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Investor attention, information diffusion and industry returns

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ABSTRACT

Using the monthly data for more than 1700 Australian stocks over the period from 1990 to 2009, we investigate whether industry portfolio returns predict the aggregate market. We find that a few industries significantly lead the market even controlling for well-recognized market predictors. However, unlike U.S. studies, we do not find that the ability of an industry to predict the market is closely related to its propensity to forecast economic growth. Instead, we find that the capacity of an industry to lead the market is significantly moderated by proxies for investor attention. In general, more neglected industries are more informative in leading the markets due to delayed investor attention to the information content of these industries; and the information contained in industry portfolio returns is incorporated into the market return more slowly during economic recession when investors pay less attention to the stock markets. Our research provides new empirical evidence in support of the gradual information diffusion hypothesis from a market that differs from the U.S. stock market.

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1. Introduction

In this paper we empirically investigate whether industry portfolio returns lead the aggregate stock market return in Australia, particularly, we examine whether the slow incorporation of information from industries to the market is a result of investors' limited cognitive capacity, and contribute to the literature on gradual information diffusion proposition by providing new empirical evidence from a market alternative to the U.S. ones.

Standard asset-pricing models are based on the assumptions that investors are rational and that new information is rapidly incorporated into asset prices in a frictionless complete market. However, a growing body of research suggests that information gradually diffuses across asset markets due to the attention

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constraints of investors. According to the gradual information diffusion hypothesis, attention is a scarce cognitive resource (Kahneman, 1973; Pashler and Johnston, 1998); thus, attention to one task automatically substitutes the cognitive resources from other tasks. Given the immense amount of information available in the markets and the inevitability of limited cognitive capacity, investors can only partially process available information. Consequently, information gradually diffuses across stock markets, which leads to a price delay effect or a lead–lag effect of stock returns (Merton, 1987; Hong and Stein, 1999; Hirshleifer and Teoh, 2003; Peng and Xiong, 2006).

Several recent studies have provided empirical evidence in support of the gradual information diffusion hypothesis. Hou and Moskowitz (2005) find that a firm's price delay can be explained by proxies for investor recognition. Hou (2007) finds that the lead-lag relationship between large and small firms is primarily driven by the slow diffusion of industry information; and small, less competitive and neglected industries experience a more pronounced lead-lag effect. Barber and Odean (2008) show that attention affects the buying and selling decisions of investors, particularly, it affects buying more than selling because investors who face a buying decision have more difficulty in searching across a larger number of stocks they can potentially buy; therefore, individual investors are more likely to buy attention-grabbing stocks. Using data for firms' customer-supplier links, Cohen and Frazzini (2008) find that news about economically related firms is not promptly incorporated into their stock prices and the extent of late response is more severe in the case of binding attention constraints. Menzly and Ozbas (2010) observe the cross predictability of industry stock returns along customer-supplier links, providing evidence in support of the hypothesis that this gradual information diffusion is attributed to investor specialization and market segmentation.

The paper closely related to ours is Hong et al. (2007), who develop a simple two-asset model in a three-period economy based on the assumption of gradual-information-diffusion in the stock market. Using U.S. data over the period from 1946 to 2002, they find that it takes two months for the information contained in industries to be completely incorporated into the market index. They attribute an industry's ability to predict the market to its propensity to forecast economic growth. However, Hong et al. (2007) do not explain why the ability to lead the market is so different across industries and do not test the gradual information diffusion hypothesis. This study fills this gap by directly testing the gradual-information-diffusion hypothesis. We examine whether the slow incorporation of information from industries to market results from investors' attention constraints, and provide additional empirical evidence from an alternative market that is significantly different from the U.S. markets in terms of market structure.

We address the issues in two steps by analyzing a large dataset from Australia, a market that is dominated by Banks and Mining industries. We first investigate whether Australian industries lead the aggregate stock market controlling for well recognized market fundamentals suggested in the literature such as market dividend yield (Campbell and Shiller, 1988), the term premium (Fama and French, 1989), market volatility (Hong et al., 2007) and changes in the USD/AUD exchange rate (Yao et al., 2005). We then interact our proxies for investor attention with industry portfolio returns to test whether the ability of an industry to predict the aggregate market is related to investor attention.

