(1.15)*	0.00198 *(0.20)*	0.00409 *(0.52)*
PD	-0.00010 *(-3.02)*						-0.00001 *(-0.28)*						-0.00007 *(-0.99)*	-0.00001 *(-0.13)*	0.00001 *(0.15)*
INDIV		0.00012 *(3.36)*					0.00007 *(1.00)*						0.00006 *(0.78)*	0.00004 *(0.68)*	0.00012 *(1.92)*
MASC			-0.00008 *(-2.61)*				-0.00007 *(-2.34)*						-0.00008 *(-2.12)*	-0.00005 *(-1.64)*	-0.00008 *(-2.19)*
UA				-0.00006 *(-2.15)*			-0.00006 *(-1.39)*						-0.00002 *(-0.56)*	-0.00004 *(-0.69)*	-0.00006 *(-1.37)*
LTO					-0.00004 *(-1.37)*		0.00001 *(0.21)*						-0.00004 *(-0.93)*	-0.00001 *(-0.18)*	-0.00002 *(-0.37)*
INDUL						0.00011 *(2.90)*	-0.00002 *(-0.39)*						-0.00003 *(-0.44)*	-0.00002 *(-0.23)*	-0.00009 *(-1.20)*
SMB								-0.02372 *(-1.44)*			-0.01218 *(-0.66)*		-0.03562 *(-1.60)*		-0.04670 *(-1.83)*
HML									-0.03970 *(-2.09)*		-0.03796 *(-1.98)*		-0.05753 *(-2.69)*		-0.06597 *(-2.87)*
WML										0.01853 *(0.95)*	0.02014 *(0.98)*		0.03184 *(1.21)*		0.02126 *(0.67)*
GDPpc												0.00000 *(3.13)*		0.00000 *(1.11)*	0.00000 *(0.85)*
Adj. R-sq.	0.0082	0.0153	0.0063	0.0007	0.0015	0.0029	0.0324	0.0207	0.0252	0.0242	0.0640	0.0238	0.1019	0.0346	0.1115

7.4 Global Panel Regressions

Table 9 reports results of pooled OLS panel regressions[36] of global firm-specific returns (r_{it+1}) as dependent variable and various lagged predictors (lag-1 respectively), including $Price$, financial control variables $FINCON_k$ (Size, LN(BTM) and MOM; $k = 1, \dots, K; K = 3$), our development/national wealth proxy GDP per capita (in U.S. dollars) of 1980 ($GDPpc$), the six ($l = 1, \dots, L; L = 6$) time-invariant[37] cultural dimensions of Hofstede (DIM_l) and price interaction effects ($Price * DIM_l$)

$$r_{it+1} = \alpha + pPrice_{it} + FINCON'_{it}c + DIM'_i d + (Price_{it} * DIM'_i)x + gGDPpc_i + u_{it} \quad (5)$$

where α is the intercept, c is a K-dimensional column vector of parameters, d and x are L-dimensional column vectors of parameters and $FINCON'_{it}$ and DIM'_i is a K-dimensional row vector of time-varying financial controls and a L-dimensional row vector of time-invariant cultural dimensions, respectively. $Price_{it}$ is our rank-scaled[38] price variable (with parameter p), $GDPpc_i$ is the used national wealth proxy (parameter g) and u_{it} is an idiosyncratic error term.

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[36] We choose this model, since the fulfillment of one of the unrelatedness assumptions *specific to* the random effects model (firm-specific effects uncorrelated with explanatory variables, i.e. a random variable) is questionable in our datasets and the appliance of this model is common in related literature (see, e.g. Chui et al., 2010). In general, panel regressions enable us to investigate one important remaining research question relating the connection of price, culture and firm-specific stock returns in an ideal way. Since standard finance asset pricing literature mainly uses basic OLS regressions, we initially follow the established methodology in Section 6 and 7. These panel regressions also serve as robustness tests for our preliminary results of the previous sections.

[37] The fixed effects model is not an option here, since it cancels all time-invariant regressors.

