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Global, local, and contagious investor sentiment ☆

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ABSTRACT

We construct investor sentiment indices for six major stock markets and decompose them into one global and six local indices. In a validation test, we find that relative sentiment is correlated with the relative prices of dual-listed companies. Global sentiment is a contrarian predictor of country-level returns. Both global and local sentiment are contrarian predictors of the time-series of cross-sectional returns within markets: When sentiment is high, future returns are low on relatively difficult to arbitrage and difficult to value stocks. Private capital flows appear to be one mechanism by which sentiment spreads across markets and forms global sentiment.

1. Introduction

We investigate the effect of global and local components of investor sentiment on major stock markets, at the level of both the country average and the time-series of the cross-section. We also consider whether and how sentiment spreads across markets. We find evidence that investor sentiment plays a significant role in international market volatility and generates return predictability of a form consistent with corrections of overreaction.

Our quantitative sentiment indices follow six stock markets: Canada, France, Germany, Japan, the United Kingdom, and the United States. We construct indices of "total" investor sentiment for each country by forming the first principal component of several time-series proxies for sentiment. We decompose the six total sentiment indices into a single "global" index and six "local" indices. The data are annual from 1980 to 2005 and drawn from several international sources. Sentiment is intrinsically difficult to measure precisely (and if there was an unambiguous, real-time measure, even the mediocre investor would be able to recalibrate himself and in the process, reduce or eliminate the information content in the measure) so we begin with an index validation test.

Our validation test is based on dual-listed shares. These so-called Siamese twins are pairs of securities that claim equal cash flows but trade in different markets and

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sometimes at substantially different prices. The large price deviations have not been explained in the context of rational markets with realistic frictions, let alone frictionless and efficient markets. We document that twins' relative prices are positively related to the relative local sentiment indices of their respective markets. This provides a relatively clean experiment that supports the empirical validity of our indices. We are not aware of other sentiment indices that have been validated by a more convincing method.

We then ask how sentiment affects international stock markets. The basic supposition is that if sentiment drives prices too far, we may observe corrections in the form of return predictability. We start with regressions to predict market returns, pooling six markets together for power in our short sample. We find that total sentiment, and particularly the global component of total sentiment, is a contrarian predictor of country-level market returns. These results are similar for both value- and equal-weighted market returns and for non-U.S. markets.

Next we examine the effect of sentiment on the time-series of cross-sectional returns. Baker and Wurgler (2006, 2007) predict that broad waves of sentiment will have greater effects on hard to arbitrage and hard to value stocks; these stocks will exhibit high "sentiment beta" (see, e.g., Glushkov, 2005). Confirming this hypothesis, we find that when a country's total sentiment is high, future returns are relatively low for its small, high return volatility, growth, and distressed stocks. These results are also apparent in the non-U.S. sample. The local component of sentiment affects the cross-section considerably more than it does the time-series market return. This result is intuitive. Many global investors are looking for diversification and simply invest in index funds rather than select specific international stocks. In addition, local investors have an overwhelming home bias toward their local market, as in, e.g., French and Poterba (1991), and can trade at lower costs than international investors. They, and their sentiment, therefore should be expected to have a disproportionate effect on the pricing of the cross-section.

Our final investigation considers whether sentiment is contagious across countries. Given the importance of global sentiment in our results, this is an important question. We use the absolute value of U.S. capital flows with the other five sample countries to obtain cross-sectional variation in the extent of integration between these markets. We find that not only do local and global sentiment predict the cross-section of those countries' returns, but so does U.S. sentiment in those countries linked with the United States by significant capital flows. This evidence suggests that capital flows are a key mechanism through which global sentiment develops and propagates, but there are surely others, including word-of-mouth and the media.

Our study contributes to a growing literature studying the role of investor sentiment. In addition to the papers above, Brown and Cliff (2004), Lemmon and Portniaguina (2006), Qiu and Welch (2004), and other papers have found evidence for a role of investor sentiment in U.S. stock market returns. Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2005) study U.S. and Japanese flows into bull and bear funds. Yu and Yuan (2011) argue that the tradeoff between risk and expected return applies only in low sentiment periods; Stambaugh, Yu, and Yuan (in press) argue that sentiment's predictive power is concentrated in high-sentiment periods and in stocks in short legs. Baker and Wurgler (forthcoming) investigate how sentiment connects the cross-section of stock returns and government bonds, while Bekaert, Baele, and Inghelbrecht (2010) discuss sentiment and the time-series relationships between government bond and stock market returns. Papers arguing that sentiment affects aggregate financing patterns include Baker and Wurgler (2000), Henderson, Jegadeesh, and Weisbach (2006), and Kim and Weisbach (2008).

To summarize, we make several contributions to this literature. First, this paper is the first to investigate the role of sentiment within and across international equity markets. We construct usable indices of total, global, and country-specific sentiment for six markets. Second, we conduct a validation exercise with Siamese twins; most of the sentiment literature is unable to provide any validation exercise. Third, we study the effects of sentiment at the index level, where we find significant predictability relationships, perhaps because the panel of countries provides more power than a single U.S. time-series. Fourth, we provide the first extensive study of the international time-series of the cross-section of stock returns, and in particular, we find that the U.S. results by Baker and Wurgler (2006) translate to other markets. Fifth, we provide some initial evidence about how global sentiment develops and propagates.

Section 2 explains the method of construction of the sentiment indices. Section 3 describes the validation test. Section 4 uses sentiment to predict the time-series of market returns, and Section 5 considers the time-series of the cross-section of returns. Section 6 investigates sentiment contagion. Section 7 concludes.

2. Total, global, and local sentiment indices

2.1. Basic approach

Our method for estimating international markets' sentiment builds on Baker and Wurgler's (2006) strategy for U.S. sentiment. We employ a number of sentiment proxies that we hypothesize contain some component of investor sentiment and some component of non-sentiment-related idiosyncratic variation. To remove the latter, we first orthogonalize the raw sentiment proxies to a variety of macro series. Each market's "total" sentiment is then estimated as the first principal component of those orthogonalized sentiment proxies. A single "global" sentiment series is then estimated as the first principal component of these total sentiment series. Finally, each market's "local" sentiment is estimated as the residual of its total sentiment regressed on global sentiment.

2.2. Sentiment proxies: motivation and data

We are constrained by the availability of international sentiment proxies and cannot employ all those that the

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predominantly U.S. investor sentiment literature has examined. We also elect to use the same four proxies for all six international markets, as much as possible, although an argument could be made that the principal components methodology outlined above should be able to tolerate different proxies for different markets.

The first proxy is a quantity that we refer to as the volatility premium and simply identifies times when valuations on high idiosyncratic volatility stocks are high or low relative to valuations on low idiosyncratic volatility stocks. This is by analogy to Baker and Wurgler's (2004) use of the U.S. dividend premium, which, as the relative valuation of dividend- and non-dividend-paying stocks, is highly related (inversely) to the U.S. volatility premium.[1]

The motivation for this variable derives from the theoretical prediction that sentiment has its strongest effects on hard to value and hard to arbitrage stocks. Obviously, all else equal, these are stocks that noise traders can plausibly defend extreme values for, as befits their current optimism or pessimism. One example is Koski, Rice, and Tarhouni (2008) who show that volatility attracts day traders. More generally, the proportion of individual ownership is increasing in volatility (Sias, 1996).[2]

Somewhat less obviously, volatile stocks are, all else equal, also particularly unattractive to arbitrageurs, which in turn redoubles the potential for those stocks to be affected by noise trader sentiment. Volatile stocks are inherently riskier to trade—volatility brings with it fundamental and arbitrage risk, as in Pontiff (1996) and Wurgler and Zhuravskaya (2002), and they are associated with noise trader risk, as just mentioned. Volatile stocks also tend to be costlier to trade. Bid-ask spreads are wider due to the probability of informed trading (Glosten and Milgrom, 1985) and higher inventory costs (Ho and Stoll, 1980). Price impact beyond spreads is larger (Chan and Lakonishok, 1997). Short-sales costs are higher because upward price movements generate more frequent margin calls (Mitchell, Pulvino, and Stafford, 2002; Bali, Scherbina, and Tang, 2011) and because the rebate rate is higher (Diether, 2008), which may reflect the fact that the supply of borrowed shares is influenced by institutional ownership, which is negatively correlated with volatility (Sias, 1996).

The volatility premium (*PVOL*) is the yearend log of the ratio of the value-weighted average market-to-book ratio of high volatility stocks to that of low volatility stocks. High (low) volatility denotes one of the top (bottom) three deciles of the variance of the previous year's monthly returns, where decile breakpoints are determined country by country.[3] Total volatility is defined as the standard deviation of the trailing 12 months of monthly returns, and to control for any association with beta and a confusion with priced risks, we compute the volatility premium based only on beta-adjusted idiosyncratic volatility (for simplicity, however, we will continue to refer to this variable as the volatility premium). This variable was available for all years and all countries. On average in our sample, the market-to-book ratio of high volatility stocks has been higher than that of low volatility stocks, but in each country this relationship has been reversed within our time period.