We construct three sets of proxies for investor attention. We firstly construct variables of industry size and liquidity as proxies for investor attention given that small, illiquid stocks are more likely to be neglected by investors (Hou and Moskowitz, 2005; Hou, 2007). However, as size and liquidity are also closely related to market frictions, it's controversial whether the explanatory power of size and liquidity on the industry leading effect is indicative of gradual information diffusion due to investor attention or market frictions. We then construct variables of financial analyst coverage that is directly linked to investor attention (Aggarwal et al., 2005; Fang and Peress, 2009). The above two sets of proxies are constructed to represent the investor attention at the industry level. We next use business cycle as a proxy for overall investor attention to the market. As both the quantity and the quality of information increase (decrease) during the expansionary (contractionary) phase of a business cycle (Veldkamp, 2005; Brockman et al., 2010), investors monitor and attend information more actively in rising markets or during economic expansion (Karlsson et al., 2009), thus, investors' attention to the stock market during economic

¹ We would like to thank an anonymous referee for pointing out this.

recession would be lower. We use the Hodrick–Prescott Filter method (Hodrick and Prescott, 1997) to estimate the cyclical component of economic activity and then construct a dummy variable representing economic contraction.

We find six industries, such as General Retailers, Industrial Engineering, and Oil & Gas Producers, significantly lead the market. Instead, the information contained in the two largest industries, Banks and Mining industries whose market capitalization jointly constitutes more than 42% of the Australian stock market, is concurrently captured by the market. Returns of Banks and Mining industries can also significantly predict future economic growth. We do not find significant evidence that the ability of an industry to predict the market is closely related to its capacity to forecast economic growth, as documented by Hong et al. (2007) for the U.S. markets. Our findings open up possible avenues for future research into potential sources of the observed industry–market lead–lag relationships, especially in the markets outside the U.S.

We find that the predictive power of industries is significantly moderated by the proxies for investor attention. The information contained in industries is either captured or mostly offset by the proxies for investor attention at the industry level. The information contained in the returns of small and illiquid industries is incorporated into the market index more slowly, while the information of the industries that are followed by more financial analysts is captured by the market more promptly. We also find that during economic recessions when the overall investor attention to the stock market is lower, the information content of industry portfolio returns diffuses across the market more slowly. Our findings provide new empirical evidence in support of the gradual information diffusion hypothesis.

This paper is structured as follows: Section 2 describes the dataset and the measurement of variables; Section 3 explains the empirical model; Section 4 presents the major empirical results of this paper, and Section 5 concludes.

2. Data and variable definitions

This study uses a large dataset over the period from 1990 to 2009.² The information for the aggregate stock market index, all individual stocks actively traded in the Australian Stock Exchange (ASX), and market fundamentals are sourced from Datastream International. The data of financial analyst coverage are extracted from the Institutional Brokers Estimate System (IBES) database. To construct industry portfolios, we use the Datastream constituent stocks of Industry Classification Benchmark (ICB) level 4 sectors as the sampling universe. Our sample is limited to equity securities with primary quotes and excludes industry sectors of investment instruments. We combine Life Insurance and Non-life Insurance to construct the Insurance portfolio as there are only two life insurance stocks and four non-life insurance stocks. The Tobacco industry is excluded as it has two stocks only and both were delisted in 2001. Finally, we end up with 37 industry portfolios for empirical investigation. Description of industries and the number of stocks included in each industry portfolio are presented in Table 1.

2.1. Measurement of variables

The following three sets of variables are used in our analyses.

2.1.1. Excess returns

Industry excess return is the difference between the value-weighted industry portfolio return and the risk free rate: $R_{i,t} = \sum_{j=1}^{n} W_{j,t}R_{j,t} - R_{f,t}$, where $R_{j,t} = Log(P_{j,t}/P_{j,t-1})$, denoting the continuous return³ on stock j in industry i over the period t (here t is month); $W_{j,t}$ is the weight of stock j in industry i for period t measured by using the ratio of the market capitalization of stock j to the total market capitalization of

² Our sample period starts from 1990 due to the lack of trading volume data and insufficient number of stocks for many industries prior to 1990.

³ The individual stock prices, $P_{j,t}$, used to calculate the continuous returns are adjusted for capital changes.

