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The mean-variance relation: A story of night and day☆

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ABSTRACT

The traditional financial framework theorizes a positive mean-variance relation, which, however, is not fully supported by empirical evidence. We provide a new explanation for the weak mean-variance relation by separately testing the relation overnight and intraday. Results at the global level present a positive mean-variance relation overnight but a negative relation intraday, while results of individual markets reveal a high degree of heterogeneity. We employ cultural dimensions, market integrity, and market development to examine the drivers of the observed cross-market differences, showing that all the three factors influence the mean-variance relation, and notably, the influence varies across night and day.

1. Introduction

The standard financial theories posit a positive mean–variance relation, i.e., that bearing high (low) risk should be rewarded by high (low) returns (Merton, 1973 & 1980). Empirical evidence is, at best, mixed, with three main streams: positive (French et al., 1987; Campbell and Hentschel, 1992; Guo and Whitelaw, 2006; Pástor et al., 2008; Rossi and Timmermann, 2015), negative (Campbell, 1987; Whitelaw, 1994; Brandt and Kang, 2004; Brandt and Wang, 2010; Baker et al., 2011; Booth et al., 2016), and mixed (Turner et al., 1989; Glosten et al., 1993; Harvey, 2001; Yu and Yuan, 2011; Wang et al., 2017; Wang and Duxbury, 2021). Explanations for the inconclusive evidence are explored from various perspectives. Yu and Yuan (2011), surveying investor sentiment, argue that retail investors, who are likely to be noise traders, tend to misestimate the variance of returns, thereby distorting the mean–variance relation in high-sentiment periods when they are more willing to trade and participate. The argument is confirmed by their empirical evidence in the US stock market, as well as in European stock markets (Wang, 2018a). Opposite to this, Wang (2018b), following DeVault et al. (2019), regards institutional investors, rather than retail investors, as noise traders, and documents that the high presence of institutional investors driven by their bullishness can also undermine the positive mean–variance relation. Wang and Duxbury (2021) confirm the role of institutional investor sentiment in the distortion of the positive risk-return tradeoff in a global context and further reveal that institutional investors with cultural proneness to overreaction are more likely to bring a negative impact on the mean–variance relation.

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In this paper, we provide a new explanation by exploring the mean–variance relation overnight and intraday in twenty-five international stock markets. As the two periods, overnight (non-trading hours) and intraday (trading hours), differ in several key dimensions, such as price impact, information flow, and borrowing costs, it is probable that investors of the two periods are not the same, i.e., that they exhibit themselves to trade in one of the two periods but not the other (Lou et al., 2019). For example, Berkman et al. (2012) suggest that retail investors tend to place orders during non-trading hours to be executed at the market open. Because of the divergent clienteles, it is reasonable to assume and possible to observe different financial relations, like the mean–variance relation, the primary focus of this paper, overnight and intraday. Of direct relevance, Hendershott et al. (2020) suggest that overnight traders are long-term investors demanding higher returns for bearing higher market risk, while intraday traders are risk-loving speculators demanding higher market risk, implying that a positive mean–variance relation overnight is expected, which may be distorted intraday. Empirically, Wang (2021) reports a positive mean–variance relation overnight but a negative one intraday in the US stock market, and we extend the initial US evidence to worldwide in this paper, which is motivated by the following four considerations.

First, adopting a global sample facilitates us to reveal new evidence. Presence, or absence, of the positive risk-return tradeoff is largely subject to investors trading in stock markets. As per Yu and Yuan (2011), Wang (2018b), and Wang and Duxbury (2021), investors who are uninformed about trading are likely to misestimate the variance of returns and their trading would, as a result, distort the mean–variance relation.[1] Irrespective of non-trading hours or trading hours, investors' trading behaviors are naturally different across markets due to various aspects and among such culture, market integrity, and market development are three of the most crucial factors. Hofstede and Bond (1988) define culture as the collective mind programming that differentiates one group of people from another and contains values that can shape people's behaviors and perceptions. The cultural dimension framework has been broadly applied in finance studies, and cultures have been confirmed to have a significant impact on stock trading decisions (Grinblatt and Keloharju, 2001; Lee et al., 2019), stock market participation (Guiso et al., 2008), and home bias in asset allocation (Beugelsdijk and Frijns, 2010; Aggarwal et al., 2012), as well as playing an important role in momentum profits (Chui et al., 2010), stock price co-movement (Eun et al., 2015), post earnings announcement drift (Dou et al., 2015; Guo and Holmes, 2022), and country-level financial systems (Kwok and Tadesse, 2006; Aggarwal and Goodell, 2009). Market integrity and market development also influence investors' trading behaviors in that the former determines information flow and dissemination, and hence market efficiency (La Porta et al., 1998; Zouaoui et al., 2011; Maung et al., 2019; Hu et al., 2022), and the latter leads to distinctions across markets in relation to short-sale constraints, stock market returns, and market efficiency (Bekaert and Harvey, 2002; Bris et al., 2007; Charoenrook and Daouk, 2009; Griffin et al., 2010; Saffi and Sigurdsson, 2011; Feng et al., 2017). Employing a collection of twenty-five global stock markets, we expect to reveal differential patterns of the mean–variance relation overnight and intraday across markets, and to the extent that market differences are detected, we can examine whether cultures, market integrity, and market development drive the presented differences, and if so, whether the influence varies across night and day in that overnight and intraday trading potentially reflects the specific demand of different clienteles (Lou et al., 2019; Hendershott et al., 2020).

Second, a diversified, global sample incorporating both developed and emerging markets helps to offer additional insights into the mean–variance relation overnight and intraday that are unlikely to be observed if sample markets have similar economic conditions and exclude those at different stages of development (Ferreira et al., 2012). Third, a global sample provides out-of-sample evidence in comparison with the US market, which is desirable in surveying market anomalies. Ang et al. (2009) posit that there is a danger if a finding depends on a small sample, like the US stock market only, since it could be due to data-snooping (see, also, Lo and MacKinlay, 1990; Griffin et al., 2003). By contrast, if a finding exists in international markets, it is more likely that there is an underlying economic source behind the phenomenon. The initial empirical evidence in Wang (2021) relies on the US stock market, and it is, hence, necessary to extend the test of the mean–variance relation overnight and intraday to a global level. Fourth, a panel dataset consisting of multiple stock markets can increase the power of statistical analyses (Ang and Bekaert, 2007; Schmeling, 2009).

Overnight and intraday returns are separately computed based on the aggregate stock market indices. Conditional volatility is measured via five models including the rolling window (RW), the mixed-data sampling (MIDAS), GARCH, GJR-GARCH, and EGARCH to account for the fact that the mean–variance relation can be dependent on volatility models (Ghysels et al., 2005). We start by surveying the mean–variance relation at the global level, showing a positive mean–variance relation overnight, but a negative one intraday, which is robust to a reduced, more balanced sample and an alternative, indirect test specification. Replicating the tests for individual markets generates a high degree of heterogeneity in terms of signs and magnitude, suggesting that the mean–variance relation overnight and intraday is market-specific. The differential patterns indicate disparate investor behaviors across markets—that is, their trading maintains or undermines the positive risk-return tradeoff in some markets but not in others, overnight or intraday, and based on this, we further investigate the potential drivers from the perspectives of cultural dimensions, market integrity, and market development. Two different empirical designs generate broadly consistent results: All the three perspectives have influences on the mean–variance relation and notably, the influence can vary across overnight and intraday.

The remainder of this paper proceeds in the following manner. Section 2 reviews related literature, followed by Section 3 presenting data and volatility models. Section 4 reports the results of the mean–variance relation at both global and market levels. Section 5 explores potential drivers from the perspectives of cultural dimensions, market integrity, and market development, and Section 6 concludes.

[1] Detailed derivation is provided in Yu and Yuan (2011).

2. Related literature

2.1. Overnight and intraday

While this paper is the first global study to survey the mean–variance relation overnight and intraday, such a decomposition is '*natural*' (Lou et al., 2019, p. 195) as the two periods are different along several key dimensions, such as price impact, information flow, and borrowing costs. Lou et al. (2019) argue that overnight returns may contain more firm-specific information, in that firms tend to submit important regulatory filings, such as earnings announcements, during non-trading hours. Fama (1965), French (1980), and French and Roll (1986) find that volatility is higher intraday than overnight, while Cai and Qiu (2008), Cliff et al. (2008), and Kelly and Clark (2011) and reveal that stock market returns, on average, are higher overnight than intraday. As a result, it is probable that investors of the two periods are not the same, i.e., that they exhibit themselves to trade in one of the two periods but not the other. For instance, Berkman et al. (2012) suggest that retail investors tend to place orders in non-trading hours to be executed at the market open.

On the mean–variance relation, Hendershott et al. (2020) suggest that intraday traders are risk-loving speculators requiring higher market risk, while overnight traders are long-term investors requiring higher returns for bearing higher market risk, evidencing that stock returns are positively related to beta overnight, but negatively related to beta intraday. Following this line of thought, Wang (2021) documents a positive mean–variance relation overnight but a negative one intraday in the US stock market.

2.2. Cultural dimensions, market integrity, and market development

Hofstede and Bond (1988) define culture as the collective mind programming distinguishing one group of people from another and containing values that can form people's behaviors and perceptions. A wide range of financial studies has applied the cultural dimension framework to international contexts, in which cultures have been shown to have a significant impact on various aspects, such as stock trading decisions (Grinblatt and Keloharju, 2001; Lee et al., 2019), stock market participation (Guiso et al., 2008), home bias in asset allocation (Beugelsdijk and Frijns, 2010; Aggarwal et al., 2012), momentum profits (Chui et al., 2010), stock price co-movement (Eun et al., 2015), post earnings announcement drift (Dou et al., 2015; Guo and Holmes, 2022), and country-level financial systems (Kwok and Tadesse, 2006; Aggarwal and Goodell, 2009).

Hofstede's cultural framework has six cultural dimensions, including individualism (IDV), the uncertainty avoidance index (UAI), masculinity (MAS), the power distance index (PDI), long-term orientation (LTO), and indulgence (IDG). As the distortion of the positive mean–variance relation can be determined by the rationality of investor trading behaviors,[2] the literature reviewed here mainly explores the possible influence of cultures on the mean–variance relation via the route of investor rationality. While the cultural dimension framework has been widely examined in the finance studies, the six cultural dimensions are not evenly examined in the literature (Wang et al., 2021). The discussion below, thus, is based on both theoretical analyses that have been established in the literature, as well as inferences drawn from the extant evidence.

Studies distinguish between IDV and its opposite, collectivism (CLT), as follows: Individuals in IDV cultures are more autonomous and independent, while those in CLT culture are more connected with others (Markus and Kitayama, 1991; Heine and Lehman, 1995; Gelfand et al., 2002; Černe et al., 2013). Investors in IDV cultures tend to exhibit overconfidence and thus to commit cognitive biases in trading (Heine et al., 1999, Chui et al., 2010, Li et al., 2013; Berk et al., 2017), while those in CLT cultures are more likely to exhibit herding and thus to trade in concert and induce overreaction (Markus and Kitayama, 1991, Beckmann et al., 2008). Cognitive biases, as well as overreaction, can potentially lead to irrational trading behaviors distorting the positive risk-return tradeoff (Wang et al., 2021). UAI measures the extent to which individuals react to uncertain circumstances (Hofstede, 2001). Investors in high UAI cultures are likely to overreact to uncertainty (Kwok and Tadesse, 2006), but it also allows them to make careful and rational trading decisions ex ante to reduce uncertainty ex post (Nguyen and Truong, 2013; Tsalavoutas and Tsoligkas, 2021). Investors in low UAI cultures, having a high level of risk tolerance, are more willing to accept uncertain situations and tend not to overreact when uncertainty occurs (Chui and Kwok, 2008), which may lead to rational reactions in uncertain situations but may also lead to irrational trading behaviors ex ante. MAS refers to the pursuit of heroism, assertiveness, and competitiveness, more related to males, while its opposite, femininity (FEM), represents modesty, cooperation, and caring for the weak and life quality, more related to females (Hofstede, 2001). Compared with those in high FEM cultures, on the one hand, investors in high MAS cultures are more subject to overconfidence and self-attribution (Lundeberg et al., 1994, Barber and Odean, 2001; Jakob and Nam, 2017) and thus would trade more irrationally, but on the other hand, overconfidence predicts excessive trading, which, although is thought to be less rational, allows more accurate ability inference that help investors to become more informed (Feng and Seasholes, 2005; Nicolosi et al., 2009; Seru et al., 2010). PDI reflects the extent to which subordinates expect and accept power to be unequally distributed (Hofstede, 2001). High PDI, implying a high level of centralized control by authorities, suggests stock markets to be more administered and thus irrational components may not be as pronounced as in low PDI markets (Wang et al., 2021). However, subordinates in high PDI markets, surrendering more authority to their superiors, are likely to expect the latter to take care of their welfare and to provide adequate protection (Chui and Kwok, 2008),

[2] Yu and Yuan (2011) find that investor sentiment, as a reflection of investor behaviors, has a strong explanatory power to the weak mean–variance relation and it outperforms some important macroeconomic variables containing business cycle information, including interest rate, term premium, default premium, dividend-price ratio, and the consumption surplus ratio in terms of the predictability (see, also, Wang and Duxbury, 2021).

which may cause their excessive reliance on the superiors, and thus, less informed trading. LTO refers to the focus of people's efforts, whether is on the future, or on the present and past (short-term orientation, STO, Hofstede and Bond, 1988). Investors in LTO cultures prefer family business and real estate, while those in STO cultures prefer stocks and mutual funds (Hofstede et al., 2010), indicating that STO markets would observe a high level of participation of retail investors who are likely, on the one hand, to be uninformed traders (Grinblatt and Keloharju, 2000; Lee and Swaminathan, 2002; Kumar and Lee, 2006; Dimpfl and Jank, 2016; Wang et al., 2021), and on the other hand, to learn by trading (Feng and Seasholes, 2005; Nicolosi et al., 2009; Seru et al., 2010). Finally, IDG refers to the restraints on gratification and basic human desires in relation to enjoying life (Hofstede et al., 2010). People in high IDG cultures are involved with enjoying life while those in low IDG (or high restraints, RES) cultures show restraints (Ortas and Gallego-Álvarez, 2020), and compared with those in high IDG cultures, consumers in low IDG cultures would purchase goods only when they need (Minkov, 2011), suggesting that high IDG markets, like STO markets, may have a high level of presence of retail investors who are likely to be uninformed traders but meanwhile also to learn by trading.