[38] We apply (for each country) a normalized ranking scale (values between 0 and 1) on country-specific (i.e., currency-dependent) values of Price and Size to get values that are both currency-independent (important for global comparability of Price and Size values) and restricted to a common scale: We separately rank each stock in each

One of the six cultural variables Power Distance (PD), Individualism (INDIV), Masculinity (MASC), Uncertainty Avoidance (UA), Long Term Orientation (LTO) and Indulgence (INDUL) – LTO – shows significant coefficients (measured by cluster-robust t-statistics with the time-specific identifier as cluster and with time (month) dummies; respective results for firm clusters and time clusters without time dummies, respectively[39] are reported in Appendix A) in all regressions.[40] Reflecting our diverse and often diametrically opposed results in the previous sections, a general, global price effect is not detectable in the majority of the performed panel regressions (see row "Price"), even when not including financial and cultural control variables as well as price and culture dimensions interaction effects (see Model 1 in Table 9).[41] On the other hand, the low variation in the coefficients and (constantly significant) t-statistics of the three financial control variables (see Model 2 and 4 to 6 in Table 9) regardless of the added cultural dimensions and interaction effects shows that cultural dimensions and financial variables unlikely capture the same return predicting/asset pricing (risk) factors. Only

country by Price and Size (bottom-up) and divide this rank by the total number of active stocks in each month. This standardized scaling also ensures that our results (regarding Size) are not driven by country samples with many internationally prominent high-cap stocks like in the US.

[39] Note that time clusters (by month) generally reduce the significance of the t-statistics in our panel regressions clearly (cp. results of A.1 and A.2 in Appendix A). Regarding the connection of price and culture dimensions, when using firm clusters, we get significant values for the interaction effects of Price with four cultural dimensions and for all cultural dimensions in the culture variables only model (Model 3). The results with time clusters but without time dummies (Table A.1) however are very similar to the outcomes in Table 9. T-statistics for LTO and Price x INDIV and Price x MASC interactions effects prove to be very robust throughout all regression configurations.

[40] An implementation of an alternative random effects model (with time/firm clusters; with or w/o time dummies), a look at standard t-statistics, using unwinsorized data and non-lagged independent variables as robustness tests does not change the results concerning the price effect, the impact of cultural variables and our conclusions materially.

[41] The significance of "Price" is particularly determined by the inclusion of financial control variables, getting insignificant again when including price and culture dimensions interaction effects.

the momentum characteristic shows some sensitivity when including the cultural dimensions, reflected in a (slightly) lower t-statistic and value of the coefficient.

We derive two main conclusions regarding our main hypothesis H2 (culture and price are linked), our sub hypotheses and the connection of stock returns and culture in general:[42] First, two cultural dimensions (LTO and INDUL) show some robust predictive power for global firm-level returns (although the values of the cultural dimensions are time-invariant) in our culture dimensions only model (and after controlling for the mentioned investment styles). Second, in conjunction with price, two other dimensions show additional predictive power (see significant t-statistics of the interaction terms and lasting robust coefficients and t-statistics of Price x INDIV and Price x MASC after controlling for GDPpc). In these regression setups (Model 5 and 6) also LTO is a marginally significant predictor when interacting with Price. Specifically, in this panel regression setup, three of our sub hypotheses (H2a, H2c and less clearly H2d) are confirmed: high individualism values foster the strength of the (high-) price effect in a global context (see robust t-statistics above 2.80 for Price x INDIV for Models 5 and 6 in Table 9), clearly supporting H2a and the assumed link of the common cultural origin of the (high-)price and momentum effect, which is also stronger in highly individualistic (Western) countries and weaker in collectivistic (Asian) countries (Chui et al., 2010). We additionally identify the cultural dimension Masculinity to be especially strongly connected with price, showing similar absolute values of robust t-statistics as Individualism (below -3.11) when multiplied with our ranking-scaled price variable. LTO displays to be a marginally important predictor in conjunction with price (t-statistics around 1.70) as well. Thus, on a global cross-sectional level, high values of Masculinity weaken a (high-)price effect, whereas high levels of LTO strengthen it (and vice

[42] We suppose however, that culture per se is very likely to be the main effect, as it is a very general, stable and far-reaching macro-social driver.

