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Long-term industry reversals

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ABSTRACT

This study investigates whether, how and why industry performance can drive long-term return reversals. Using data from the UK, we find that firms in losing industries significantly outperform those in winning industries over the subsequent five years. These industry reversals remain strong and persistent after controlling for stock momentum, industry momentum, seasonal effects and traditional risk factors. We find a strong influence of past industry performance on stock return reversals. Our results also show that past industry performance is the driving force behind long-term reversals. Specifically, we find that industry components drive stock reversals, while past stock performance does not explain industry reversals. Further analysis suggests that industry reversals are present in both good and bad states of the economy and are stronger in industries with high valuation uncertainty. This implies that industry reversals are more likely to be a result of mispricing.

1. Introduction

DeBondt and Thaler (1985) show that loser stocks over the past three to five years outperform winners by 25% in the next three years. Many subsequent studies also report evidence of long-term reversals in major international equity markets.[1] Despite this evidence, the causes of these reversals are highly controversial in the literature. Prominent behavioural theories suggest that reversals occur due to investors' behavioural biases in forecasting firm growth (DeBondt and Thaler, 1987; Daniel et al., 1998; Barberis et al., 1998; Hong and Stein, 1999). However, Klein (2001) and George and Hwang (2007) contend that reversals reflect investors' rational reactions to a delay in the payment of capital gains taxes. Rational asset pricing models also suggest that reversals represent compensation for risk (Fama and French, 1993, 1996; Zhang, 2005; Liu, 2006).

This study contributes to this ongoing debate by investigating whether, how and why industry performance can drive long-term return reversals. As firms in the same industry share similar fundamentals and are affected by common shocks, arising from shifts in demand and supply for their products, industry components can cause the returns of these firms to comove (e.g. Welch, 2004; Mackay and Philips, 2005). The rational view of asset pricing suggests that this comovement represents industry-specific risk. Theoretical asset pricing models demonstrate that a firm's risk and return can be a function of its industry characteristics (e.g. Berk et al., 1999; Carlson et al., 2004, 2014; Preress, 2010; Bustamante, 2015).[2] Consistent with this theoretical prediction, several empirical studies document that industry components can explain asset pricing regularities (e.g. Moskowitz and Grinblatt, 1999; Hou and Robinson, 2006; Hameed and Mian, 2015). Kogan (2001), Zhang (2005) and Hou et al. (2015) show that firms have greater investment adjustment costs in downturn industries and the potential risk associated with having irreversible investments in place can cause higher returns for firms operating in poorly performing industries than for those in well performing industries. The models of Fama and French (1997) and Cohen et al. (2003) also indicate that poor past performance represents distress risk and firms in losing industries are, therefore, expected to offer higher returns to their shareholders for bearing industry distress risk.

Market frictions and investors' irrational behaviour can also induce industry components in stock returns. Barberis et al. (2005) and Peng and Xiong (2006) argue that investors allocate funds at a category rather than individual stock level. If these category investors are noise traders with correlated sentiment, their coordinated demand may cause excess comovement in the returns of stocks in the same category. Barberis et al. (2005) also argue that

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[1] E.g. Chou et al. (2007) in Japan, Clare and Thomas (1995) in the UK and George and Hwang (2007) in the US.

[2] Fama and French (1997) find that neither the Sharp–Linter–Black capital asset pricing model (CAPM) nor their three-factor model can precisely estimate industry costs of equity. Lewellen et al. (2010) show that macro-economic (e.g. consumption, consumption-to-wealth, and investment-to-growth) based asset pricing models fail to explain cross-sectional returns for industry portfolios.

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investors trade only a subset of securities. When these investors' risk aversion, sentiment, or liquidity needs change, they alter their exposure to the securities in their habitat, thereby causing comovement beyond fundamentals. If an industry represents a category or a habitat, the coordinated demand of noise traders at the industry level can generate industry components that are unrelated to firm fundamentals.

The behavioural models proposed by Daniel et al. (1998), Barberis et al. (1998) and Hong and Stein (1999) suggest that these industry components may drive long-term return reversals. In Daniel et al.'s model, investors exhibit overconfidence and self-attribution biases. The degree of investors' overconfidence and self-attribution may vary over time and across industries, causing mispricing and subsequent reversals. For example, Moskowitz and Grinblatt (1999) argue that the difficulty in assessing the value of new or changing industries promotes overconfidence among investors who are related to these industries. They also argue that investors' conservatism bias can reduce the speed at which investors update their priors about new and changing industries. In Barberis et al.'s (1998) model, investors exhibit representativeness bias, causing them to become too optimistic (pessimistic) about firms with a sequence of good (bad) news. Moskowitz and Grinblatt (1999) argue that if investors focus more on industry than firm specific news, the representativeness bias can lead them to extrapolate performance too far from the industry as a whole, yielding long-term reversals. Finally, several studies show that analysts and institutional investors have more industry- and market-wide information than firm-specific information (e.g. Piotroski and Doulstone, 2004; Irvine and Pontiff, 2009; Preress, 2010). As analysts and institutional investors usually pay more attention to industry leaders, the prices of these leaders will reflect market- and industry-wide news more quickly than those of their followers. Similarly, industries with more analysts and institutional holdings are shown to incorporate market-wide news faster than other industries (e.g. Hong et al., 2007). When traders seek to exploit sluggish price adjustments to industry- or market-wide information, they can create excess industry momentum and subsequent industry reversals may happen as prices revert back to their equilibrium levels (e.g. Hong and Stein, 1999).

Given the above arguments, it is surprising that little attention is given to the industry reversals and their role in explaining stock reversals. This study fills the gap. Using stocks listed on the London Stock Exchange (LSE), we find significant long-term industry reversals in the UK market. Specifically, we show that stocks in losing industries outperform those in winning industries over the subsequent five years after controlling for stock momentum, industry momentum, seasonal patterns and traditional risk factors. We also show that industry reversals are much stronger than stock reversals. In particular, we find that industry reversals are present in all calendar months, in neutral (neither winner nor loser) stocks and after adjusting for past stock performance. However, stock reversals exhibit strong seasonal patterns, are non-existent in neutral (neither winning nor losing) industries and disappear when adjusting for past industry performance. This evidence supports the prediction that industry components are the main driving force behind long-term return reversals.

In the subsequent analysis, we also investigate whether the long-term industry reversals are consistent with rational explanations or are a result of mispricing. To this end, we investigate whether stock and industry reversals survive after stringent risk adjustments. By using both the Fama and French (1993, 2015) three- and five-factor model,[3] we find that stock reversals completely disappear, while industry reversals remain positive and significant, albeit weak in the five-factor model. Since industry reversals are not fully explained by risk factors, it is plausible that mispricing is also at play. To shed further light on this issue, we compare the performance of the industry contrarian strategies in different states of the economy. Lakonishok et al. (1994) argue that, if loser stocks are fundamentally riskier than winner stocks, then contrarian strategies should be profitable only in good states, as the high marginal utility of wealth in bad states makes loser stocks unattractive to risk-averse investors. However, if industry reversals represent a form of market inefficiency, one would expect them to be more pronounced in industries with high information uncertainty (see, e.g. Hirshleifer et al., 2013). We find that the profits of industry contrarian strategies exist in both good and bad states of the economy and are higher in industries with less competition, high accruals, high idiosyncratic volatility and low analyst coverage.[4] These findings suggest that industry reversals are more likely to represent mispricing rather than compensation for risk.

This study contributes to the literature in many ways. First, to the best of our knowledge, we are the first to study long-term industry reversals and their impact on the well-documented long-term stock reversals. Our study is related to the work of Moskowitz and Grinblatt (1999), who document strong industry components in the short-term stock momentum anomaly. However, while several studies argue that short-term momentum and long-term reversals are related (Hong and Stein, 1999; Jegadeesh and Titman, 2001), others show that they are two independent phenomena (George and Hwang, 2004).[5] Thus, whether industry reversals have an impact on stock reversals remains an open empirical question. In this study, we document the presence of strong industry reversals, which fully subsume the stock reversals. This finding has important implications for the asset pricing literature. Specifically, while several early studies show that contemporaneous industry returns have little impact on stock returns (e.g. Fama and French, 1997; Heston and Rouwenhorst, 1994; Griffin and Karolyi, 1998), we find that past industry performance strongly affects future stock returns. Second, we investigate whether the importance of industry returns in the conditional asset pricing is consistent with rational expectations or is better explained by behavioural biases. We find that industry reversals are more consistent with behavioural explanations and represent a challenge to the rational asset pricing models. Third, we evaluate the ability of the Fama and French (2015) five-factor model to explain anomalies outside the US. Using data from the UK, we find that the five-factor model fully explains the stock return reversals, but its ability to explain industry reversals is relatively limited. Finally, the institutional setting of the UK market provides a unique opportunity to test the role of taxes in long-term return reversals. George and Hwang (2007) show that stock reversals in the US come exclusively in January. Since the UK tax year end is 5 April, investigating stock reversals in the month of April helps us understand whether the strong January reversals in the US are caused by tax loss selling or are merely the turn-of-the-year effect. Consistent with the tax loss selling argument, we find that stock reversals in the UK are particularly strong in April. However, the finding that industry reversals are not confined to the months of January or April is inconsistent with the tax loss selling hypothesis.

The remainder of the paper is structured as follows. Section 2 describes the data and the methodology. Section 3 provides summary statistics. Section 4 provides empirical results, and Section 5 concludes.

[3] Note that it is yet to be established whether the profitability and investment factors in Fama and French (2015) reflect rational risk or mispricing. See Hou et al. (2015) for further discussions.

[4] Dhaliwal et al. (2011) use accruals as a proxy for information opacity, Hong et al. (2000) use firm size as a proxy for investors' attention, and Kumar (2009) uses idiosyncratic volatility as a proxy for valuation uncertainty.

[5] George and Hwang (2004, 2007) show that the momentum captured by the nearness of a stock's price to its 52-week high does not reverse in the long term.

2. Data, variables and methodology

2.1. Sample data

Our sample consists of all stocks listed on the LSE from January 1970 to December 2011. The stock monthly and daily return series, market capitalisations, international industry classification (ICB) and firm characteristics are extracted from Thomson Reuters Datastream. We only include common stock, filtering on the data type and company name (e.g. Griffin et al., 2010; Ince and Porter, 2006).[6] The final sample includes a total of 6216 stocks with 995,717 firm-month observations. This sample is considerably larger than those used in prior UK studies.[7] Since Datastream reports the stock return index (RI) to the nearest hundredth, stock returns computed from the RI measure may round very small returns to zero values. To avoid potential rounding errors, we set a monthly return to be missing if the RI is less than or equal to 0.10. If a stock is delisted and no delisting reason is given in DataStream, we assign the last trading month return as −50%. Shumway (1997) finds that −30% is the average return for delisted firms traded over the counter. Setting a delisting return lower than that of Shumway would cause a downward bias in the magnitude of long-term return reversals.

We use ICB system to classify the sample stocks into 20 super-sectors.[8] This classification strikes a balance between having enough stocks in an industry and grouping stocks with homogeneous business environments together. The average number of stocks for each super-sector in each month is provided in Table 1. The table shows that stocks are not evenly distributed across super-sectors, ranging from 364 in industrial goods and services to 6 in the automobile and parts industry. Because the automobile and parts and telecommunications industries include fewer than 20 stocks, we use the remaining 18 industries to construct long-term winning and losing industry portfolios.[9]

Table 1
Description and summary statistics of industry.