The second and third proxies we employ are derived from initial public offering (IPO) data. They are the total volume of IPOs and their initial, first-day returns (sometimes called underpricing). The theoretical motivation for using the volume of IPOs is simply that insiders and long-run shareholders have strong incentives to time the equity market for when valuations are greatest, which is presumably when sentiment is highest. Low long-run returns to IPOs have been noted by Stigler (1964), Ritter (1991), and Loughran, Ritter, and Rydqvist (1994), which is ex post evidence of successful market timing relative to a market index. But issuers need not care that much whether their firm's misvaluation is due to firm-specific or marketwide factors; consistent with that notion, equity issues as a fraction of total new issues forecast low market returns as well (Baker and Wurgler, 2000). The worst future returns occur for IPOs and equity issues from "hot market" cohorts with high total issuance volume.

It has been widely noted that the initial returns on IPOs increase in hot markets. In the United States in 1999, for example, there were 477 IPOs and the *average* raw first-day return was 70%. And in Japan that year, the average first-day return was 137%! It is implausible that these figures reflect just adverse selection premiums, for example. If anything, the anecdotal evidence suggests that the issues with the highest first-day returns were in the greatest demand. Ritter (1998) sums up our motivation for these two sentiment proxies: "rational explanations for hot markets are difficult to come by" (p. 10).

The number of IPOs (*NIPO*) is the log of the total number of IPOs that year. The initial returns on IPOs (*RIPO*) are the average initial (most often, first-day) return on that year's offerings. The returns are equal-weighted across firms. The data were obtained from a variety of sources. We were able to find both variables for the full sample with the exception of France for 1980 through 1982 and Germany for 2003 through 2005. In the United States, the annual number of IPOs has ranged from 64 to 953 in the sample period, and the average first-day return on IPOs has ranged from around 7% to a high of 70% (exponentiate the Min and Max values from Table 2), as noted above. Most other countries have also seen high variation in these quantities.[4]

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[1] We cannot form the dividend premium in some markets because dividends are relatively uncommon and, in some countries, dividends do not appear to be viewed by local investors as connoting "stability" in the way they historically have for U.S. investors.

[2] We will later describe, and control for, a non-sentiment association between valuations and volatility based on Pastor and Veronesi (2003).

[3] We follow Fama and French (1993), who use the top three deciles and bottom three deciles for factor construction.

[4] An important question is whether IPO market measures have the same meaning in bank-oriented countries (in our sample, France, Germany, and Japan) as they do in market-oriented countries. The survey of international IPO market studies in Loughran, Ritter, and Rydqvist (1994) does not indicate any obvious differences in dimensions of particular interest, including mean IPO underpricing; the relationships between IPO volume, market returns, and future gross national product (GNP) growth; and mean abnormal returns on IPOs.

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Table 1
Data sources.

Country	Item	Period	Data source
Panel A: Volatility premium (*PVOL*)			
All countries	Stock return	1980–2005	Datastream (http://www.datastream.com/default.htm)
	Market value	1980–2005	Datastream
	Book value	1980–2005	Worldscope (http://www.thomsonreuters.com/)
Panel B: IPO volume (*NIPO*)			
Japan, U.K., and U.S.	*NIPO*	1980–2005	Updated version of Loughran et al. (1994) (http://bear.cba.ufl.edu/ritter/Int2008.pdf)
Canada	*NIPO*	1980–1983	Jog and Riding (1987) via updated version of Loughran et al. (1994)
		1984–1991	Jog and Srivastava (1994) via updated version of Loughran et al. (1994)
		1992–2005	Updated version of Loughran et al. (1994)
France	*NIPO*	1983–2005	Updated version of Loughran et al. (1994)
Germany	*NIPO*	1980–2002	Alexander Ljungqvist
Panel C: IPO First-day returns (*RIPO*)			
Japan, U.K., and U.S.	*RIPO*	1980–2005	Updated version of Loughran et al. (1994)
Canada	*RIPO*	1980–1983	Jog and Riding (1987) via updated version of Loughran et al. (1994)
		1984–1991	Jog and Srivastava (1994) via updated version of Loughran et al. (1994)
		1992–2005	Updated version of Loughran et al. (1994)
France	*RIPO*	1983–1998	Updated version of Loughran et al. (1994)
		1999–2005	Dealogic via updated version of Loughran et al. (1994)
Germany	*RIPO*	1980–2002	Alexander Ljungqvist
Panel D: Turnover (*TURN*)			
Canada; U.K.; and U.S.	Dollar volume	1980–2005	Datastream
France	Dollar volume	1980–2005	EUROFIDAI (http://www.eurofidai.org/)
Japan	Dollar volume	1980–1989	Global Financial Data (https://www.globalfinancialdata.com/)
		1990–2005	Datastream
Canada; Japan; U.K.; and U.S.	Market value	1980–2005	Datastream
France	Market value	1980–2005	EUROFIDAI

Data sources for proxies for sentiment from 1980 to 2005. The first proxy (*PVOL*) is the log ratio of the equal-weighted average market-to-book ratios of stocks with high idiosyncratic volatility (top three deciles) and stocks with low idiosyncratic volatility (bottom three deciles). The second proxy (*NIPO*) is the log number of initial public offerings over the year. The third proxy (*RIPO*) is the average first-day returns of initial public offerings in the year. The fourth proxy (*TURN*) is detrended log turnover over the year.

The fourth sentiment proxy is market turnover. Commentators on speculative episodes such as Bagehot (1873) and Kindleberger (1978) have noted that high trading volume in the overpriced asset is a pattern that goes back to the tulip bubble. Cochrane (2002) states that "the association of price and volume is a generic feature of the historical 'bubbles'" (p. 17). Lamont and Thaler (2003) examine tech stock carve-outs and find that the relatively overpriced IPO subsidiaries have an average turnover rate of 38% *per day* over the first 20 days of trading (not including the first day), which is more than five times that of parent turnover. There was much greater volume in Internet relative to non-Internet stocks between 1998 and 2000 (Ofek and Richardson, 2003). In a cleaner test, Mei, Scheinkman, and Xiong (2009) find a correlation between trading and price differentials in fundamentally identical Chinese A–B shares. Smith, Suchanek, and Williams (1988) find experimental evidence that bubbles are associated with high turnover. Subsequent research indicates that this correlation is robust to the introduction of trading fees, short-sales constraints, and the use of business professionals as test subjects.

There is also ample theory to connect sentiment and trading volume. Any greater-fool theory of rational bubbles (Harrison and Kreps, 1978) or models of positive feedback trading by informed investors essentially requires that those who believe the asset is overvalued be able to trade it away before the mispricing corrects (De Long, Shleifer, Summers, and Waldmann, 1990b). Uninformed fund managers can churn bubbles to confuse their clients into thinking they are informed (Allen and Gorton, 1993). Baker and Stein (2004) point out that when shorting is relatively costly, sentimental investors are more likely to trade when they are optimistic, and overall volume goes up. Scheinkman and Xiong (2003) provide a complementary argument based on overconfidence for using turnover as a proxy for sentiment. So, as with the other three measures, we expect a positive relationship between the observed proxy and underlying sentiment.

Market turnover (*TURN*) is the log of total market turnover, i.e., total dollar volume over the year divided by total capitalization at the end of the prior year. We detrend this with an up-to-five-year moving average. We could obtain market-level turnover statistics for all markets but Germany. We detrend because all markets except Japan display a positive trend in turnover.[5]

Overall, we used roughly a dozen primary data sources to construct these proxies. They are listed in Table 1 and summary statistics are given by country in Table 2.

[5] For Canada, France, and the United States, the data are obtained from a single source. For Japan and the United Kingdom, the data from two different sources were combined to provide long series from 1980 to 2005. To make the series from different sources consistent, we multiply the later series by constants to render it to have the same standard deviations with the early series in the overlapping periods.

Table 2
Total investor sentiment, 1980–2005.

	Mean	SD	Min	Max	Correlations with $SENT_c^{Total}$ $SENT_c^{Total}$	*p*-value	Loadings	Correlations with sentiment components *PVOL*	*NIPO*	*RIPO*	*p*-values *PVOL*	*NIPO*	*RIPO*
Panel A: Canada													
PVOL	0.70	0.42	0.05	1.82	0.65	(0.00)	0.36	1.00			(.)		
NIPO	2.70	0.83	1.61	4.26	0.13	(0.54)	0.07	−0.23	1.00		(0.27)	(.)	
RIPO	0.07	0.06	−0.04	0.24	0.90	(0.00)	0.49	0.50	0.04	1.00	(0.01)	(0.86)	(.)
TURN	0.21	0.30	−0.35	1.03	0.75	(0.00)	0.41	0.15	0.29	0.54	(0.47)	(0.15)	(0.00)
Panel B: France													
PVOL	0.28	0.57	−0.36	2.11	0.12	(0.58)	0.06	1.00			(.)		
NIPO	3.39	0.73	1.61	4.69	0.84	(0.00)	0.42	0.34	1.00		(0.12)	(.)	
RIPO	0.11	0.07	0.02	0.26	0.66	(0.00)	0.33	−0.21	0.26	1.00	(0.35)	(0.23)	(.)
TURN	0.16	0.30	−0.59	0.62	0.91	(0.00)	0.46	−0.03	0.67	0.50	(0.89)	(0.00)	(0.02)
Panel C: Germany													
PVOL	0.19	0.44	−0.74	1.23	0.62	(0.00)	0.31	1.00			(.)		
NIPO	3.02	0.85	1.79	5.12	0.90	(0.00)	0.45	0.35	1.00		(0.10)	(.)	
RIPO	0.12	0.12	−0.00	0.43	0.89	(0.00)	0.45	0.34	0.75	1.00	(0.11)	(0.00)	(.)
Panel D: Japan													
PVOL	0.57	0.40	−0.65	1.46	0.91	(0.00)	0.40	1.00			(.)		
NIPO	4.34	0.73	2.64	5.14	0.45	(0.02)	0.20	0.38	1.00		(0.06)	(.)	
RIPO	0.31	0.22	0.07	0.86	0.79	(0.00)	0.35	0.67	0.02	1.00	(0.00)	(0.93)	(.)
TURN	−0.05	1.97	−5.88	2.65	0.80	(0.00)	0.35	0.57	0.27	0.48	(0.00)	(0.19)	(0.01)
Panel E: U.K.													
PVOL	0.20	0.44	−0.77	0.94	0.67	(0.00)	0.36	1.00			(.)		
NIPO	4.41	0.69	2.56	5.43	0.64	(0.00)	0.34	0.23	1.00		(0.26)	(.)	
RIPO	0.16	0.12	0.06	0.61	0.50	(0.01)	0.27	0.00	0.15	1.00	(0.98)	(0.45)	(.)
TURN	0.88	1.17	−0.81	3.63	0.87	(0.00)	0.47	0.49	0.37	0.37	(0.01)	(0.06)	(0.06)
Panel F: U.S.													
PVOL	0.17	0.48	−1.29	1.25	0.74	(0.00)	0.35	1.00			(.)		
NIPO	5.83	0.75	4.16	6.86	0.54	(0.00)	0.26	0.06	1.00		(0.76)	(.)	
RIPO	0.17	0.11	0.07	0.53	0.71	(0.00)	0.34	0.48	0.14	1.00	(0.01)	(0.48)	(.)
TURN	0.22	0.26	−0.28	0.68	0.86	(0.00)	0.41	0.51	0.52	0.40	(0.01)	(0.01)	(0.04)