versa),[43] confirming H2c and H2d.[44] Also striking is that Price becomes completely insignificant (t-statistic falls from 2.03 to virtually zero) when including the price and culture dimensions interaction effects (cp. Models 4 to 6). That is, a general global high-price effect evident in Model 4 is completely attributable to cultural effects. With respect to the connection of UA and INDUL to price, our hypothesis H2e is also underpinned (correct sign), but on a clearly insignificant level, whereas we find no support for H2b in our panel regressions (wrong sign and insignificant). PD also shows a marginal predictive power when connected to price, as opposed to the weak, inconsistent effect of PD on its own (Table 7 and 8 however show contradictory results). Thus, when predicting firm-specific returns, the general acceptance of hierarchical structures in the population could possibly also foster a high-price effect to some degree (whereas a society that strives for equality is in tendency linked to a low-price effect). As additional significant control variable, GDP per capita predicts lower stock returns for stocks from countries with higher national wealth and vice versa (t-statistic of -2.44) and absorbs the predictive power of some cultural dimensions like LTO to a certain degree (cp. fn. 34) at the same time nearly not at all impacting the t-statistics of the price and culture dimensions interaction effects (Model 6).

[43] A good example of a country fulfilling all these characteristics in an "ideal typical" way is the Netherlands, showing high values on INDIV and LTO, but low levels on MASC, resulting in a high-price effect. Inversely, the Philippines, for example, shows low levels of INDIV and LTO and (moderately) high levels of MASC which is connected to a low-price effect.

[44] In an earlier version of this paper we use the top 20 countries ranked by yearly GDP in U.S. dollars (projected data for 2017, received from the IMF website) which cover about 80% of global yearly GDP and perform nearly the same panel regressions. We find similar results regarding our price and culture dimensions interaction effects: Price x INDIV, Price x MASC and Price x LTO are all clearly significant (respective t-statistics of 3.27, -2.41 and 2.85). Also the main conclusions regarding our other hypotheses remain unchanged in this alternative dataset, showing that the robustness of our findings is not sample-dependent.

8. Conclusion

With this paper, we contribute to the emerging field of cultural finance trying to explain (puzzling) financial phenomena with cultural effects. Investigating the international price effect (to our knowledge for the first time based on a comprehensive, internationally diverse sample covering several decades), we manage to link another stock market investment strategy to culture (or more specifically, to the cultural dimensions of Hofstede et al.) as was already successfully demonstrated for momentum by Chui et al. (2010) apart from other studies like Weigert (2015) and Cheon and Lee (2017) that (also) link less prominent anomalies to Individualism. However, beyond that, by using international panel data, we make a further step toward generalization and additionally show that cultural differences on their own are capable of predicting and explaining individual stock returns around the world (we know no other paper that investigated this before). Although, or even more due to its regional/country-specific dependency, the price effect is a quite ideal specimen of a capital market anomaly for cultural finance issues, as it is, in contrast to momentum, not only connected to Individualism, but to other cultural dimensions (especially Masculinity and partly Long Term Orientation) when predicting international stock returns.

Furthermore, the two regional price effect clusters (Europe and Asia) that we document, are not only interesting for culture-based asset pricing, but also in the context of international investment styles. As we find, the (main) drawback of investing in high-priced stocks in Europe is the associated negative skewness of returns as opposed to low-priced stocks which generally (worldwide) show higher/positive values for skewness of returns. By investing in high-priced European stocks and low-priced Asian (and US) stocks, this weakness can be mitigated and an investor is enabled to profit from both price effect worlds. However, the (future) robustness of these price effect clusters has to be witnessed with open eyes and with caution as our (diverse)

findings regarding standard-finance asset pricing and robustness tests on country level suggest.[45] On the other hand, the consistently escalating high-price effect in Europe over the course of the last two decades creates a cheerful sentiment for the profitableness of price as legitimate, culture-based investment strategy.