Industry code	Industry name	Avg. No. of stocks	Avg. % of market cap.	5-year raw return	5-year excess market return
1	Oil & gas	43	8.48%	0.7220	0.1594
2	Chemicals	40	3.21%	0.5103	−0.0512
3	Basic resources	51	2.99%	0.5454	−0.0200
4	Constructions & materials	54	2.18%	0.4859	−0.0748
5	Industrial goods & services	364	7.68%	0.1853	−0.3768
6	Automobiles & parts	6	0.79%	0.0924	−0.4699
7	Food & beverage	70	5.07%	0.6780	0.1169
8	Personal & household goods	138	3.58%	0.7781	0.2163
9	Health care	50	5.27%	0.9026	0.3389
10	Retail	137	5.56%	0.5772	0.0155
11	Media	86	4.12%	0.4488	−0.1123
12	Travel & leisure	90	2.65%	0.4998	−0.0622
13	Telecommuincations	18	6.67%	1.2969	0.7309
14	Utilities	31	4.14%	0.5856	0.2063
15	Banks	26	20.03%	0.4146	−0.1467
16	Insurance	38	8.77%	0.5106	−0.0505
17	Financial services	90	2.31%	0.6368	0.0738
18	Technology	83	0.99%	0.2801	−0.2832
19	Real estate	95	1.92%	0.5202	−0.0425
20	Others	96	3.50%	0.2414	−0.4879
	Average	98	6.70%	0.5418	−0.0135

The table reports basic characteristics of the 20 super-sector based industry portfolios according to the International Classification of Benchmarks (ICB). The 20 industries are formed monthly from January 1975 to December 2011. The average number of stocks included in each industry is reported. The average percentage of total market capitalisations, five-year raw returns, and five-year excess market returns are the time-series means of cross-sectional industry averages in each month. Five-year raw returns are calculated from five-year value-weighted industry return indexes and five-year excess market returns are calculated from five-year industries' raw returns minus five-year FTSE All Share market index returns. The last row reports the times series means for the statistics across 20 industries.

2.2. Variable construction

(i) Stock's five-year past performance measure (*stock_5yret*): This variable measures a stock's return over the past 60-month period, $\frac{P_t - P_{t-60}}{P_{t-60}}$, plus the return from reinvesting dividends. Following DeBondt and Thaler (1985, 1987) and George and Hwang (2007), we set the *5-year winner* (*loser*) dummy to unity if a stock is ranked in the top (bottom) 30% of all stocks in terms of the five-year performance measure, and zero otherwise.

(ii) Long-term winning and losing industries: We define an industry's monthly return index (*RI*) as the value-weighted monthly returns of stocks in that industry. Industry five-year past performance (*ind_5yret*) is measured as $\frac{RI_t - RI_{t-60}}{RI_{t-60}}$. The long-term winning (losing) industries are defined as the three industries with the highest (lowest) *ind_5yret* (e.g. Moskowitz and Grinblatt, 1999). We also set the *5-year winning* (*losing*) *Ind* dummy to unity if a stock belongs to winning (losing) industries, and zero otherwise.

(iii) Stock momentum: We use the price relative to the 52-week high to control for stock momentum. Following George and Hwang (2004), we define *52wkhWinner* (*52wkhLoser*) as a dummy variable that equals one if $\frac{P_i}{high_i}$ is ranked among the top (bottom) 30% of all sample stocks in month *t*, and zero otherwise. Here, P_i is the price of stock *i* at the end of month *t* and $high_i$ is the highest month-end price of stock *i* during the 12-month period that ends on the last day of month *t*.[10]

(iv) Industry momentum: Following Moskowitz and Grinblatt (1999), we select the three best and worst performing industries according to each industry's value-weighted past 12-month returns (i.e. $ind\_12m\_ret = \frac{RI_t - RI_{t-12}}{RI_{t-12}}$). We then set the *IndMomWinner* (*IndMomLoser*) dummy to unity if a stock belongs to the three best (worst) performing industries, and zero otherwise.

(v) Neutral portfolios: We use two dummy variables to denote neutral stocks and neutral industries. $Neutral^{stock}$ is equal to one if a stock belongs to neither the five-year winner nor loser portfolio, and zero otherwise. Similarly, $Neutral^{industry}$ is equal to one if a stock belongs to neither winning nor losing industries, and zero otherwise. We interact $Neutral^{stock}$ with *5-year winning Ind.* and then with *5-year losing Ind.* to capture the return pattern of winning and losing industries

[6] Details on the screening procedures are provided in Appendix A1.

[7] While Clare and Thomas (1995) employ a random sample of 1000 UK stocks, Wu and Li (2011) use 1745 UK stocks that are constituents of the FTSE All Share Index.

[8] The ICB system is a commonly used industry classification outside the US markets. It uses four tiers of classifications, namely 10 industries, 20 super-sectors, 41 sectors, and 114 sub-sectors. Thomson Reuters Datastream provides only static information on ICB. It is possible that firms' industry classifications change over time. However, since the super-sectors are reasonably broad, these changes probably do not occur frequently.

[9] Our results are not sensitive to the inclusion or exclusion of the two industries among the benchmark industries. Further results are available upon request.

[10] George and Hwang (2004) find that the 52-week high (*52wkh*) measure is superior to the 12-month past performance measure (Jegdeesh and Titman, 1993) and the industry 12-month past performance measure (Moskowitz and Grinblatt, 1999) in capturing short-term momentum.

with neutral stock performance, respectively. We also interact*Neutral*^{industry} with *5-year winner* and then with *5-year loser* to identify the return pattern of winner and loser stocks with neutral industry performance, respectively. The four interaction terms evaluate the relative strength of stock and industry reversals. Specifically, we examine whether stock reversals exist in neutral industries and whether industry reversals are present among neutral stocks.

(vi) Excess industry and stock portfolios: We redefine five-year winner and loser stocks in terms of excess industry returns. An excess industry return is calculated as a stock's five-year return minus the five-year value-weighted return of the industry that the stock belongs to. All stocks are then ranked by their industry excess returns in a given month. A dummy variable *5year winner*^{Excess} (*5year loser*^{Excess}) is equal to one if a stock is in the top (bottom) 30% in terms of its excess industry return, and zero otherwise. This approach to identifying winner and loser stocks takes into account past industry performance. We also redefine winning and losing industries in terms of excess stock returns. All stocks are first placed into quintile portfolios according to their past five-year performance (*stock_5yret*). An individual stock's excess return is computed as the stock's five-year return minus the value-weighted five-year return of the quintile portfolio to which the stock belongs. The excess returns on individual stocks are then averaged within each industry. The winning and losing industries are defined as the three industries with the highest (lowest) average excess stock returns. We set the *5year winning Ind*^{Excess} (*5year losing Ind*^{Excess}) dummy to unity if the stock belongs to the winning (losing) industries, and zero otherwise. The four dummies described above can evaluate which of the two types of performance is the driving force behind long-term reversals. Specifically, if past industry performance drives long-term reversals, industry reversals should not be wiped out after adjusting for past stock performance. Alternatively, if past stock performance is responsible for the reversals, stock reversals should not disappear after adjusting for past industry performance.

2.3. Methodology

Following George and Hwang (2004, 2007, 2010) and Grinblatt and Moskowitz (2004), we use the Fama and MacBeth (1973) style regression to measure and compare returns to different long-term investment strategies. This approach has the advantage of isolating the performance of a particular investment strategy from other factors that could affect returns. It also allows us to assess the performance of the long-term investment strategies across different investment horizons.

If an investor forms portfolios of winners and losers every month and holds these portfolios for the next T months, the return earned in a given month t is the equal-weighted average of the returns to T portfolios, each formed in one of the past T months $t-j$ (for j = 1 to T).[11] Thus, the contribution of the portfolio formed in month $t-j$ to the month-t return can be estimated by the following cross-sectional regression:

$$\begin{aligned} R_{it} = {} & b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}size_{i,t-1} + b_{3jt}BM_{i,t-1} \\ & + b_{4jt}52wkhWinner_{i,t-j} + b_{5jt}52wkhLoser_{i,t-j} \\ & + b_{6jt}IndMomWinner_{i,t-j} + b_{7jt}IndMomLoser_{i,t-j} \\ & + b_{8jt}5yearWinner_{i,t-j} + b_{9jt}5yearLoser_{i,t-j} \\ & + b_{10jt}5yearwinningInd_{i,t-j} + b_{11jt}5yearlosingInd_{i,t-j} + e_{ijt} \end{aligned} \quad (1)$$

where R_{it} is the return to stock i in month t; $size_{i,t-1}$ is the log of market capitalisation; $R_{i,t-1}$ is the previous month's return; $BM_{i,t-1}$ is the past month's book-to-market ratio; and the remaining eight dummy variables are as defined earlier. The variable $size_{i,t-1}$, $R_{i,t-1}$ and $BM_{i,t-1}$ are expressed as deviations from their cross-sectional means and are included in the regression to control for the size effect, the bid-ask bounce and the book-to-market effect, respectively.[12]

The intercept b_{0jt} is the return to the risk-neutral portfolio that was formed in month $t-j$ and has hedged out the effects of average size, bid-ask bounce, book-to-market, momentum and long-term winners and losers in predicting returns. The sum $b_{ojt}+b_{8jt}$ is the month t return to a portfolio formed in month $t-j$ by longing five-year winner stocks in order to hedge out all other effects. Consequently, b_{8jt} can be interpreted as the return in excess of b_{0jt}, achieved by taking a long position in five-year winners j months ago. Similar interpretations hold for the coefficients on the remaining variables (see Fama, 1976).

The coefficients b_{10jt} and b_{11jt} represent the equally weighted excess returns of stocks that belong to the winning and losing industries, respectively. $b_{11jt}-b_{10jt}$ can be interpreted as long-term industry contrarian performance from a zero investment strategy that is formed by longing the winning industry portfolio and shorting the losing industry portfolio (see, e.g. Moskowitz and Grinblatt, 1999). Similarly, $b_{9jt}-b_{8jt}$ represents long-term stock contrarian performance resulting from a zero investment strategy of longing loser stocks and shorting winner stocks. The comparison of the performance of these two zero investment strategies is the main interest of this study.

The total month-t returns involve portfolios formed over the prior 60 months (see George and Hwang, 2007). For example, the total month-t returns to five-year winner and loser stocks can be calculated as $S_{8t}=\frac{1}{60}\sum_{j=1}^{60}b_{8jt}$ and $S_{9t}=\frac{1}{60}\sum_{j=1}^{60}b_{9jt}$, where the individual coefficients are calculated from separate cross-sectional regressions for each j = 1,..., 60. Dividing by 60 rescales the sums to be monthly returns. We then estimate the time-series means of the month-by-month estimates of these sums and their Newey and West (1987) adjusted t-statistics. We also obtain risk-adjusted returns for each portfolio by employing the Fama and French (1993, 2015) three- and five-factor models. Specifically, the time series of each coefficient (e.g. S_{8t}, S_{9t}, S_{10t} and S_{11t}) is regressed on the contemporaneous Fama and French factor realizations to hedge out the factor exposure. The intercept (alpha) of the time-series regression is a risk-adjusted return to a particular portfolio. We also regress $(S_{9t}-S_{8t})$ and $(S_{11t}-S_{10t})$ on the Fama–French factors to obtain risk-adjusted contrarian returns.