Table 1Summary statistics of industry excess returns and Market Fundamentals, January 1990 to December 2009. Panel A presents the summary statistics for the excess returns of 37 industry portfolios. The excess return is calculated as the value-weighted industry portfolio return in excess of the risk-free rate, proxied by the 90-day bank accepted bill rate. Panel B presents summary statistics for the market fundamentals. All the data are sourced from Datastream International. The variables are at monthly frequency and presented as percentage.

Industry description	No. of stocks	No. of observations	Mean	Std Dev	Max	Min
Panel A. Industry portfolio returns						
Aerospace & Defense	4	124	-2.78	18.66	131.59	-42.55
Alternative Energy	14	231	-2.91	14.20	61.21	-78.78
Automobiles & Parts	9	240	-1.58	8.65	20.78	-48.28
Banks	9	240	0.07	5.26	13.67	-15.96
Beverages	12	240	-0.53	5.99	15.08	-30.69
Chemicals	16	240	-0.14	6.85	28.68	-29.00
Construction & Materials	48	240	-0.09	5.64	16.51	-33.47
Electricity	18	240	-1.18	13.19	53.41	-49.52
Electronic & Electrical Equipments	21	240	-1.35	13.34	36.24	-82.64
Financial Services (Sector)	121	240	-0.62	6.06	15.20	-27.74
Fixed Line Telecommunications	11	165	-0.30	10.27	65.87	-48.94
Food & Drug Retailers	7	196	0.52	5.03	13.61	- 15.96
Food Producers	38	240	-0.43	5.51	10.75	-30.79
Forestry & Paper	8	204	-0.88	7.56	17.51	-25.79
Gas, Water & Multi-utilities	6	240	0.02	5.45	30.48	-23.85
General Industrials	8	240	-0.33	5.41	19.61	-29.64
General Retailers	35	240	0.24	5.87	15.90	-26.90
Health Care Equipment & Services	58	240	-0.60	5.57	11.88	-24.18
Household Goods & Home Const.	16	240	-0.78	7.29	23.34	-29.49
Industrial Engineering	25	240	-0.91	8.11	22.35	-39.69
ndustrial Metals & Mining	122	240	-0.44	7.89	21.71	-47.59
ndustrial Transportation	21	240	-0.08	6.71	26.96	-28.50
Leisure Goods	8	166	0.26	8.00	30.00	-36.52
Life Insurance & non-life insurance	6	240	0.30	6.07	16.38	-29.0
Media	39	240	-0.24	7.34	17.49	-45.28
Mining	538	240	0.08	6.25	17.13	-28.35
Mobile Telecommunications	13	240	-2.15	18.77	68.38	-57.00
Oil & Gas Producers	124	240	0.08	6.09	18.01	-25.68
Oil Equipment & Services	7	166	-0.12	9.65	18.12	-65.20
Personal Goods	11	240	- 0.57	10.19	33.89	-67.3°
Pharmaceuticals & Biotechnology	68	240	0.44	10.13	62.68	-44.0
Real Estate Investment & Services	41	240	-0.33	4.99	11.72	- 19.38
Real Estate Investment Trusts	56	240	-0.35	4.73	11.72	-33.72
Software & Computer Services	59	240	-0.43 -2.76	12.82	46.20	-62.23
Support Services	74	240	-2.70 -0.48	5.65	12.55	-43.38
Technology Hardware & Equipment	13	240	-0.48 -2.51	13.34	69.64	-66.8
Travel & Leisure	36	240	-0.29	5.94	14.56	-22.79
Panel B. Market fundamentals						
Growth rate of economic activity			0.256	0.332	1.658	-0.67
Excess market return			0.017	3.927	7.135	- 14.52
Conditional market volatility			0.195	0.109	0.842	0.08
Dividend yield on the market index			3.819	0.874	7.060	2.68
Term premium			0.702	1.362	4.510	-4.99
Rate change in the USD/AUD exchange rate			0.065	3.215	8.571	- 17.80

industry i at the end of period t-1; $R_{f,t}$ is the risk free rate over period t. The risk-free rate is proxied by the 90-day bank accepted bill (BAB) rate as the Treasury-note rate is not available over the full sample period.⁴

⁴ Treasury note rates are not available for the period from May 2002 to February 2009.

Excess market return is the difference between return on the Datastream total market index and the 90-day BAB rate: $R_{M,t} = Log(Pl_t / Pl_{t-1}) - R_{f,t}$, where Pl_t is the Datastream total market price index at the end of period t, and $R_{f,t}$ is the risk-free rate over the period t.