To conclude, a collection of influencing and stimulating findings for future research are: (1) the price effect is by far the most robust in the US (unexpectedly turning out to be a low-price effect), showing for example a very highly significant 4-factor model alpha t-statistic below -4. This outcome is also one of the most puzzling and needs more detailed country-specific investigation, as in general individualistic countries show a high-price effect, the US, though, as very individualistic country shows the opposite. However, Individualism is only one of our incorporated six cultural dimensions and thus only partly determines cultural differences between nations. (2) Expensive portfolios are virtually worldwide also portfolios with low volatility. At the same time, our evidence indicates that the price effect is not the volatility effect in disguise. Merging these effects together with low beta (e.g., in a multi-style strategy) which is also associated with (high-)price portfolios could reveal interesting opportunities from a risk management perspective. (3) We find that HML returns can predict EMC returns. Furthermore, EMC returns can *predict* WML returns on a cross-country level, but not vice versa. On the other hand, both EMC returns and WML returns can *explain* each other on country level. The question that arises here is the nature of the causal structure between these factor-mimicking hedge portfolios. (4) We find culture to be a vital variable in predicting and explaining stock returns in a

[45] Given the evidence of Jacobs and Mueller (2018) on a non-existent (or even inverse) international publication effect (publications of papers on country-specific anomalies lead *not* to deteriorating returns of associated investment strategies, but for most countries even to an amplification) apart from the US (McLean and Pontiff, 2016), our results should not (with the exception of the US low-price effect) be affected "negatively" by a publication of this study (or other papers on the price effect and associated anomalies).

global dataset.[46] This is certainly the most far-reaching indication of our paper, which is however at the same time a very difficult to interpret and challenging to isolate effect (e.g., due to the inherently pervasive, contemporaneous, and steady nature of culture that for example deters from executing event studies regarding cultural change). We hope these aspects can stimulate further potentially eye-opening research on the price effect and especially on culture-based asset pricing and asset management.

[46] We feel confident in drawing the conclusion that it is indeed culture per se having an effect on stock returns. First, Chui et al. (2010) show that even the inclusion of numerous control variables varying between countries (like culture) and over time (unlike culture) cannot destroy the link of individualism and the momentum effect. Since Chui et al. (2010) also have, as opposed to us (due to the limited research on the price effect and even more on culture-based asset pricing), a vast fund of literature regarding expected determinants of momentum to rely on, we focused (as a pioneer of culture-based asset pricing) on exploring the impact of the full spectrum of culture (six cultural dimensions instead of one) instead. Second, what cultural dimensions respectively cultural differences separates from e.g. macroeconomic measures is that they are accepted and expected to be time-invariant (see, e.g., Hofstede et al., 2010). That is, from the time of their measurement on (around 1970 for the initial four dimensions), cultural differences between nations are the most steady "variable", whereas all other candidates to predict and explain international stock returns are fluctuating. There are virtually no (man-made) factors that impact and pervade the broad cultural heritage (see, e.g., Inglehart and Baker, 2000) – culture however is capable of affecting all of them.

Table 9: Global panel regressions results with price and culture indexes interaction effects

This table presents the results of pooled OLS panel regressions (see Eq. (5)) of monthly global firm-specific stock returns on price, culture variables, culture and price interactions, as well as size, logarithm of book-to-market (LN(BTM)), one-year return momentum (MOM) and GDP per capita (GDPpc) as control variables. All independent variables are lag-1 predictors (apart from the time-invariant variables). We test six different regression configurations marked in the first row as Model (1) to (6). The coefficients of the respective predictors are given in the first line; cluster-robust (Huber/White) t-statistics (clustered by time/month) allowing for heteroscedasticity and serial correlation of the (time-specific) error term and with time (month) dummies are reported below in italics and square brackets. Price and Size are normalized, rank-scaled variables with a 0 to 1 scale. Low values depict low-priced and low-sized stocks; high values assign high-priced and high-sized stocks. Values for Price, Size, LN(BTM) and MOM, are measured within a country-specific stock market. PD (Power Distance), INDIV (Individualism), MASC (Masculinity), UA (Uncertainty Avoidance), LTO (Long Term Orientation) and INDUL (Indulgence) are the six culture dimensions proposed by Hofstede. Each stock gets its (time-invariant) country-specific value for these six variables, depending on in which home country it is listed in our dataset (the same holds for our development proxy GDPpc). Predictors linked with a cross ("x") mark interaction effects between the named predictors. "n" and "N" show the number of stocks and the total number of observations available for each panel regression, respectively. Adj. R^2 reports the adjusted R^2 for each regression. To ensure that results are not driven by any remaining extreme values, we additionally winsorize values of returns, LN(BTM) and MOM by replacing each value above the 99.9%- and below the 0.1%-quantile by this quantile value. The panel regressions comprise the time frame June 1981 to April 2017 (430 months; we need the 12 months prior to June 1981 to calculate initial momentum returns which reduces the effective time frame by one year).