3. Summary statistics

Table 1 reports the basic characteristics of the 20 industry portfolios. The average percentage of total market capitalisation, the

[11] The portfolio formation and testing technique used here is in the same spirit as Jegadeesh and Titman (1993), which avoids test statistics that are based on overlapping returns. This technique makes use of the fact that ranking on the past 60 months and holding for the next 60 months produces a time series of monthly returns in which each month's return is a combination of 60 ranking strategies. For example, a January 2000 reversal strategy return is 1/60 determined by winners and losers from November 1994 to December 1999, 1/60 by rankings from October 1994 to November 1999, 1/60 by rankings from September 1994 to October 1999, and so on until the last 1/60 is determined by rankings from February 1990 to January 1995. The return estimation procedure used here also takes account of other factors in predicting returns.

[12] For robustness purposes, we also include the Amihud (2002) illiquidity measure as an additional control in the Fama–MacBeth regression. Our results for industry contrarian performance remain quantitatively unchanged, albeit stock contrarian performance becomes relatively weak. These results are available upon request.

Table 2
Correlation matrix for long term reversal variables.

	5-year winner	5-year loser	5-year winning Ind	5-year losing Ind	5-year winner^{Excess}	5-year loser^{Excess}	5 year winning Ind^{Excess}	5 year losing Ind^{Excess}
5-year winner	1							
5-year loser	−0.4279	1						
5-year winning Ind	0.1754	−0.1467	1					
5-year losing Ind	−0.1743	0.1651	−0.1845	1				
5-year winner^{Excess}	0.7932	−0.4272	−0.1437	0.0505	1			
5-year loser^{Excess}	−0.4202	0.7229	0.1329	−0.2312	−0.4282	1		
5 year winning Ind^{Excess}	0.1059	−0.1245	0.0977	−0.1158	0.1238	−0.0343	1	
5 year losing Ind^{Excess}	−0.1130	0.1268	−0.0815	0.1736	−0.1179	0.0539	−0.1278	1

The table is a correlation matrix for long term reversal variables and reports time-series means of cross-sectional correlations in each month. The variables in the matrix are various winner and loser identities according to individual stock and industry past performance and their interactions. *5-year winner* (*5-year loser*) is a long term stock performance dummy that takes the value of 1 if a stock *i*'s past five-year return is ranked in the top (bottom) 30% of all stocks in month *t*, and zero otherwise. *5-year winning Ind.* (*5-year losing Ind.*) is a dummy that takes the value of one if a stock *i* belongs to long-term winning and losing industry in month *t*, and zero otherwise. Long term winning and losing industry are defined as the top and bottom three industries ranked on five-year value-weighted average industry returns. 5 *year Winner*^{Excess} (5 *year Loser*^{Excess}) is a dummy variable that takes the value of one if a stock *i*'s industry adjusted five-year return is ranked in the top (bottom) 30% of all stocks in month *t*, and zero otherwise. The industry adjusted five-year return is calculated as the stock's own five-year return minus the value-weighed five-year return for the industry to which the stock belongs. Conversely, we re-define winning and losing industries in terms of excess stock returns. All stocks are first placed into quintile portfolios according to the stock five-year performance measure. The excess stock return is a stock's five-year return minus the value-weighted five-year return of the quintile portfolio to which the stock belongs. For each o industry, we then average the excess stock returns according to each stock's industry membership. We choose top and bottom 3 portfolios as new winning and losing industries based on each industry's excess stock returns. If a stock belongs to the winning (losing) industries, the dummy 5 *year winningInd*^{Excess} (5 *year losingInd*^{Excess}) is equal to one, and zero otherwise.

five-year raw return, and the five-year excess market return are the time-series means of the cross-sectional industry averages in each month. The five-year raw returns are calculated from the five-year value-weighted industry return indices, and the five-year market excess returns are calculated from the five-year industry raw returns minus the five-year FTSE All Share market index returns. In terms of the relative market capitalisations, the banking sector has the highest market share (of around 20%), while the automobiles and parts industry has the lowest number of firms and the lowest market share (of only 0.79%). The average five-year raw and the market excess returns vary considerably across industries, ranging from 0.73% (telecommunications) to −0.48% (others).

Table 2 reports the time-series means of the cross-sectional correlations between the long-term reversal variables (see the variables in Section 2.2). The positive correlation between the five-year winner (loser) stocks and the winning (losing) industries indicates that the portfolios formed on past industry performance share some similarities with those formed on past stock performance. The positive correlation between *5year winning Ind*^{Excess} (*5year losing Ind*^{Excess}) and *5-year winner* (*loser*) suggests these similarities are maintained after adjusting for past stock performance. However, the negative correlation between *5-year winner*^{Excess} (*5-year loser*^{Excess}) and *5-year winning* (*losing*) *Ind* implies that the similarities disappear after adjusting for past industry performance. These findings highlight the importance of taking industry past performance into consideration when defining long-term winners and losers.

4. Results

4.1. Identifying long-term industry reversals

We first estimate Eq. (1) to investigate the presence of long-term industry reversals after controlling for other variables that could affect returns. George and Hwang (2007) and Grinblatt and Moskowitz (2004) find that the outperformance of losers over winners is significantly weaker outside January. They conclude that long-term reversals are driven by tax loss selling at the tax year end. Since the UK tax year end is 5 April, we report the results separately with January and April included and with these two months excluded. This separation allows us to account for both the turn-of-the-year and the tax loss selling effects in the reversals. Table 3 reports the results for the entire five-year period (columns (11) and (12)) and the five individual holding periods (columns (1) to (10)).

The key variables in Table 3 are *5year winning Ind.*, *5year losing Ind.*, *5-year winner* and *5-year loser*. In column (11), losing industries and loser stocks experience significant positive returns of 0.27% (t-statistic = 3.86) and 0.11% (t-statistic = 2.07) per month, respectively, over the five-year period. Column (12) shows that the return on loser stocks loses its significance, whereas the return on losing industries remains significantly positive (0.30% per month), after the exclusion of January and April. This indicates that the significantly positive returns on loser stocks come exclusively from January and April, while stocks in losing industries experience positive returns across all calendar months.

Columns (1) to (10) show the results for the individual holding periods. The returns on losing industries are significantly positive from the second to the fifth year, regardless of whether January and April are included. Loser stocks also have significant positive returns of 0.11% per month in the second year, 0.12% per month in the third year and 0.16% per month in the fourth year. However, columns (4), (6) and (8) show that the returns on loser stocks are not statistically significant outside January and April. This finding suggests that the returns on loser stocks have strong seasonal patterns, consistent with George and Hwang (2007) and Grinblatt and Moskowitz (2004).

In the last three rows, we evaluate stock and industry contrarian performance. Over the five-year period, losing industries significantly outperform winning industries by 0.29% per month (column (11)). This outperformance remains significant after the exclusion of January and April (column (12)). The industry contrarian spread is statistically significant from the second to the fifth year. Column (11) also suggests that the return on loser stocks is significantly higher (0.12% per month) than that of winner stocks. However, this return difference becomes insignificant when January and April are excluded. Thus, the outperformance of loser stocks over winner stocks is confined to January and April, while stocks in losing industries have persistently and significantly higher returns than those in winning industries across all months. In terms of economic significance, our results suggest that the industry contrarian spread is at least two times greater than the stock contrarian spread (e.g. 0.29% against 0.12% in column (12)). We also find that losing industries are the main contributor to the industry contrarian spread,

Table 3
Identifying industry reversals.

	(1) Monthly return (1,12)	(2) Monthly return (1,12) Jan & Apr Excl.	(3) Monthly return (13,24)	(4) Monthly return (13,24) Jan & Apr Excl.	(5) Monthly return (25,36)	(6) Monthly return (25,36) Jan & Apr Excl.	(7) Monthly return (37,48)	(8) Monthly return (37,48) Jan & Apr Excl.	(9) Monthly return (49,60)	(10) Monthly return (49,60) Jan & Apr Excl.	(11) Monthly return (1,60)	(12) Monthly return (1,60) Jan & Apr Excl.
Intercept	0.78	0.54	0.68	0.45	0.70	0.49	0.75	0.41	0.78	0.46	0.73	0.47
	(2.94)	(2.54)	(3.54)	(1.96)	(2.91)	(1.95)	(2.76)	(1.88)	(2.89)	(1.78)	(2.94)	(1.82)
$R_{i,t-1}$	−1.21	−0.83	−1.18	−0.97	−1.27	−1.00	−1.05	−0.79	−1.10	−0.73	−1.16	−0.87
	(−2.69)	(−1.89)	(−2.54)	(−2.47)	(−2.76)	(−2.17)	(−2.43)	(−1.83)	(−2.69)	(−2.54)	(−3.49)	(−2.67)
$Size_{i,t-1}$	−0.02	−0.01	−0.04	−0.02	−0.06	−0.03	−0.05	−0.03	−0.05	−0.03	−0.03	−0.02
	(−1.66)	(−1.67)	(−2.23)	(−1.79)	(−2.18)	(−1.78)	(−1.88)	(−1.60)	(−2.20)	(−1.87)	(−2.52)	(−2.00)
$BM_{i,t-1}$	0.28	0.31	0.28	0.30	0.27	0.30	0.26	0.30	0.26	0.29	0.27	0.30
	(5.94)	(5.79)	(5.88)	(5.72)	(5.73)	(5.58)	(5.37)	(5.25)	(5.22)	(5.09)	(5.65)	(5.51)
52 week high winner	0.46	0.54	0.03	0.10	−0.00	0.05	0.04	0.09	−0.01	0.00	0.10	0.15
	(5.94)	(7.17)	(0.74)	(2.00)	(−0.10)	(1.25)	(1.39)	(2.58)	(−0.61)	(0.23)	(3.51)	(3.16)
52 week high loser	−1.05	−1.16	−0.27	−0.43	−0.26	−0.36	−0.25	−0.31	−0.16	−0.20	−0.39	−0.49
	(−7.68)	(−8.71)	(−3.11)	(−4.60)	(−3.22)	(−4.27)	(−3.57)	(−4.03)	(−2.49)	(−2.89)	(−5.57)	(−6.72)
Ind_mom_winner	0.15	0.05	−0.00	0.05	−0.12	−0.08	−0.06	−0.03	0.03	0.07	−0.03	0.02
	(1.93)	(0.75)	(−0.13)	(0.49)	(−1.38)	(−0.80)	(−0.77)	(−0.39)	(0.29)	(0.59)	(−0.57)	(0.23)
Ind_mom_loser	−0.18	−0.14	0.07	0.05	−0.11	−0.10	−0.00	0.03	−0.01	0.03	−0.05	−0.03
	(−2.00)	(−1.44)	(0.91)	(0.52)	(−1.47)	(−1.19)	(−0.07)	(0.30)	(−0.09)	(0.31)	(−1.04)	(−0.57)
5-year winner	−0.04	0.02	−0.01	0.00	−0.02	−0.01	0.01	0.03	−0.01	−0.01	−0.01	0.00
	(−0.79)	(0.43)	(−0.25)	(0.13)	(−0.44)	(−0.19)	(0.15)	(0.47)	(−1.22)	(−0.40)	(−0.40)	(0.15)
5-year loser	0.07	−0.07	0.11	0.02	0.12	0.07	0.16	0.10	0.10	0.06	0.11	0.04
	(0.79)	(−0.89)	(1.80)	(0.29)	(1.83)	(0.96)	(2.24)	(1.34)	(1.59)	(0.93)	(2.07)	(0.78)
5-year winning Ind	−0.09	0.01	−0.04	−0.02	0.06	0.06	0.08	0.09	−0.13	−0.12	−0.02	0.02
	(−0.88)	(0.13)	(−0.98)	(−1.00)	(1.01)	(0.95)	(0.76)	(0.80)	(−1.29)	(−1.21)	(−0.09)	(0.26)
5-year losing Ind	0.06	0.08	0.17	0.22	0.32	0.32	0.37	0.40	0.45	0.49	0.27	0.30
	(0.71)	(0.89)	(1.88)	(2.20)	(3.43)	(3.33)	(3.91)	(3.79)	(4.30)	(4.26)	(3.86)	(3.90)
5-year loser	0.10	−0.10	0.12	0.01	0.13	0.08	0.15	0.07	0.11	0.08	0.12	0.04
5-year winner	(1.24)	(−0.94)	(1.68)	(0.15)	(1.76)	(0.88)	(1.90)	(0.98)	(1.47)	(0.95)	(1.96)	(0.56)
5-year losing Ind-	0.15	0.07	0.21	0.23	0.26	0.27	0.29	0.31	0.57	0.60	0.29	0.29
5-year winning Ind	(1.42)	(0.48)	(1.75)	(1.85)	(2.01)	(1.99)	(2.45)	(2.50)	(3.81)	(3.56)	(2.69)	(2.51)
Avg. obs	1439		1330		1269		1204		1137		1265	