Means, standard deviations, and correlations for proxies for sentiment. The first proxy (*PVOL*) is the log ratio of the equal-weighted average market-to-book ratios of stocks with high idiosyncratic volatility (top three deciles) and stocks with low idiosyncratic volatility (bottom three deciles). The second proxy (*NIPO*) is the log number of initial public offerings over the year. The third proxy (*RIPO*) is the average first-day returns of initial public offerings in the year. The fourth proxy (*TURN*) is detrended log turnover over the year. Total investor sentiment, $SENT_c^{Total}$, is the first principal component of four time-series proxies for sentiment for the given country.

Finally, to remove information about expected returns that may be contained in our sentiment proxies that is not related to sentiment, we follow Baker and Wurgler (2006) and orthogonalize each proxy to six macro series. These are consumption growth (Breeden, 1979), from the Penn World Tables, and industrial production growth (Chen, Roll, and Ross, 1986), inflation (Fama and Schwert, 1977; Chen, Roll, and Ross, 1986), employment growth (Santos and Veronesi, 2006), the short-term rate (Fama and Schwert, 1977), and the term premium (Keim and Stambaugh, 1986; Fama and French, 1989), from the Organisation for Economic Co-operation and Development (OECD).

The macro series turn out to explain comparatively little of the variation in the sentiment proxies. Consequently, the correlation between the orthogonalized and raw proxies is, on average across the four proxies, 0.88. It is comforting that macro series that contain a great deal of contemporaneous and forward-looking information about economic fundamentals are, even in combination, so unrelated to our proxies. Admittedly, however, it is impossible to rule out that an as-yet undiscovered risk factor drives all of the various relationships between the sentiment proxies and expected returns that we find later.

2.3. Total sentiment indices

The total sentiment index coefficients for each country are reported in the loadings column of Table 2. The index coefficients are estimated using the first principal component of each of the macro-orthogonalized sentiment proxies. The resulting indices are linear functions of the within-country standardized values of the proxies and thus have mean zero:

$$SENT^{Total}_{Canada,t} = 0.36PVOL_t + 0.07NIPO_t + 0.49RIPO_t + 0.41TURN_t, \quad (1)$$

$$SENT^{Total}_{France,t} = 0.06PVOL_t + 0.42NIPO_t + 0.33RIPO_t + 0.46TURN_t, \quad (2)$$

$$SENT^{Total}_{Germany,t} = 0.31PVOL_t + 0.45NIPO_t + 0.45RIPO_t, \quad (3)$$

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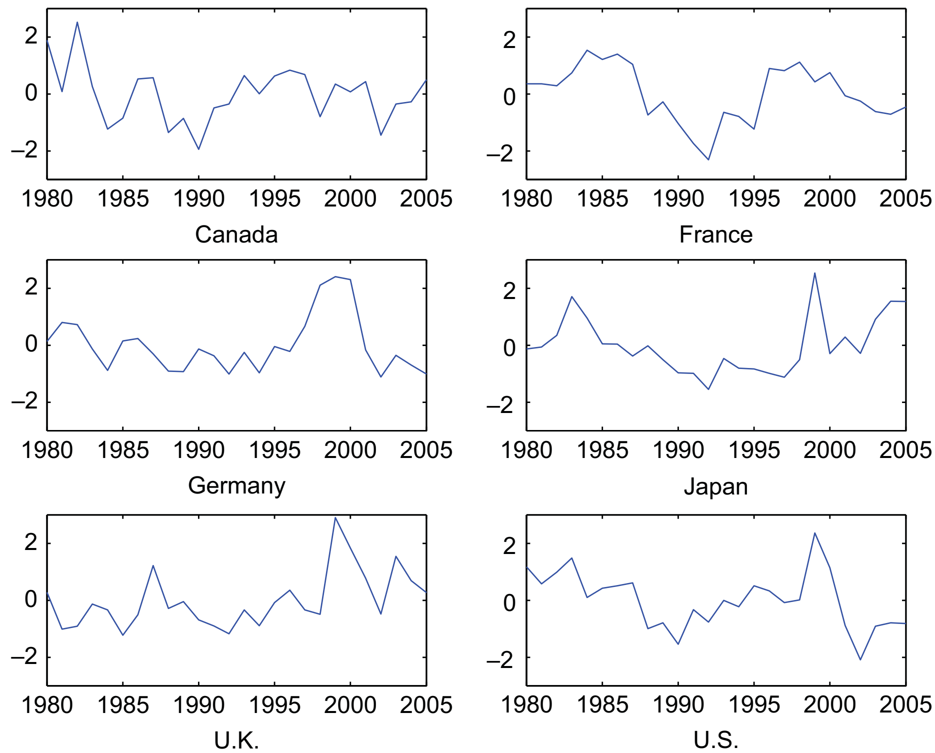

Fig. 1. Total investor sentiment, 1980–2005. Total investor sentiment, $SENT_c^{Total}$, is the first principal component of four time-series proxies for sentiment for the given country. The first proxy (*PVOL*) is the log ratio of the equal-weighted average market-to-book ratios of stocks with high idiosyncratic volatility (top three deciles) and stocks with low idiosyncratic volatility (bottom three deciles). The second proxy (*NIPO*) is the log number of initial public offerings over the year. The third proxy (*RIPO*) is the average first-day returns of initial public offerings in the year. The fourth proxy (*TURN*) is detrended log turnover over the year. Prior to forming the first principal component, the proxies are orthogonalized with respect to consumption growth, industry production growth, employment growth, the short-term interest rate, inflation, and the term premium.

$$SENT^{Total}_{Japan,t} = 0.40PVOL_t + 0.20NIPO_t + 0.35RIPO_t + 0.35TURN_t, \tag{4}$$

$$SENT^{Total}_{UK,t} = 0.36PVOL_t + 0.34NIPO_t + 0.27RIPO_t + 0.47TURN_t, \tag{5}$$

$$SENT^{Total}_{US,t} = 0.35PVOL_t + 0.26NIPO_t + 0.34RIPO_t + 0.41TURN_t, \tag{6}$$

where the country subscripts on the proxies have been suppressed.[6] The fraction of variance explained by the first principal components are, in order of the countries listed above, 38%, 40%, 48%, 37%, 37%, and 42%, and in each country there is at least one eigenvalue that exceeds unity. These figures resemble the 49% reported in Baker and Wurgler (2006) for a six-factor index of U.S. sentiment.

We standardize the total sentiment indices and plot them in Fig. 1. A prominent feature is the Internet bubble of the late 1990s and its subsequent crash; this is clearly represented not only in the United States but in at least three other countries. These results serve as a reminder that Germany's Neuer Markt, France's Nouveau Marche, and London's TECHMark—only the last of which still exists—were overseas cousins of the more familiar Nasdaq in both composition and performance.[7]

A feature that we will return to when we discuss empirical hypotheses is mean-reversion of the sentiment indices. For now, we just mention the facts. The first-order autocorrelations of *changes* in the indices are −0.423 (Canada), −0.163 (France), 0.092 (Germany), −0.373 (Japan), −0.287 (UK), and −0.138 (US). The second-order autocorrelations of changes are 0.036 (Canada), 0.028 (France), −0.222 (Germany), 0.034 (Japan), −0.311 (UK), and −0.219 (US). Thus, only changes in Germany's index have a positive first-order autocorrelation, and this is ultimately outweighed by its larger negative second-order autocorrelation. This feature of the German index is suggested in a close look at Fig. 1: whereas a few other countries experienced one-year sentiment spikes around the Internet bubble, German sentiment, as measured by our indices, stayed at a peak for one or two years more.