2.1.2. Market fundamentals and control variables

The second set of variables includes indicators of market fundamentals and well-recognized market predictors.

The economic growth rate is approximated by the growth rate of the Westpac–Melbourne Institute Coincident Index of Economic Activity since monthly figures for GDP or the industrial production index are not available for Australia. The growth rate is calculated as the first difference of logarithm of the Coincident index, $Log(IE_t / IE_{t-1})$, where IE_t is the weighted average of six economic series typically coincident with economic activity, including real retail trade, civilian employment, unemployment, industrial production, non-farm production and real household income.

Market volatility is estimated from a GARCH(1, 1) model of the following form: $R_{M,t} = 0.009702 + \varepsilon_t$ and $h_t = 0.000145 + 0.182346\varepsilon_{t-1}^2 + 0.780746h_{t-1}$, where h_t is our estimate of market volatility, representing the conditional variance of the random error term, ε_t . All parameters have a p-value of less than 0.01. The forecast variance can be viewed as a weighted sum of the long run variance, the lagged return shock and the lagged variance forecast. Unlike historical volatility, forecast volatility from the GARCH(1,1) model captures the time-varying aspect of volatility and does not require researchers to arbitrarily specify a particular sample window.

Dividend yield on the market index is obtained from Datastream. Dividend is based on gross dividend inclusive of tax credits, excluding special or once-off dividends. Term premium is measured as the difference between the ten-year commonwealth government bond rate and the risk-free rate, proxied by the 90-day BAB rate. The final control variable is the rate of change in USD/AUD exchange rate measured as the first difference of log USD/AUD exchange rates.

2.1.3. Proxies for investor attention

We construct three sets of variables as the proxies for investor attention at the industry and market levels. We interact each of these variables, respectively, with the industry portfolio returns to test whether the predictive power of industry portfolio returns is moderated by investors' attention.

The first set of proxies includes industry size and liquidity given that investor recognition is positively correlated with firm size and liquidity (Grullon et al., 2004; Hou and Moskowitz, 2005; Bodnaruk and Ostberg, 2009), and generally small, illiquid stocks are more likely to be neglected by investors (Hou and Moskowitz, 2005; Hou, 2007). At the industry level, size is measured as the ratio of the market capitalization of the industry portfolio i at period t to the total market capitalization of all stocks at period t. We use two alternative industry level measures of liquidity — turnover and value traded. Turnover is measured as the ratio of the total value traded for the industry portfolio i to the total market capitalization of the industry portfolio at the end of period t — 1. Value traded is the ratio of the total value traded for the industry portfolio i to the total value traded for the whole market in period t. Value traded measures the liquidity of the industry portfolio relative to market-wide liquidity.

However, size and liquidity are also closely related to market frictions (Hou and Moskowitz, 2005). Thus, it's arguable whether the effect of size and liquidity on industry predictive power is due to investor attention or market frictions. We then construct a second set of proxies, financial analyst coverage, which is directly linked to investor attention. More specifically, we create both absolute and relative measures of financial analyst coverage using financial analysts' earnings per share (EPS) forecasts from the IBES database. We first match the companies in each ICB sector with the IBES company codes, and then verify the accuracy of matched observations using other IBES identifiers such as company SEDOL code and local ticker code. Eventually, we end up with 871 stocks that have analyst EPS forecasts, giving a total of 48,913 firm—month observations over our sample period. For each industry, we measure absolute analyst coverage as $\log(1 + N_{i,t})$, and relative analyst coverage as $N_{i,t}/\sum_{i=1}^{\infty} N_{i,t}$, where $N_{i,t}$ is the number of analysts that follow the companies in industry i in period t.

⁵ As a robustness check, we also use the number of companies followed by financial analysts in an industry to measure investor attention. The corresponding empirical results are not reported but they are qualitatively similar.

So far we have focused on two sets of proxies that represent investor attention to individual industries. To measure the investor attention to the overall stock market, we introduce a dummy variable for economic recession, capturing pro-cyclical movement in investors' stock market attention. We decompose the Westpac-Melbourne Institute Coincident Index of Economic Activity into trend and cyclical components using the Hodrick-Prescott Filter method (Hodrick and Prescott, 1997). The dummy variable for economic recession takes a value of one when the Hodrick-Prescott cyclical component is negative and zero otherwise.