We estimate 60 ($j = 1, \ldots, 60$) cross-sectional regressions on a monthly basis between February 1980 and December 2011 as following.
$R_{it} = b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}size_{i,t-1} + b_{3jt}BM_{i,t-1} + b_{4jt}52wkhWinner_{i,t-j} + b_{5jt}52wkhLoser_{i,t-j} + b_{6jt}IndMomWinner_{i,t-j} + b_{7jt}IndMomLoser_{i,t-j} + b_{8jt}5yearWinner_{i,t-j} + b_{9jt}5yearLoser_{i,t-j} + b_{10jt}5yearWinningInd_{i,t-j} + b_{11jt}5yearLosingInd_{i,t-j} + e_{ijt}$.
R_{it} is the return to stock i in month t. $R_{i,t-1}$, $size_{i,t-1}$ and $BM_{i,t-1}$ are the return, book-to-market ratio and natural logarithm of market capitalisation of stock *i* in month $t-1$ net of the month $t-1$ cross-sectional mean. $52wkhWinner_{i,t-j}$($52wkhLoser_{i,t-j}$) is the 52 week high winner (loser) dummy that takes the value of 1 if the 52-week high measure for stock *i* is ranked in the top (bottom) 30% in month $t-j$. The 52-week high measure in month $t-j$ is the ratio of the price level in month $t-j$ to the maximum price achieved in month $t-j-12$ to $t-j$. $IndMomWinner_{i,t-j}$ ($IndMomLoser_{i,t-j}$) is an industry momentum dummy that takes the value of one if a stock *i* belongs to short-term winning (losing) industries in month $t-j$. Short term winning and losing industries are defined the top and bottom three industries ranked on value-weighted 12-month industry average returns. *5-year winner* (*5-year loser*) is a dummy that takes the value of one if a stock *i*'s past five-year return is ranked in the top (bottom) 30% of all stocks in month *t*, and zero otherwise. $5\text{-}year\ winningInd_{i,t-j}$ ($5\text{-}year\ losing\ Ind_{i,t-j}$) is a dummy that takes the value of one if a stock *i* belongs to long-term winning and losing industry in month $t-j$. Long term winning and losing industry are defined as the top and bottom three industries ranked on value-weighted five-year average industry returns. The coefficient estimates of a given independent variable are average over $j = 1, 2, \ldots, 12$ for column labelled (1, 12), $j = 13, 14, \ldots, 24$ for column (13, 24)... and $j = 1, 2, \ldots, 60$ for columns labelled (1, 60). The numbers reported in the table are the time series averages of these averages in percentage per month. Time series average numbers of observations for each month based on cross-sectional regressions are reported in the last row. Newey and West (1987) adjusted *t*-statistics are reported in parentheses.

consistent with the limits to arbitrage argument (see, e.g. Baker and Wurgler, 2006; Stambaugh et al., 2012).[13]

The institutional setting of the UK market provides us with a unique opportunity to test the role of taxes in explaining long-term return reversals. Unlike that in the US, the UK tax year ends on 5 April. The calendar month of April allows us to test the hypothesis that tax loss selling is fully responsible for loser stock reversals (e.g. George and Hwang, 2007; Klein, 1999).[14] Lakonishok et al. (1991), Sias and Starks (1997) and Ng and Wang (2004) argue that, when the calendar year end is approaching, institutional investors "dress" up their portfolios by selling stocks with poor past performance in order to impress their clients with their stock-picking skills.[15] The selling pressure depresses the prices of loser stocks in December. When the pressure eases in January, the prices revert back to equilibrium and losers will have higher returns. Thus, if this "window dressing" is exclusive to the calendar year end, returns in April are more likely to provide a clean test of the tax loss selling hypothesis. We regress the contrarian spreads on January and April dummy variables. In untabulated results, the January and April dummies are positively and significantly associated with the stock contrarian spread, but none of these dummies can explain the industry contrarian spread.[16] These findings imply that stock reversals can be attributed, at least partly, to tax loss selling or the turn-of-the-year, but industry reversals are independent of these effects.

[13] See Section 4.5.4 for further discussion.

[14] The tax loss selling hypothesis states that investors seek to reduce their taxes by realising losses at the tax year end, thereby depressing stock prices. Stock prices revert back to their equilibrium levels in the first month of the new tax year, causing higher returns.

[15] The window dressing effect also affects short-term momentum, as momentum profits are significantly lower in January than other calendar months (e.g. Jegadeesh and Titman (1993), Sias and Starks, 1997).

[16] These results are available upon request.

The remaining variables in Table 3 are included as controls in Eq. (1). The significantly negative coefficient on $R_{i,t-1}$ is consistent with the month-by-month return reversals discovered by Jegadeesh (1990) and Lehmann (1990). The lagged book-to-market ratio exhibits a positive relationship with stock returns. The stock momentum effect measured by the price relative to the 52-week high (George and Hwang, 2004) is much stronger than the industry momentum effect (Moskowitz and Grinblatt, 1999).[17]

4.2. Comparisons between industry and stock reversals

In this section, we evaluate the relative strength of stock and industry reversals. We first search for industry reversals among neutral (neither loser nor winner) stocks. Then, we examine whether stock reversals exist in stocks with neutral industry performance. The results are reported in Table 4, without control variables for the sake of brevity.

The two interactions $Neutral^{stock} \times 5yearWinningInd$ and $Neutral^{stock} \times 5yearLosingInd$ are used to identify neutral stocks within winning and losing industries. Panel A shows that neutral stocks within losing industries have significantly positive returns over the five-year period and across the last four holding periods. However, the returns on neutral stocks within winning industries are not significant, except for the fifth year (column 5), where the return is negative (−0.22% per month) and weakly significant (t-stat = −1.77). This lack of significance is in line with our earlier results that losing industries are the main source of industry reversals. The last two rows in Panel A show the presence of industry contrarian performance in stocks with neutral performance. Specifically, neural stocks in losing industries outperform their counterparts in winning industries by 0.29% per month over the 5-year period. In the five individual holding periods, the industry contrarian spreads are significantly positive from the third to the fifth year (columns (2) to (5)). These findings suggest that industry reversals are not confined to stocks with extreme past performance.

Panel B in Table 4 provides the results on whether stock contrarian performance exists in stocks with neutral industry performance. Column (6) shows that in industries with neutral performance, winner and loser stocks do not exhibit significant returns over the 5-year period. The returns on winner and loser stocks are also not significant in the individual holding periods, except in the fourth year. The last two rows show that in industries with neutral performance, the return to a zero-investment strategy of longing loser stocks and shorting winner stocks is not significant for both the 5-year period and the individual holding periods. In contrast to the results in Panel A, this evidence implies that extreme performance of stocks from neutral industries does not generate significant contrarian profits.

4.3. Adjusting for past performance

While the previous section focuses on the relative strength of stock and industry reversals, this section investigates whether past stock or past industry performance is the main driving force behind long-term reversals. Specifically, we adjust stock and industry reversals for past industry and past stock performance, respectively, to identify which type of reversal survives the adjustment.

We first investigate whether stock reversals exist after accounting for past industry performance. Recall that the dummy variable *5 year winner* ^{Excess} (*5 year loser* ^{Excess}) is set to unity for 30% of stocks with highest (lowest) industry-adjusted returns. We refer to these dummies as excess industry portfolios and the returns on these portfolios are shown in Panel A of Table 5. Column (6) shows that the return to the loser excess industry portfolio over the five-year period is not significant. This portfolio's return is only significantly positive (0.15% per month) in the fourth year (column (4)). The last two rows in Panel A provide much stronger evidence that past industry performance drives stock reversals. The contrarian returns between the two excess industry portfolios are not significant. The disappearance of stock reversals after adjusting for past industry performance implies that industry components are the main source of contrarian profits.

Our previous results suggest that stock reversals disappear after adjusting for the industry effect. Here, we investigate whether the reverse is true. If industry reversals exist and are independent of stock reversals, then industry reversals should not disappear after adjusting for past stock performance. The two dummy variables *5year winning Ind*^{Excess} and *5year losing Ind*^{Excess} are specifically designed to account for the impact of past stock performance on industry reversals. We refer to these two dummies as excess stock portfolios. The returns on these portfolios are reported in Panel B.

Column (6) shows that, over the five-year period, the losing industry excess stock portfolio has a significant positive return of 0.16%. This return is smaller than that in Table 4 (i.e. 0.27%), suggesting that past stock performance only plays a partial role in the reversals for losing industries. The returns on the losing industry excess stock portfolio are also significantly positive in the third and the fifth year. The last two rows in Panel B show that the contrarian return between the two industry excess stock portfolios is significantly positive over the five-year period as well as in the second and fifth years. However, the significance level is slightly lower than that reported in Table 4.

In untabulated results, we also investigate whether the outperformance of losing over winning industries is a within-industry effect. We rank stocks in each industry on their past 5-year performance and define the 30% highest (lowest) performing stocks as the within-industry winners (losers). We find that the contrarian performance of buying within-industry losers and selling within-industry winners is not significant.

In summary, this section shows that past industry performance is the driving force behind long-term reversals and these reversals are unlikely to be a within-industry phenomenon.

4.4. Are long-term industry reversals driven by risk or mispricing?

4.4.1. Risk-adjusted returns

This section examines whether stock and industry reversals are attributable to risk exposures. Each coefficient in the Fama–MacBeth regressions (Eq. (1)) is a time-series average of sums (e.g. S_{7t} and S_{8t} in Section 2.3) of monthly raw returns to a particular portfolio strategy. We first estimate the risk-adjusted return on a particular strategy by running a time-series regression of the strategy's sums on the Fama and French (1993) factor realizations.[18] We then report the intercepts (risk-adjusted returns) for the strategy in Table 6.

Panel A shows that neither winner nor loser stocks have significant returns over the five-year period. The economic magnitude of the loser stocks' reversals is negligible (only 0.05% per month with a *t*-statistic of 0.86) (see column (6)). The stock contrarian performance is also insignificant in the five individual holding periods. However, the returns on losing industries and the industry

[17] We also use past 12-month returns to identify momentum winners and losers in Eq. (1). Our main results of long-term industry reversals remain unchanged. These results are available upon request.

[18] We are grateful to Gregory et al. (2013) for providing the UK Fama–French factors on their website, http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/files/

Table 4
Comparisons between stock and industry reversals.