In addition to the cross-market culture, the notion of intra-market cultural diversity has been reintroduced following Au (1999), Lenartowicz and Roth (2001), Tung (2008), Gelfand et al. (2011), and Dheer et al. (2015). Some markets exhibit tight cultures with pervasive norms and low tolerance for deviance from norms, while some other markets demonstrate loose cultures with weak norms and high tolerance for deviance from norms (Gelfand et al., 2006; Gelfand et al., 2011; Uz, 2015). Therefore, the influence of cultural dimensions can also be determined by the degree of intra-market cultural diversity (Beugelsdijk et al., 2014; Chua et al., 2015; Dow et al., 2016; Shin et al., 2016; Beugelsdijk et al., 2017). More importantly, if the impact of cultures on the observed cross-market heterogeneity in overnight and intraday differences in the mean–variance relation varies with changes in cultural tightness-looseness, it will further confirm cultures to be a significant determinant in such a relation.[3]

Another perspective that may influence the mean–variance relation overnight and intraday is market integrity. A high level of market integrity would improve information flow and dissemination, making markets more efficient (La Porta et al., 1998). Schmeling (2009), for example, reports that the impact of investor sentiment is weaker (stronger) in markets with a high (low) level of market integrity. Likewise, Zouaoui et al. (2011) document a lower (higher) probability of occurrence of stock market crises led by investor sentiment in markets with a high (low) level of market integrity. Therefore, investors in markets with high market integrity tend to be more rational and the positive mean–variance relation is, hence, more likely to be maintained. Finally, market development, referring to the classification of developed and emerging markets, may also determine the mean–variance relation overnight and intraday. There are important distinctions between developed and emerging markets, particularly in terms of short-sale constraints, stock market returns, and market efficiency (Bekaert and Harvey, 2002; Bris et al., 2007; Charoenrook and Daouk, 2009; Griffin et al., 2010; Saffi and Sigurdsson, 2011; Feng et al., 2017), all of which are fundamental to the mean–variance relation.

3. Data and volatility models

3.1. Data

We include twenty-five international stock markets. One of the most important selection criteria is that sample markets should not contain too many zero overnight returns. Our sample is a sound representative of global stock markets, including both developed and emerging markets, and spanning major areas of the world, including America, Asia-Pacific, and Europe. We source daily market data, including market open and close prices, from Bloomberg, and cross-check them with Refinitiv and the corresponding stock exchanges where possible for quality control. Due to data availability, starting dates vary across markets while the ending dates are all at the end of 2018. Following Lou et al. (2019), Hendershott et al. (2020), and Wang (2021), we define the daily intraday return in market i on day s, $r_{i,s}^{intraday}$, as the index appreciation between market close and open indices of the same day s, and impute the overnight return, $r_{i,s}^{overnight}$, based on the standard daily total return (i.e., the close-to-close return) and this intraday return, following,

$$r_{i,s}^{intraday} = \frac{p_{i,s}^{close}}{p_{i,s}^{open}} - 1 \tag{1}$$

where $p_{i,s}^{close}$ and $p_{i,s}^{open}$ denote the market close and open indices, respectively, and

$$r_{i,s}^{overnight} = \frac{1 + r_{i,s}^{total}}{1 + r_{i,s}^{intraday}} - 1 \tag{2}$$

For cases where a zero overnight return is obtained, we manually compute the value-weighted average of index constituents overnight returns as a replacement. Based on daily intraday and overnight returns, we accumulate them each month t, following,[4]

[3] We thank one anonymous reviewer for drawing our attention to the need to consider cultural tightness-looseness in our analyses.

[4] Aboody et al. (2018) accumulate weekly overnight returns as the average daily overnight returns for that week multiplied by 5, i.e., an average approach. Wang (2021) accumulates monthly overnight returns as the average daily overnight multiplied by the actual number of trading days of that month, i.e., a sum approach. Using the two approaches generates qualitatively consistent results with our main multiplication approach as specified in Eq. (3) and (4).

$$r_{i,t}^{intraday} = \prod_{s \in t}(1 + r_{i,s}^{intraday}) - 1 \quad (3)$$

$$r_{i,t}^{overnight} = \prod_{s \in t}(1 + r_{i,s}^{overnight}) - 1 \quad (4)$$

Descriptive statistics of overnight and intraday returns appear in Table 1. Over sample periods, most markets present positive average overnight returns, except for two markets, Austria (–0.0761 %) and China (–0.8812 %), but this number significantly increases for intraday returns with sixteen markets showing negative average intraday returns, accounting for over half of the sample markets. For the same reason, on average, overnight returns are higher than intraday returns for most markets, consistent with Cliff et al. (2008), Cai and Qiu (2008), and Kelly and Clark (2011). In total, eighteen stock markets show an opposite return pattern overnight and intraday, suggesting that positive (negative) overnight returns tend to be reversed during trading hours, in line with Berkman et al. (2012). Except for Taiwan, overnight returns are less volatile than intraday returns in all other markets, supporting French (1980) and French and Roll (1986). The literature well documents stock returns to show negative skewness and, in our sample, it appears that the negative skewness is more likely to be driven by intraday returns. Kurtosis is usually higher for overnight returns, and we notice platykurtosis in a few cases, which can be explained by Lux (1998) that high kurtosis is '*reduced under time aggregation*' (p. 160).

For volatility, we note that the average of volatility is very close to the variance of returns, again confirming intraday returns are more volatile than overnight returns, and the difference can be explained by Jensen's inequality (Ghysels et al., 2005). The variance of volatility is higher for intraday than for overnight returns, and both exhibit positive skewness and leptokurtosis in a consistent way.

3.2. *Volatility models*

As prior literature suggests that the presented mean–variance relation is subject to the choice of volatility models (Ghysels et al., 2005), we select five different approaches, including the rolling window (RW), the mixed-data sampling (MIDAS), GARCH, GJR-GARCH, and EGARCH, to filter conditional volatility.

3.2.1. *Rolling window model*

The RW model measures volatility following,

$$Var_t(R_{t+1}) = \sigma_t^2 = \frac{22}{N_t}\sum_{d=1}^{N_t} r_{t-d}^2 \quad (5)$$

where $Var_t(R_{t+1})$ is the conditional volatility for forecasting next-month market returns R_{t+1}; σ_t^2 is the realized volatility in month t; r_{t-d} is the demeaned daily market return in month t, computed by subtracting the within-month mean daily return from daily raw returns; N_t is the number of actual trading days in month t; and 22 is the conventionally employed number of trading days in one month (Yu and Yuan, 2011).

3.2.2 *Midas*

MIDAS has a similar structure to RW but differs in horizon, flexibility, and the weighting function, following,

$$Var_t(R_{t+1}) = 22\sum_{d=0}^{252} \omega_d r_{t-d}^2 \quad (6)$$

where r_{t-d} is the demeaned daily return and the subscript $(t - d)$ corresponds to the date t minus d days; ω_d is the weight on r_{t-d}^2, following,

$$\omega_d(\kappa_1, \kappa_2) = \frac{exp\{\kappa_1 d + \kappa_2 d^2\}}{\sum_{d=0}^{252} exp\{\kappa_1 d + \kappa_2 d^2\}} \quad (7)$$

where κ_1 and κ_2 are the parameters in the weight function. The monthly conditional volatility is filtered by the previous 252 trading days (Ghysels et al., 2005).

3.2.3. *GARCH, GJR-GARCH, and EGARCH*

For GARCH, GJR-GARCH, and EGARCH, we first estimate the mean equation, following,

$$r_{t+1} = \mu + \varepsilon_{t+1} \quad (8)$$

where r_{t+1} is the daily market return at day $(t + 1)$; μ is the conditional mean of the daily market return; and ε_{t+1} is the residual. The daily conditional volatility models are,

$$\sigma_{t+1}^2 = \omega + \alpha\varepsilon_t^2 + \beta\sigma_t^2 \quad (9)$$

$$\sigma_{t+1}^2 = \omega + \alpha_1\varepsilon_t^2 + \alpha_2 I_t \varepsilon_t^2 + \beta\sigma_t^2 \quad (10)$$

Table 1
Descriptive statistics.

Market	Start	Excess return (I)								Realized volatility (II)							
		Overnight				Intraday				Overnight				Intraday			
		Avg. ($\times 10^2$)	*Var.* ($\times 10^2$)	*Skew.*	*Kurt.*	*Avg.* ($\times 10^2$)	*Var.* ($\times 10^2$)	*Skew.*	*Kurt.*	*Avg.* ($\times 10^2$)	*Var.* ($\times 10^4$)	*Skew.*	*Kurt.*	*Avg.* ($\times 10^2$)	*Var.* ($\times 10^4$)	*Skew.*	*Kurt.*
Argentina	Jan 1997	0.9915	0.0404	1.6490	8.6350	0.6171	1.0855	0.0462	2.2061	0.0366	0.0078	8.0776	92.2172	0.9727	1.3554	3.9669	23.9726
Australia*	Jul 2003	0.2157	0.0127	–0.1860	4.4732	0.1330	0.1358	–0.3596	0.6629	0.0153	0.0007	4.0690	23.0750	0.1754	0.0526	4.9283	35.3443
Austria*	Oct 1991	–0.0761	0.0014	–1.9880	11.5170	0.3732	0.3927	–0.6418	1.9680	0.0014	0.0001	10.2793	115.6055	0.3814	0.4072	6.9863	70.0339
Belgium*	Jun 1992	0.8060	0.0862	1.1445	5.5333	–0.4487	0.2637	–1.5817	4.9983	0.0851	0.0400	10.1625	136.3031	0.2000	0.0816	3.9806	22.9087
Brazil	Jan 2001	0.1662	0.0024	2.2345	9.4964	0.6558	0.6018	–0.1478	0.1242	0.0013	0.0000	5.2649	40.3187	0.6731	0.7327	7.0450	69.1878
Canada*	Jul 1979	0.5071	0.1062	0.0538	1.1847	–0.0098	0.1116	0.2954	1.8388	0.1424	0.0221	2.9502	14.1374	0.1420	0.0219	2.9472	14.2161
Chile	Jan 1990	1.2212	0.1905	2.3849	9.7723	0.1442	0.2250	–0.4542	5.9257	0.0919	0.0616	5.3950	42.6375	0.1831	0.1066	6.9709	68.5038
China	Jul 1997	–0.8812	0.1481	–0.7379	7.8083	1.2629	0.4603	0.1076	1.2413	0.0944	0.0508	5.4094	38.9559	0.4722	0.2430	2.1646	7.6673
Czech Republic	Sep 1999	0.7050	0.0603	1.0281	3.8523	–0.3662	0.3831	–0.9179	3.7811	0.0817	0.0590	9.1835	106.9372	0.2818	0.2020	8.5695	99.7262
France*	Mar 1990	0.5199	0.1016	–0.3180	5.2331	–0.2617	0.2685	–0.6917	2.6181	0.1425	0.0674	7.9038	93.0770	0.2775	0.1001	3.1714	14.7087
Germany*	Dec 1993	0.8620	0.0630	–0.4716	9.1577	–0.3067	0.3873	–0.6042	2.9733	0.0693	0.0211	7.2711	70.5050	0.3699	0.2641	3.8973	22.2101
Hong Kong*	Oct 1989	0.8978	0.1833	–0.2825	4.0216	–0.2450	0.2719	0.7071	4.2612	0.1883	0.1194	4.8009	31.5574	0.3122	0.2364	6.9592	72.4258
Ireland*	Mar 2005	0.7710	0.0348	0.8711	6.5532	–0.7827	0.4570	–0.8950	3.1183	0.0261	0.0031	9.1163	99.8014	0.4383	0.5585	4.6940	29.6485
Italy*	Jun 2003	1.0062	0.0690	0.2343	2.4274	–1.1606	0.3410	–0.0684	2.3934	0.1038	0.0296	6.3614	59.7038	0.3814	0.2101	2.7465	11.3875
Japan*	Apr 1988	0.6988	0.0731	–0.2042	1.7821	–0.7830	0.2759	–0.3569	2.4674	0.0804	0.0080	2.1425	11.6125	0.3343	0.2669	8.4995	111.8199
Mexico	Oct 1993	0.2130	0.0102	2.0094	22.9971	0.8440	0.4741	–0.3712	1.8193	0.0078	0.0010	9.1647	110.3540	0.4557	0.3654	4.3025	29.1366
Netherlands*	Sep 1991	0.7025	0.0554	0.3762	2.5201	–0.2706	0.2970	–0.8457	3.9244	0.1029	0.0565	9.3115	122.6096	0.2690	0.1638	3.6832	19.1609
Philippines	Nov 1995	0.8773	0.0627	0.9686	4.8462	–0.4265	0.3624	0.2288	5.2009	0.0697	0.0238	4.5846	28.6456	0.2893	0.0885	3.2353	16.9286
Portugal*	Jul 1997	0.7784	0.0943	0.0303	7.2688	–0.9308	0.3156	–0.1842	1.8012	0.1143	0.1100	11.5550	160.7616	0.2401	0.0830	4.0395	26.0503
South Korea	Jun 1987	1.4478	0.2144	0.3483	2.4083	–0.9469	0.3734	0.5753	2.2291	0.1571	0.0609	3.7545	21.6724	0.3671	0.2107	3.3463	19.3206
Spain*	Aug 1991	0.3040	0.0979	0.1823	2.0670	0.0944	0.3870	–0.4326	1.0018	0.1247	0.0505	7.8809	82.2428	0.3238	0.1510	3.2305	16.8212
Switzerland*	May 1991	0.4947	0.0469	0.0179	2.7391	–0.0045	0.2051	–0.7757	3.7140	0.0742	0.0308	8.8091	111.3232	0.2064	0.0791	3.7311	19.4070
Taiwan	Jan 1996	3.2280	0.4051	–0.1677	4.5676	–2.7936	0.2651	0.0390	2.6723	0.1626	0.0573	3.8096	22.4673	0.2736	0.0791	2.2816	10.1650
Thailand	Jul 1993	1.5836	0.1132	0.4709	4.6082	–1.2049	0.5370	1.1746	8.7965	0.0825	0.0228	5.2945	44.5528	0.4132	0.3130	3.3711	16.4978
US*	Apr 1982	0.0555	0.0042	0.0006	5.5394	0.6392	0.2116	–0.7418	3.4618	0.0059	0.0002	4.0643	23.1597	0.2617	0.3042	9.4367	117.6181

This table presents descriptive statistics of excess returns (Column I) and realized volatility (Column II) for twenty-five sample markets, overnight and intraday. In particular, we report mean (*Avg.*), variance (*Var.*), skewness (*Skew.*), and kurtosis (*Kurt.*). Realized volatility is computed from the within-month daily market returns.

* denotes developed markets following the Morgan Stanley Capital International (MSCI) market classification.

$$\sigma^2_{t+1} = exp\left\{\omega + \alpha_1[|\varepsilon_t|/\sqrt{\sigma^2_t}] + \alpha_2[\varepsilon_t/\sqrt{\sigma^2_t}] + \beta ln\sigma^2_t\right\} \quad (11)$$

for GARCH, GJR-GARCH, and EGARCH, respectively. The term I_t in Eq. (4) is the dummy variable for bad news (i.e., $\varepsilon_t^2 < 0$) to account for the leverage effect, i.e., allowing for asymmetry in the response of the conditional volatility to return innovations (Glosten et al., 1993). We store daily conditional volatility series,σ^2_{t+1}, and compute monthly conditional volatility as the linear sum of daily conditional volatility (Engle, 2001),

$$Var_t(R_{t+1}) = E_t\left(\sum_{d=1}^{N_t}\sigma^2_{t+d}\right). \quad (12)$$

4. The mean–variance relation

To test the risk-return tradeoff, we regress monthly returns of market *i* in month *t* ($R_{i,t+1}$) on the corresponding monthly conditional volatility [$Var_{i,t}(R_{i,t+1})$],

$$R_{i,t+1} = \alpha + \beta Var_{i,t}(R_{i,t+1}) + \varepsilon_{i,t+1}. \quad (13)$$

where β reflects the mean–variance relation, and prior literature suggests that β can be positive, negative, or close to zero. We, examine the mean–variance relation overnight and intraday for global markets and individual markets in Subsection 4.1 and 4.2, respectively.