Model	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.01198	0.01304	0.02708	0.02622	0.02871	0.02577
	[18.71]	*[16.47]*	*[5.96]*	*[6.29]*	*[4.51]*	*[4.23]*
Price	-0.00046	0.00357		0.00342	-0.00072	-0.00003
	[-0.36]	*[2.11]*		*[2.03]*	*[-0.12]*	*[-0.01]*
Size		-0.00242		-0.00243	-0.00269	-0.00279
		[-1.90]		*[-1.90]*	*[-2.07]*	*[-2.15]*
LN(BTM)		0.00389		0.00415	0.00411	0.00406
		[6.94]		*[7.43]*	*[7.39]*	*[7.30]*
MOM		0.00362		0.00322	0.00321	0.00318
		[3.59]		*[3.20]*	*[3.19]*	*[3.14]*
PD			0.00003	0.00003	-0.00001	-0.00003
			[0.73]	*[0.81]*	*[-0.19]*	*[-0.47]*
INDIV			-0.00004	0.00000	-0.00007	-0.00001
			[-0.93]	*[0.01]*	*[-1.30]*	*[-0.10]*
MASC			-0.00005	-0.00004	0.00004	0.00003
			[-1.40]	*[-1.12]*	*[0.71]*	*[0.58]*

Table 9: continued.

Model	(1)	(2)	(3)	(4)	(5)	(6)
UA			-0.00001	-0.00003	-0.00002	-0.00000
			[-0.18]	*[-0.76]*	*[-0.43]*	*[-0.03]*
LTO			-0.00011	-0.00009	-0.00013	-0.00010
			[-3.37]	*[-2.88]*	*[-2.72]*	*[-2.10]*
INDUL			-0.00012	-0.00011	-0.00010	-0.00007
			[-2.27]	*[-2.34]*	*[-1.34]*	*[-0.94]*
Price x PD					0.00008	0.00008
					[1.49]	*[1.40]*
Price x INDIV					0.00014	0.00014
					[2.94]	*[2.80]*
Price x MASC					-0.00015	-0.00016
					[-3.11]	*[-3.20]*
Price x UA					-0.00001	-0.00001
					[-0.27]	*[-0.35]*
Price x LTO					0.00007	0.00007
					[1.63]	*[1.70]*
Price x INDUL					-0.00003	-0.00003
					[-0.53]	*[-0.55]*
GDPpc						-0.00000
						[-2.44]
n	29333	27221	29235	26871	26871	26679
N	4365718	3555905	4375762	3522306	3522306	3509103
Adj. R^2	0.085463	0.098490	0.084766	0.099238	0.099290	0.099407

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Appendix A. Alternative panel regression configurations

Table A.1: Global panel regressions results with time clusters (without time dummies)