2.2. Descriptive statistics

Table 1 presents the summary statistics for the variables of primary interest. Columns 1 and 2 of Panel A describe the industry portfolios and the number of stocks that are used to construct each of these portfolios. The third column provides the number of monthly observations available for each industry portfolio. In total, the sample includes 1720 actively traded ASX-listed stocks, with the maximum number of 538 stocks for the Mining industry and a minimum of 4 stocks for the Aerospace & Defense industry. Panel A of Table 1 presents the summary statistics for the monthly excess returns of 37 industry portfolios. Monthly excess returns vary substantially across industries and time. In our sample, 28 out of 37 industries have a negative mean excess return, with the lowest of -2.91% for the Alternative Energy industry and the highest of 0.52% for the Food & Drug Retailers industry. The Mobile Telecommunications industry seems to be the most volatile with the highest standard deviation of 18.77%, while Real Estate Investment Trusts has the lowest of 4.73%. Panel B of Table 1 presents summary statistics for excess market returns, economic growth rates together with those for the control variables, being market volatility, dividend yield, term premium and the rate of change in the USD/AUD exchange rate. The monthly excess market return over the sample period ranges from -14.527% to 7.135% with a mean of 0.017%, while the monthly economic growth rate varies between 1.658% and -0.678% with a mean of 0.256%.

Summary statistics for our industry level indicators of investor attention are presented in Table 2. The Australian stock market is dominated by a few major industries. The five largest industries (Banks, Mining, Fixed Line Telecommunications, Industrial Metals & Mining, and Real Estate Investment Trusts) make up 62% of the whole market capitalization, while Banks and Mining industries jointly constitute about 42% of the whole market. Conversely, the combined market capitalization of the ten smallest industries only represents 0.786% of the whole market. The largest industries are also heavily traded in the market. The value traded of Banks and Mining industries alone stands at about 46% of the value traded of the whole market, whereas the total value traded of the bottom 10 industries only constitutes 0.656%. The turnover ratio indicates the industry liquidity relative to the industry size. We don't see much variation in the turnover ratio across industries compared to that of market capitalization and value traded. The last two columns of Table 2 present the descriptive statistics for both absolute and relative measures of financial analyst coverage, which are derived from the number of analyst EPS forecasts for the companies of each industry. The total number of EPS forecasts has increased from 435 in January 1990 to 2637 in December 2009. We observe that the analyst coverage is relatively concentrated. The top-five industries that are followed most by analysts (Banks, Mining, Construction & Materials, Media, and Real Estate Investment Trust) attract an average of 42.62% of the total analyst EPS forecasts. On the contrary, 13 out of 37 industries each has less than 1% of coverage.

3. Empirical framework

Hong et al. (2007) provide a simple model where non-synchronous transmission of information occurs as investors may not participate in all markets because of taxes, regulations or a fixed market entry cost. In their two-asset model, investors are assumed to participate in either market X or market Y and use signals from the respective market to form expectations about future asset prices. Thus, the price of Y can be

⁶ We have run the autocorrelation tests for variables. Among 37 industry return series, 8 report positive first-order autocorrelation, and 5 industry return series exhibit negative first-order autocorrelation. We cannot reject the null hypothesis of no first-order autocorrelation for other industry return series, the market excess return, and the control variables except for term premium. The results are available upon request.

Table 2Summary statistics of proxies for industry investor attention, January 1990 to December 2009.