4.1. Global evidence

4.1.1. Main results

Panel A of Table 2 reports results from the global markets, i.e., a panel regression, showing an evident, consistent difference in the mean–variance relation overnight and intraday. There is a positive mean–variance relation overnight, while a negative one intraday, supporting the initial evidence of the US stock market evidenced by Wang (2021). The difference in the mean–variance relation overnight and intraday is significant at 1 % level for all five volatility models. As per the RW, a 1 % upward (downward) revision in conditional volatility overnight would cause a 0.5269 % increase (decrease) in overnight market returns, but a same magnitude change intraday would lead to a 0.4022 % decrease (increase) in intraday market returns, with a difference of 0.9291 %. Therefore, while the theorized positive mean–variance relation does not hold during trading hours, as revealed in Campbell (1987), Brandt and Kang (2004), and Baker et al. (2011), our findings confirm it to be present during non-trading hours, as documented in French et al. (1987), Guo and Whitelaw (2006), and Rossi and Timmermann (2015). The relation is also of economic significance: On average, a 1 % change in conditional volatility would lead to around 60 bps and 50 bps change in overnight and intraday returns, respectively.

As discussed above, the mean–variance relation is influenced by various factors,[5] and apart from econometrical specifications, such as different volatility models (Ghysels et al., 2005; Müller et al., 2011), which are exogenous to the nature behind the relation, investors' trading behaviors play a crucial role. Wang and Duxbury (2021), for example, suggest that irrational investors tend to misestimate return variance and their trading will distort the positive mean–variance relation. Our results reporting the differential mean–variance relations overnight and intraday imply that first, investors trading overnight and intraday belong to two clienteles, as suggested by Lou et al. (2019), and second, overnight traders tend to be more informed than intraday counterparts in that their participation maintains the theorized, positive risk-return tradeoff. Berkman et al. (2012) and Aboody et al. (2018) argue that retail investors tend to place orders during non-trading hours; in our paper, however, we do not strictly follow this notion due to our global setting in which the US evidence may not be unconditionally applicable to other markets, so we do not equate 'overnight traders' to 'retail investors', or 'intraday traders' to 'institutional traders', but just use 'overnight traders' and 'intraday traders' for accuracy. Note also that a specific investor can trade both overnight and intraday, i.e., that it is not necessarily an exclusive situation, so our terms of 'overnight traders' and 'intraday traders' are defined at the aggregate level, rather than at the individual level.

In the studies examining the impact of investor sentiment on the mean–variance relation, Yu and Yuan (2011), for instance, split the entire sample into high- and low-sentiment periods, reporting a positive mean–variance relation during low-sentiment periods, while a negative one during high-sentiment periods. Berkman et al. (2012) suggest that overnight returns may serve as a measure of firm-specific investor sentiment, which is subsequently extended to the market level by Guo et al. (2019). While the overnight return is one of our focuses in this paper, our sample separation is not made on investors sentiment, thus making our results not directly comparable with Yu and Yuan (2011). The main premise of using overnight returns as investor sentiment is that retail investors are more likely to be affected by sentiment and they tend to place orders in non-trading hours to be executed at the market open. As it is established on the US stock market, the validity of using overnight returns as the proxy for investor sentiment may not hold worldwide: Investigating six G7 markets and five Asia-Pacific markets, Xiong et al. (2020) find that overnight returns fail to proxy firm-specific investor sentiment. Meanwhile, a number of more recent studies challenge the conventional wisdom that institutional investors are more sophisticated than retail investors, and less susceptible to behavioral biases, and thus the latter are to blame when markets

[5] At the firm level, many studies explore potential reasons for the weak positive risk-return relation as well, such as Tinic and West (1984), Cohen et al. (2005), Pástor et al. (2008), Nyberg (2012), Savor and Wilson (2014), Antoniou et al. (2016), Jylhä (2018), and Wang (2020).

Table 2
Panel regression.

Market	Overnight (I)		Intraday (II)		Difference (III)	
	β	*p*-value	β	*p*-value	*Diff.*	*p*-value
Panel A: Full sample						
RW	0.5269	(0.0041)[a]	–0.4022	(0.0031)[a]	0.9291	(0.0000)[a]
MIDAS	0.5445	(0.0019)[a]	–0.4806	(0.0021)[a]	1.0252	(0.0001)[a]
GARCH	0.6225	(0.0014)[a]	–0.4817	(0.0064)[a]	1.1042	(0.0000)[a]
GJR-GARCH	0.6504	(0.0005)[a]	–0.5433	(0.0016)[a]	1.1936	(0.0000)[a]
EGARCH	0.7681	(0.0002)[a]	–0.7415	(0.0005)[a]	1.5095	(0.0000)[a]
Panel B: Removing pre-1990 observations						
RW	0.4948	(0.0079)[a]	–0.2113	(0.1144)	0.7060	(0.0059)[a]
MIDAS	0.5416	(0.0056)[a]	–0.2519	(0.0970)[c]	0.7935	(0.0009)[a]
GARCH	0.5758	(0.0036)[a]	–0.2865	(0.0913)[c]	0.8622	(0.0005)[a]
GJR-GARCH	0.5763	(0.0017)[a]	–0.3080	(0.0649)[c]	0.8844	(0.0000)[a]
EGARCH	0.6067	(0.0010)[a]	–0.3759	(0.0589)[c]	0.9827	(0.0000)[a]

This table presents panel regression results of the mean–variance relation overnight (Column I) and intraday (Column II). The regression specification follows,

$R_{i,t+1} = \alpha + \beta Var_{i,t}(R_{i,t+1}) + \varepsilon_{i,t+1}$,

where $R_{i,t+1}$ is the excess return of stock market *i*; $Var_{i,t}(R_{i,t+1})$ is the conditional volatility computed by five different ways, i.e., RW, MIDAS, and three GARCH-family models including GARCH, GJR-GARCH, and EGARCH; and β reflects the mean–variance relation. The regression is run separately for overnight and intraday. Column III presents the differences in the mean–variance relations overnight and intraday. Panel A uses the full sample while Panel B removes pre-1990 observations, for robustness purposes.

[a] and [c] represent statistical significance at the 1 % and 10 % level, respectively.

deviate from efficiency, documenting that institutional investors can also be noise traders (Chelley-Steeley et al., 2019; DeVault et al., 2019). In this paper, therefore, we interpret 'overnight returns' as its original meaning and focus our analyses on different times during trading days, rather than different sentiment conditions.

4.1.2. Robustness tests

We conduct two robustness tests in this part. The starting dates for most sample markets are after 1990 s, so to avoid our results from being mainly driven by the markets with longer sample periods, such as Canada and the US, we remove pre-1990 data and run Eq. (13) again. Results in Panel B of Table 2 largely support our main results, showing the positive risk-return tradeoff overnight, ranging from 0.4948 (RW) to 0.6067 (EGARCH), which is distorted intraday, ranging from –0.2113 (RW) to –0.3759 (EGARCH), with a significant overnight-intraday difference, ranging from 0.7060 (RW) to 0.9827 (EGARCH). For instance, as EGARCH suggests, a 1 % upward (downward) revision in conditional volatility overnight would cause a 0.6067 % increase (decrease) in market returns during non-trading hours, but a same magnitude change intraday would lead to a 0.3759 % decrease (increase) in market returns during trading hours, with a significant difference of 0.9827 %.

French et al. (1987) provide an indirect test of the risk-return relation by examining a return-innovation relation. If there is a positive risk-return tradeoff, i.e., that high conditional volatility predicts low current prices and thus high expected returns, the volatility innovation should forecast low realized returns, implying a negative return-innovation relation. Likewise, if there is a negative mean–variance relation, a positive return-innovation relation is expected. The regression follows,

$$R_{i,t+1} = \alpha + \beta Var_{i,t}(R_{i,t+1}) + \eta Var_i(R_{i,t+1})^i + \varepsilon_{i,t+1}. \tag{14}$$

where $Var_i(R_{i,t+1})^i$ is the volatility innovation, defined as the unexpected change in concurrent volatility; η is the return-innovation relation and is expected to be negative when a positive mean–variance relation is present but positive when a negative relation is present. Results in Table 3 reveals a negative return-innovation relation overnight while a positive one intraday, with a significant difference, in line with our main results of the mean–variance relation, confirming a positive mean–variance relation overnight but a negative one intraday.[6]

In general, our results indicate that at the global level, the market risk premium is positive during non-trading hours but negative during trading hours, echoing Hendershott et al. (2020) that overnight traders are long-term investors demanding higher returns for bearing higher market risk, but intraday traders are risk-loving speculators demanding higher market risk.

4.2. Individual markets

Results of individual markets appear in Table 4, showing that the mean–variance relation overnight and intraday is market-specific, with around 60 % of the sample markets exhibiting a significant difference in the relation overnight and intraday. Despite differences

[6] Robustness of our results is also embodied in the cross-market investigations provided below. See, for example, Footnote 14.

Table 3
Indirect test.

Market	Overnight (I)		Intraday (II)		Difference (III)	
	η	*p*-value	η	*p*-value	*Diff.*	*p*-value
RW	–2.6237	(0.0000)[a]	0.8527	(0.0000)[a]	–3.4764	(0.0000)[a]
MIDAS	–2.6271	(0.0000)[a]	1.0891	(0.0000)[a]	–3.7163	(0.0000)[a]
GARCH	–2.6627	(0.0000)[a]	1.0964	(0.0000)[a]	–3.7592	(0.0000)[a]
GJR-GARCH	–2.7246	(0.0000)[a]	1.6078	(0.0000)[a]	–4.3323	(0.0000)[a]
EGARCH	–2.8672	(0.0000)[a]	1.7102	(0.0000)[a]	–4.5773	(0.0000)[a]

This table presents panel regression results of the return-innovation relation overnight (Column I) and intraday (Column II). The regression specification follows,

$$R_{i,t+1} = \alpha + \beta Var_{i,t}(R_{i,t+1}) + \eta Var_i(R_{i,t+1})^i + \varepsilon_{i,t+1},$$

where $Var_i(R_{i,t+1})^i$ is the volatility innovation, defined as the unexpected change in concurrent volatility; η is the return-innovation relation. The regression is run separately for overnight and intraday. Column III presents the differences in the mean–variance relations overnight and intraday.
[a] represents statistical significance at the 1 % level, respectively.

in estimates across volatility models, which is expected, results are largely qualitatively consistent, and we mainly use RW results for interpretation. We classify the twenty-five markets into four main tiers as per different mean–variance relation patterns overnight and intraday.

The first tier contains four markets including Belgium, Czech Republic, Ireland, and the US, where there is a positive mean–variance relation overnight but a negative relation intraday, the same as the global panel regression and suggesting more sophisticated overnight traders. For the US stock market, a 1 % upward (downward) revision in conditional volatility overnight would cause a 4.4996 % increase (decrease) in overnight market returns, but a 0.9682 % decrease (increase) in intraday market returns, in line with Wang (2021) in terms of both sign and magnitude. The second tier has two sub-tiers. The first sub-tier includes Argentina, Brazil, Canada, Chile, France, Germany, Hong Kong, Mexico, and Philippines, in which there is a positive mean–variance relation overnight, in line with the global evidence, but no relation intraday, with six of them showing a significant difference in the relation overnight and intraday. The second sub-tier includes Australia, Austria, Portugal, and Thailand, where there is a negative mean–variance relation intraday, in line with the global evidence, but no relation overnight, with two exhibiting a significant difference in the relation overnight and intraday. Overnight traders of the first sub-tier are rational and their trading results in a positive mean–variance relation, while intraday traders of the second sub-tier are uninformed and their trading brings about an undermined risk-return tradeoff. As a result, for the second tier we also tend to observe different clienteles across night and day, and in particular, informed overnight traders but uninformed intraday traders. While in some stock markets, such as Hong Kong and Thailand, the difference in the mean–variance relation overnight and intraday is insignificant, it does not weaken our argument on the different clienteles: In Hong Kong, for example, despite the insignificant overnight-intraday difference, there exists a positive mean–variance overnight but no relation intraday, indicating different clienteles, though such a difference is not substantial enough to eventually lead to a significant spread in the mean–variance relation overnight and intraday. The third tier reflects an opposite situation to the first two tiers where intraday traders are more informed than overnight traders, and it has three markets including China, South Korea, and Taiwan. And finally, the remaining five markets, Italy, Japan, Netherlands, Spain, and Switzerland, form the fourth tier in which there is no mean–variance relation overnight or intraday. The above four tiers cover all our presented results of the twenty-five stock markets, and notably, no single market exhibits consistently, significantly positive or negative mean–variance relation overnight and intraday, evidencing a fairly strong differential pattern across overnight and intraday.

In addition to different relation patterns across night and day, magnitude also varies across markets. In markets such as Argentina, Brazil, China, and Mexico, returns react strongly to conditional variance overnight, while in markets such as France, Hong Kong, and Philippines, such reaction is mild. For example, RW suggests that a 1 % upward (downward) revision in conditional volatility in Argentina would cause an 8.7778 % increase (decrease) in market returns during non-trading hours, nearly five times that in France (1.7760 %). Similarly, in markets such as Australia, Belgium, Ireland, and Portugal, intraday returns are sensitive to intraday conditional volatility, while in markets such as Austria, South Korea, and the US, we do not see the high responsiveness.[7]

5. Cross-market investigation

Given the cross-market differences in the mean–variance relation overnight and intraday reported in Section 4, we explore possible determinants and explanations from the perspective of cultural dimensions, market integrity, and market development in this section.

[7] Results of individual markets are robust to the indirect test specification.

Table 4
Individual market results.