2.4. *Global and local sentiment indices*

We separate the total sentiment indices into one global and six local components. The global index is the

[6] French IPO data for 1980–1982 and Germany IPO data for 2003–2005 were not available. For each country, we fit their total sentiment indices to the other other five countries' indices in the period of overlap, and then used the predicted value to fill the missing data points.

[7] Other examples include the Italian Nuovo Mercato, the Nordic New Market, and approximately ten other European markets that opened between 1996 and 2001.

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Table 3
Global and local investor sentiment, 1980–2005. Global sentiment ($SENT^{Global}$) is the first principal component of the total sentiment indices ($SENT_c^{Total}$) in the six countries. Local sentiment ($SENT_c^{Local}$) is the residual from the regression: $SENT_c^{Total}=b_c\,SENT^{Global}+SENT_c^{Local}$, for each country.

Panel A: Total and global sentiment

	Correlations with $SENT^{Global}$		Loading	Correlations among $SENT_c^{Total}$ indices						*p*-values					
	Global	*p*-value		Canada	France	Germany	Japan	U.K.	U.S.	Canada	France	Germany	Japan	U.K.	U.S.
Canada	0.57	(0.00)	0.20	1.00						(.)					
France	0.66	(0.00)	0.23	0.20	1.00					(0.34)	(.)				
Germany	0.76	(0.00)	0.27	0.26	0.45	1.00				(0.19)	(0.02)	(.)			
Japan	0.55	(0.00)	0.20	0.10	0.28	0.15	1.00			(0.63)	(0.16)	(0.45)	(.)		
U.K.	0.63	(0.00)	0.23	0.18	0.19	0.40	0.53	1.00		(0.39)	(0.35)	(0.04)	(0.01)	(.)	
U.S.	0.88	(0.00)	0.31	0.60	0.51	0.66	0.33	0.34	1.00	(0.00)	(0.01)	(0.00)	(0.10)	(0.09)	(.)

Panel B: Local sentiment

	Correlations among $SENT_c^{Local}$ indices						*p*-values					
	Canada	France	Germany	Japan	U.K.	U.S.	Canada	France	Germany	Japan	U.K.	U.S.
Canada	1.00						(.)					
France	−0.28	1.00					(0.16)	(.)				
Germany	−0.31	−0.10	1.00				(0.12)	(0.64)	(.)			
Japan	−0.31	−0.12	−0.48	1.00			(0.12)	(0.56)	(0.01)	(.)		
U.K.	−0.28	−0.37	−0.14	0.29	1.00		(0.16)	(0.06)	(0.48)	(0.15)	(.)	
U.S.	0.25	−0.18	−0.02	−0.37	−0.55	1.00	(0.21)	(0.37)	(0.90)	(0.06)	(0.00)	(.)

first principal component of the six total indices. The loadings are reported in Table 3 as

$$SENT_t^{Global}=0.20SENT_{Canada,t}^{Total}+0.23SENT_{France,t}^{Total}+0.27SENT_{Germany,t}^{Total}+0.20SENT_{Japan,t}^{Total}+0.23SENT_{UK,t}^{Total}+0.31SENT_{US,t}^{Total}. \tag{7}$$

The United States is widely considered the world's bellwether market. Consistent with this position, the United States' total sentiment index exhibits a high degree of commonality with other countries' indices and receives the highest loading in the global index.

The standardized version of the global index is plotted in Fig. 2. Not surprisingly, Fig. 2 indicates that global sentiment rose steadily through the mid-1990s, peaked in 1999 and 2000, and then dropped by a few standard deviations within three years. Before entering the Internet bubble, global sentiment had declined from the late 1980s to the early 1990s.

Local indices are defined as the components of the total indices orthogonal to the global index. That is, we regress the total sentiment indices on the global index in each country and define local indices as the residuals. We standardize these and plot them in Fig. 2.

Qualitative interpretations of the indices involve a large degree of conjecture as well as an understanding of historical market conditions. Proper interpretation of the local indices, in particular, requires a grasp of both global and market conditions, as well as some caution given the unavoidable noise in the estimates. With these qualifications in mind, one can speculate on some of the variation in the U.S. local index. The index reaches high levels in the early 1980s, perhaps reflecting speculative activity in biotech and natural resources shares that was concentrated in the United States. The index declines somewhat following the 1987 crash, but not dramatically, reflecting the fact that the crash was a global phenomenon (Roll, 1988).

Perhaps because the technological advances of the Internet were concentrated in the United States, the local index suggests that the sentiment associated with the bubble may have materialized there (and in Canada) first. Interestingly, while the U.S. total sentiment was high at the bubble's peak, it was not uniquely high relative to other countries in the sample. However, U.S.-specific sentiment did decline to an unusual degree with the crash, most likely reflecting the combination of the crash and the terrorist attacks on September 11, 2001.

3. Validation with Siamese twins

3.1. The Siamese twins

The existing investor sentiment literature rarely provides any external validation test for its proxies. In this paper we attempt to do somewhat better, because an experiment exists in the international context that does not exist in the U.S. context. Specifically, we connect our sentiment indices to the international violations of the law of one price observed in dual-listed companies. Dual-listed companies, often termed "Siamese twins," are literally textbook violations of arbitrage (see, e.g., Bodie, Kane, and Marcus, 2008).

More background will help to motivate this validation exercise. A twin pair comprises two companies which are incorporated in different countries and whose shares trade locally in those countries but, frequently as a result of a merger, have contractually agreed to operate their business as one and divide its cash flows to shareholders in a fixed ratio. There are around a dozen such company pairs as of the time of this writing, but the pair of Royal Dutch (traded mainly in the United States and the

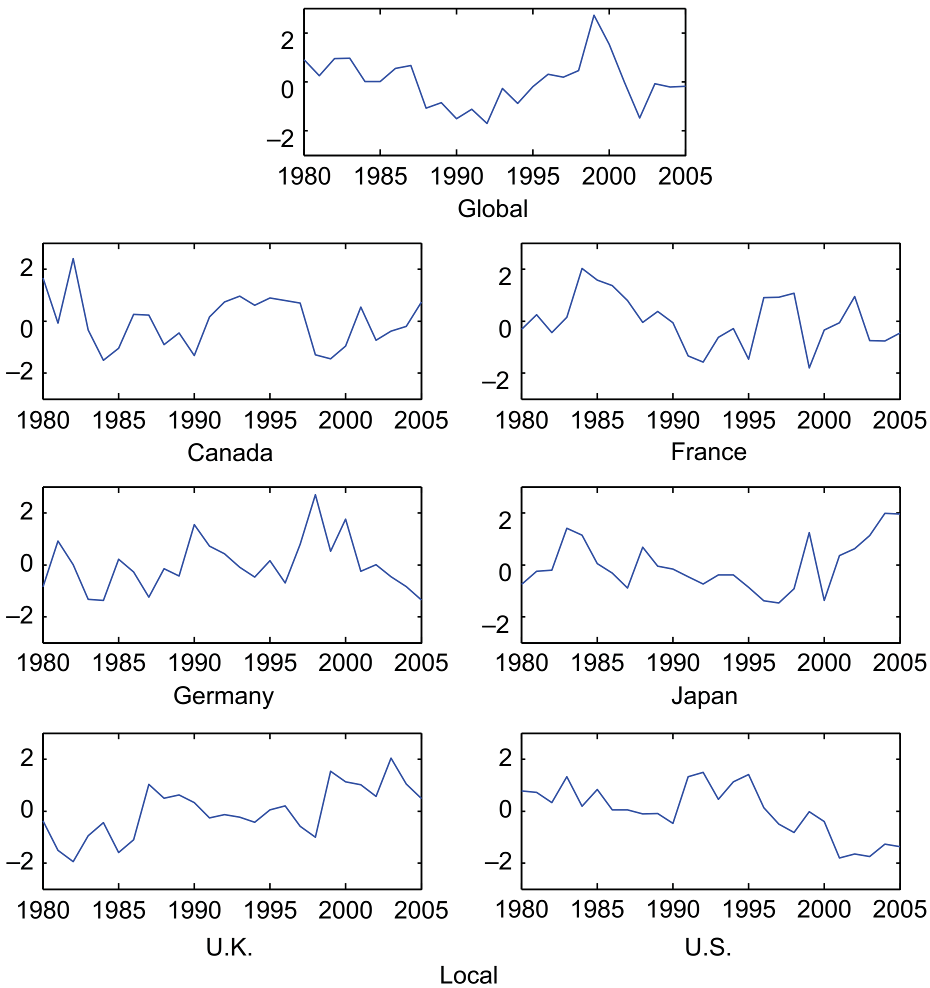

Fig. 2. Global and local investor sentiment, 1980–2005. Global sentiment ($SENT^{Global}$) is the first principal component of the total sentiment indices ($SENT_c^{Total}$) in the six countries. Local sentiment ($SENT_c^{Total}$) is the residual from the regression: $SENT_c^{Total} = b_c SENT^{Global} + SENT_c^{Local}$, for each country.

Netherlands) and Shell Transport (traded mainly in the United Kingdom) is still the best-known example, despite their recent unification.