Industry	Size (%)		Turnover (%)		Value trade (%)		Absolute analyst coverage		Relative analyst coverage (%)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Aerospace & Defense	0.03	0.027	3.555	7.237	0.018	0.046	0.061	0.196	0.006	0.02
Alternative Energy	0.018		5.86	9.046	0.018	0.032	0.213	0.507	0.022	0.06
Automobiles & Parts	0.024		1.668	1.797	0.009	0.011	0.493	0.539		0.074
Banks	22.176	3.099	5.376	1.853	23.558	5.218	4.418	0.241		3.389
Beverages	3.505	1.625	4.964	2.955	2.823	1.284	2.836	0.219	1.783	0.703
Chemicals	1.31	0.595	4.759	3.963	0.848	0.522	2.899	0.413	1.782	
Construction & Materials	2.196	0.399	4.135	2.48	1.642	0.648	4.414	0.358	8.542	2.172
Electricity	0.165	0.196	4.65	3.004	0.133	0.164	1.74	1.173	0.583	0.475
Electronic & Electrical Equipments	0.1	0.05	3.109	2.029	0.072	0.077	0.829	0.699	0.152	0.175
Financial Services (Sector)	3.316	2.443	4.992	4.233	3.658	3.894	2.943	1.702	3.081	2.377
Fixed Line Telecommunications	9.388	6.927	4.566	3.142	5.616	3.684	1.793	1.473	0.814	0.726
Food & Drug Retailers	2.351	0.609	5.346	1.944	2.223	0.898	2.739	1.308	1.901	0.987
Food Producers	0.502	0.181	3.875	2.728	0.375	0.262	2.596	1.167	1.494	0.837
Forestry & Paper	0.208	0.169	4.819	3.547	0.195	0.199	2.06	1.157	0.836	0.517
Gas, Water & Multi-utilities	2.177	1.014	4.959	2.557	2.027	1.083	3.327	0.187	3.071	1.475
General Industrials	3.953	1.995	5.859	3.13	3.965	1.816	3.404	0.185	3.539	2.092
General Retailers	1.911	0.677	3.439	2.518	1.238	0.81	3.721	0.606	4.111	0.633
Health Care Equipment & Services	2.003	1.216	5.279	1.881	2.164	1.607	3.518	0.649	3.361	0.661
Household Goods & Home Const.	0.266	0.075	2.826	1.673	0.158	0.141	2.559	0.706	1.248	0.417
Industrial Engineering	0.103	0.095	3.859	3.938	0.096	0.13	1.432	1.394	0.531	0.641
Industrial Metals & Mining	5.293	2.721	7.068	2.555	7.264	4.103	3.835	0.4	4.85	1.775
Industrial Transportation	1.263	1.153	4.913	3.435	1.341	1.39	2.613	1.505	1.829	1.185
Leisure Goods	0.042	0.029	3.263	2.319	0.026	0.028	1.009	0.909	0.199	0.215
Life Insurance & non-life insurance	2.146	1.173	4.954	6.53	1.946	1.58	3.206	0.57	2.424	0.487
Media	2.771	1.162	5.087	4.982	2.572	1.414	4.148	1.071	7.335	2.737
Mining	19.869	7.685	6.468	3.254	22.379	6.667	4.687	0.364	11.566	4.196
Mobile Telecommunications	0.06	0.107	5.121	5.824	0.057	0.161	1.259	1.246	0.374	0.395
Oil & Gas Producers	4.191	1.131	5.819	2.735	4.712	2.453	4.013	0.405	5.636	1.263
Oil Equipment & Services	0.326	0.332	3.94	3.854	0.264	0.379	1.406	1.348	0.478	0.524
Personal Goods	0.192	0.193	4.44	4.726	0.213	0.264	1.42	1.391	0.519	0.557
Pharmaceuticals & Biotechnology	0.831	0.627	5.103	3.143	0.827	0.674	2.26	1.265	1.119	0.717
Real Estate Investment & Services	2.448	0.505	3.681	1.726	1.947	1.003	3.112	0.384	2.276	0.681
Real Estate Investment Trusts	5.089	2.476	4.504	2.934	4.389	2.98	4.1	0.775		1.796
Software & Computer Services	0.24	0.227	5.254	4.236	0.295	0.695		1.879	1.659	1.755
Support Services		0.384	3.362	1.836	0.711		3.666	1.164	4.496	1.999
Technology Hardware & Equipment	0.052	0.034	4.998	7.836	0.069	0.127	1.077	0.809	0.231	0.218
Travel & Leisure	1.923			4.545		1.952	2.999	1.617		1.724

Note: Refer to Section 2 for data sources and variable measurements. The variables are at monthly frequency.

efficient with respect to its own asset information but inefficient with respect to information from market X. Hong et al. (2007) argue that in the presence of market segmentation, information from asset X in period 1 can predict return on asset Y in period 2. Considering asset Y as the aggregate market portfolio (M) and asset X as an industry portfolio (i), they hypothesize that industry portfolios lead the aggregate market portfolio.

$$R_{M,t} = \alpha_{i} + \beta_{i} R_{i,t-1} + \lambda_{i}^{'} X_{t-1} + e_{i,t}$$
(1)

where the subscripts i and t denote industry and time period, respectively; $R_{M,t}$ is the excess market return in month t; and $R_{i,t-1}$ is the value-weighted excess return on industry portfolio i over period t-1. X_{t-1} is a vector of control variables, which includes lagged values of market excess return, market volatility, market dividend yield, term premium, and the rate of change in the USD/AUD exchange rate. The rejection of the null hypothesis that β_i is zero will indicate that industry i leads the market.