	Overnight (I)		Intraday (II)		Difference (III)	
Market	*β*	*p*-value	*β*	*p*-value	*Diff.*	*p*-value
Panel A: Rolling window						
Argentina	8.7778	(0.0000)[a]	–0.1292	(0.8157)	8.9070	(0.0000)[a]
Australia	4.5958	(0.1297)	–4.0460	(0.0005)[a]	8.6417	(0.0075)[a]
Austria	1.5497	(0.5859)	–1.4582	(0.0067)[a]	3.0079	(0.2983)
Belgium	3.2636	(0.0001)[a]	–3.7939	(0.0001)[a]	7.0575	(0.0000)[a]
Brazil	11.5884	(0.0067)[a]	–0.2551	(0.6809)	11.8435	(0.0003)[a]
Canada	2.3276	(0.0214)[b]	–0.5250	(0.6135)	2.8526	(0.0488)[b]
Chile	3.0196	(0.0013)[a]	0.5405	(0.4898)	2.4790	(0.0415)[b]
China	–6.3113	(0.0000)[a]	1.3882	(0.1067)	–7.6995	(0.0000)[a]
Czech Republic	3.4513	(0.0000)[a]	–3.0850	(0.0006)[a]	6.5363	(0.0000)[a]
France	1.7760	(0.0072)[a]	–0.3908	(0.6586)	2.1669	(0.0490)[b]
Germany	2.1284	(0.0331)[b]	0.3548	(0.6132)	1.7736	(0.1448)
Hong Kong	1.2394	(0.0001)[a]	–0.2242	(0.6967)	1.4636	(0.2512)
Ireland	4.3188	(0.0981)[c]	–3.3240	(0.0000)[a]	7.6428	(0.0043)[a]
Italy	0.5338	(0.6453)	0.1375	(0.8838)	0.3963	(0.7773)
Japan	0.9943	(0.5311)	0.1867	(0.7254)	0.8076	(0.6292)
Mexico	7.5372	(0.0000)[a]	0.6403	(0.3302)	6.8969	(0.0003)[a]
Netherlands	0.3126	(0.5695)	0.2866	(0.7015)	0.0261	(0.9776)
Philippines	1.7080	(0.0805)[c]	0.6130	(0.6155)	1.0950	(0.4829)
Portugal	0.4211	(0.5115)	–3.1426	(0.0096)[a]	3.5637	(0.0076)[a]
South Korea	–0.1909	(0.8436)	1.5274	(0.0257)[b]	–1.7184	(0.1465)
Spain	0.8558	(0.2665)	0.7214	(0.4154)	0.1344	(0.9087)
Switzerland	0.6162	(0.3650)	1.2752	(0.1499)	–0.6591	(0.5543)
Taiwan	–4.9620	(0.0019)[a]	1.1790	(0.2876)	–6.1410	(0.0015)[a]
Thailand	–0.2721	(0.8363)	–1.3638	(0.0694)[c]	1.0917	(0.4709)
US	4.4996	(0.0713)[c]	–0.9682	(0.0149)[b]	5.4677	(0.0300)[b]
Panel B: MIDAS						
Argentina	11.5457	(0.0000)[a]	–0.1905	(0.7771)	11.7363	(0.0000)[a]
Australia	3.6498	(0.2279)	–4.4883	(0.0006)[a]	8.1381	(0.0130)[b]
Austria	0.9925	(0.6744)	–1.5215	(0.0114)[b]	2.5140	(0.3018)
Belgium	3.6014	(0.0001)[a]	–4.3926	(0.0001)[a]	7.9939	(0.0000)[a]
Brazil	11.2900	(0.0041)[a]	–0.2400	(0.7464)	11.5301	(0.0011)[a]
Canada	2.5526	(0.0601)[c]	–1.5327	(0.2713)	4.0853	(0.0354)[b]
Chile	3.3422	(0.0005)[a]	0.6622	(0.4310)	2.6800	(0.0349)[b]
China	–7.2212	(0.0000)[a]	1.2986	(0.1890)	–8.5198	(0.0000)[a]
Czech Republic	3.5762	(0.0000)[a]	–3.1731	(0.0013)[a]	6.7494	(0.0000)[a]
France	1.9080	(0.0108)[b]	–0.7581	(0.4448)	2.6660	(0.0314)[b]
Germany	2.2972	(0.0416)[b]	0.3922	(0.6208)	1.9049	(0.0989)[c]
Hong Kong	1.8446	(0.0000)[a]	–0.2567	(0.7169)	2.1013	(0.0625)[c]
Ireland	4.9134	(0.0946)[c]	–3.5450	(0.0000)[a]	8.4584	(0.0058)[c]
Italy	0.5894	(0.4333)	0.4389	(0.6674)	0.1505	(0.9066)
Japan	1.0688	(0.5379)	0.3852	(0.5360)	0.6836	(0.7105)
Mexico	8.1155	(0.0000)[a]	0.6886	(0.3545)	7.4269	(0.0000)[a]
Netherlands	0.3146	(0.5738)	0.1833	(0.8236)	0.1314	(0.8948)
Philippines	2.1049	(0.0668)[c]	0.5177	(0.7189)	1.5872	(0.3874)
Portugal	0.5251	(0.4051)	–2.7414	(0.0392)[b]	3.2665	(0.0134)[b]
South Korea	–0.1960	(0.8383)	1.4979	(0.0445)[b]	–1.6939	(0.1628)
Spain	0.8745	(0.3036)	0.7842	(0.4290)	0.0902	(0.9464)
Switzerland	0.6541	(0.3654)	1.4194	(0.1646)	–0.7653	(0.5400)
Taiwan	–5.0739	(0.0009)[a]	0.5414	(0.6670)	–5.1153	(0.0135)[b]
Thailand	–0.2987	(0.7716)	–1.4853	(0.0781)[c]	1.1866	(0.4707)
US	4.7576	(0.0448)[b]	–0.9941	(0.0287)[b]	5.7517	(0.0169)[b]
	Overnight (I)		Intraday (II)		Difference (III)	
Market	*β*	*p*-value	*β*	*p*-value	*Diff.*	*p*-value
Panel C: GARCH						
Argentina	12.7387	(0.0000)[a]	–0.2675	(0.7513)	13.0062	(0.0000)[a]
Australia	1.8155	(0.4958)	–4.7878	(0.0010)[a]	6.6032	(0.0289)[b]
Austria	1.2252	(0.7142)	–1.4762	(0.0335)[b]	2.7014	(0.4286)
Belgium	3.6001	(0.0001)[a]	–4.3529	(0.0001)[a]	7.9530	(0.0000)[a]
Brazil	9.4106	(0.0064)[a]	0.0262	(0.9778)	9.3844	(0.0026)[a]
Canada	5.8124	(0.0040)[a]	–5.3368	(0.0094)[a]	11.1492	(0.0001)[a]
Chile	4.1052	(0.0000)[a]	0.6786	(0.3864)	3.4265	(0.0040)[a]
China	–5.1038	(0.0000)[a]	0.7289	(0.5087)	–5.8327	(0.0001)[a]
Czech Republic	3.6878	(0.0000)[a]	–2.8608	(0.0076)[a]	6.5486	(0.0000)[a]

(*continued on next page*)

Table 4 (*continued*)

Market	Overnight (I)		Intraday (II)		Difference (III)	
	β	*p*-value	β	*p*-value	*Diff.*	*p*-value
France	2.0099	(0.0307)[b]	–1.5388	(0.1704)	3.5487	(0.0142)[b]
Germany	2.4771	(0.0267)[b]	0.2073	(0.8093)	2.2698	(0.0961)[c]
Hong Kong	2.1848	(0.0000)[a]	0.0138	(0.9871)	2.1711	(0.0733)[c]
Ireland	5.0399	(0.0901)[c]	–3.4645	(0.0000)[a]	8.5044	(0.0068)[c]
Italy	0.6404	(0.5528)	0.8034	(0.4630)	–0.1630	(0.9324)
Japan	1.2639	(0.5051)	0.6869	(0.3373)	0.5770	(0.7757)
Mexico	8.5472	(0.0000)[a]	0.7438	(0.3586)	7.8034	(0.0000)[a]
Netherlands	0.3749	(0.4848)	–0.1249	(0.8876)	0.4997	(0.6228)
Philippines	2.4869	(0.0576)[c]	0.4849	(0.7809)	2.0020	(0.3477)
Portugal	0.5602	(0.3882)	–0.5668	(0.6582)	1.1271	(0.0796)[c]
South Korea	–0.1693	(0.8497)	1.2393	(0.1144)	–1.4087	(0.2356)
Spain	0.8960	(0.3074)	1.0156	(0.3389)	–0.1196	(0.9356)
Switzerland	0.6631	(0.3826)	1.6545	(0.1726)	–0.9914	(0.4717)
Taiwan	–4.9747	(0.0013)[a]	–0.3912	(0.7719)	–4.5835	(0.0289)[b]
Thailand	–0.3121	(0.7507)	–1.6014	(0.0803)[c]	1.2893	(0.4299)
US	4.8748	(0.0218)[b]	–1.1436	(0.0323)[b]	6.0184	(0.0078)[a]
Panel D: GJR-GARCH						
Argentina	13.0937	(0.0000)[a]	–0.3014	(0.7203)	13.3951	(0.0000)[a]
Australia	1.8649	(0.4887)	–4.5231	(0.0009)[a]	6.3879	(0.0334)[b]
Austria	2.3171	(0.7059)	–1.4216	(0.0352)[b]	3.7387	(0.6319)
Belgium	3.3821	(0.0002)[a]	–4.5243	(0.0000)[a]	7.9065	(0.0000)[a]
Brazil	10.8528	(0.0036)[a]	–0.0592	(0.9492)	10.9121	(0.0041)[a]
Canada	4.6784	(0.0082)[a]	–3.8211	(0.0335)[b]	8.4995	(0.0007)[a]
Chile	2.7975	(0.0005)[a]	0.7808	(0.3228)	2.0167	(0.0713)[c]
China	–5.1690	(0.0000)[a]	0.7115	(0.5124)	–5.8804	(0.0001)[a]
Czech Republic	3.8740	(0.0000)[a]	–2.5245	(0.0088)[a]	6.3986	(0.0000)[a]
France	2.2245	(0.0254)[b]	–1.5945	(0.1349)	1.8189	(0.0112)[b]
Germany	2.4989	(0.0261)[b]	0.5476	(0.5453)	1.9514	(0.1553)
Hong Kong	2.3782	(0.0000)[a]	–0.2194	(0.8031)	2.5976	(0.0502)[c]
Ireland	5.4150	(0.0766)[c]	–3.1037	(0.0000)[a]	8.5187	(0.0062)[a]
Italy	0.8682	(0.4135)	1.0213	(0.3166)	–0.1530	(0.9340)
Japan	1.5498	(0.4433)	0.8999	(0.2117)	0.6499	(0.7414)
Mexico	9.2830	(0.0000)[a]	0.5629	(0.4924)	8.7201	(0.0000)[a]
Netherlands	0.4145	(0.4417)	–0.1037	(0.9042)	0.5182	(0.5954)
Philippines	2.5552	(0.0428)[b]	–0.1585	(0.9231)	2.7137	(0.1767)
Portugal	0.5587	(0.3671)	–1.3313	(0.3059)	1.8900	(0.0601)[c]
South Korea	–0.2291	(0.7684)	1.1329	(0.1391)	–1.3620	(0.2115)
Spain	0.9346	(0.2946)	0.8645	(0.4223)	0.0701	(0.9616)
Switzerland	0.6988	(0.3047)	1.5705	(0.1752)	–0.8716	(0.5104)
Taiwan	–5.1441	(0.0004)[a]	–1.4498	(0.3171)	–3.6943	(0.0800)[c]
Thailand	–0.3575	(0.7067)	–1.5960	(0.0828)[c]	1.2385	(0.4542)
US	4.9383	(0.0186)[b]	–1.1486	(0.0119)[b]	6.0869	(0.0021)[a]
	Overnight (I)		Intraday (II)		Difference (III)	
Market	β	*p*-value	β	*p*-value	*Diff.*	*p*-value
Panel E: EGARCH						
Argentina	15.4405	(0.0000)[a]	–0.5184	(0.6245)	15.9590	(0.0000)[a]
Australia	2.6241	(0.4385)	–5.4261	(0.0014)[a]	8.0502	(0.0328)[b]
Austria	2.5214	(0.6985)	–1.6449	(0.0346)[b]	4.1663	(0.6600)
Belgium	5.3890	(0.0000)[a]	–5.8321	(0.0000)[a]	11.2211	(0.0000)[a]
Brazil	12.8511	(0.0086)[a]	–0.3261	(0.7770)	13.1773	(0.0070)[a]
Canada	6.3522	(0.0013)[a]	–5.3135	(0.0085)[a]	11.6658	(0.0000)[a]
Chile	4.4692	(0.0004)[a]	1.3245	(0.3374)	3.1448	(0.0920)[c]
China	–8.5268	(0.0000)[a]	0.4834	(0.6857)	–9.0102	(0.0000)[a]
Czech Republic	4.8280	(0.0000)[a]	–3.9321	(0.0056)[a]	8.7602	(0.0000)[a]
France	2.4904	(0.0242)[b]	–1.4073	(0.2573)	3.8977	(0.0187)[b]
Germany	3.7990	(0.0126)[b]	0.5304	(0.6110)	3.2686	(0.0572)[c]
Hong Kong	2.4995	(0.0280)[b]	–0.5941	(0.5755)	3.0936	(0.0461)[b]
Ireland	6.1752	(0.0315)[b]	–3.8143	(0.0000)[a]	9.9896	(0.0000)[a]
Italy	1.4982	(0.3545)	1.1540	(0.3346)	0.3442	(0.8430)
Japan	1.9757	(0.3512)	1.3068	(0.1734)	0.6689	(0.7580)
Mexico	9.7520	(0.0001)[a]	0.6352	(0.5035)	9.1168	(0.0000)[a]
Netherlands	0.5125	(0.5245)	0.0274	(0.9783)	0.4850	(0.7068)
Philippines	2.7153	(0.0394)[c]	–0.3042	(0.8807)	3.0195	(0.2200)
Portugal	0.6045	(0.3230)	–2.8945	(0.0996)[c]	3.4990	(0.0088)[c]
South Korea	–0.2658	(0.8189)	1.2208	(0.1602)	–1.4866	(0.3048)

(continued on next page)

Table 4 (*continued*)

	Overnight (I)		Intraday (II)		Difference (III)	
Market	β	*p*-value	β	*p*-value	*Diff.*	*p*-value
Spain	1.1703	(0.2696)	0.3348	(0.7967)	0.8355	(0.6496)
Switzerland	1.1913	(0.3246)	1.3278	(0.3729)	–0.1365	(0.9432)
Taiwan	–5.7003	(0.0001)[a]	–1.9684	(0.1978)	–3.7319	(0.0942)[c]
Thailand	–0.4216	(0.6910)	–1.9317	(0.0740)[c]	1.5100	(0.5109)
US	5.3910	(0.0100)[b]	–1.5077	(0.0284)[b]	6.8987	(0.0001)[a]

This table presents individual market results of the mean–variance relation overnight (Column I) and intraday (Column II). The regression specification follows,

$R_{t+1} = \alpha + \beta Var_t(R_{t+1}) + \varepsilon_{t+1}$,

where R_{t+1} is the excess return; $Var_{i,t}(R_{i,t+1})$ is the conditional volatility computed by five different ways, i.e., RW, MIDAS, and three GARCH-family models including GARCH, GJR-GARCH, and EGARCH; and β reflects the mean–variance relation. The regression is run separately for overnight and intraday. Column III presents the differences in the mean–variance relation overnight and intraday.

[a] ,[b], and [c] represent statistical significance at the 1 %, 5 %, and 10 % level, respectively.

5.1. *Cultural dimensions, market integrity, and market development*

5.1.1. *Cultural dimensions*

For cultural dimensions, we assess individualism (IDV), the uncertainty avoidance index (UAI), masculinity (MAS), the power distance index (PDI), long-term orientation (LTO), and indulgence (IDG). A clear message emanated from the theoretical analyses and inferences in Subsection 2.2 is that each culture dimension can result in opposing effects, i.e., that cultures at one end (high, or low) can either imply rational investors or irrational investors. Put differently, it suggests that each cultural dimension has two elements, rational and irrational, with respect to its influence on investor behaviors. For instance, high IDV can predict a low chance of herd-led overreaction (i.e., a rational element), but meanwhile, it may bring about overconfidence and cognitive biases (i.e., an irrational element). The opposite applies to CLT: High CLT may lead to a low level of overconfidence and cognitive biases (i.e., a rational element) but can also incur overreaction (i.e., an irrational element). This is also seen in empirical evidence. Schmeling (2009) and Wang et al. (2021), for example, report contradictory findings that investors in CLT and IDV markets are more irrational, respectively, and hence the impact of investor sentiment on stock market returns in these markets is more pronounced. Therefore, instead of putting forward formal hypotheses, we shall let the empirical findings show the influence. Also, given the potential influence of cultural tightness-looseness as presented in Subsection 2.2 (Beugelsdijk et al., 2014; Chua et al., 2015; Dow et al., 2016; Shin et al., 2016; Beugelsdijk et al., 2017), we control for tightness-looseness for each cultural dimension in our analysis.