	(1) Monthly return (1,12)	(2) Monthly return (13,24)	(3) Monthly return (25,36)	(4) Monthly return (37,48)	(5) Monthly return (49,60)	(6) Monthly return (1,60)
Panel A						
5-year winner	0.03	0.03	0.04	0.03	−0.09	0.00
	(0.56)	(0.58)	(0.72)	(0.56)	(−1.53)	(0.08)
5-year loser	0.14	0.13	0.11	0.17	0.05	0.11
	(1.61)	(1.65)	(1.44)	(2.35)	(0.08)	(1.90)
$Neutral^{stock*}$	−0.00	−0.01	0.04	0.06	−0.22	−0.03
5 year Winning Ind	(−0.04)	(−0.07)	(0.41)	(0.51)	(−1.77)	(−0.17)
$Neutral^{stock*}$	0.11	0.17	0.31	0.37	0.36	0.26
5 year Losing Ind	(1.25)	(1.76)	(3.17)	(3.64)	(3.57)	(3.75)
5 year losing Ind- 5 year winning Ind	0.11	0.17	0.26	0.31	0.58	0.29
amg $Neutral^{stock}$	(0.82)	(1.52)	(1.95)	(2.03)	(3.98)	(2.08)
Panel B						
5 year winning Ind	−0.11	−0.04	0.14	0.12	−0.14	−0.01
	(−1.03)	(−0.42)	(1.42)	(1.12)	(−1.39)	(−0.08)
5 year losing Ind	0.04	0.15	0.31	0.40	0.44	0.27
	(0.38)	(1.59)	(3.12)	(3.96)	(4.14)	(3.54)
$Neutral^{industry*}$	0.02	0.01	0.06	0.08	−0.03	0.03
5-year winner	(0.34)	(0.27)	(1.11)	(1.46)	(−0.52)	(0.68)
$Neutral^{industry*}$	−0.03	0.03	0.01	0.13	0.02	0.03
5-year loser	(−0.30)	(0.34)	(0.15)	(1.68)	(0.24)	(0.44)
5-year loser-5-year winner	−0.05	0.01	−0.06	0.05	0.05	−0.00
amg $Neutral^{industry}$	(−0.42)	(0.11)	(−0.78)	(0.55)	(0.32)	(−0.04)

We estimate 60 ($j = 1, \ldots, 60$) cross-sectional regressions on a monthly basis between February 1980 and December 2011 as following for Panel A

$R_{it} = b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}size_{i,t-1} + b_{3jt}BM_{i,t-1} + b_{4jt}52wkhWinner_{i,t-j} + b_{5jt}52wkhLoser_{i,t-j} + b_{6jt}IndMomWinner_{i,t-j} + b_{7jt}IndMomLoser_{i,t-j} + b_{8jt}5yearWinner_{i,t-j} + b_{9jt}5yearLoser_{i,t-j} + b_{10jt}Neutral^{Stock}_{i,t-j} \times 5yearWinningInd_{i,t-j} + b_{11jt}Neutral^{stock}_{i,t-j} \times 5yearLosingInd_{i,t-j} + e_{ijt}$

The following equation is estimated for Panel B

$R_{it} = b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}size_{i,t-1} + b_{3jt}BM_{i,t-1} + b_{4jt}52wkhWinner_{i,t-j} + b_{5jt}52wkhLoser_{i,t-j} + b_{6jt}IndMomWinner_{i,t-j} + b_{7jt}IndMomLoser_{i,t-j} + b_{8jt}5yearWinningInd_{i,t-j} + b_{9jt}5yearLosingInd_{i,t-j} + b_{10jt}Neutral^{industry}_{i,t-j} \times 5yearWinnner_{i,t-j} + b_{11jt}Neutral^{industry}_{i,t-j} \times 5yearLoser_{i,t-j} + e_{ijt}$

R_{it} is the return to stock i in month t. $R_{i,t-1}$, $BM_{i,t-1}$ and $size_{i,t-1}$ are the return, book-to-market ratio and natural logarithm of market capitalisation of stock i in month $t-1$ net of the month $t-1$ cross-sectional mean. $52wkhWinner_{i,t-j}$ ($52wkhLoser_{i,t-j}$) is the 52 week high winner (loser) dummy that takes the value of one if the 52-week high measure for stock i is ranked in the top (bottom) 30% in month $t-j$, and zero otherwise. The 52-week high measure in month $t-j$ is the ratio of the price level in month $t-j$ to the maximum price achieved in month $t-j-12$ to $t-j$. $IndMomWinner_{i,t-j}$($IndMomLoser_{i,t-j}$) is a dummy that takes the value of one if a stock i belongs to short-term winning (losing) industries in month $t-j$, and zero otherwise. Short term winning and losing industries are defined the top and bottom 3 industries ranked on 12-month value-weighted average industry returns. *5-year winner*$_{i,t-j}$ (*5-year loser*$_{i,t-j}$) is a dummy that takes the value of one if a stock i's past five-year return is ranked in the top (bottom) 30% of all stocks in month $t-j$, and zero otherwise. $Neutral^{stock}_{i,t-j}$ is a dummy variable that takes the value of one if a stock i is neither five-year losers nor five-year winners in month $t-j$, and zero otherwise. $Neutral^{industry}_{i,t-j}$ is a dummy variable that takes value of one if a stock i belongs to neither winning nor losing industries according to five-year value-weighted industry returns, and zero otherwise. *5-year winning Ind*$_{i,t-j}$ (*5-year losing Ind*$_{i,t-j}$) is a dummy that takes the value of one if a stock i belongs to long-term winning and losing industry in month $t-j$, and zero otherwise. Long-term winning and losing industry are defined as the top and bottom three industries ranked on five-year value-weighted average industry returns. The coefficient diffidence between $b_{11jt} - b_{10jt}$ in Panel A can be interpreted as industry contrarian returns with neutral stock performance. The coefficient diffidence between $b_{11jt} - b_{10jt}$ in Panel B can be interpreted as stock contrarian returns with neutral industry performance. The coefficient estimates of a given independent variable are average over $j = 1, 2, \ldots, 12$ for column labelled (1, 12), $j = 13, 14, \ldots, 24$ for column (13, 24)… and $j = 1, 2, \ldots, 60$ for columns labelled (1, 60). The numbers reported in the table are the time series averages of these averages in percentage per month. Newey and West (1987) adjusted t-statistics are reported in parentheses. Coefficients on control variables are omitted for brevity.

contrarian performance remain positive and significant. Thus, although the cross-sectional analysis in Table 4 shows the co-existence of stock and industry reversals, only industry reversals remain significant after the Fama–French three-factor risk adjustments.[19]

[19] Our risk adjustments are the same as the procedure of Fama and French (1996). We first estimate the portfolios' returns based on Fama and MacBeth (1973) regressions, in which we use all sample stocks (not just winners or losers) and are able to hedge out the effect of size, momentum (e.g. from both stocks and industries), and bid-ask bounce (or monthly reversals) to isolate monthly returns attributable only to whether a stock belongs to stock- or industry-past performance portfolios. This first procedure ensures that the second one, which assesses the significance of risk-adjusted returns to the portfolios of interest, produces powerful tests. To further justify the risk adjustment procedure, we follow George and Hwang (2007) and regress the intercepts (e.g.$S_{0t} = \frac{1}{60}\sum_{j=1}^{60} b_{0jt}$) in Eq. (1) on the Fama–French three-factor model. The intercepts from these Fama and French regressions are interpreted as the risk-adjusted returns to the neutral portfolios (i.e. portfolios that hedge out the bid-ask bounce, size, book-to-market, momentum and long-term returns for winner-loser stocks and winning and losing industries). The intercepts of the Fama and French regressions are insignificant across all investment horizons, suggesting that the Fama and French factors do a good job explaining the returns to neutral portfolios. This evidence confirms that the risk adjustment procedure used in this study is well specified.

Recent asset pricing studies (e.g. Novy-Marx, 2013; Fama and French, 2006, 2008; Titman et al., 2004) show that firm fundamentals, beyond those in the Fama and French (1996) model, predict stock returns. Building upon the discounted cash flow model, two additional factors, namely investment and profitability, are introduced to explain cross-sectional stock returns (Fama and French, 2015; Hou et al., 2015). To re-evaluate contrarian profits, we use the Fama and French five-factor model (Fama and French, 2015) to adjust contrarian returns. Panel B provides the results.

The results show that the returns to both loser and winner stocks over the five-year period are not significant. Loser stocks have a significantly positive return only in the fourth year (column (4)). The stock contrarian returns are statistically insignificant, except in columns (4) and (5).[20] The five-factor adjusted returns of loser and winner stocks are almost the same as those of the three-factor model (Panel A). The returns on stocks from losing industries remain significantly positive both over the five-year period and across the last three individual holding periods. The last two rows show that the industry contrarian profits over the five-year

[20] The statistical significance of the returns in columns (4) and (5) disappears when January and April are excluded.

Table 5
Adjusting for past performance.

	(1) Monthly return (1,12)	(2) Monthly return (13,24)	(3) Monthly return (25,36)	(4) Monthly return (37,48)	(5) Monthly return (49,60)	(6) Monthly return (1,60)
Panel A						
5-year winning Ind	−0.06	−0.01	0.09	0.09	−0.10	0.01
	(−0.60)	(−0.09)	(1.21)	(0.83)	(−1.20)	(0.17)
5-year losing Ind	0.04	0.15	0.31	0.37	0.44	0.26
	(0.45)	(1.68)	(3.30)	(4.01)	(4.30)	(3.70)
5-year winner^{Excess}	0.05	0.02	0.03	0.05	−0.04	0.03
	(1.05)	(0.50)	(0.60)	(1.02)	(−0.82)	(0.62)
5-year loser^{Excess}	0.04	0.04	0.01	0.15	0.02	0.05
	(0.47)	(0.56)	(0.22)	(1.96)	(0.35)	(1.01)
5-year loser^{Excess}- 5-year winner^{Excess}	−0.02	0.01	−0.02	0.10	0.06	0.03
	(−0.20)	(0.11)	(−0.24)	(1.33)	(0.82)	(0.42)
Panel B						
5-year winner	0.01	0.01	0.01	−0.00	−0.06	−0.00
	(0.17)	(0.14)	(0.14)	(−0.08)	(−1.16)	(−0.16)
5-year loser	−0.00	0.08	0.09	0.15	0.12	0.08
	(−0.01)	(1.04)	(1.33)	(1.96)	(2.06)	(1.68)
5 year winning Ind^{Excess}	−0.07	−0.12	−0.06	−0.08	−0.18	−0.09
	(−0.67)	(−1.09)	(−0.42)	(−0.57)	(−1.53)	(−0.88)
5 year losing Ind^{Excess}	0.12	0.14	0.17	0.10	0.19	0.16
	(1.33)	(1.49)	(1.83)	(1.11)	(2.01)	(2.29)
5 year losing Ind^{Excess}- 5 year winning Ind^{Excess}	0.18	0.26	0.23	0.18	0.35	0.25
	(1.25)	(1.66)	(1.29)	(1.01)	(2.53)	(1.93)

We estimate 60 ($j = 1, \ldots, 60$) cross-sectional regressions on a monthly basis between February 1980 and December 2011 as following for Panel A

$$R_{it} = b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}size_{i,t-1} + b_{3jt}BM_{i,t-1} + b_{4jt}52wkhWinner_{i,t-j} + b_{5jt}52wkhLoser_{i,t-j} + b_{6jt}IndMomWinner_{i,t-j} + b_{7jt}IndMomLoser_{i,t-j} + b_{8jt}5yearWinningInd_{i,t-j} + b_{9jt}5yearLosingInd_{i,t-j} + b_{10jt}5yearWinner^{Excess}_{i,t-j} + b_{11jt}5yearLoser^{Excess}_{i,t-j} + e_{ijt}$$