This table presents the results of pooled OLS panel regressions (see Eq. (5)) of monthly global firm-specific stock returns on price, culture variables, culture and price interactions, as well as size, logarithm of book-to-market (LN(BTM)), one-year return momentum (MOM) and GDP per capita (GDPpc) as control variables. All independent variables are lag-1 predictors (apart from the time-invariant variables). We test six different regression configurations marked in the first row as Model (1) to (6). The coefficients of the respective predictors are given in the first line; cluster-robust (Huber/White) t-statistics (clustered by time/month) allowing for heteroscedasticity and serial correlation of the (time-specific) error term are reported below in italics and square brackets. Price and Size are normalized, rank-scaled variables with a 0 to 1 scale. Low values depict low-priced and low-sized stocks; high values assign high-priced and high-sized stocks. Values for Price, Size, LN(BTM) and MOM, are measured within a country-specific stock market. PD (Power Distance), INDIV (Individualism), MASC (Masculinity), UA (Uncertainty Avoidance), LTO (Long Term Orientation) and INDUL (Indulgence) are the six culture dimensions proposed by Hofstede. Each stock gets its (time-invariant) country-specific value for these variables, depending on in which home country it is listed in our dataset (the same holds for our development proxy GDPpc). Predictors linked with a cross ("x") mark interaction effects between the named predictors. "n" and "N" show the number of stocks and the total number of observations available for each panel regression, respectively. Adj. R^2 reports the adjusted R^2 for each regression. To ensure that results are not driven by any remaining extreme values, we additionally winsorize values of returns, LN(BTM) and MOM by replacing each value above the 99.9%- and below the 0.1%-quantile by this quantile value. The panel regressions comprise the time frame June 1981 to April 2017 (430 months; we need the 12 months prior to June 1981 to calculate initial momentum returns which reduces the effective time frame by one year).

Model	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.01060	0.01053	0.02496	0.02414	0.02709	0.02388
	[4.30]	*[4.03]*	*[4.56]*	*[3.96]*	*[3.24]*	*[3.04]*
Price	-0.00060	0.00448		0.00426	-0.00081	-0.00017
	[-0.47]	*[2.77]*		*[2.65]*	*[-0.13]*	*[-0.03]*
Size		-0.00148		-0.00135	-0.00158	-0.00167
		[-1.14]		*[-1.03]*	*[-1.19]*	*[-1.26]*
LN(BTM)		0.00485		0.00513	0.00510	0.00505
		[5.92]		*[6.18]*	*[6.14]*	*[6.07]*
MOM		0.00168		0.00129	0.00128	0.00127
		[0.87]		*[0.66]*	*[0.65]*	*[0.65]*
PD			0.00003	0.00003	-0.00002	-0.00003
			[0.65]	*[0.84]*	*[-0.27]*	*[-0.55]*
INDIV			-0.00003	0.00001	-0.00006	0.00000
			[-0.64]	*[0.25]*	*[-1.14]*	*[0.05]*
MASC			-0.00004	-0.00003	0.00004	0.00004
			[-0.97]	*[-0.76]*	*[0.76]*	*[0.64]*

Table A.1: continued.

Model	(1)	(2)	(3)	(4)	(5)	(6)
UA			-0.00001	-0.00004	-0.00003	-0.00001
			[-0.28]	*[-0.93]*	*[-0.52]*	*[-0.13]*
LTO			-0.00011	-0.00009	-0.00013	-0.00010
			[-3.20]	*[-2.94]*	*[-2.72]*	*[-2.17]*
INDUL			-0.00011	-0.00012	-0.00010	-0.00007
			[-1.92]	*[-2.05]*	*[-1.19]*	*[-0.86]*
Price x PD					0.00009	0.00009
					[1.66]	*[1.59]*
Price x INDIV					0.00014	0.00013
					[2.89]	*[2.77]*
Price x MASC					-0.00014	-0.00015
					[-2.87]	*[-2.98]*
Price x UA					-0.00001	-0.00002
					[-0.34]	*[-0.41]*
Price x LTO					0.00007	0.00007
					[1.56]	*[1.62]*
Price x INDUL					-0.00003	-0.00004
					[-0.55]	*[-0.58]*
GDPpc						-0.00000
						[-2.21]
n	29333	27221	29235	26871	26871	26679
N	4365718	3555905	4375762	3522306	3522306	3509103
Adj. R^2	0.000001	0.001317	0.000435	0.001792	0.001836	0.001914

Table A.2: Global panel regressions results with firm clusters (without time dummies)