We collect culture data from Hofstede's website.[8] Scores, ranging between 0 and 100, are assigned to twenty-five stock markets in our sample for each dimension, and compiled in Panel A of Table 5. Scores of our sample markets scatter widely in the six cultural dimensions and the range varies from 70 (UAI) to 83 (PDI), with an average as high as 78. This is an important feature considering the discussion in Subsection 2.2 that for every cultural dimension, both ends, like LTO and STO, or IDG and RES, may lead to distortion of the positive mean–variance relation. If scores center around one end, we may fail to reveal the influence of the other end on the mean–variance relation and thus draw inaccurate conclusions.[9] Cultural tightness-looseness is sourced from Uz (2015), and a high (low) value indicates a loose (tight) culture. The data are available for eighteen out of twenty-five sample markets.[10]

We compute pairwise correlations and report them in Table 5. Overall, the correlation tends to be low and only three out of fifteen are significant. IDV and PDI are negatively correlated (–0.6127), indicating that people in collectivistic cultures are more likely to expect and accept cultures to be unevenly distributed, partly in line with Hofstede (1983) documenting that there is a global relation that collectivistic cultures always exhibit large power distance. IDG is positively correlated with IDV (0.3594) and negatively correlated with LTO (–0.4957), indicating that people in individualistic and short-term orientation cultures are more likely to enjoy life. While some studies argue that high UAI and low IDV both suggest overreaction (Schmeling, 2009; Wang and Duxbury, 2021), the correlation between the two in our sample is not significant despite being negative. Correlations between tightness-looseness and the six cultural dimensions are insignificant in all cases, consistent with Carpenter (2016) and Aktas et al. (2015) showing that tightness-looseness is distinct from other cultural dimensions. Despite that, the positive correlation between IDV and tightness-looseness appears to imply that people in individualistic cultures tend to behave more differently than those in collectivistic cultures, which is expected given the nature of the IDV cultures.

5.1.2. *Market integrity and market development*

We consider seven market integrity variables, including anti-director rights (ADR), government corruption (GVC), accounting

[8] We are grateful to Prof. Geert Hofstede for making the data available at https://www.hofstede-insights.com.

[9] Noting the contradictory findings between Schmeling (2009) and Wang et al. (2021), the latter conjecture that it could be due to their enlarged sample markets significantly extending the IDV scale. This confirms the importance of having extended cultural dimension scales.

[10] Uz (2015) measures tightness-looseness from a within-market variation in responses to a few questions of World Values Survey (WVS), which is different from Gelfand et al. (2011) that measures via direct questions. As only fourteen sample markets are covered in Gelfand et al. (2011), we use Uz's (2015) data in our paper.

Table 5
Cultural dimensions and market integrity.

Panel A.1 Cultural dimensions: values

Market	IDV	UAI	MAS	PDI	LTO	IDG	Tightness-looseness
Argentina	46	86	56	49	20	62	75
Australia	90	51	61	36	21	71	–
Austria	55	70	79	11	60	63	75.8
Belgium	75	94	54	65	82	57	119.8
Brazil	38	76	49	69	44	59	–
Canada	80	48	52	39	36	68	84.6
Chile	23	86	28	63	31	68	86.8
China	20	30	66	80	87	24	–
Czech Republic	58	74	57	57	70	29	59.6
France	71	86	43	68	63	48	99.6
Germany	67	65	66	35	83	40	82.9
Hong Kong	25	29	57	68	61	17	–
Ireland	70	35	68	28	24	65	71.2
Italy	76	75	70	50	61	30	67.8
Japan	46	92	95	54	88	42	43.3
Mexico	30	82	69	81	24	97	74.7
Netherlands	80	53	14	38	67	68	78.9
Philippines	32	44	64	94	27	42	31.5
Portugal	27	99	31	63	28	33	87.4
South Korea	18	85	39	60	100	29	20.1
Spain	51	86	42	57	48	44	83.9
Switzerland	68	58	70	34	74	66	–
Taiwan	17	69	45	58	93	49	–
Thailand	20	64	34	64	32	45	–
US	91	46	62	40	26	68	58

Panel A.2 Cultural dimensions: pairwise correlations

	IDV	UAI	MAS	PDI	LTO	IDG	Tightness-looseness
IDV							
UAI	–0.1529						
	(0.4657)						
MAS	0.1908	–0.1725					
	(0.3610)	(0.4095)					
PDI	–0.6127	0.1284	–0.1887				
	(0.0011)[a]	(0.5408)	(0.3664)				
LTO	–0.1286	0.1158	0.1137	–0.0075			
	(0.5401)	(0.5814)	(0.5882)	(0.9715)			
IDG	0.3594	0.0529	0.0126	–0.2990	–0.4957		
	(0.0777)[c]	(0.8018)	(0.9524)	(0.1466)	(0.0117)[b]		
Tightness-looseness	0.3813	0.2566	–0.2840	–0.1432	–0.1224	0.3204	
	(0.1185)	(0.3040)	(0.2534)	(0.5708)	(0.6284)	(0.1949)	

Panel B.1 Market integrity: values

Market	ADR	GVC	ACS	EJS	ROL	ROE	RCR	MKI
Argentina	4	6.02	45	6	5.35	5.91	4.91	22.6612
Australia	4	8.52	75	10	10	9.27	8.71	37.1219
Austria	2	8.57	54	9.5	10	9.69	9.6	31.1989
Belgium	0	8.82	61	9.5	10	9.63	9.48	32.8416
Brazil	3	6.32	54	5.75	6.32	7.62	6.3	26.3170
Canada	5	10	74	9.25	10	9.67	8.96	37.4843
Chile	3	5.3	52	7.25	7.02	7.5	6.8	26.2742
China	–	–	–	–	–	–	–	–
Czech Republic	–	–	–	–	–	–	–	–
France	2	9.05	69	8	8.98	9.65	9.19	34.5241
Germany	1	8.93	62	9	9.23	9.9	9.77	33.0607
Hong Kong	4	8.52	69	10	8.22	8.29	8.82	34.5594
Ireland	–	–	–	–	–	–	–	–
Italy	1	6.13	62	6.75	8.33	9.35	9.17	30.5991
Japan	4	8.52	65	10	8.98	9.67	9.69	34.4171
Mexico	1	4.77	60	6	5.35	7.29	6.55	26.8140
Netherlands	2	10	64	10	10	9.98	9.35	34.6834
Philippines	3	2.92	65	4.75	2.73	5.22	4.8	25.3402
Portugal	3	7.38	36	5.5	8.68	8.9	8.57	23.5180
South Korea	2	5.3	62	6	5.35	8.31	8.59	28.6703
Spain	4	7.38	64	6.25	7.8	9.52	8.4	31.5724
Switzerland	2	10	68	10	10	9.98	9.98	35.9838

(*continued on next page*)

Table 5 (*continued*)

Taiwan	3	6.85	65	6.75	8.52	9.12	9.16	32.0146
Thailand	3	5.18	64	3.25	6.25	7.42	7.57	28.1017
US	5	8.63	71	10	10	9.98	9	36.5347

Panel B.2 Market integrity: pairwise correlations

	ADR	GVC	ACS	EJS	ROL	ROE	RCR	MKI
ADR								
GVC	0.0774							
	(0.7322)							
ACS	0.1908	0.3438						
	(0.3950)	(0.1172)						
EJS	0.0638	0.8395	0.4524					
	(0.7779)	(0.0000)[a]	(0.0345)[b]					
ROL	0.0078	0.9211	0.2925	0.7977				
	(0.9724)	(0.0000)[a]	(0.1865)	(0.0000)[a]				
ROE	–0.1044	0.8479	0.3592	0.6994	0.9208			
	(0.6440)	(0.0000)[a]	(0.1006)	(0.0000)[a]	(0.0000)[a]			
RCR	–0.1868	0.7861	0.3769	0.6711	0.8632	0.9497		
	(0.4051)	(0.0000)[a]	(0.0838)[c]	(0.0006)[a]	(0.0000)[a]	(0.0000)[a]		
MKI	0.1522	0.7959	0.8198	0.8124	0.7717	0.7805	0.7633	
	(0.4990)	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	

This table presents cultural dimensions and market integrity in Panel A and B, respectively. Cultural dimensions include IDV, UAI, MAS, PDI, LTO, IDG, and cultural tightness-looseness, sourced from Hofstede's website at https://www.hofstede-insights.com, and market integrity include ADR, GVC, ACS, EJS, ROL, ROE, RCR, and MKI, sourced from La Porta et al. (1998). Pairwise correlations are also provided.

[a] ,[b], and [c] represent statistical significance at the 1 %, 5 %, and 10 % level, respectively.

standards (ACS), efficiency of judicial systems (EJS), the rule of law (ROL), risk of expropriation (ROE), and risk of contract repudiation (RCR), all sourced from La Porta et al. (1998).[11] The data are available for twenty-two sample markets. Scores are assigned to each factor with high scores indicating high-level market integrity. As the seven variables capture different aspects of market integrity, instead of examining them separately, we use the principal component analysis (PCA) to construct a composite indicator of overall market integrity capturing common information across the variables. We employ the first two PCs explaining about 81.4433 % of the total variance and construct the market integrity indicator (MKI) for each market based on available data (see, Table 5). Pairwise correlations between the seven variables are positive in most cases, suggesting that markets with higher levels of market integrity in one aspect tend to be advanced in other aspects as well.

Finally, to examine the influence of market development (DVL) on the mean–variance relation overnight and intraday, our twenty-five international stock markets are classified as developed and emerging markets following Morgan Stanley Capital International (MSCI) market classification (see, Table 1),[12] and in particular, our twenty-five markets consist of fifteen developed markets and ten emerging markets.

5.2. Cross-market results

Our empirical model is described by the following equation,

$$R_{i,t+1} = \alpha + \beta f + (\gamma_0 + \gamma_1 f) Var_{i,t}(R_{i,t+1}) + \varepsilon_{i,t+1}, \tag{15}$$

where f is the cultural dimensions, market integrity, and market development: For cultural dimensions, we use a matrix containing the six cultural dimensions; for market integrity, we use MKI as the composite indicator; and for market development, we use a dummy variable denoting 'one' as developed markets while 'zero' as emerging markets. If γ_1 is positive (negative), an increase in the

[11] See, Bilinski et al. (2013), Nguyen and Truong (2013), Ahern et al. (2015), Scharfstein (2018), Maung et al. (2019), Loureiro and Silva (2021), Hu et al. (2022), for the recent application of the La Porta et al. (1998) data.

[12] While developed and emerging markets exhibit differences in short-sale constraints (Bris et al., 2007; Charoenrook and Daouk, 2009; Griffin et al., 2010; Saffi and Sigurdsson, 2011; Feng et al., 2017; Wang et al., 2021), it could be better if we use a direct, clean measure of short-sale constraints to classify our sample markets. However, we have some practical difficulties in directly including the short-sale constraints into our analyses. First, as per Bris et al. (2007), Charoenrook and Daouk (2009), Jain et al. (2013), and Feng et al. (2017), short selling has been legally allowed in all our sample markets by the end of 2018, i.e., the end of our sample, and therefore it might be difficult to separate the entire sample into two subsamples as what we do based on cultural dimensions, along with market integrity as you suggest below, or at least into two relatively balanced subsamples. Second, trading bans have been applied to short selling in many sample markets. For example, a ban on naked short selling of financial stocks was applied to Austria from October 27, 2008 to November 30, 2010. Also, only 33 stocks can be sold short in 1994–1995 in Hong Kong. Similarly, only underlying stocks of SET 50 index, ETF, and underlying stocks of ETF, can be sold short in Thailand. In fact, at least twenty-three out of twenty-five sample markets have trading bans on short selling, which makes it practically infeasible for us to categorize the sample markets into groups, as there is no consensus which types of bans are stricter or looser than the others. We, therefore, acknowledge this as a potential caveat in our paper.

determinants' values makes the mean–variance relation more positive (negative). For cultural dimensions, we also add an interaction term to control for cultural tightness-looseness,

$$R_{i,t+1} = \alpha + \beta f + [\gamma_0 + \gamma_1 f + \gamma_2 (f \times tl)] Var_{i,t}\left(R_{i,t+1}\right) + \delta tl + \varepsilon_{i,t+1}, \tag{16}$$

where *tl* is cultural tightness-looseness; and $f \times tl$ is the interaction between cultural dimensions and tightness-looseness. Results appear in Table 6.

At the first glance, we see a strong explanatory power of culture to the mean–variance relation in that all six dimensions have predictability, and notably, the influence exhibits evident differences overnight and intraday. To start, IDV has a positive impact on the mean–variance relation overnight, meaning that a positive risk-return tradeoff overnight is more likely in high IDV markets. During trading hours, however, we observe an opposite pattern that IDV has a negative impact on the mean–variance relation and the increased IDV, as a result, tends to distort the positive mean–variance relation intraday. In particular, a 1 % increase (decrease) in IDV would lead to a 0.0395 % increase (decrease) in the mean–variance relation overnight and a 0.0269 % decrease (increase) in the relation intraday, as implied by GARCH. The influence is of economic significance as well—a one-standard-deviation increase (decrease) in IDV would bring about a 0.9742 % (24.6635 × 0.0395 %) and 0.6634 % (24.6635 × 0.0269 %) increase (decrease) in the relation overnight and intraday, respectively.[13] The results imply that when stock markets are closed, with increases in IDV, the informed trading caused by non-overreaction, i.e., the rational element of IDV, dominates the noise trading caused by overconfidence and cognitive biases, i.e., the irrational element of IDV, so that misestimation of variance of returns is reduced; by contrast, when stock markets are open, with increases in IDV, the noise trading caused by overconfidence and cognitive biases dominates the non-overreaction, so that a distortion of the positive risk-return tradeoff is present. The finding concurs with our theoretical discussion that the two poles of individualism, i.e., individualism and collectivism, can be related to irrational trading behaviors, and based on our design, there is a clear cut across non-trading and trading hours. Linking the mean–variance relation with investor rationality, it seems that in IDV cultures overnight traders are more informed than intraday traders, which implies that the two traders can be fundamentally different.

A similar, opposing pattern is also seen for PDI and LTO: Increased PDI and LTO cultures tend to bring a negative impact on the mean–variance relation overnight but a positive impact on the relation intraday. When stock markets are closed, the positive risk-return tradeoff is more distorted in markets with high PDI and high LTO, while by contrast, when stock markets are opened, the positive risk-return tradeoff is more distorted in markets with low PDI and low LTO. In markets with high PDI cultures where people more expect and accept power to be unevenly distributed, as an example, overnight traders, as subordinates to authorities, appear to rely excessively on the latter and the high level of reliance leads to uninformed trading that finally causes a negative impact on the mean–variance relation, but the intraday traders rely on authorities to a lesser extent and hence their trading, either is more informed so that it brings a positive impact on the mean–variance relation, or is uninformed but less pronounced so that the distortion to the positive risk-return tradeoff, if any, can be alleviated by authorities.