The following equation is estimated for Panel B.

$$R_{it} = b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}size_{i,t-1} + b_{3jt}BM_{i,t-1} + b_{4jt}52wkhWinner_{i,t-j} + b_{5jt}52wkhLoser_{i,t-j} + b_{6jt}IndMomWinner_{i,t-j} + b_{7jt}IndMomLoser_{i,t-j} + b_{8jt}5yearWinner_{i,t-j} + b_{9jt}5yearLoser_{i,t-j} + b_{10jt}5yearWinnningInd^{Excess}_{i,t-j} + b_{11jt}5yearLosingInd^{Excess}_{i,t-j} + e_{ijt}$$

R_{it} is the return to stock i in month t. $R_{i,t-1}$, $BM_{i,t-1}$ and $size_{i,t-1}$ are the return, book-to-market ratio and natural logarithm of market capitalisation of stock i in month $t-1$ net of the month $t-1$ cross-sectional mean. $52wkhWinner_{i,t-j}$($52wkhLoser_{i,t-j}$) is the 52 week high winner (loser) dummy that takes the value of one if the 52-week high measure for stock i is ranked in the top (bottom) 30% in month $t-j$, and zero otherwise. The 52-week high measure in month $t-j$ is the ratio of the price level in month $t-j$ to the maximum price achieved in month $t-j-12$ to $t-j$. $IndMomWinner_{i,t-j}$ ($IndMomLoser_{i,t-j}$) is a dummy that takes the value of one if a stock i belongs to short-term winning (losing) industries in month $t-j$, and zero otherwise. Short term winning and losing industries are defined the top and bottom three industries ranked on 12-month value-weighted average industry returns. *5-year winner*$_{i,t-j}$ (*5-year loser*$_{i,t-j}$) is a dummy that takes the value of one if a stock i's past five-year return is ranked in the top (bottom) 30% of all stocks in month $t-j$, and zero otherwise. *Ind. 5-year winner*$_{i,t-j}$ (*Ind. 5-year loser*$_{i,t-j}$) is a dummy that takes the value of one if a stock i belongs to long-term winning and losing industry in month $t-j$, and zero otherwise. Long term winning and losing industry are defined as the top and bottom three industries ranked on five-year value-weighted average industry returns. $5yearWinner^{Excess}_{i,t-j}$ ($5yearLoser^{Excess}_{i,t-j}$) is a dummy variable that takes value of one if a stock i's industry adjusted five-year return is ranked in the top (bottom) 30% of all stocks in month $t-j$, and zero otherwise. The industry adjusted five-year return is calculated as the stock's own five-year return minus the value-weighed five-year return for the industry to which the stock belongs. Conversely, we re-define winning and losing industries in terms of an excess stock return. All stocks are first placed into quintile portfolios according to the stock five-year performance measure. The excess stock return is a stock's five-year return minus the value-weighted five-year return of the quintile portfolio to which the stock belongs. For each industry, we then average the excess stock returns according to each stock's industry membership. We choose top and bottom three portfolios as new winning and losing industries based on each industry's excess stock returns. If a stock belongs to the new winning (losing) industries, the dummy $5yearwinningInd^{Excess}_{i,t-j}$ ($5yearlosingInd^{Excess}_{i,t-j}$) is equal to one in month $t-j$, and zero otherwise. The coefficient diffidence between $b_{11jt} - b_{10jt}$ in Panel A can be interpreted as stock contrarian returns in excess of past industry performance. The coefficient diffidence between $b_{11jt} - b_{10jt}$ in Panel B can be interpreted as industry contrarian returns in excess of past stock performance. The coefficient estimates of a given independent variable are average over $j = 1, 2, \ldots, 12$ for column labelled (1, 12), $j = 13, 14, \ldots, 24$ for column (13, 24)... and $j = 1, 2, \ldots, 60$ for columns labelled (1, 60). The numbers reported in the table are the time series averages of these averages in percentage per month. Newey and West (1987) adjusted t-statistics are reported in parentheses. Coefficients on control variables are omitted for brevity.

period are positive (0.19% per month) and significant at the 10% level. The contrarian profits are also significant in three out of the five individual holding periods, albeit their magnitude is slightly smaller than those reported in the case of the three-factor model.

In untabulated results, we find that the loading on the value factor for the five-year industry contrarian spread is positive, while those on the size and market factors are negative in both the three- and five-factor models. This implies that, relative to a neutral portfolio, the industry contrarian portfolio has low market risk and tends to be heavily weighted towards big firms (which makes sense because large firms are the main contributors to industry performance) and value stocks (as losing industries' market value has decreased and book-to-market is large). In the five-factor model, the loadings on the investment and profitability factors are positive and negative, respectively. This suggests that industry contrarian profits come mainly from firms with low profitability (poor earnings may lead to poor performance) and those with fewer investment opportunities (firms in losing industries may find it difficult to expand their business). These findings suggest that industry contrarian returns are related to firm fundamentals.[21]

However, does the above evidence mean that industry reversals are a risk premium? We argue that this may not necessarily be the case. First, even though one third of industry-contrarian performance disappears (0.27% vs. 0.19% per month) after controlling for the Fama and French five factors, the returns on losing industries remain significantly positive over the five-year period and the contrarian performance continues to be significant in some of the individual holding periods. This means that the mispricing explanation cannot be ruled out. Second, Fama and French (2015)

[21] We also undertake an event study approach to investigate whether time-varying betas and factor loadings can explain the positive returns to losing industries (e.g. Ball and Kothari, 1989). Generally, we find that the loadings on the value and investment factors have significantly increased in the post-event period. However, even after controlling for the changes in the loadings, stocks in losing industries still have significantly positive abnormal returns. These results are available upon request.

Table 6
Risk-adjusted returns.

	(1) Monthly return (1,12)	(2) Monthly return (13,24)	(3) Monthly return (25,36)	(4) Monthly return (37,48)	(5) Monthly return (49,60)	(6) Monthly return (1,60)
Panel A: Fama–French 3-factor adjusted returns						
5-year winner	−0.03	−0.04	−0.03	−0.01	−0.05	−0.03
	(−0.60)	(−0.67)	(−0.49)	(−0.23)	(−1.18)	(−0.80)
5-year loser	−0.04	0.05	0.06	0.12	0.02	0.05
	(−0.49)	(0.60)	(0.95)	(1.68)	(0.46)	(0.86)
5 year winning Ind	−0.05	−0.04	0.05	0.10	−0.12	−0.00
	(−0.46)	(−0.34)	(0.54)	(1.15)	(−1.15)	(−0.07)
5 year losing Ind	0.04	0.17	0.30	0.36	0.43	0.26
	(0.47)	(1.93)	(3.42)	(3.54)	(3.66)	(3.09)
5-year loser-	−0.00	0.09	0.09	0.13	0.07	0.09
5-year winner	(−0.05)	(0.85)	(1.06)	(1.55)	(1.05)	(1.42)
5 year losing Ind-	0.09	0.20	0.25	0.25	0.54	0.27
5 year winning Ind	(0.67)	(1.69)	(1.92)	(2.32)	(3.18)	(2.54)
Panel B: Fama–French 5-factor adjusted returns						
5-year winner	−0.05	−0.06	−0.06	−0.05	−0.07	−0.05
	(−0.98)	(−1.02)	(−1.12)	(−1.03)	(−1.26)	(−1.41)
5-year loser	−0.09	−0.03	0.00	0.14	0.11	0.03
	(−1.16)	(−0.40)	(0.08)	(1.93)	(1.62)	(0.48)
5 year winning Ind	0.06	0.08	0.11	0.13	−0.12	0.05
	(0.59)	(0.81)	(1.01)	(1.19)	(−1.20)	(0.65)
5 year losing Ind	0.02	0.13	0.31	0.38	0.31	0.24
	(0.04)	(1.53)	(3.31)	(2.75)	(2.78)	(2.89)
5-year loser-	−0.04	0.03	0.07	0.19	0.17	0.08
5-year winner	(−0.42)	(0.31)	(0.78)	(2.37)	(2.18)	(1.28)
5 year losing Ind-	−0.04	0.05	0.21	0.25	0.43	0.19
5 year winning Ind	(−0.36)	(0.40)	(1.78)	(1.83)	(2.89)	(1.86)

We estimate 60 ($j = 1, \ldots, 60$) cross-sectional regressions on a monthly basis between January 1975 and December 2011
$R_{it} = b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}size_{i,t-1} + b_{4jt}BM_{i,t-1} + b_{4jt}52wkhWinner_{i,t-j} + b_{5jt}52wkhLoser_{i,t-j} + b_{6jt}IndMomWinner_{i,t-j} + b_{7jt}IndMomLoser_{i,t-j} + b_{8jt}5yearWinner_{i,t-j} + b_{9jt}5yearLoser_{i,t-j} + b_{10jt}5yearWinningInd_{i,t-j} + b_{11jt}5yearLosingInd_{i,t-j} + e_{ijt}$
R_{it} is the return to stock i in month t. $R_{i,t-1}$, $BM_{i,t-1}$ and $size_{i,t-1}$ are the return, book-to-market ratio and natural logarithm of market capitalisation of stock i in month $t-1$ net of the month $t-1$ cross-sectional mean. $52wkhWinner_{i,t-j}$($52wkhLoser_{i,t-j}$) is the 52 week high winner (loser) dummy that takes the value of one if the 52-week high measure for stock i is ranked in the top (bottom) 30% in month $t-j$, and zero otherwise. The 52-week high measure in month $t-j$ is the ratio of the price level in month $t-j$ to the maximum price achieved in month $t-j-12$ to $t-j$. $IndMomWinner_{i,t-j}$($IndMomLoser_{i,t-j}$) is a dummy that takes the value of one if a stock i belongs to short-term winning (losing) industries in month $t-j$, and zero otherwise. Short term winning and losing industries are defined the top and bottom three industries ranked on 12-month value-weighted average industry returns, respectively. $5\text{-}year\ winner_{i,t-j}$ ($5\text{-}year\ loser_{i,t-j}$) is a dummy that takes the value of one if a stock i's past five-year return is ranked in the top (bottom) 30% of all stocks in month $t-j$, and zero otherwise. $5\text{-}year\ winning\ Ind_{i,t-j}$ ($5\text{-}year\ losing\ Ind_{i,t-j}$) is a dummy that takes the value of one if a stock i belongs to long-term winning and losing industry in month $t-j$, and zero otherwise. Long term winning and losing industry are defined as the top and bottom three industries ranked on five-year value-weighted average industry returns. Long term industry contrarian performance is measured by buying stocks in losing industries and selling those in winning industries (e.g. $b_{11jt} - b_{10jt}$) in month $t-j$. The coefficient estimates of a given independent variable are average over $j = 1, 2, \ldots, 12$ for column labelled (1, 12), $j = 13, 14, \ldots, 24$ for column (13, 24)... and $j = 1, 2, \ldots, 60$ for columns labelled (1, 60). To obtain risk-adjusted returns, we run time series averages (one for each average), which are computed from the cross-sectional regressions, on the Fama and French (1996) three-factor model in Panel A. We also run the averages on the Fama and French (2015) five-factor model, including two additional factors (the profitability factor and the asset growth factor) and the intercepts from the time-series regression is reported in Panel B. The numbers in the table are in percentage per month. t-statistics are reported in parentheses.

note that, as investment and profitability are two elements in the discounted cash flow model, the return prediction is the same whether the price is rational or irrational. Therefore, the loadings on the investment and profitability factors cannot be interpreted directly as risk exposures. Hou et al. (2015, p. 34) made a similar argument in stating that "... we wish to emphasize that the q-factor model is silent about the debate between rational asset pricing and mispricing. This interpretation is somewhat weaker than the risk factors interpretation per Fama and French (1993, 1996)."