For the Royal Dutch-Shell pair, as determined by a 1907 alliance, all cash flows, adjusting for corporate tax considerations and control rights, are split in the proportion 60:40. However, as shown by Rosenthal and Young (1990), Froot and Dabora (1999), and De Jong, Rosenthal, and Van Dijk (2009), the Siamese twins, among the largest and most liquid securities in the world, trade at prices that differ from the fixed cash flow ratio, and often by considerable amounts. For example, in our sample period, deviations from parity of more than 50 cents on the dollar—from −35% to +17%—are observed. De Jong, Rosenthal, and Van Dijk (2009) report that such deviations are observed in all Siamese twin pairs to a greater or lesser degree.

Froot and Dabora (1999) provide a comprehensive examination of structural reasons why these price gaps may occur. They consider six explanations in depth: "discretionary uses of dividend income by parent companies; differences in parent expenditures; voting rights issues; currency fluctuations; ex-dividend-date timing issues; and tax-induced investor heterogeneity. Only that latter hypothesis can explain some (but not all) of the facts." Shleifer (2000) further points out that any fixed structural or differences-in-risk explanation would have trouble explaining how the deviation from parity changes sign over time: "there is no story in which the cash flows of one stock are subjected to a different fundamental risk than the cash flows of the other" (p. 31).[8] He and others conclude that the deviation exists and persists because arbitrageurs fear noise trader risk, i.e., the risk that noise trader sentiment drives the mispricing to get worse before it gets better.[9,10]

[8] Shleifer (2000) and Bodie, Kane, and Marcus (2008) also point out that this is a cleaner demonstration of the violation of the law of one price than the closed-end fund discount, which does involve management fees and other structural features.

[9] Lowenstein (2000) reports that Long Term Capital Management bet \$2.3 billion on Royal Dutch-Shell alone, illustrating that it was viewed as a mispricing by sophisticated investors, and lost almost \$200 million on the trade, illustrating noise trader risk. See De Jong, Rosenthal, and Van Dijk (2009) for a detailed examination of the risks and return of dual-listed company arbitrage.

[10] On July 9, 2002, Royal Dutch was removed from the Standard and Poor (S&P) 500 Index along with several other non-U.S. firms. What was a Royal Dutch premium became a discount in a matter of days, as index

With our putative sentiment measures we are able to examine this explanation more directly. To the extent that it is borne out in the data, it supports the joint hypothesis that our sentiment indices are valid and that the drivers of the Siamese twins' price gaps include differential investor sentiment. Note that this joint hypothesis is the principal limitation of this exercise. It could be true that the twins' discount does not reflect relative sentiment, but some other unidentified economic force that is driving both the discount and our indices. This resembles the standard joint hypothesis problem that arises in tests of market efficiency: to test market efficiency, one must take a stand on the market's model of expected returns (Fama, 1970). But in the case of the Siamese twins, this argument has considerably less force. As Shleifer (2000) points out, given the unique features of the experiment, ''the Fama (1970) critique is irrelevant'' (p. 31).

In summary, after more than 20 years of research on the Siamese twins, we could find no paper that finds or even asserts the existence of such a hidden explanation. Those who do advance specific explanations generally assert that noise trader risk is what allows the deviation to exist and persist. As such, the validation test would seem informative. At the very least, it provides a better test than any yet presented in the sentiment literature.

3.2. Data and results

We obtain the relative prices of Siamese twin pairs from 1981 through 2002 from Mathias Van Dijk (http://mathijsavandijk.com/dual-listed-companies). Three pairs of twins have both companies in our sample markets and provide 51 annual observations. They all involve the United States and United Kingdom. Fig. 1 indicates that our sentiment measures in these countries are highly correlated, which reduces the power of the test and thus the ability to document a connection with the Siamese twins.[11]

The sentiment indices include both changes or return-like components, such as first-day returns on IPOs and perhaps detrended turnover, and level components, like the volatility premium. We therefore compare them to both changes in and levels of twin relative prices. We use annual observations on the yearend log price ratio, scaled such that a value of zero represents theoretical parity, and compare the changes and levels to the prevailing difference between U.S. sentiment and U.K. sentiment. The specifications are:

$$\Delta dev_{i,t} = a + b(SENT^*_{US,t} - SENT^*_{UK,t}) + c\Delta dev_{i,t-1} + u_{i,t} \tag{8}$$

and

$$dev_{i,t} = a + b(SENT^*_{US,t} - SENT^*_{UK,t}) + c dev_{i,t-1} + u_{i,t}, \tag{9}$$

where i denotes one of the three twin pairs. We use the asterisk superscript because we test both total and local sentiment indices. We control for the lagged relative price level because it is empirically quite persistent; because the sentiment indices are not measured without error; and because both sentiment indices have been standardized, removing any differences in means or scales. The change in the deviation is not very persistent, so its inclusion in the first specification is not material.

Table 4 indicates that the relative level of investor sentiment has a significant relationship to the relative level and changes of twins' prices. Given the sample size and low power of this test, the magnitude of the coefficient is surprisingly statistically significant and economically important. The standard deviation of the change of the log price ratio is 9.38%, while the standard deviation of the total sentiment gap is 0.992, so a one-standard-deviation change in the latter is associated with a change in the log price ratio swift of $4.43\% \times 0.992 = 4.39\%$, or approximately half of a standard deviation. Note that we report two-sided p-values, based on clustered standard errors, by convention, although our hypothesis is one-sided. We has also conducted Stambaugh (1986) corrections and added control variables with little statistical or economic change in the results.

The results provide some extra support that a sentiment interpretation of our indices is reasonable. To repeat, we aknowledge that this interpretation is conditional on this test having largely resolved the joint hypothesis problem. If, as Shleifer (2000) and others

Table 4

Time series regressions for Siamese twins. The dependent variable is the change or level of the annual log deviation of the relative price of three pairs of Siamese twins trading in the U.S. and the U.K. between 1981 and 2002. The independent variables are the difference between total (or local) sentiment. Clustered p-values are in braces.

	N	Constant	$SENTdiff \times 10^2$	Δdev_{t-1}	R^2
Panel A: Deviation change					
$\Delta dev_{i,t} = a + b(SENT^*_{US,t} - SENT^*_{UK,t}) + c\Delta dev_{i,t-1} + u_{i,t}$					
Total sentiment	48	0.01	**4.43**	−0.21	36%
		[0.36]	**[0.00]**	[0.17]	
Local sentiment	48	0.01	**2.42**	−0.11	29%
		[0.54]	**[0.00]**	[0.44]	
Panel B: Deviation level					
$dev_{i,t} = a + b(SENT^*_{US,t} - SENT^*_{UK,t}) + c dev_{i,t-1} + u_{i,t}$					
Total sentiment	51	0.01	**2.40**	0.82	74%
		[0.35]	**[0.02]**	[0.00]	
Local sentiment	51	0.01	**1.29**	0.81	72%
		[0.40]	**[0.09]**	[0.00]	

(*footnote continued*)
funds and benchmark-sensitive investors sold Royal Dutch over this period. Royal Dutch dropped by 25% between the announcement and the effective date. Shell fell too, as arbitrage maintained relative prices, but only by 17%. Both prices rebounded in the following weeks, but the deviation in prices did not revert to its previous level. Unilever, operating in a very different sector, had the same pattern of returns in its twin shares. This case study illustrates that the Siamese twin deviations capture index level differences in nonfundamental demand. While this particular demand shock had nothing to do with country-level sentiment, it proves the point that country-level relative demand for broad baskets of stocks would be apparent in Siamese twin deviations.

[11] Royal Dutch (U.S.) and Shell Transport (U.K.) from 1981 through 2002; Smithkline Beecham H shares (U.S.) and Smithkline Beecham E shares (U.K.) from 1990 through 1996; and Unilever NV (U.S.) and Unilever PLC (U.K.) from 1981 through 2002.

argue, that is the case, then in addition to supporting the indices, the results also provide further evidence that they are right that noise trader sentiment-driven mispricing helps to explain why the Siamese twins deviate so far from parity. With a joint hypothesis, it is all or nothing. We conclude that the exercise does, at a minimum, provide a more compelling validation test for a sentiment index than any in the literature.

4. Sentiment and market-level returns

4.1. Prior evidence, hypotheses, and market-level data

Baker and Wurgler (2006) provide an anecdotal history of investor sentiment in the United States since the early 1960s. They note the electronics boom in the early 1960s, the growth stocks boom in the late 1960s, the Nifty Fifty preference of the early 1970s, various industry-specific bubbles through the late 1970s through the mid-1980s, and the Internet bubble. We shall not attempt to catalog other (asserted) stock market bubbles and sentiment-driven variation for each of our non-U.S. markets, although this is a worthy task.

The empirical literature has employed sentiment-type measures as contrarian market-level return predictors only sporadically and mainly in the U.S. context. Kothari and Shanken (1997) discuss the predictability of the aggregate book-to-market ratio for annual U.S. market returns. They propose a sentiment-type explanation based on evidence of predictably negative risk premiums, which is inconsistent with market efficiency since rational risk premiums must be positive. Baker and Wurgler (2000) adopt this approach using the equity share in total equity and debt issues and find results consistent with Kothari and Shanken; they, too, find periods of predictably negative market returns. Henderson, Jegadeesh, and Weisbach (2006) extend this evidence to financing patterns in international markets. Baker and Wurgler (2007) find some evidence that an index similar to that estimated here predicts market-level U.S. returns, while Brown and Cliff (2004) do not find evidence of predictability.

The general impression from the time-series predictability literature, not just that involving sentiment, is that there are few if any variables that strongly reject the null of no predictability. Our panel of six countries has more power to reject the null of no market return predictability than returns from the United States alone (Ang and Bekaert, 2007), although due to cross-correlation, this amounts to fewer than six independent observations per period.