Hong et al. (2007) also argue that an industry's ability to predict the market is directly related to its ability to predict economic growth. To examine an industry's ability to predict economic growth, the following equation is estimated:

$$Growth_t = \gamma_i + \chi_i R_{i,t-1} + \varphi_i' Z_{t-1} + \eta_{i,t}$$
(2)

where, the subscripts, i and t denote industry and time period, respectively. $Growth_t$ is the growth rate of economic activity index proxied by the Westpac–Melbourne Institute Coincident Index of Economic Activity. Z is the vector of lagged control variables, which is the same as X in Eq. (1) plus the lagged dependent variable, $Growth_{t-1}$. The coefficient χ_i measures the strength of the lead–lag relationship running from industry returns to economic growth.

We argue that an industry's ability to predict the market is moderated by investor attention. Hou and Moskowitz (2005) and Hou (2007) show that the differential speed of information diffusion across firms or industries is related to investor attention. Price-sensitive information from well-recognized (neglected) industries may be transmitted quickly (slowly) across the markets. Thus, regardless of the extent of asset market segmentation, investors due to cognitive limitations may not be able to process price-sensitive information from all industries in a timely fashion. In the presence of investors' cognitive limitations, information contained in attention-grabbing or well-recognized industries may be captured by the market immediately, while information embedded in neglected industries may be reflected in market return with a lag. To examine this proposition, we augment Eq. (1) by including a proxy for investor attention (I_{t-1}) as a moderating variable:

$$RM_{t} = \alpha_{i} + \beta_{i}R_{i,t-1} + \delta_{i}(I_{t-1} \times R_{i,t-1}) + \lambda'_{i}X_{t-1} + e_{i,t}.$$
(3)

The predictive ability of an industry is captured by $\beta_i + \delta_i I_{i,t-1}$, where $\delta_i I_{i,t-1}$ represents the incremental effect of investor attention on industry i's ability to lead the market. For any given level of investor attention, $I_{i,t-1}$, the sign and magnitude of δ_i determine whether the ability of an industry to lead the market is strengthened or weakened by investors' attention.

We employ the Generalized-Method-of-Moments (GMM) techniques for estimation of all equations to obtain estimated parameters that are robust to heteroskedasticity and autocorrelation. The robustness of our results for Eqs. (1) and (2) is also checked by adding all lagged excess industry returns as predictors to these regressions.

4. Empirical results

4.1. Predictive ability of industry returns

First, we estimate Eq. (1) to investigate the hypothesis that industry portfolios lead the aggregate market portfolio. Table 3 presents the coefficient estimates for the lagged excess industry returns. The estimated coefficients of the control variables are not reported here but are available upon request. When each of the excess industry portfolio returns enters the regression of Eq. (1) separately, we find that five industries, being Oil Equipments & Services, Oil & Gas Producers, Insurance, Industrial Engineering, and General Retailers, significantly lead the market at the 5% level, while Alternative Energy industry leads the market at the 10% significance level. When we include more lags of excess industry portfolio return into the regression, the results remain the same. Among 37 industries, the above six industries significantly lead the market by one month even with more lags added into the regressions; one industry (Industry Metal & Mining) leads the market by two months at 10% significance level, and another two industries (Travel & Leisure, and Software & Computer Services) lead the market by three months at 5% significance level. The two largest industries, Banks and Mining industries, do not lead the excess market return, which is reasonable given that the Australian stock market is dominated by Banks and Mining industries, and therefore the information contained in both industries' stock prices is immediately captured by the contemporaneous market index. The lagged excess market return has no predictive power in all 37 regressions except for those for the Insurance and Oil & Gas Producers industries. Consistent with previous

Table 3Individual industry predictive regressions of market return, January 1990 to December 2009. This table presents the estimated coefficients of the lagged excess industry returns based on regressions of excess market returns on the lagged excess returns of individual industry portfolios and the lagged values of market fundamentals — the excess market return, conditional market volatility, dividend yield on the market index, term premium, and rate of change in the USD/AUD exchange rate. The coefficients of the lagged market fundamentals are not presented in this table. The p-values are based on heteroskedasticity and autocorrelation consistent standard errors.