4.4.2. Sharpe ratio analysis

The reduction of industry reversals in the five-factor model would be consistent with the risk-based explanation, if the five-factor model were a rational asset pricing model. However, the debate on whether the five-factor model captures risk or mispricing is still ongoing. Balakrishnan et al. (2010) report that the level of profits after controlling for the unexpected change in earnings predicts stock returns. Hirshleifer et al. (2011) provide a theoretical model in which profitability predicts returns because of investors' imperfect rationality. In the mean–variance framework, MacKinlay (1995) argues that risk-based explanations of asset pricing anomalies are bounded by the plausibility of the (squared) Sharpe ratio of the tangency portfolio that they imply. As such, the mean–variance efficient combination of the factors should have a Sharpe ratio greater than or equal to the maximum Sharpe ratio from anomalies. Table 7 reports Sharpe ratios for the three-factor model, the five-factor model, and the long-short contrarian portfolios. The monthly Sharpe ratio for each individual factor is calculated as the mean factor return divided by its standard deviation. Following MacKinlay (1995), we also estimate the maximum Sharpe ratio achievable from a given factor model as $\sqrt{\mu_f' V_f^{-1} \mu_f}$, where μ_f is the vector of mean factor returns and V_f is the variance–covariance matrix of the factor returns.

Panel A shows that the value and investment factors in the five-factor model have the highest Sharpe ratios of 0.10 and 0.25, respectively. The Sharpe ratio of the five-year industry contrarian performance is 0.13, which is greater than that of the MKT, SMB and HML in the three-factor model. However, the Sharpe ratio of the five-year stock contrarian performance is nearly the same as the HML factor (0.10). Panel B shows that the three-factor model

Table 7
The Sharpe ratio.

Individual factors							Contrarian performance	
MKT	SMB	HML	5F_SMB	5F_HML	5F_ROE	5F_INV	5-year Ind.	5-year stock
Panel A: Sharpe ratios								
0.1098	0.0285	0.1032	0.0242	0.1005	0.0802	0.2512	0.1337	0.1017
Factor models			Contrarian performance					
CAPM	3F-model	5F-model	5-year Ind.	5-year stock				
Panel B: Maximum sharpe ratios								
0.1098	0.1503	0.2981	0.2525	0.1351				
(0.01)	(0.05)	(0.00)	(0.00)	(0.00)				

Panel A reports the monthly Sharpe ratio for each individual factor and long term contrarian performance for stocks and industries. *5-year Ind.* is industry contrarian performance by longing in stocks in losing industries and shorting in stocks in winning industries. *5-year stock* is stock contrarian performance by longing in loser stocks and shorting in winner stocks. The two types of contrarian performance are estimated by the previous cross-sectional Fama–MacBeth regressions. The Sharpe ratio is calculated as the ratio of the mean return to its standard deviation for each factor and type of contrarian performance. MKT, SMB and HML stands for the market, the size and the value factors in Fama and French (1993) three-factor model. 5F_SMB, 5F_HML, 5F_ROE and 5F_INV are the size, the value, the profitability and the investment factors in Fama and French (2015) five-factor model. Panel B reports the maximum monthly Sharpe ratio achievable from each factor model (i.e. the three-factor model and the five-factor model) and each type of contrarian performance. The maximum Sharpe ratio is calculated as $\sqrt{\mu_f' V_f^{-1} \mu_f}$, in which μ_f is the vector of mean factor returns and V_f is the variance–covariance matrix of the factor returns. The last row in Panel B reports the p-value for the null hypothesis that the factor risk premia are jointly equal to zero [(T-N)/N]SSR is distributed central F(N, T-N) where N is the number of portfolios, T is the number of time-series observations and SSR is the maximum squared Sharpe ratio.

produces a maximum Sharpe ratio (0.15) that is lower than that of the industry contrarian performance (0.25), but greater than that of the stock contrarian performance (0.13). The tangency portfolio implied by the three-factor model encompasses the maximum risk-reward trade-off generated by the stock contrarian performance, which is consistent with the risk-based explanation. In contrast, the risk-return relationship in the three-factor model suggests that the industry contrarian performance is likely to be a mispricing effect. The Sharpe ratios associated with the stock and industry contrarian performance in the three-factor model are significant at the 5% level or better.[22] For the five-factor model, the maximum achievable Sharpe ratio is 0.29, which is greater than the Sharpe ratio associated with the industry contrarian performance and the three-factor model. Consistent with the previous results, the five-factor model is possibly more effective in explaining industry contrarian performance than its three-factor counterpart. However, the profitability and investment factors in the five-factor model do not necessarily represent risk (Fama and French, 2015; Hou et al., 2015). This is because comovement of stocks with similar profitability or investment opportunities does not contradict the mispricing effect. For instance, if investors have similar bias in processing earnings information, as modelled by Hirshleifer et al. (2011), returns on stocks with similar profitability will also comove. Hence, investors' imperfect rationality and firm fundamentals can jointly generate the predictive power of profitability for returns. Furthermore, MacKinlay (1995) argues that the maximum Sharpe ratio for the three-factor model is too high to be consistent with rational asset pricing. We show that the maximum Sharpe ratio of the five-factor model (0.298) is even higher. This implies that the five-factor model may capture some elements of mispricing in stock returns and therefore we cannot fully rule out the mispricing effect in the industry contrarian performance.[23]

4.4.3. State of the economy

Our previous results show that although fundamental-related risks have explained some portion of industry contrarian performance, a considerable proportion of the positive returns on losing industries are left unexplained, suggesting a possible mispricing effect. To investigate this issue, we undertake a nonparametric approach similar to that of Lakonishok et al. (1994). The risk-based argument says that, if losing industries are riskier than winning industries, the former should outperform the latter particularly in good states of the economy. However, there should be no contrarian performance in bad states of the economy, in which the marginal utility of wealth is high, making the risky losing industries unattractive to risk-averse investors. To test this prediction, we examine the consistency of the performance of the industry contrarian strategies across different states of the economy. The profits of these strategies are estimated from Eq. (1).

The first approach examines industry contrarian performance during extremely bad times. Our sample period includes three waves of UK economic recessions, which are defined as negative GDP growth in two consecutive quarters as reported by the Office of National Statistics (ONS). We define the rest of the sample period as "other times". Panel A of Table 8 reports the results. In the first two waves of recessions (1980: Q1 to 1981: Q2 and 1991: Q1 to 1991: Q4), losing and winning industries have very similar performance. The difference between the two portfolios' returns is insignificant. However, in the most recent recession (2008: Q2 to 2009: Q3), losing industries have significantly higher returns than winning industries. This result indicates that the industry contrarian strategy is still profitable in recession times, inconsistent with the risk-based explanation. Following Lakonishok et al. (1994), we also evaluate the industry contrarian performance across four states of the economy, according to the overall market performance, using the equally weighted market return.[24] The four states are the 25 worst stock return months, the remaining 149 negative return months, the 184 positive months other than the 25 best, and the best 25 months in the sample. Panel B provides the results. The first two columns show that industry contrarian strategies are profitable when the overall market experiences the worst and best performance. The evidence that industry

[22] Under the null hypothesis that the factor risk premiums are jointly equal to zero, [(T-N)/N]SSR is distributed as a central F(N, T-N), where N is the number of portfolios, T is the number of time-series observations and SSR is the squared Sharpe ratio (for details, see MacKinlay (1995) and Brennan et al. (1998)).

[23] The maximum Sharpe ratios for the three- and four-factor models are 0.21 and 0.41 in US markets, as reported by Hou et al. (2015). The four-factor model is based on the *q*-theory without the value factor. Hou et al. (2015) argue that the value effect is captured by the profitability and investment factors. We find that the value factor plays an important role in explaining industry-contrarian performance. Without the value factor in the five-factor model, industry-contrarian profits are significantly positive at the 5% level. Hou et al. (2015) argue that the maximum Sharpe ratio for their four-factor model is not too high (0.41) compared with the maximum Sharpe ratio of 1.6, which is estimated by factors containing 28 anomalies.

[24] Note that using real GDP growth to define the states of the economy does not affect our conclusions. Further details of these results are available upon request.

Table 8
Economic States and industry contrarian performance.

	1980:Q1-1981:Q2	1991:Q1-1991:Q4	2008:Q2-2009:Q3	Other times
Panel A: ONS recessions				
Losing industries	0.01	0.37	−0.15	0.32
	(0.04)	(1.46)	(−0.89)	(3.04)
Winning industries	0.23	0.15	−1.55	0.05
	(0.33)	(0.49)	(−2.37)	(0.90)
Losing industries-	−0.21	0.23	1.40	0.26
Winning industries	(−0.36)	(0.74)	(2.42)	(2.30)
Avg. GDP growth	−2.41	−1.49	−4.41	3.15
	Best 25 months	Worst 25 months	Next best and positive (184)	Next worst and negative (149)
Panel B: Classified by the overall market performance				
Losing industries	1.17	−0.22	0.43	0.07
	(2.61)	(−1.18)	(4.87)	(0.91)
Winning industries	0.30	−1.28	0.10	0.03
	(0.69)	(−3.37)	(1.56)	(0.42)
Losing industries-	0.87	1.06	0.33	0.03
Winning industries	(1.84)	(1.98)	(2.05)	(0.21)
Avg. market ret	8.38	−12.65	2.37	−2.54

This table reports results of industry contrarian performance according to different economic states. The monthly industry contrarian performance is estimated by the cross-sectional Fama–MacBeth regressions (Eq. (1)). Panel A reports the industry contrarian performance in the three waves of economic recessions according to the Office of National Statistics (ONS) in the UK. The rest of the months are defined as "other times". Panel B reports the performance of industry contrarian portfolios in four states according to the overall market performance measured by the equally weighted market return index. The four states the 25 worst stock return months, the remaining 149 negative return months, the 184 positive months other than the 25 best, and the best 25 months in the sample. The last rows in Panel A and B report average GDP growth rates and market returns during each sub-sample period. The numbers in the table are in percentage. Newey and West (1987) adjusted t-statistics are reported in parentheses.

contrarian performance also happens in bad states of the economy contradicts the risk-based explanation, suggesting that losing industries are not riskier than winning industries.

4.4.4. Valuation uncertainty

Previous studies show that stocks with a great amount of valuation uncertainty, which makes arbitrage risky, costly and limited, are likely to be mispriced (e.g. Merton, 1987; Shleifer and Vishny, 1997; Lam and Wei, 2011). The uncertainty can rise from a poor information environment, which can be a barrier to fair valuation of firms. Thus, if long-term industry reversals are due to mispricing, the reversals should be more pronounced for stocks from industries with high informational opacity. We use four proxies for valuation uncertainty, namely accruals, idiosyncratic volatility (IVOL), competitiveness and analyst coverage.