A consistent impact of UAI on the mean–variance relation overnight and intraday is shown, with increased UAI cultures leading to a more positive mean–variance relation, meaning that traders in high UAI cultures, both overnight and intraday, tend to be more informed than those in low UAI cultures, which could be explained by the fact that the former would like to avoid potential uncertainty or ambiguity in the future so that they have to be more informed during trading, while the latter are more comfortable with uncertainty and thus their trading may not be fairly rational. It is still possible for high UAI traders to overreact when uncertainty happens at some certain point, but typically, the overreaction is largely restrained by their informed trading ex ante. Finally, increased MAS distorts the positive mean–variance relation overnight, but not intraday, and increased IDG maintains the positive relation overnight but not intraday, meaning that the two cultural dimensions only affect a specific clientele but not the other.[14]

While the different or opposing influences of cultural dimensions on the mean–variance relation overnight and intraday seem to be somewhat counter-intuitive, Grinblatt and Keloharju (2001) document that compared with households and less savvy institutions, the most investment-savvy institutions are less influenced by culture, meaning that for a given market with the same culture, different trader types are influenced to varying extents. Although we do not strictly follow the notion in Berkman et al. (2012) and Aboody et al. (2018) that retail investors tend to place orders during non-trading hours as mentioned in Part 4.1.1, this, at least, suggests that investor types can vary overnight and intraday and therefore, leads to the reported different or opposing influences of cultural dimensions on the mean–variance relation overnight and intraday. Our argument is further supported by some other prior studies. From the perspective of retail investor sentiment, Zouaoui et al. (2011) find that the probability of occurrence of stock market crises is higher (lower) in markets with CLT (IDV) cultures, while in contrast, by analyzing managers' behaviors, An et al. (2018) reveal that stock crash risk is more (less) likely to happen in markets with IDV (CLT) cultures, suggesting that cultural dimensions may influence individuals within a given market in different, or even opposite, ways. Likewise, Wang et al. (2021) report a stronger (weaker) impact of

[13] The standard deviation of IDV in our sample markets is 24.6635.

[14] In a series of unreported results, we also obtain γ_0 from Eq. (15). We compute the sum of γ_0 and the product of γ_1 and the average value of the cultural dimension (i.e., $\gamma_0 + \gamma_1 \times$ *avg.*(*culture*)). For example, in Column (II) of Table 6, the MIDAS model suggests that γ_1 is 0.0168 (p-value = 0.0351) for UAI. The unreported γ_0 is –1.6485 (p-value = 0.0042) and the average of UAI in our sample is 67. So, we compute –1.6485 + 0.0168 × 67 = –0.5213 (p-value = 0.0009), suggesting that on average, the mean–variance relation is negative intraday. We compute this for every regression result and find that on average, there is a positive mean–variance relation overnight and a negative one intraday, again, confirming our main findings in Table 2.

Table 6
The impact of cultural dimensions on the mean–variance relation.

	Overnight (I)				Intraday (II)			
Market	γ_1	*p*-value	γ_2	*p*-value	γ_1	*p*-value	γ_2	*p*-value
Panel A.1 IDV								
RW	0.0464	(0.0000)[a]			–0.0244	(0.0001)[a]		
MIDAS	0.0472	(0.0000)[a]			–0.0264	(0.0003)[a]		
GARCH	0.0395	(0.0000)[a]			–0.0269	(0.0008)[a]		
GJR-GARCH	0.0376	(0.0000)[a]			–0.0233	(0.0020)[a]		
EGARCH	0.0398	(0.0000)[a]			–0.0279	(0.0036)[a]		
Panel A.2 IDV: tightness-looseness								
RW			–0.0002	(0.3700)			0.0002	(0.1781)
MIDAS			–0.0003	(0.2143)			0.0002	(0.1871)
GARCH			–0.0003	(0.1102)			0.0002	(0.1386)
GJR-GARCH			–0.0005	(0.0236)[b]			0.0003	(0.0822)[c]
EGARCH			–0.0006	(0.0127)[b]			0.0004	(0.0495)[b]
Panel B.1 UAI								
RW	0.0422	(0.0000)[a]			0.0127	(0.0665)[c]		
MIDAS	0.0248	(0.0009)[a]			0.0168	(0.0351)[b]		
GARCH	0.0387	(0.0000)[a]			0.0222	(0.0132)[b]		
GJR-GARCH	0.0284	(0.0003)[a]			0.0207	(0.0163)[b]		
EGARCH	0.0406	(0.0011)[a]			0.0246	(0.0220)[a]		
Panel B.2 UAI: tightness-looseness								
RW			–0.0003	(0.0037)[a]			–0.0003	(0.0018)[a]
MIDAS			–0.0003	(0.0004)[a]			–0.0004	(0.0012)[a]
GARCH			–0.0003	(0.0006)[a]			–0.0004	(0.0025)[a]
GJR-GARCH			–0.0003	(0.0010)[a]			–0.0004	(0.0007)[a]
EGARCH			–0.0004	(0.0002)[a]			–0.0005	(0.0007)[a]
Panel C.1 MAS								
RW	–0.0181	(0.0323)[b]			–0.0067	(0.4180)		
MIDAS	–0.0176	(0.0331)[b]			–0.0061	(0.5071)		
GARCH	–0.0128	(0.0664)[c]			–0.0051	(0.6168)		
GJR-GARCH	–0.0108	(0.0850)[c]			–0.0033	(0.7428)		
EGARCH	–0.0095	(0.1221)			–0.0029	(0.8143)		
Panel C.2 MAS: tightness-looseness								
RW			0.0005	(0.0034)[a]			–0.0001	(0.6462)
MIDAS			0.0004	(0.0335)[b]			–0.0002	(0.3762)
GARCH			0.0006	(0.0006)[a]			–0.0002	(0.2674)
GJR-GARCH			0.0004	(0.0052)[a]			–0.0002	(0.2219)
EGARCH			0.0006	(0.0009)[a]			–0.0004	(0.1103)
Panel D.1 PDI								
RW	–0.0389	(0.0074)[a]			0.0271	(0.0002)[a]		
MIDAS	–0.0274	(0.0009)[a]			0.0291	(0.0005)[a]		
GARCH	–0.0360	(0.0174)[b]			0.0305	(0.0011)[a]		
GJR-GARCH	–0.0266	(0.0307)[b]			0.0261	(0.0041)[a]		
EGARCH	–0.0211	(0.0504)[c]			0.0294	(0.0065)[a]		
Panel D.2 PDI: tightness-looseness								
RW			0.0003	(0.0060)[a]			–0.0003	(0.0148)[b]
MIDAS			0.0003	(0.0116)[b]			–0.0004	(0.0094)[a]
GARCH			0.0004	(0.0014)[a]			–0.0004	(0.0119)[b]
GJR-GARCH			0.0003	(0.0058)[a]			–0.0004	(0.0061)[a]
EGARCH			0.0005	(0.0007)[a]			–0.0005	(0.0050)[a]
Panel E.1 LTO								
RW	–0.0485	(0.0000)[a]			0.0143	(0.0061)[a]		
MIDAS	–0.0328	(0.0000)[a]			0.0157	(0.0083)[a]		
GARCH	–0.0394	(0.0000)[a]			0.0139	(0.0379)[b]		
GJR-GARCH	–0.0236	(0.0002)[a]			0.0145	(0.0269)[b]		
EGARCH	–0.0389	(0.0009)[a]			0.0192	(0.0158)[b]		
	Overnight (I)		Intraday (II)					
Market	γ_1	*p*-value	γ_2	*p*-value	γ_1	*p*-value	γ_2	*p*-value
Panel E.2 LTO: tightness-looseness								
RW			0.0003	(0.0061)[a]			–0.0003	(0.0025)[a]
MIDAS			0.0005	(0.0000)[a]			–0.0004	(0.0022)[a]
GARCH			0.0003	(0.0031)[a]			–0.0004	(0.0031)[a]
GJR-GARCH			0.0003	(0.0003)[a]			–0.0004	(0.0022)[a]
EGARCH			0.0006	(0.0011)[a]			–0.0004	(0.0044)[a]
Panel F.1 IDG								
RW	0.0421	(0.0001)[a]			–0.0070	(0.3466)		
MIDAS	0.0291	(0.0095)[a]			–0.0084	(0.3202)		
GARCH	0.0468	(0.0000)[a]			–0.0091	(0.3309)		
GJR-GARCH	0.0156	(0.0178)[b]			–0.0105	(0.2564)		

(*continued on next page*)

Table 6 (*continued*)

	Overnight (I)				Intraday (II)			
Market	γ_1	*p*-value	γ_2	*p*-value	γ_1	*p*-value	γ_2	*p*-value
EGARCH	0.0366	(0.0204)[a]			–0.0119	(0.2824)		
Panel F.2 IDG: tightness-looseness								
RW			0.0001	(0.7039)			0.0002	(0.2552)
MIDAS			0.0002	(0.2316)			0.0003	(0.1485)
GARCH			–0.0000	(0.9025)			0.0004	(0.1178)
GJR-GARCH			0.0001	(0.5448)			0.0004	(0.0962)[c]
EGARCH			–0.0000	(0.8006)			0.0006	(0.0371)[b]
Panel G MKI								
RW	0.1334	(0.0022)[a]			–0.0250	(0.4384)		
MIDAS	0.0739	(0.0384)[b]			–0.0307	(0.4191)		
GARCH	0.0888	(0.0576)[c]			–0.0420	(0.3491)		
GJR-GARCH	0.0751	(0.0745)[c]			–0.0370	(0.3903)		
EGARCH	0.0805	(0.0811)[c]			–0.0369	(0.5105)		
Panel H DVL								
RW	1.3350	(0.0005)[a]			–0.5061	(0.0929)[c]		
MIDAS	0.9010	(0.0005)[a]			–0.5571	(0.1190)		
GARCH	0.9592	(0.0144)[b]			–0.4626	(0.1902)		
GJR-GARCH	1.0764	(0.0016)[a]			–0.4209	(0.2204)		
EGARCH	0.9894	(0.0001)[a]			–0.6010	(0.1574)		

This table presents the results of the influence of cultural dimensions, market integrity, and market development on the mean–variance relation overnight (Column I) and intraday (Column II). The regression follows,

$$R_{i,t+1} = \alpha + \beta f + (\gamma_0 + \gamma_1 f) Var_{i,t}(R_{i,t+1}) + \varepsilon_{i,t+1},$$

where *f* is the cultural dimensions, market integrity, and market development. Cultural dimensions include IDV (Panel A), UAI (Panel B), MAS (Panel C), PDI (Panel D), LTO (Panel E), and IDG (Panel F). Market integrity, MKI (Panel G), incorporates the common information from ADR, GVC, ACS, EJS, ROL, ROE, and RCR. Market development, DVL (Panel H), distinguishes between developed and emerging markets.

For cultural dimensions, the impact of tightness-looseness is also considered, and the regression follows,

$$R_{i,t+1} = \alpha + \beta f + [\gamma_0 + \gamma_1 f + \gamma_2 (f \times tl)] Var_{i,t}(R_{i,t+1}) + \delta tl + \varepsilon_{i,t+1},$$

where *tl* is tightness-looseness; and $f \times tl$ is the interaction between cultural dimensions and tightness-looseness.

[a], [b], and [c] represent statistical significance at the 1 %, 5 %, and 10 % level, respectively.

retail investor sentiment on stock market returns in IDV (CLT) markets, meaning that retail investors in IDV (CLT) markets tend to be less (more) rational, while Wang and Duxbury (2021) show a stronger (weaker) impact of institutional investor sentiment on the mean–variance relation in CLT (IDV) markets, drawing an opposite conclusion to Wang et al. (2021) that institutional investors in IDV (CLT) markets tend to be more (less) rational. Jointly, our findings, along with those reported in the four papers mentioned above, appear to highlight a potentially critical role of the interaction between cultural dimensions and clienteles in the determination of financial relations. The influence of cultural dimensions on the mean–variance relation as explored in our paper, and more widely on other financial relations as well, may be subject to different clienteles, particularly concerning investor sophistication, such as investors/managers, retail/institutional investors, and overnight/intraday traders. Given the data availability and the paper's scope, we leave detailed investigations into this to future studies.

The influence of cultural tightness-looseness on the mean–variance is also observed from our results. High PDI cultures, for instance, distorts the positive mean–variance relation overnight while maintains the positive relation intraday, which is moderated by loose cultures as indicated by the significant, but opposite signs of estimates both during non-trading and trading hours, suggesting that the influence of cultural dimensions on the mean–variance relation is stronger in tight cultures while weaker in loose cultures. The moderation effect is also exhibited in UAI, MAS (overnight), and LTO. However, we note a less significant influence for IDV and IDG, and an even opposite (though insignificant) influence for MAS (intraday), which might be explained from two perspectives. First, as we developed in Subsection 2.2, the influence of cultural dimensions is not monotonic, and the role of cultural tightness-looseness, hence, may be more complicated than theorized: For some cultural dimensions, like UAI, MAS (overnight), PDI, and LTO, tight (loose) cultures may lead to a stronger (weaker) relation/impact, while for some other cultural dimensions, like IDV, MAS (intraday), and IDG, tightness-looseness may hold a weaker, or an opposite explanatory power. Second, the tests are performed based on a reduced sample containing eighteen stock markets, which might lead to biases in our results. Despite this, the fact that the impact of cultural dimensions on the mean–variance relation overnight and intraday can vary with changes in cultural tightness-looseness further confirms cultures as the valid channel for the observed cross-market heterogeneity in the mean–variance relation overnight and intraday.

The influence of market integrity and market development on the mean–variance relation overnight and intraday is also revealed in Table 6. During non-trading hours, MKI and DVL have a positive influence on the mean–variance relation, signifying that a positive risk-return tradeoff overnight is more likely in high MKI or developed markets. During trading hours, however, we observe an opposite pattern that MKI and DVL have a negative, although insignificant, impact on the mean–variance relation. While the intraday finding of DVL might be at odds with the perceptions that investors in developed markets are generally thought to be more rational and thus less succumb to behavioral biases, our results find support in the work of Griffin et al. (2010), Jacobs (2016), Cai et al. (2018), and Altanlar et al. (2019) demonstrating that anomalies are at least as strong, and sometimes stronger, in mature markets than emerging markets. We add to this stream of evidence from the perspective of the mean–variance relation overnight and intraday.

In the analyses above, we assume a linear impact of cultural dimensions, market integrity, and market development on the mean–variance relation as in Shao et al. (2010), Zheng et al. (2013), An et al. (2018), and Cardella et al. (2018). In an alternative test, as a way of robustness check, we adopt a median approach as in Ji et al. (2021) and Wang and Duxbury (2021), which, meanwhile, helps present the actual mean–variance relations of different groups. To elucidate, we rank the sample markets based on each factor in a descending order and split them into upper (above-median) and lower (below-median) groups. The overall weak pairwise correlation, as reported in Table 5, reassures our separation to be unique. Regressions are run for upper and lower groups jointly, following,

$$R_{i,t+1} = \alpha_u + \alpha_l + \beta_u Var_{u,i,t}\left(R_{u,i,t+1}\right) + \beta_l Var_{l,i,t}\left(R_{l,i,t+1}\right) + \varepsilon_{i,t+1}, \tag{17}$$

where β_u and β_l denote the mean–variance relation for upper and lower groups, respectively. For cultural dimensions, we further divide the upper- and lower-layer portfolios into four smaller samples conditional on tightness-looseness. For example, for IDV, in addition to looking into the mean–variance relation overnight and intraday separately in (i) high, and (ii) low IDV markets, we also examine the relation in (i) high IDV and tight, (ii) high IDV and loose, (iii) low IDV and tight, and (iv) low IDV and loose markets.