Motivated by the prior sentiment literature using U.S. data, we hypothesize that our sentiment indices are contrarian predictors of international index-level returns. As in the cross-sectional literature that derives predictability implications from cross-sectional limits to arbitrage, contrarian predictability at the market level can arise from at least two mechanisms. One is that arbitrageurs are essentially sidelined in extreme periods by noise trader risk (De Long, Shleifer, Summers, and Waldmann, 1990a; Shleifer and Vishny, 1997)—the variability of investor sentiment—and prices correct when noise traders' own beliefs correct, perhaps because the noise traders are confronted by realizations of economic fundamentals.

A second mechanism behind predictability is that noise traders' beliefs and hence mispricing stabilize at an extreme level, perhaps because they are fully invested, at which arbitrageurs find the expected returns so great that they outweigh the noise trader risk. They, too, wait for the facts to materialize, and as this happens in the expected direction, which it does on average if the arbitrageurs are correct, they are willing to become more and more heavily invested, pushing the aggregate demand curve and restoring fundamental value.

It is not easy to distinguish between these mechanisms, and we do not attempt to do so here. Earlier we showed that our total sentiment series exhibited mean-reversion over the horizon of one or two years. This is consistent with an explanation for predictability involving reversion in noise trader beliefs. Regarding the reason for this change, Baker and Wurgler (2006), where sentiment indices predict the time-series of the cross-section of earnings announcement returns—high sentiment forecasts lower earnings announcement returns on hard to value and hard to arbitrage stocks.[12] This is consistent with an information-based mechanism, but it cannot determine the extent to which this information is changing noise trader beliefs or confirming to arbitrageurs that they can be more aggressive.

We collect monthly market return data from Datastream, which cover the stocks from the largest exchange in each country except in the United States. For the United States, it covers the union of the NYSE, Amex, and Nasdaq. We gather both value-weighted and equal-weighted indexes; the difference in predictive effects between these will foreshadow the results in the time-series of the cross-section to come later.

4.2. Predicting market returns

We pool monthly returns from 1981 to 2006 for our countries and regress the monthly market returns for country c in year t on its beginning-of-year investor sentiment index value (i.e., the value prevailing as of the end of the previous year, which we shall call $t-1$ in an abuse of monthly and yearly notation):

$$R_{MKT,c,t} = a + dSENT^{Total}_{c,t-1} + u_{c,t}, \tag{10}$$

and

$$R_{MKT,c,t} = b + eSENT^{Global}_{t-1} + fSENT^{Local}_{c,t-1} + u_{c,t}. \tag{11}$$

Because of the cross-correlation in returns, our significance tests use month-clustered standard errors.

Table 5 indicates that total investor sentiment serves as a statistically significant contrarian predictor of market returns across these six markets.[13] The economic

[12] We do not attempt this test here because of the low quality of international earnings announcement dates data.

[13] Once again, we report two-sided p-values per convention, though the sign of all theoretical predictions in the paper is unambiguous and thus the statistical hypotheses are, in fact, one-sided.

Table 5
Time series regressions for country-level index returns, 1981–2006. Regressions of monthly country-level value- and equal-weighted index returns on previous yearend $SENT_c^{Total}$ (in Eq. (1)), or on previous yearend $SENT^{Global}$and previous yearend $SENT_c^{Local}$ (in Eq. (2)). In Panel A, the sample includes monthly country-level index returns from 1981 to 2006 in six countries. In Panel B, the sample excludes U.S. data. The first column shows the results from Eq. (1), and the second and third columns show the results from Eq. (2). Clustered *p*-values are in braces.

$$R_{MKT,C,t} = a + dSENT_{c,t-1}^{Total} + u_{c,t} \tag{1}$$

$$R_{MKT,C,t} = b + eSENT_{t-1}^{Global} + fSENT_{c,t-1}^{Local} + u_{c,t} \tag{2}$$

	$SENT_{c,t-1}^{Total}$			$SENT_{t-1}^{Global}$		$SENT_{c,t-1}^{Local}$		
	d	$p(d)$	R^2	e	$p(e)$	f	$p(f)$	R^2
Panel A: Including U.S.								
VW	−0.29	[0.08]	0.3%	−0.45	[0.05]	0.03	[0.68]	0.7%
EW	−0.36	[0.04]	0.4%	−0.47	[0.05]	−0.07	[0.48]	0.8%
Panel B: Excluding U.S.								
VW	−0.27	[0.10]	0.2%	−0.44	[0.06]	0.01	[0.91]	0.6%
EW	−0.33	[0.05]	0.4%	−0.45	[0.05]	−0.06	[0.57]	0.7%

significance of the effect is nontrivial. All sentiment indices are standardized, so a one-standard-deviation increase in a country's total investor sentiment index is associated with 3.5 percentage points per year (29 basis points per month) lower value-weighted market returns and 4.3 percentage points (36 basis points per month) lower equal-weighted returns. The stronger equal-weighted results presumably reflect smaller stocks being harder to value (due to spottier information and less certain prospects) and to arbitrage (due to generally greater costs and risks). This logic is developed a bit further in the next section, which focuses solely on cross-sectional tests.

Interestingly, the country-level results are mainly driven by global sentiment. A one-standard-deviation increase in the global sentiment index is associated with 5.4 percentage points per year (45 basis points per month) lower value-weighted market returns and 5.6 percentage points (47 basis points per month) lower equal-weighted market returns. This conclusion also does not depend on including the United States in the sample, and it raises the important issue of cross-country sentiment contagion. We consider this below. For now, Table 5 represents new evidence that sentiment affects markets around the world, not just in the United States where it has been most extensively studied.

We performed but do not report a number of additional robustness tests for the results in Table 5 that were prompted by referee suggestions. None of the following had a major effect on these results: excluding Germany, for which we are missing a few years of sentiment data; controlling for the lagged dividend yield (see, e.g., Shiller, 1984; Campbell and Shiller, 1988; Fama and French, 1988, and others) and the short-term interest rate (Fama and Schwert, 1977); excluding turnover from the sentiment proxy set; excluding the idiosyncratic volatility premium from the proxy set; using a total volatility premium rather than an idiosyncratic volatility premium; using an idiosyncratic volatility premium where idiosyncratic volatility is first orthogonalized to firm age, to control for a Pastor and Veronesi (2003) effect in which valuations depend on uncertainty about firm profitability that changes over time.

Finally, in unreported results we tested whether the U.S.-the U.K. Siamese twin premium predicts relative market returns on those two markets, consistent with the presumption of our validation approach that it reflects sentiment. We find that a one-standard-deviation higher deviation from twin parity predicts a −7.2% relative equal-weighted market return (Newey-West two-sided *p*-value of 0.07) and a −4.0% relative value-weighted return (Newey-West two-sided *p*-value of 0.12) in the coming year. The economic magnitude is nontrivial and the statistical significance is not unimpressive given the 22-year sample period and single time-series.

5. Sentiment and the cross-section of returns

5.1. Prior evidence, hypotheses, and firm-level data

The literature on predicting the time-series of the cross-section of expected stock returns is fairly small and uses only U.S. data, often with a focus on investor sentiment. Brown and Cliff (2004), Lemmon and Portniaguina (2006), and most extensively, Baker and Wurgler (2006) investigate the ability of sentiment to explain the time-series of the cross-section. Brown and Cliff (2004) find little connection using their sentiment measures, and Lemmon and Portniaguina (2006) find stronger evidence of sentiment as a contrarian predictor of small stocks and low institutional ownership stocks but not value or momentum portfolios. Qiu and Welch (2004) also use sentiment to predict small stocks. Also, from a non-sentiment perspective, Ghosh and Constantinides (2011) develop a predictor based on economic regimes.

Baker and Wurgler (2006) find robust predictability of the time-series of the cross-section using a U.S. index similar to that used here. Their stronger results may indicate more informative sentiment proxies and/or sharper cross-sectional predictions. In particular, they observe that sentiment should have relatively stronger effects on stocks that are hard to arbitrage—those that arbitrageurs find relatively costly or risky to trade against mispricings. For a recent survey of the theoretical literature on limits to arbitrage, see Gromb and Vayanos (2010); a large empirical literature documents cross-sectional variation in frictions such as short-selling costs, transaction costs and asymmetric information, arbitrage risk, and noise trader risk. These frictions lead certain stocks' aggregate demand curves to be more downward sloping and thus their prices more sensitive to sentiment-driven demand shifts. Second and perhaps more novel, Baker and Wurgler (2006) observe that sentiment should have relatively stronger effects on stocks that are hard or highly subjective to value properly. Both extremely high or low valuations on such stocks can be plausibly defended by sentimental investors, as befits their current sentiment.

The basic empirical prediction of all this is that sentiment may serve as a contrarian predictor of "high sentiment beta" portfolios. Again, as discussed above, contrarian predictability can arise from corrections in noise traders' own beliefs, consistent with the negative autocorrelations of changes in the sentiment indices, or eventual pressure from arbitrageurs, who become more aggressive as earnings realizations confirm mispricing. Baker and Wurgler (2006) find that sentiment indices predict the time-series of the cross-section of U.S. earnings announcement returns, consistent with an information-based mechanism.