Accruals are important accounting information which should be used by investors to adjust operating cash flows and earnings. However, Hirshleifer et al. (2012) and Sloan (1996) find that investors have limited resources to incorporate accruals into the share valuation process. Hirshleifer et al. (2009) show that industry-based accruals can also predict future returns for industry portfolios, implying that accruals can be a barrier to the proper valuation of industries. We define accruals in the same way as Sloan (1996). We aggregate the accrual elements at the industry level to obtain the industry accrual ratio.[25] Then, in June of each year, we rank industries by their accrual ratios and use the median accrual ratio to define high and low accrual industries from July of this year to June of next year. Finally, we repeat the Fama–MacBeth regressions (Eq. (1)) for stocks in high and low accrual industries. If industry contrarian performance is a mispricing effect, we expect industry reversals to be more pronounced in industries with high accruals. Panel A of Table 9 reports the average monthly returns across the entire five-year period. It shows that the industry contrarian strategy is profitable only in high accrual industries, consistent with the mispricing effect.

IVOL is also widely used as a proxy for informational opacity. Krishnaswami and Subramaniam (1999) use IVOL as a measure of information asymmetry between firm insiders and outsiders. West (1988) and Kelly (2014) document a negative association between price informativeness and IVOL. In the context of industries, industry IVOL would indicate how well industry portfolios absorbed industry- and market-wide information. Boutchkova et al. (2012) show that the sensitivity of an industry's returns to political events can be a function of its IVOL. More recent studies show that IVOL is also a salient characteristic for short-sell constraints and risky arbitrage (Stambaugh et al., 2015; Mashruwala et al., 2006; Lam and Wei, 2011). We argue that, if industry contrarian performance is driven by the mispricing effect, this effect should be stronger in industries with high IVOL. To estimate industry level IVOL, we construct daily value weighted returns for the 20 industries. Industry IVOL is the standard deviation of the residuals obtained by regressing daily industry portfolio returns on the daily FTSE All Share Index return from July of the previous year to June of the current year. The 20 industries are then ranked by their IVOL, and the top (bottom) 10 industries are defined as high (low) IVOL industries from July of one year to June of the next. The sample stocks are separated into those in high and low IVOL industries for the running of the Fama-MacBeth regressions (Eq. (1)). Panel B shows that the industry contrarian strategy is profitable only in high IVOL industries, consistent with the mispricing effect.

Competition across industries provides another important informational channel for investors to value stocks. Because firms in more concentrated industries can exercise significant pricing power on their products, they tend to disclose less information to the public, obscuring the fair value of stocks (e.g. Gal-Or, 1985; Botosan and Stanford, 2005; Ali et al., 2014). On the other

[25] The accruals are defined as $ACC_{industry} = (\Delta CA - \Delta CL - \Delta Cash + \Delta STDEBT - DEP)$ (Sloan, 1996), where ΔCA = change in current assets during period t; ΔCL = change in current liabilities during period t; $\Delta Cash$ = the change in cash and cash equivalents during period t; $\Delta STDEBT$ = the change in the current maturities of long-term debt and other short-term debt included in current liabilities during period t; and DEP = depreciation and amortization expenses during period t. $ACC_{industry}$ is divided by an industry's lagged total assets to obtain the accrual ratio. The aggregated elements at the industry level reflect the value-weighted accruals. We also use the equally weighted approach to calculate industry-based accruals and our results remain quantitatively the same.

Table 9
Valuation Uncertainty and Industry Contrarian Performance.

	High accrual industries	Low accrual industries		High concentrated industries	Low concentrated industries
	Panel A			*Panel C*	
	High accrual industries	Low accrual industries		High concentrated industries	Low concentrated industries
	Panel A			*Panel C*	
	(1, 60)	(1, 60)		(1, 60)	(1, 60)
Losing industries (L)	0.39	0.30		0.32	0.27
	(3.12)	(2.99)		(3.01)	(2.72)
Winning industries (W)	−0.01	0.16		0.02	0.09
	(−0.09)	(1.42)		(0.30)	(0.88)
L–W	0.41	0.15		0.30	0.18
	(2.53)	(0.66)		(2.31)	(1.20)
FF3	0.49	0.12		0.22	0.14
	(3.22)	(1.06)		(1.99)	(1.34)
FF5	0.32	0.00		0.18	0.05
	(2.33)	(0.06)		(1.70)	(0.36)
Avg. obs	633	592		741	506
Avg. the accual ratio	0.1373	−0.1825	Avg. Herf	0.4968	0.1020
	High IVOL industries	Low IVOL industries		High analyst Cov. industries	Low analyst Cov. industries
	Panel B			*Panel D*	
Losing industries (L)	0.46	0.19		0.07	0.70
	(3.98)	(2.39)		(0.10)	(3.86)
Winning industries (W)	0.08	0.08		−0.05	−0.01
	(0.77)	(0.87)		(−0.20)	(−0.10)
L–W	0.39	0.11		0.12	0.71
	(2.60)	(0.80)		(0.67)	(3.99)
FF3	0.44	0.11		−0.08	0.72
	(3.20)	(1.03)		(−0.20)	(3.65)
FF5	0.25	−0.05		−0.10	0.53
	(1.98)	(−0.42)		(−1.02)	(3.60)
Avg. obs	551	698		780	541
Avg. IVOL	0.0358	0.0068	Avg. analyst	13	4

This table reports industry contrarian performance conditioning on accruals, idiosyncratic volatility, competition and analyst coverage. All four conditioning variables are constructed on the industry level. We define accruals the same as Sloan (1996). Industry IVOL is the standard deviation of the residuals from regressing daily industry portfolio returns on daily FTSE All index return (the market return) from July of the last year to June of the current year. We measure industry concentration using the Herfindahl index. According to each stock's industry membership, the number of analysts is aggregated in a given industry and then is divided by the total number of firms in the industry. The sample 20 industries are separated into the top (bottom) 10 industries according to one of the four measures. We then re-run the Fama–MacBeth regressions for the two groups to obtain raw returns. By using the Fama–French three-factor (FF3) and five-factor (FF5) models, we obtain risk-adjusted returns for each portfolio. *t*-statistics are reported in parentheses.

hand, firms in more competitive industries can attract a great amount of attention from investors, who will demand more information from analysts (e.g. Kross et al., 1990; Lys and Soo, 1995; Das et al., 1998; Barth et al., 2001). As such, firms have more incentives to supply information to analysts in more competitive industries. Thus, the mispricing effect would predict a higher industry contrarian spread in more concentrated industries. We measure industry concentration using the Herfindahl index.[26] Specifically, we calculate the Herfindahl index according to the last year's financial reports for the 20 industries. The top (bottom) 10 industries are defined as highly (less) concentrated industries from July of one year to June of the next. Then, we run the Fama-MacBeth regressions for the highly and less concentrated industries separately. The results in Panel C suggest that, in highly concentrated industries, losing industry not only earn a positive return of 0.32% per month, but also significantly outperform winning industries by 0.30% per month. However, the industry contrarian profit disappears in less concentrated industries. This evidence is consistent with the notion that industry competition improves stock price adjustments to information.

Our final proxy for informational opacity is the number of analysts following. The role of financial analysts in disseminating information in financial markets has been widely documented (e.g. Grossman and Stiglitz, 1980; Admati, 1985; Bhushan, 1989). Piotroski and Doulstone (2004) and Chan and Hameed (2006) report that analyst activities help impound both industry and market relevant information into stock prices. This implies that industry contrarian performance should be weaker in industries with more analysts. We collect the number of analysts following each firm in June of each year. According to each stock's industry membership, the number of analysts is aggregated in a given industry and then divided by the total number of firms in the industry.[27] We define the top (bottom) 10 industries as high (low) analyst coverage industries from July of one year to June of the next. We run the Fama-MacBeth regressions for the high and low analyst coverage industries separately. Panel D shows that, in high analyst coverage industries, industry contrarian performance is virtually zero. However, in low analyst coverage industries, losing industries significantly outperform winning industries. These findings highlight the role of financial analysts in improving information dissemination and are also consistent with the mispricing explanation for industry contrarian performance.

Securities with highly subjective valuations are risky and costly to arbitrage and therefore are likely to be affected by sentiment (see, e.g. Baker and Wurgler, 2006; Stambaugh et al., 2012). In this study, we find that the valuation uncertainty, measured by accruals, idiosyncratic volatility (IVOL), competitiveness and analyst

[26] The Herfindahl index is defined as $Herfindahl_j = \sum_{i=1}^{I} S_{ij}^2$, where S_{ij} is the market share of firm *i* in industry *j* in terms of net sales in each sample year.

[27] The data for analyst coverage is extracted from the Bloomberg database. The sample period is from 1997 to 2011. We also use the aggregated number of analysts at the industry level to define high and low analyst coverage industries. The results are similar to those by using the number of analysts per firm in a given industry.

coverage, is significantly higher in losing than winning industries.[28] This suggests that stocks in losing industries are more difficult to value and riskier and costlier to arbitrage than their counterparts in winning industries. Because of the limits to arbitrage, stocks in losing industries should be more affected by sentiment and their returns are more likely to reverse in the long term.

Overall, we show that the contrarian spreads are only significant in industries with high valuation uncertainty and these findings are robust to various risk-adjustment techniques.

5. Conclusion

This study investigates the role of past industry performance in predicting future stock returns in the UK market. We find that firms in losing industries significantly outperform those in winning industries over the subsequent five years. These industry reversals remain strong and persistent after controlling for stock momentum, industry momentum, seasonal effects and traditional risk factors. We also find a strong industry influence on stock return reversals when we condition industry returns on past performance. Furthermore, we compare industry reversals with the stock reversals generated from individual stocks' past performance. We find that stock reversals come exclusively in January and April, consistent with the tax loss selling hypothesis. However, the absence of seasonal patterns in industry reversals does not support the tax-based explanation. Further analysis suggests that past industry performance is the main determinant of stock reversals. However, past stock performance cannot explain industry reversals. The overall results suggest that past industry performance contains salient information about long-term stock returns. Next, we investigate whether industry reversals are driven by risk or are a result of mispricing. We show that industry contrarian performance appears in both good and bad states of the economy, inconsistent with the risk-based explanation. We also find that industry contrarian performance is more prominent in industries with high valuation uncertainty, consistent with the mispricing effect.

Our results have several important implications. First, we show that industries play an important role in conditional asset pricing. Specifically, while previous studies show that contemporaneous industry returns have a negligible impact on stock returns (e.g. Fama and French, 1997; Heston and Rouwenhorst, 1994; Griffin and Karolyi, 1998), we find that past industry performance affects future stock returns. Second, we highlight the importance of industry components in explaining stock reversals and show that the contrarian profits are more likely to represent mispricing rather than risk. Finally, our study suggests that investors are better off exploiting contrarian profits by focusing on industry portfolios.

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Appendix A

See Table A1.

[28] These results are available upon request.

Table A1
Data type filters.

Non common equity	Company name or data type search
Duplicate[a]	DUPLICATE DUPL DUP DUPE DULP DUPLI
American depository receipt[b]	ADR GDR
Preferred stocks	PREFERRED PF PFD PREF 'PF'
Warrants	WARRANT WARRANTS WARRT
Debt	DEB DB DCB DEBT DEBENTURES
Unit trust	TRUST UNIT TST UNIT UNIT TRUST UT
Investment company	INVESTMENT TRUST INVESTMENT

Note: This table lists words used in a screen to identify Datastream securities for which the underlying asset is not common equity. The search is carried out in the data type and in company name.

[a] If two firms have a same name without other distinguishable characteristics, we choose the firm with an earliest coverage in the Datastream to ensure no duplicated firms included.

[b] We also check each stock's quoted currency and remove those that are not quoted in the British Sterling. This procedure screens out American Depository Receipts traded on LSE.

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