Results in Table 7 are largely in line with those in Table 6. For example, the mean–variance relation in high IDV markets is positive during non-trading hours, ranging from 1.7961 (RW) to 3.0589 (EGARCH), but negative during trading hours, ranging from –0.9029 (RW) to –1.0708 (EGARCH), i.e., an opposing influence; however, the relation remains flat in high CLT markets across night and day. Also, the difference in the mean–variance relation of IDV and CLT markets, denoted as β_u – β_l, is significant. Table 6 reveals that increased UAI leads to a more positive mean–variance relation during both non-trading and trading hours, which, as Table 7 presents, is realized differently overnight and intraday: During non-trading hours, it is mainly driven by the significantly positive mean–variance relation in high UAI markets, while during trading hours, it is mainly driven by the significantly negative mean–variance relation in low UAI markets. The mean–variance relation is flat in high MAS markets irrespective of overnight or intraday but that in low MAS markets tends to be positive overnight but negative intraday. In high PDI markets, the mean–variance relation is positive overnight and flat intraday and in low PDI markets, the relation is positive overnight but negative intraday. While the spreads, $\beta_u - \beta_l$, are insignificant across volatility models, overnight and intraday, the signs are in line with the predictions of Table 6. IDG shows a very similar results with PDI: In high IDG markets, there is positive mean–variance relation overnight and flat intraday and in low IDG markets, there is positive relation overnight and negative intraday. The spreads, however, are significant during non-trading hours, indicating a more positive risk-return tradeoff for high IDG markets than low IDG markets.

One notable difference between the two approaches is the influence of LTO on the mean–variance relation intraday. Table 6 presents that LTO is positively related to the mean–variance relation, i.e., that in markets with high LTO a positive risk-return tradeoff is more likely to be observed; however, Table 7 reports that there is a negative mean–variance relation in high LTO markets, but such relation tends to be flat in low LTO markets, which could be explained by the high variance of LTO in our sample markets distorting our linear regression results. In addition, looking at the impact of cultural tightness-looseness, we find that results from the tight cultures are consistent with Table 6: There is an insignificant, positive mean–variance relation in high LTO markets, while a significant, negative relation in low LTO markets, and the difference is significantly positive. In loose cultures, by contrast, the mean–variance relation tends to be insignificant. Results for MKI and DVL are also in line with those reported Table 6, showing the role of MKI and DVL in maintaining the positive mean–variance tradeoff overnight, but not intraday.

In an interesting way, we note that although there are significant differences in the mean–variance relation overnight and intraday, the relation still tends to be positive overnight and negative intraday, either significant or insignificant, regardless of upper or lower layers, and tight or loose cultures, further confirming our main findings at the global level. For example, when stock markets are closed, the mean–variance relation in high IDG markets is more positive than that in low IDG markets, as indicated by the significant spreads, but there is always a positive risk-return tradeoff for two layers, varying from 1.6979 (RW) to 3.3090 (EGARCH) and from 0.5467 (RW) to 1.8080 (EGARCH) for high and low IDG cultures, respectively, and likewise, when stock markets are open, the mean–variance relation is always negative for two layers, varying from –0.1107 (GARCH) to –0.2113 (EGARCH) and –0.4847 (RW) to –0.8162 (EGARCH), for high and low IDG cultures, respectively.

Overall, we document a significant influence of cultural dimensions, market integrity, and market development on the mean–variance relation, and importantly, the influence can vary across night and day. In addition, revealing the difference in the influence of the three perspectives on the mean–variance relation overnight and intraday, our results suggest that first, different types of traders in stock markets tend to trade at different times during the day (Lou et al., 2019; Hendershott et al., 2020), and such difference in trader types can be surprisingly considerable in that their trading behaviors is different or even completely opposite; and second, looking into the aggregate influence of cultural dimensions, market integrity, and market development on financial markets without distinguishing different times or clienteles might be misleading, and based on this, we suggest future studies that apply the cross-market analysis framework to explain financial markets or relations distinguish different clienteles.

6. Conclusion

While traditional financial theories have established a positive mean–variance relation that bearing high (low) risk should be compensated by high (low) returns, empirical evidence is inconclusive, revealing positive, negative, and mixed relations. Explanations are explored from various perspectives (see, e.g., Yu and Yuan, 2011; Wang and Duxbury, 2021), and in this paper, we provide new evidence by distinguishing between non-trading hours (overnight) and trading hours (intraday).

Based on twenty-five leading international stock markets, we examine the mean–variance relation overnight and intraday. Empirical evidence reveals differential patterns of the mean–variance relation at different times of the trading day. At the global level,

Table 7
Cross-market results of the impact of cultural dimensions on the mean–variance relation.

	Overnight (I)						Intraday (II)					
Model	β_u	*p-value*	β_l	*p-value*	$\beta_u - \beta_l$	*prob.*	β_u	*p-value*	β_l	*p-value*	$\beta_u - \beta_l$	*prob.*
Panel A.1 IDV												
RW	1.7961	(0.0000)[a]	–0.3090	(0.1997)	2.1051	(0.0000)[a]	–0.9029	(0.0000)[a]	0.0202	(0.8936)	–0.9231	(0.0001)[a]
MIDAS	1.9826	(0.0000)[a]	–0.0981	(0.6408)	2.0807	(0.0000)[a]	–0.9663	(0.0000)[a]	–0.0025	(0.9885)	–0.9638	(0.0002)[a]
GARCH	1.8184	(0.0000)[a]	–0.0826	(0.7403)	1.9011	(0.0000)[a]	–0.9429	(0.0002)[a]	0.0120	(0.9500)	–0.9548	(0.0005)[a]
GJR-GARCH	1.9699	(0.0000)[a]	–0.1056	(0.6103)	2.0755	(0.0000)[a]	–0.9390	(0.0001)[a]	–0.0309	(0.8712)	–0.9081	(0.0007)[a]
EGARCH	3.0589	(0.0000)[a]	–0.1867	(0.4458)	3.2456	(0.0000)[a]	–1.0708	(0.0002)[a]	–0.1295	(0.5576)	–0.9413	(0.0024)[a]
Panel A.2 IDV: tight cultures												
RW	2.9845	(0.0000)[a]	0.7346	(0.1166)	2.2499	(0.0039)[a]	–1.8431	(0.0000)[a]	0.2682	(0.2353)	–2.1114	(0.0000)[a]
MIDAS	3.0240	(0.0000)[a]	0.5199	(0.1577)	2.5041	(0.0001)[a]	–1.9456	(0.0000)[a]	0.3110	(0.2416)	–2.2567	(0.0000)[a]
GARCH	2.5308	(0.0000)[a]	0.5632	(0.1916)	1.9676	(0.0072)[a]	–1.8229	(0.0000)[a]	0.3715	(0.2328)	–2.1943	(0.0000)[a]
GJR-GARCH	2.5630	(0.0000)[a]	0.2779	(0.3305)	2.2851	(0.0005)[a]	–1.6030	(0.0000)[a]	0.0602	(0.9391)	–1.9164	(0.0001)[a]
EGARCH	4.0156	(0.0000)[a]	1.0867	(0.1579)	2.9290	(0.0003)[a]	–2.1928	(0.0000)[a]	0.3353	(0.3757)	–2.5281	(0.0000)[a]
Panel A.3 IDV: loose cultures												
RW	1.6318	(0.0000)[a]	1.7902	(0.0000)[a]	–0.1584	(0.7581)	–0.7953	(0.0126)[b]	–0.8070	(0.2918)	0.0117	(0.9887)
MIDAS	1.8562	(0.0000)[a]	1.5991	(0.0001)[a]	0.2571	(0.6376)	–0.9521	(0.0077)[a]	–0.5568	(0.5012)	–0.3953	(0.6611)
GARCH	1.7833	(0.0000)[a]	1.7726	(0.0000)[a]	0.0107	(0.9848)	–1.1467	(0.0040)[a]	0.2495	(0.7490)	–1.3962	(0.1110)
GJR-GARCH	1.5631	(0.0000)[a]	1.2939	(0.0007)[a]	0.2692	(0.6029)	–1.1462	(0.0034)[a]	0.3133	(0.3122)	–1.2064	(0.1706)
EGARCH	2.9392	(0.0000)[a]	1.8703	(0.0000)[a]	1.0689	(0.3905)	–1.2591	(0.0060)[a]	–0.6302	(0.6124)	–0.6288	(0.6352)
Panel B.1 UAI												
RW	1.5668	(0.0000)[a]	–0.0259	(0.9196)	1.5926	(0.0000)[a]	0.0158	(0.9201)	–0.5285	(0.0091)[a]	0.5443	(0.0200)[b]
MIDAS	1.6119	(0.0000)[a]	–0.0445	(0.8663)	1.6564	(0.0000)[a]	0.0189	(0.9149)	–0.6442	(0.0044)[a]	0.6631	(0.0098)[a]
GARCH	1.5825	(0.0000)[a]	0.3146	(0.2469)	1.2679	(0.0003)[a]	0.0860	(0.6605)	–0.7257	(0.0035)[a]	0.8117	(0.0033)[a]
GJR-GARCH	1.6697	(0.0000)[a]	0.4506	(0.3361)	1.2192	(0.0091)[a]	0.0176	(0.9277)	–0.7622	(0.0014)[a]	0.7798	(0.0039)[a]
EGARCH	2.0515	(0.0000)[a]	0.5754	(0.2092)	1.4762	(0.0001)[a]	–0.0276	(0.9038)	–0.9190	(0.0013)[a]	0.8914	(0.0040)[a]
Panel B.2 UAI: tight cultures												
RW	1.8196	(0.0000)[a]	0.9427	(0.0513)[c]	0.8769	(0.1184)	0.0354	(0.8701)	–1.6803	(0.0000)[a]	1.7157	(0.0001)[a]
MIDAS	1.8240	(0.0000)[a]	1.1674	(0.0302)[b]	0.6566	(0.2897)	0.0620	(0.8058)	–1.8856	(0.0000)[a]	1.9476	(0.0001)[a]
GARCH	1.9119	(0.0000)[a]	1.1415	(0.0307)[b]	0.7704	(0.2149)	0.1330	(0.6485)	–1.9066	(0.0000)[a]	2.0396	(0.0002)[a]
GJR-GARCH	1.5487	(0.0000)[a]	0.9856	(0.0435)[b]	0.5631	(0.3267)	0.1054	(0.7133)	–1.7461	(0.0000)[a]	1.8515	(0.0002)[a]
EGARCH	2.2839	(0.0031)[a]	1.1728	(0.0000)[a]	1.1111	(0.1706)	0.1338	(0.7056)	–2.4669	(0.0000)[a]	2.6007	(0.0001)[a]
	Overnight (I)						Intraday (II)					
Model	β_u	*p-value*	β_l	*p-value*	$\beta_u - \beta_l$	*prob.*	β_u	*p-value*	β_l	*p-value*	$\beta_u - \beta_l$	*prob.*
Panel B.3 UAI: loose cultures												
RW	1.4892	(0.0004)[a]	1.9312	(0.0712)[c]	–0.4420	(0.7004)	–0.7326	(0.1045)	0.2657	(0.5873)	–0.9983	(0.1338)
MIDAS	1.1318	(0.0000)[a]	2.3790	(0.0583)[c]	–1.2472	(0.3211)	–0.8187	(0.0997)[c]	0.2109	(0.7029)	–1.0296	(0.1662)
GARCH	1.2030	(0.0014)[a]	1.7768	(0.1826)	–0.5739	(0.6787)	–0.5457	(0.2838)	–0.0837	(0.8899)	–0.4621	(0.5588)
GJR-GARCH	0.6267	(0.0220)[b]	2.4532	(0.0537)[c]	–1.8266	(0.1601)	–0.8252	(0.1006)	0.0954	(0.8763)	–0.9206	(0.2453)
EGARCH	1.6012	(0.0000)[a]	2.8883	(0.0618)[c]	–1.2871	(0.3040)	–1.4661	(0.0284)[b]	0.0790	(0.9113)	–1.5452	(0.1132)
Panel C.1 MAS												
RW	0.0716	(0.8027)	1.4008	(0.0000)[a]	–1.3291	(0.0001)[a]	–0.2629	(0.1350)	–0.2412	(0.1443)	–0.0217	(0.9216)
MIDAS	0.0722	(0.2114)	1.4026	(0.0000)[a]	–1.3305	(0.0000)[a]	–0.2667	(0.1742)	–0.3135	(0.0911)[c]	0.0467	(0.8464)
GARCH	0.1318	(0.6515)	1.6461	(0.0000)[a]	–1.5143	(0.0000)[a]	–0.1816	(0.4015)	–0.3445	(0.0938)[c]	0.1629	(0.5324)
GJR-GARCH	0.1551	(0.5966)	1.4189	(0.0000)[a]	–1.2638	(0.0000)[a]	–0.2480	(0.2350)	–0.4134	(0.0428)[b]	0.1654	(0.5190)
EGARCH	0.2460	(0.5038)	1.7230	(0.0000)[a]	–1.4770	(0.0000)[a]	–0.2693	(0.2830)	–0.5421	(0.0221)[b]	0.2729	(0.3512)
Panel C.2 MAS: tight cultures												
RW	0.6677	(0.2311)	2.2463	(0.0000)[a]	–1.5786	(0.0372)[b]	–0.5635	(0.0253)[b]	–0.1270	(0.6521)	–0.4365	(0.2479)
MIDAS	0.7343	(0.2600)	2.2573	(0.0004)[a]	–1.5229	(0.0411)[b]	–0.6289	(0.0265)[b]	–0.1234	(0.7123)	–0.5055	(0.2489)

(*continued on next page*)

Table 7 (*continued*)