This table presents the results of pooled OLS panel regressions (see Eq. (5)) of monthly global firm-specific stock returns on price, culture variables, culture and price interactions, as well as size, logarithm of book-to-market (LN(BTM)), one-year return momentum (MOM) and GDP per capita (GDPpc) as control variables. All independent variables are lag-1 predictors (apart from the time-invariant variables). We test six different regression configurations marked in the first row as Model (1) to (6). The coefficients of the respective predictors are given in the first line; cluster-robust (Huber/White) t-statistics (clustered by time/month) allowing for heteroscedasticity and serial correlation of the (firm-specific) error term are reported below in italics and square brackets. Price and Size are normalized, rank-scaled variables with a 0 to 1 scale. Low values depict low-priced and low-sized stocks; high values assign high-priced and high-sized stocks. Values for Price, Size, LN(BTM) and MOM, are measured within a country-specific stock market. PD (Power Distance), INDIV (Individualism), MASC (Masculinity), UA (Uncertainty Avoidance), LTO (Long Term Orientation) and INDUL (Indulgence) are the six culture dimensions proposed by Hofstede. Each stock gets its (time-invariant) country-specific value for these variables, depending on in which home country it is listed in our dataset (the same holds for our development proxy GDPpc). Predictors linked with a cross ("x") mark interaction effects between the named predictors. "n" and "N" show the number of stocks and the total number of observations available for each panel regression, respectively. Adj. R^2 reports the adjusted R^2 for each regression. To ensure that results are not driven by any remaining extreme values, we additionally winsorize values of returns, LN(BTM) and MOM by replacing each value above the 99.9%- and below the 0.1%-quantile by this quantile value. The panel regressions comprise the time frame June 1981 to April 2017 (430 months; we need the 12 months prior to June 1981 to calculate initial momentum returns which reduces the effective time frame by one year).

Model	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.01060	0.01053	0.02496	0.02414	0.02709	0.02388
	[67.66]	*[54.23]*	*[30.94]*	*[25.45]*	*[12.54]*	*[10.99]*
Price	-0.00060	0.00448		0.00426	-0.00081	-0.00017
	[-2.42]	*[14.26]*		*[13.59]*	*[-0.24]*	*[-0.05]*
Size		-0.00148		-0.00135	-0.00158	-0.00167
		[-4.65]		*[-4.37]*	*[-5.06]*	*[-5.35]*
LN(BTM)		0.00485		0.00513	0.00510	0.00505
		[44.73]		*[46.43]*	*[46.41]*	*[46.17]*
MOM		0.00168		0.00129	0.00128	0.00127
		[10.44]		*[7.94]*	*[7.88]*	*[7.78]*
PD			0.00003	0.00003	-0.00002	-0.00003
			[4.32]	*[4.49]*	*[-0.96]*	*[-1.95]*
INDIV			-0.00003	0.00001	-0.00006	0.00000
			[-4.97]	*[1.64]*	*[-4.89]*	*[0.23]*
MASC			-0.00004	-0.00003	0.00004	0.00004
			[-10.06]	*[-7.44]*	*[4.73]*	*[4.05]*

Table A.2: continued.

Model	(1)	(2)	(3)	(4)	(5)	(6)
UA			-0.00001	-0.00004	-0.00003	-0.00001
			[-2.66]	*[-8.78]*	*[-3.11]*	*[-0.75]*
LTO			-0.00011	-0.00009	-0.00013	-0.00010
			[-23.01]	*[-19.19]*	*[-11.36]*	*[-8.98]*
INDUL			-0.00011	-0.00012	-0.00010	-0.00007
			[-16.89]	*[-15.28]*	*[-5.75]*	*[-3.86]*
Price x PD					0.00009	0.00009
					[3.49]	*[3.39]*
Price x INDIV					0.00014	0.00013
					[6.63]	*[6.46]*
Price x MASC					-0.00014	-0.00015
					[-9.74]	*[-10.01]*
Price x UA					-0.00001	-0.00002
					[-0.98]	*[-1.19]*
Price x LTO					0.00007	0.00007
					[3.71]	*[3.88]*
Price x INDUL					-0.00003	-0.00004
					[-1.25]	*[-1.32]*
GDPpc						-0.00000
						[-14.78]
n	29333	27221	29235	26871	26871	26679
N	4365718	3555905	4375762	3522306	3522306	3509103
Adj. R^2	0.000001	0.001317	0.000435	0.001792	0.001836	0.001914