Conveniently, several key stock portfolios are classifiable as either relatively easy to arbitrage and easy to value or as relatively hard to arbitrage and hard to value, making this prediction straightforward to test.[14] Examples of stock portfolios with high sentiment beta characteristics are small, high volatility, non-dividend paying, unprofitable, distressed, or extreme growth portfolios; their complement portfolios are lower, perhaps even negative sentiment beta.

An interesting subtlety is how to capture growth and distress characteristics using value or sales growth portfolios. Baker and Wurgler (2006) find that the effects of sentiment on these portfolios are roughly U-shaped. Very high book-to-market or very low (negative) sales growth can be associated with distress; very low book-to-market can be associated with extreme growth, as is very high sales growth. In other words, when sorting stocks along value or sales growth dimensions, high sentiment beta stocks commonly reside in the extreme high and low deciles where staid, low sentiment beta stocks are typically found in the middle. We account for this U-shape in our tests.[15]

Our cross-sectional portfolios are formed based on four firm or stock characteristics that are easy to gather for each market: firm size, total risk, book-to-market equity ratio, and sales growth. Returns and market capitalization are from Datastream. Book equity values (item WC05476) and annual sales (item WC05508) are from Worldscope. We exclude observations with negative book equity. Total risk is the volatility of monthly total returns over the prior year. Decile breakpoints vary by country-year. Returns are equal-weighted within each decile portfolio.

5.2. Predicting the time-series of the cross-section

Simple two-way sorts are presented in Table 6. We sort stocks across years according to whether the level of their total sentiment index is positive or negative. The basic predictions are borne out. The top volatility decile stocks earn 134 basis points per month lower returns when the year starts in a high-sentiment state, consistent with a correction of sentiment-driven overpricing. This return difference cumulates to 16.1 percentage points over the year. High-sentiment periods also portend 100 basis points per month lower returns on the smallest capitalization portfolio, another large effect. As hypothesized, the effect of sentiment is much smaller on low volatility stocks or large stocks, their being relatively easy to arbitrage and value.

As mentioned above, we predict a somewhat U-shaped effect of sentiment on book-to-market and sales growth portfolios. This is borne out to a greater extent in the sales growth than the book-to-market portfolios. In the sales growth portfolios, the bottom decile earns 69 less basis points per month coming out of high-sentiment periods, and the top decile earns 107 basis points less, whereas the differences in the middle deciles (12 and 18 basis points in portfolios five and six) are typically smaller. Cumulated over the year, the differences between the extreme and middle deciles are meaningful, though not as strong as the volatility and capitalization results. In unreported results, we exclude the United States and the results are similar.

Next, we move to time-series regressions to predict long-short portfolios. This provides a simpler setting in which to conduct hypothesis tests and also allows us to look at the separate effects of global and local sentiment. The basic regression models are:

$$R_{X_{it}=long,c,t} - R_{X_{it}=short,c,t} = a + dSENT^{Total}_{c,t-1} + u_{c,t}, \tag{12}$$

and

$$R_{X_{it}=long,c,t} - R_{X_{it}=short,c,t} = b + eSENT^{Global}_{t-1} + fSENT^{Local}_{c,t-1} + u_{c,t}. \tag{13}$$

Again, the significance tests incorporate month-clustered standard errors.

The total sentiment column in Table 7 is highly consistent with the results from the sorts. In five out of six hypothesis tests, the effect of total sentiment is statistically significant with the expected sign. The remaining long-short portfolio, which sorts on distress by using high value against medium value, is of the expected negative sign. The economic significance of the effects implied here is naturally similar to that from the sorts, with the effects for the volatility portfolios again

[14] Notably, momentum does not fall clearly in either set.

[15] Not accounting for this nonmonotonicity in sentiment beta may explain why some prior research found no clear connection between sentiment and value portfolios.

Table 6

Two-way sorts: Total sentiment and firm characteristics, 1981 to 2006. For each month, we form ten portfolios according to the total risk (σ), firm size (ME), book-to-market ratio (*BE*/*ME*), and sales growth (*GS*). We report equal-weighted portfolio returns over months where total sentiment ($SENT_c^{Total}$) from the previous yearend is higher than within-country median, lower than within-country median, and the difference between the two averages. The sample includes monthly country-level portfolio returns from 1981 to 2006 in the six countries.

	$SENT_{t-1}^{Total}$	Decile										Overall		
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**	**10-5**	**5-1**
σ	High	0.86	1.07	1.13	1.18	1.14	1.15	1.07	0.89	0.69	0.63	−0.23	−0.52	0.29
	Low	0.87	1.04	1.16	1.33	1.45	1.59	1.57	1.69	1.86	1.97	1.09	0.52	0.58
	Difference	−0.01	0.03	−0.03	−0.14	−0.30	−0.44	−0.50	−0.81	−1.17	−1.34	−1.32	−1.04	−0.29
ME	High	1.83	1.34	1.01	0.84	0.81	0.81	0.84	0.87	0.91	0.95	−0.88	0.15	−1.03
	Low	2.83	2.06	1.69	1.52	1.46	1.33	1.20	1.19	1.15	1.19	−1.64	−0.26	−1.37
	Difference	−1.00	−0.72	−0.69	−0.68	−0.65	−0.52	−0.36	−0.32	−0.24	−0.24	0.76	0.41	0.35
BE/*ME*	High	0.93	0.88	0.86	1.00	1.04	1.05	1.08	1.18	1.27	1.50	0.57	0.46	0.11
	Low	1.86	1.53	1.44	1.43	1.37	1.49	1.51	1.48	1.60	2.08	0.22	0.72	−0.50
	Difference	−0.93	−0.65	−0.58	−0.43	−0.32	−0.44	−0.43	−0.29	−0.33	−0.58	0.35	−0.26	0.61
GS	High	0.77	0.96	1.05	1.21	1.30	1.32	1.33	1.28	1.19	0.97	0.20	−0.33	0.53
	Low	1.45	1.33	1.39	1.37	1.41	1.50	1.63	1.61	1.77	2.03	0.58	0.62	−0.04
	Difference	−0.69	−0.36	−0.34	−0.16	−0.12	−0.18	−0.30	−0.33	−0.59	−1.07	−0.38	−0.95	0.57

Table 7

Time series regressions for cross-sectional returns, 1981–2006. Regressions of long-short equal-weighted portfolio returns on previous yearend $SENT_c^{Total}$ (in Eq. (1)), or on previous yearend $SENT^{Global}$ and previous yearend $SENT_c^{Local}$ (in Eq. (2)). The first column shows the results from Eq. (1), and the second and third columns show the results from Eq. (2). The sample includes monthly country-level portfolio returns from 1981 to 2006 in the six countries. The long-short portfolios are formed based on firm characteristics (X): firm size (*ME*), total risk (σ), book-to-market ratio (*BE*/*ME*), and sales growth (*GS*). High includes the top two deciles; low includes the bottom two deciles; medium includes the middle two deciles. Clustered p-values are in braces:

$$R_{X_{it}=long,c,t} - R_{X_{it}=short,c,t} = a + dSENT_{c,t-1}^{Total} + u_{c,t} \tag{1}$$

$$R_{X_{it}=long,c,t} - R_{X_{it}=short,c,t} = b + eSENT_{t-1}^{Global} + fSENT_{c,t-1}^{Local} + u_{c,t} \tag{2}$$

		$SENT_{c,t-1}^{Total}$			$SENT_{t-1}^{Global}$		$SENT_{c,t-1}^{Local}$		
		d	$p(d)$	R^2	e	$p(e)$	f	$p(f)$	R^2
Panel A: Size and risk									
σ	High-Low	−0.73	[0.00]	1.8%	−0.82	[0.00]	−0.27	[0.08]	2.4%
ME	SMB	−0.24	[0.05]	0.2%	−0.21	[0.04]	−0.17	[0.30]	0.3%
Panel B: Growth opportunities									
BE/*ME*	Low-Medium	−0.32	[0.00]	0.9%	−0.23	[0.03]	−0.20	[0.00]	0.8%
GS	High-Medium	−0.40	[0.00]	1.7%	−0.29	[0.03]	−0.25	[0.03]	1.5%
Panel C: Distress									
BE/*ME*	High-Medium	−0.03	[0.80]	0.0%	−0.09	[0.52]	0.03	[0.64]	0.1%
GS	Low-Medium	−0.20	[0.03]	0.5%	−0.13	[0.15]	−0.15	[0.09]	0.5%
Panel D: Size and risk, excluding U.S.									
σ	High-Low	−0.65	[0.00]	1.5%	−0.76	[0.00]	−0.25	[0.12]	2.3%
ME	SMB	−0.22	[0.04]	0.2%	−0.23	[0.05]	−0.12	[0.52]	0.3%
Panel E: Growth opportunities, excluding U.S.									
BE/*ME*	Low-Medium	−0.28	[0.00]	0.7%	−0.16	[0.13]	−0.23	[0.00]	0.7%
GS	High-Medium	−0.37	[0.01]	1.5%	−0.22	[0.17]	−0.28	[0.01]	1.4%
Panel F: Distress, excluding U.S.									
BE/*ME*	High-Medium	0.01	[0.89]	0.0%	−0.07	[0.58]	0.07	[0.24]	0.1%
GS	Low-Medium	−0.17	[0.05]	0.5%	−0.08	[0.35]	−0.16	[0.04]	0.5%

being largest. Sorting on volatility leads to particularly clear contrasts on both arbitrage risk and valuation ambiguity dimensions. Excluding the United States leads to similar results.