Model	Overnight (I) β_u	*p-value*	β_l	*p-value*	$\beta_u - \beta_l$	*prob.*	Intraday (II) β_u	*p-value*	β_l	*p-value*	$\beta_u - \beta_l$	*prob.*
GARCH	0.3999	(0.4527)	1.8291	(0.0001)[a]	–1.4291	(0.0438)[b]	–0.5215	(0.0974)[c]	–0.1407	(0.7261)	–0.3808	(0.4556)
GJR-GARCH	0.2781	(0.5503)	1.6530	(0.0020)[a]	–1.3749	(0.0504)[b]	–0.5457	(0.0618)[c]	–0.1820	(0.6475)	–0.3637	(0.4615)
EGARCH	0.8510	(0.2206)	3.2510	(0.0000)[a]	–2.4001	(0.0011)[a]	–0.7578	(0.0462)[b]	–0.2325	(0.6316)	–0.5253	(0.3938)
Panel C.3 MAS: loose cultures												
RW	2.1269	(0.0544)[c]	1.5662	(0.0000)[a]	0.5608	(0.6204)	–0.7804	(0.0534)[c]	–0.4883	(0.4483)	–0.2921	(0.6010)
MIDAS	2.5897	(0.0388)[b]	1.6207	(0.0000)[a]	0.9690	(0.4492)	–0.8164	(0.0717)[c]	–0.6053	(0.1574)	–0.2111	(0.7349)
GARCH	2.4742	(0.0458)[b]	1.6600	(0.0000)[a]	0.8141	(0.5211)	–0.8058	(0.1144)	–0.5253	(0.2397)	–0.2804	(0.6793)
GJR-GARCH	2.3425	(0.0507)[c]	1.3478	(0.0000)[a]	0.9948	(0.4169)	–0.7129	(0.1634)	–0.7205	(0.1007)	0.0076	(0.9910)
EGARCH	3.7961	(0.0253)[b]	0.6791	(0.0038)[a]	3.1170	(0.0689)[c]	–0.8604	(0.1446)	–1.1583	(0.0401)[b]	0.2979	(0.7151)
Panel D.1 PDI												
RW	0.8603	(0.0000)[a]	1.0855	(0.0004)[a]	–0.2252	(0.5275)	–0.1236	(0.5118)	–0.3330	(0.0336)[b]	0.2094	(0.3487)
MIDAS	0.8918	(0.0000)[a]	0.9667	(0.0034)[a]	–0.0749	(0.7123)	–0.1984	(0.3449)	–0.3516	(0.0458)[b]	0.1532	(0.5315)
GARCH	1.1817	(0.0000)[a]	1.1899	(0.0003)[a]	–0.0082	(0.9823)	–0.2220	(0.3311)	–0.3002	(0.1276)	0.0782	(0.7666)
GJR-GARCH	1.2720	(0.0000)[a]	1.4636	(0.0002)[a]	–0.1916	(0.5819)	–0.3305	(0.1458)	–0.3348	(0.0792)[c]	0.0043	(0.9867)
EGARCH	1.6720	(0.0000)[a]	1.9088	(0.0000)[a]	–0.2368	(0.3058)	–0.4507	(0.0857)[c]	–0.3934	(0.0851)[c]	–0.0574	(0.8459)
	Overnight (I)						Intraday (II)					
Model	β_u	*p-value*	β_l	*p-value*	$\beta_u - \beta_l$	*prob.*	β_u	*p-value*	β_l	*p-value*	$\beta_u - \beta_l$	*prob.*
Panel D.2 PDI: tight cultures												
RW	0.3156	(0.5350)	3.0467	(0.0000)[a]	–2.7311	(0.0003)[a]	0.9664	(0.0160)[b]	–0.7856	(0.0002)[a]	1.7520	(0.0001)[a]
MIDAS	0.2163	(0.4120)	3.1414	(0.0000)[a]	–2.9251	(0.0000)[a]	0.9887	(0.0277)[b]	–0.9052	(0.0002)[a]	1.8939	(0.0002)[a]
GARCH	0.3615	(0.4197)	2.6584	(0.0000)[a]	–2.2969	(0.0015)[a]	0.9293	(0.0567)[c]	–0.9274	(0.0013)[a]	1.8558	(0.0010)[a]
GJR-GARCH	0.1925	(0.5093)	2.6458	(0.0000)[a]	–2.4532	(0.0001)[a]	0.7422	(0.1241)	–0.8988	(0.0009)[a]	1.6410	(0.0030)[a]
EGARCH	0.3897	(0.2997)	3.8506	(0.0000)[a]	–3.4609	(0.0000)[a]	0.8207	(0.1405)	–1.2168	(0.0006)[a]	2.0375	(0.0020)[a]
Panel D.3 PDI: loose cultures												
RW	2.0091	(0.0000)[a]	0.9150	(0.0179)[b]	1.0941	(0.0258)[b]	–1.3387	(0.0130)[b]	–0.3680	(0.2586)	–0.9707	(0.1232)
MIDAS	1.9590	(0.0000)[a]	1.1103	(0.0112)[b]	0.8487	(0.1179)	–1.4573	(0.0135)[b]	–0.4155	(0.2561)	–1.0418	(0.1335)
GARCH	2.0556	(0.0000)[a]	1.0735	(0.0164)[b]	0.9820	(0.0797)[c]	–1.0944	(0.0654)[c]	–0.4365	(0.2839)	–0.6579	(0.3610)
GJR-GARCH	1.6400	(0.0000)[a]	0.9477	(0.0224)[b]	0.6923	(0.1819)	–1.3781	(0.0178)[b]	–0.3946	(0.3312)	–0.9834	(0.1654)
EGARCH	2.2451	(0.0000)[a]	1.2568	(0.0454)[b]	0.9882	(0.1437)	–2.2401	(0.0053)[a]	–0.5919	(0.2105)	–1.6483	(0.0769)[c]
Panel E.1 LTO												
RW	0.6221	(0.0043)[a]	1.3698	(0.0000)[a]	–0.7477	(0.0385)[b]	–0.2584	(0.2127)	–0.1338	(0.3886)	–0.1246	(0.5977)
MIDAS	0.7135	(0.0039)[a]	1.3855	(0.0000)[a]	–0.6719	(0.0498)[b]	–0.3725	(0.1069)	–0.1328	(0.4473)	–0.2397	(0.3534)
GARCH	0.8272	(0.0002)[a]	1.4512	(0.0000)[a]	–0.6240	(0.0896)[c]	–0.4958	(0.0475)[b]	–0.0421	(0.8290)	–0.4537	(0.1012)
GJR-GARCH	1.0891	(0.0001)[a]	1.4642	(0.0000)[a]	–0.3751	(0.2863)	–0.5354	(0.0299)[b]	–0.1322	(0.4868)	–0.4032	(0.1401)
EGARCH	1.2279	(0.0000)[a]	1.8577	(0.0000)[a]	–0.6298	(0.0733)[c]	–0.6821	(0.0176)[b]	–0.1608	(0.4788)	–0.5213	(0.0928)[c]
Panel E.2 LTO: tight cultures												
RW	1.2220	(0.0043)[a]	3.1010	(0.0009)[a]	–1.8790	(0.0673)[c]	0.0049	(0.9891)	–0.5523	(0.0117)[b]	0.5573	(0.1871)
MIDAS	1.1808	(0.0066)[a]	2.8219	(0.0024)[a]	–1.6411	(0.0382)[b]	0.0953	(0.8135)	–0.6908	(0.0067)[a]	0.7861	(0.0999)[c]
GARCH	1.0301	(0.0109)[b]	2.1167	(0.0073)[a]	–1.0866	(0.2319)	0.2300	(0.6020)	–0.7586	(0.0109)[b]	0.9886	(0.0632)[c]
GJR-GARCH	1.1151	(0.0029)[a]	3.2950	(0.0004)[a]	–2.1799	(0.0349)[b]	0.2639	(0.5332)	–0.8504	(0.0026)[a]	1.1144	(0.0286)[b]
EGARCH	1.4178	(0.0098)[a]	3.5867	(0.0001)[a]	–2.1689	(0.0409)[b]	0.4363	(0.4098)	–1.1244	(0.0018)[a]	1.5607	(0.0149)[b]
Panel E.3 LTO: loose cultures												
RW	1.6844	(0.0000)[a]	1.5203	(0.0000)[a]	0.1642	(0.7397)	–0.3546	(0.4006)	–0.1419	(0.7925)	–0.2127	(0.7560)
MIDAS	1.7782	(0.0000)[a]	1.5690	(0.0000)[a]	0.2092	(0.6970)	–0.5416	(0.2492)	–0.0059	(0.9218)	–0.4826	(0.5271)
GARCH	1.5778	(0.0001)[a]	1.8103	(0.0000)[a]	–0.2325	(0.6759)	–0.8656	(0.0887)[c]	0.3747	(0.5369)	–1.2403	(0.1172)
GJR-GARCH	1.3881	(0.0002)[a]	1.3968	(0.0001)[a]	–0.0087	(0.9866)	–0.9057	(0.0724)[c]	0.2075	(0.7341)	–1.1132	(0.1600)
EGARCH	2.0685	(0.0003)[a]	1.9579	(0.0000)[a]	0.1105	(0.8615)	–0.8914	(0.1347)	–0.4323	(0.6098)	–0.4591	(0.6576)
	Overnight (I)						Intraday (II)					

(*continued on next page*)

Table 7 (*continued*)

Model	Overnight (I)						Intraday (II)					
	β_u	*p-value*	β_l	*p-value*	$\beta_u-\beta_l$	*prob.*	β_u	*p-value*	β_l	*p-value*	$\beta_u-\beta_l$	*prob.*
Model	β_u	*p-value*	β_l	*p-value*	$\beta_u-\beta_l$	*prob.*	β_u	*p-value*	β_l	*p-value*	$\beta_u-\beta_l$	*prob.*
Panel F.1 IDG												
RW	1.6979	(0.0000)[a]	0.5467	(0.0019)[a]	1.1512	(0.0010)[a]	−0.1790	(0.2449)	−0.4847	(0.0140)[b]	0.3056	(0.1810)
MIDAS	1.7263	(0.0000)[a]	0.7606	(0.0008)[a]	0.9657	(0.0081)[a]	−0.1884	(0.2771)	−0.5761	(0.0086)[a]	0.3877	(0.1210)
GARCH	2.1272	(0.0000)[a]	0.8482	(0.0001)[a]	1.2790	(0.0000)[a]	−0.1107	(0.5699)	−0.6132	(0.0096)[a]	0.5025	(0.1050)
GJR-GARCH	2.3357	(0.0000)[a]	1.0765	(0.0000)[a]	1.2591	(0.0070)[a]	−0.1957	(0.3006)	−0.6341	(0.0068)[a]	0.4384	(0.1080)
EGARCH	3.3090	(0.0000)[a]	1.8080	(0.0000)[a]	1.5010	(0.0000)[a]	−0.2113	(0.3486)	−0.8162	(0.0028)[a]	0.6049	(0.0544)[c]
Panel F.2 IDG: tight cultures												
RW	2.5635	(0.0001)[a]	1.2853	(0.0009)[a]	1.2782	(0.0209)[b]	−0.5936	(0.0079)[a]	0.0567	(0.8700)	−0.6503	(0.1148)
MIDAS	2.5119	(0.0004)[a]	1.2735	(0.0015)[a]	1.2385	(0.0280)[b]	−0.7326	(0.0049)[a]	0.1280	(0.7423)	−0.8606	(0.0660)[c]
GARCH	2.4298	(0.0121)[b]	1.0659	(0.0047)[a]	1.3638	(0.0195)[b]	−0.7984	(0.0086)[a]	0.2462	(0.5651)	−1.0446	(0.0466)[b]
GJR-GARCH	2.4449	(0.0085)[a]	0.9211	(0.0084)[a]	1.5238	(0.0076)[a]	−0.8728	(0.0024)[a]	0.2360	(0.5655)	−1.1088	(0.0270)[b]
EGARCH	3.1622	(0.0049)[a]	1.5338	(0.0023)[a]	1.6283	(0.0067)[a]	−1.1530	(0.0017)[a]	0.3862	(0.4513)	−1.5392	(0.0148)[b]
Panel F.3 IDG: loose cultures												
RW	1.9761	(0.0000)[a]	1.2758	(0.0391)[b]	0.7002	(0.1438)	−1.0098	(0.0057)[a]	−0.0905	(0.8343)	−0.9192	(0.1046)
MIDAS	2.2986	(0.0000)[a]	1.0929	(0.0320)[b]	1.2057	(0.0805)[c]	−1.1282	(0.0054)[a]	−0.0985	(0.8391)	−1.0297	(0.1035)
GARCH	2.1817	(0.0000)[a]	1.0034	(0.0510)[c]	1.1783	(0.0975)[c]	−1.1238	(0.0108)[b]	0.0158	(0.9757)	−1.1396	(0.0945)[c]
GJR-GARCH	1.9801	(0.0000)[a]	0.6611	(0.0722)[c]	1.3190	(0.0804)[c]	−1.1466	(0.0075)[a]	−0.0629	(0.9053)	−1.0837	(0.1115)
EGARCH	2.5980	(0.0000)[a]	1.4223	(0.0488)[b]	2.1757	(0.0490)[b]	−1.5134	(0.0046)[a]	−0.3179	(0.6148)	−1.1954	(0.1482)
Panel G MKI												
RW	1.0054	(0.0000)[a]	0.5417	(0.1837)	0.8637	(0.0270)[b]	−0.3195	(0.1883)	−0.1891	(0.2812)	0.1305	(0.6632)
MIDAS	1.0429	(0.0000)[a]	0.5556	(0.0508)[c]	0.4874	(0.0919)[c]	−0.4134	(0.1392)	−0.1931	(0.3404)	0.2202	(0.5235)
GARCH	1.0486	(0.0005)[a]	0.5405	(0.0609)[c]	0.5081	(0.2229)	−0.4733	(0.1359)	−0.0838	(0.7180)	0.3896	(0.3217)
GJR-GARCH	1.1383	(0.0000)[a]	0.6359	(0.0190)[b]	0.5024	(0.1634)	−0.5450	(0.0741)[c]	−0.1303	(0.5706)	0.4147	(0.2776)
EGARCH	1.3090	(0.0000)[a]	0.7234	(0.0655)[c]	0.5855	(0.0877)[c]	−0.7185	(0.0649)[c]	−0.2842	(0.3096)	0.4343	(0.3649)
Panel H DVL												
RW	1.0065	(0.0000)[a]	−0.3285	(0.2801)	1.3350	(0.0005)[a]	−0.5272	(0.0076)[a]	−0.3211	(0.0861)[c]	−0.2061	(0.4488)
MIDAS	1.0092	(0.0001)[a]	0.2082	(0.3358)	0.8010	(0.0112)[b]	−0.6207	(0.0055)[a]	−0.3636	(0.0946)[c]	−0.2571	(0.4097)
GARCH	0.9208	(0.0005)[a]	0.2116	(0.3683)	0.7092	(0.0225)[b]	−0.5615	(0.0243)[b]	−0.3988	(0.1110)	−0.1626	(0.6451)
GJR-GARCH	0.9484	(0.0000)[a]	0.0720	(0.7585)	0.8764	(0.0027)[a]	−0.5893	(0.0133)[b]	−0.4685	(0.0585)[c]	−0.1209	(0.7249)
EGARCH	1.0894	(0.0000)[a]	0.3010	(0.3211)	0.7883	(0.0060)[a]	−0.8817	(0.0030)[c]	−0.5807	(0.0561)[c]	−0.3010	(0.4789)

This table presents cross-market results of the mean–variance relation overnight (Column I) and intraday (Column II). The regression specification follows,

$R_{i,t+1} = \alpha_u + \alpha_l + \beta_u Var_{u,i,t}\left(R_{u,i,t+1}\right) + \beta_l Var_{l,i,t}\left(R_{l,i,t+1}\right) + \varepsilon_{i,t+1}$,

where β_u and β_l denote the mean–variance relation for upper- and lower-layer portfolios, respectively. Upper- and lower-layer portfolios are identified by cultural dimensions, market integrity, and market development. Cultural dimensions include IDV (Panel A), UAI (Panel B), MAS (Panel C), PDI (Panel D), LTO (Panel E), and IDG (Panel F). Market integrity, MKI (Panel G), incorporates the common information from ADR, GVC, ACS, EJS, ROL, ROE, and RCR. Market development, DVL (Panel H), distinguishes between developed and emerging markets. For cultural dimensions, we further divide the upper- and lower-layer portfolios into four smaller samples conditional on tightness-looseness.

[a], [b], and [c] represent statistical significance at the 1 %, 5 %, and 10 % level, respectively.

there is a positive mean–variance relation overnight, which is reversed intraday, i.e., a negative relation. At the individual market level, there appear heterogeneous patterns across markets, with some supporting but some contradicting the global evidence. To the extent that different results are observed, we explore the potential drivers from perspectives of cultural dimensions, market integrity, and market development. Empirical results present that all the three perspectives have a strong influence on the mean–variance relation and notably, the influence can differ overnight and intraday. Given the different, or even opposing, influences, it appears that the influence of cultures, market integrity, and market development on financial relations may be more complicated than we have thought. We, therefore, recommend that the future studies applying the framework of cross-market analyses take account of the divergent clienteles.

CRediT authorship contribution statement

Wenzhao Wang: Conceptualization, Methodology, Data curation, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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