The influence of local sentiment is much more prominent in the cross-section. With the exception of the volatility portfolios, where global sentiment remains three times as important as local sentiment, local and global sentiment are roughly equally important. Also, local sentiment tends to be more statistically significant in specifications where global sentiment is not, at least in part, because it includes cross-sectional variation.

The greater effect of local sentiment on the cross-sectional results is intuitive. Global investors have less information on individual companies and face higher transaction costs. Many global investors are simply looking for diversification, and this is available at lowest cost through a market-tracking investment such as an index fund or Exchange-Traded Fund. More in a sentiment vein, local investors are more likely to act on rumors or develop unusual beliefs about specific local stocks. They also have a comparative trading cost advantage. All this, and given the very strong home bias (French and Poterba, 1991), leads to the prediction that local sentiment will have greater effects in the local cross-section.

We conducted but do not report various robustness exercises for the results in Tables 6 and 7. We find that controlling for the Fama and French (1993) factors tends to attenuate statistical significance but the qualitative results are similar. In a sense, this is not really a robustness test, because some attenuation is predicted under our hypotheses: for example, controlling for small and medium enterprises (SMBs) or market return minus risk-free return ($Rm-Rf$) amounts to controlling for effects that we predict and show in Tables 5 and 7, and reduces the variation in sentiment that is orthogonal to the independent variables. We also repeat exercises that we performed to investigate the robustness of the market-level preditability patterns: excluding Germany; excluding turnover from the sentiment proxy set; excluding the idiosyncratic volatility premium from the proxy set; using a total volatility premium rather than an idiosyncratic volatility premium; using an idiosyncratic volatility premium where idiosyncratic volatility is first orthogonalized to firm age. None of these variants made a noteworthy difference to the results.

6. Sentiment contagion

Our results suggest that both global and local sentiment affect stock prices. When global and local sentiment are high, future local stock returns are low, and particularly so for stocks predicted to have high sentiment betas. The local sentiment effects extend the evidence from the United States on sentiment and the cross-section of stock returns. The effect of global sentiment suggests a more novel mechanism: sentiment may be contagious.

There are two sources of contagion. One possibility is that investors in one country are optimistic (for example) about investment prospects in another and bid up the shares of that particular country. Using our measures, this will be captured by local sentiment. Local sentiment rises with the local volatility premium, the local number of IPOs, the local first-day return on IPOs, and the local rate of share turnover. These are local measures, but they reflect capital market activity, which in principle can come from foreign as well as local investors. The evidence in Klibanoff, Lamont, and Wizman (1998) and Hwang (2011), who examine the pricing of closed-end funds, is suggestive of this channel.

Another possibility is that investors in one country, say, e.g., the United States, are simply optimistic and this leads to a shift into risky assets more broadly, including international equities. United States sentiment will then affect prices in another target country, above and beyond local sentiment, provided that our measure of local sentiment is not absolutely complete, as it surely is not, and provided that there is a robust flow of private capital from the United States into the target.

To be specific, what we care about is the round-trip flow of capital, both from the United States to another country in our sample and back to the United States. Countries with high absolute flows, we hypothesize, will be subject to sentiment propagation. High U.S. sentiment will predict negative future returns to a greater extent if capital flows from the United States are high. Low U.S. sentiment will predict positive future returns to a greater extent if capital flows back to the United States are high. This pattern suggests using the interaction of the absolute value of flows with sentiment to predict future returns.

We test this hypothesis in Table 8. We regress future returns of long-short portfolios formed on size, volatility, growth, and distress in the five countries excluding the United States on lagged sentiment in the local country, as before. But we now include U.S. sentiment, and more interestingly, U.S. sentiment interacted with capital flows from the United States to each of the five other countries

$$R_{X_{it}=high,c,t}-R_{X_{it}=low,c,t}=a+bSENT^{Total}_{c,t-1}+cSENT^{Total}_{US,t-1}+d\left|Flow_{US\leftrightarrow c,t-1}\right|+eSENT^{Total}_{US,t-1}\left|Flow_{US\leftrightarrow c,t-1}\right|+u_{c,t}. \tag{14}$$

The data on capital flows come from the Treasury Bulletin and are normalized by the market value of the foreign stock market. In every case where the effect of sentiment of the local country is statistically significant, there is also a strong and conditional effect of U.S. sentiment. Provided the capital flows between the United States and Canada, to take an example, are high in absolute value, then U.S. sentiment has the same effect on hard to value and to arbitrage Canadian stocks as Canadian sentiment. The results are consistent with private capital flows being a mechanism that spreads sentiment across markets.

There are, of course, other mechanisms to spread sentiment. One is social influence, i.e., word-of-mouth sharing of positive investment experiences. Shiller (1984) discusses this mechanism, and Hirshleifer (2009) models how the bias toward sharing positive information leads to the spread of investing, particularly in volatile, hard to value stocks. Kaustia and Knüpfer (in press) show that high stock returns of local peers in Finland encourage additional stock market participation. Hong, Kubik, and Stein (2004) find that mutual fund managers in the same city exhibit common trading patterns. Brown, Ivkovic, Smith, and Weisbenner (2008) find that stock market participation depends on that of neighbors. Strictly speaking, this evidence pertains to the spread of sentiment

Table 8

Time series regressions for sentiment contagion, 1981–2006. The dependent variable is the long-short equal-weighted portfolio return from five countries: Canada, France, Germany, Japan, and the U.K. $|Flow_{US\leftrightarrow c,t-1}|$ is the absolute value of the normalized capital flow between U.S. and the other five countries. It is normalized by the market value of the foreign stock market. The long-short portfolios are formed based on firm characteristics (X): firm size (ME), total risk (σ), book-to-market ratio (BE/ME), and sales growth (GS). High includes the top two deciles; low includes the bottom two deciles; medium includes the middle two deciles. Clustered p-values are in braces.

$$R_{X_{it}=long,c,t}-R_{X_{it}=short,c,t}=a+bSENT^{Total}_{c,t-1}+cSENT^{Total}_{US,t-1}+d|Flow_{US\leftrightarrow c,t-1}|+eSENT^{Total}_{US,t-1}\times|Flow_{US\leftrightarrow c,t-1}|+u_t$$

		Constant	$SENT^{Total}_{c,t-1}$	$SENT^{Total}_{US,t-1}$	$\|Flow_{US\leftrightarrow c,t-1}\|$	$SENT^{Total}_{US,t-1}\times\|Flow_{US\leftrightarrow c,t-1}\|$	R^2
Panel A: Size and risk							
σ	High-Low	−0.38	−0.41	−0.07	0.06	**−0.45**	3.6%
		[0.31]	[0.03]	[0.86]	[0.01]	**[0.02]**	
ME	SMB	0.23	−0.20	0.24	0.58	**−0.40**	1.6%
		[0.37]	[0.30]	[0.24]	[0.01]	**[0.01]**	
Panel B: Growth opportunities							
BE/ME	Low-Medium	0.01	−0.30	0.29	0.11	**−0.18**	0.8%
		[0.95]	[0.01]	[0.07]	[0.34]	**[0.12]**	
GS	High-Medium	0.25	−0.29	0.11	−0.01	**−0.13**	1.5%
		[0.29]	[0.07]	[0.49]	[0.81]	**[0.09]**	
Panel C: Distress							
BE/ME	High-Medium	0.11	0.05	−0.20	0.17	**0.03**	0.6%
		[0.52]	[0.62]	[0.32]	[0.08]	**[0.76]**	
GS	Low-Medium	−0.21	−0.14	0.29	−0.02	**−0.19**	0.9%
		[0.11]	[0.11]	[0.01]	[0.80]	**[0.00]**	

within a geographic area. The effects tail off with the distance between actors.

Technology and mass-media can reduce the effects of distance and represent another distinct mechanism by which sentiment can spread, potentially across borders, in the absence of direct investment. Shiller (1984) discusses this as well. Tetlock (2007) shows a causal effect of business news on stock returns, for instance, and Antweiler and Frank (2004) try to connect them to the conversations of Internet chat rooms.

7. Conclusion

We summarize by reviewing the main contributions of the paper. The first is to construct practical indices of investor sentiment for six major stock markets and global markets as a whole; prior literature and available sentiment indices focus on the United States. Specifically, we construct sentiment indices for Canada, France, Germany, Japan, the United Kingdom, and the United States, and from these total sentiment indices we extract one global and six local, or country-specific, indices. Second, we connect these indices to Siamese twins' share prices, providing a degree of external validation that the existing sentiment literature does not.

The third and fourth contributions of the paper are to document that investor sentiment affects the time-series of international market-level returns as well as the time-series of the cross-section of international stock returns. We find that global sentiment is a statistically and economically significant contrarian predictor of market returns. Both global and local components of sentiment help to predict the time-series of the cross-section; namely, they predict the returns on high sentiment-beta portfolios such as those including high volatility stocks or stocks of small, distressed, and growth companies. Our paper appears to be the first to study the international time-series of the cross-section of stock returns, and the results indicate that the U.S. results of Baker and Wurgler (2006) extend to the international context. All of these results are directionally consistent with theoretical predictions.

Our fifth contribution is to investigate how global sentiment emerges and propagates. We find evidence that it emerges at least in part because sentiment is contagious across markets, and at least one of the mechanisms at play is international capital flows. Ours is a simple investigation of the contagion question; there is considerable scope for further research on investor sentiment within and across international markets.

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