Lagged excess returns on industry portfolio	Coefficient	\mathbb{R}^2	Lagged excess returns on industry portfolio	Coefficient	R ²
Aerospace & Defense	0.006	0.185	Industrial Engineering	0.100**	0.075
Alternative Energy	-0.029*	0.046	Industrial Metals & Mining	-0.053	0.049
Automobiles & Parts	-0.029	0.047	Industrial Transportation	0.040	0.048
Banks	0.018	0.044	Leisure Goods	0.019	0.081
Beverages	0.003	0.044	Life Insurance & non-life insurance	-0.112**	0.065
Chemicals	0.053	0.049	Media	-0.024	0.045
Construction & Materials	0.096	0.053	Mining	-0.040	0.046
Electricity	-0.016	0.047	Mobile Telecommunications	-0.006	0.045
Electronic & Electrical Equipments	0.022	0.049	Oil & Gas Producers	-0.124**	0.067
Financial Services (Sector)	0.026	0.045	Oil Equipment & Services	0.077**	0.104
Fixed Line Telecommunications	0.006	0.083	Personal Goods	0.018	0.046
Food & Drug Retailers	-0.028	0.048	Pharmaceuticals & Biotechnology	0.014	0.045
Food Producers	-0.063	0.049	Real Estate Investment & Services	0.008	0.044
Forestry & Paper	0.060	0.068	Real Estate Investment Trusts	0.098	0.052
Gas, Water & Multi-utilities	-0.012	0.044	Software & Computer Services	0.001	0.044
General Industrials	-0.028	0.045	Support Services	-0.041	0.046
General Retailers	0.125**	0.064	Technology Hardware & Equipment	-0.011	0.045
Health Care Equipment & Services	0.004	0.044	Travel & Leisure	-0.004	0.044
Household Goods & Home Const.	-0.035	0.047			

Notes: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

empirical literature (e.g., Campbell and Shiller, 1988; Fama and French, 1989; Hong et al., 2007), we find that the lagged market volatility, dividend yield and term premium are significant predictors of excess market returns, while the rate of change in USD/AUD exchange rates has no predictive power.

Since industry returns can be contemporaneously correlated, the regression results of Eq. (1) may be subject to the omitted variable bias. Hence, Eq. (1) is also run with an augmented specification by simultaneously including all 37 lagged industry portfolio returns as regressors. The results reported in Table 4 suggest that nine industries, including Alternative Energy, Beverages, Financial Services, Forestry & Paper, Industrial Engineering, Oil Equipment & Services, Personal Goods, Real Estate Investment Trusts, and Travel & Leisure, significantly lead the market at the 5% level, while another five industries lead the market at the 10% significance level. The Oil & Gas Producers industry, which leads the market individually, loses its significance in predicting the market when all industries are included in the regression.

Next, we estimate Eq. (2) to investigate the hypothesis that the ability of an industry to lead the market is directly related to its capacity to predict economic growth. The estimates for the primary interest variable, industry portfolio excess returns, are reported in Table 5. The results show that six industries can significantly predict the future economic growth rate, with Banks, Food Producers, and Mining at the 5% significance level, and Electricity, Industrial Engineering, and Support Services at the 10% significance level. Of the six industries which significantly lead the market individually, only Industrial Engineering can significantly predict future economic activity. After augmenting Eq. (2) by simultaneously including thirty-seven lagged industry returns as regressors, we observe that thirteen industries can significantly predict future economic growth at the 10% level (of which eight industries are significant at the 5% level). The industries of Electricity, Food Producers, and Support Services, which can significantly predict future economic activity individually, remain significant in the augmented regression. Only five out of the thirteen industries leading the market significantly in the augmented specification of Eq. (1) can also significantly predict future economic growth in the augmented specification of Eq. (2). Therefore, we are

⁷ The results are not tabulated here but available upon request.

not able to conclude that the ability of an industry to lead the market is closely related to its ability to predict market fundamentals.

Our results are incomparable with Hong et al. (2007) who report that 18 out of 31 industries lead the market whereas 11 out of 31 industries significantly predict market fundamentals for the Australian market due to the following reasons: Firstly, Hong et al. (2007) use the raw returns on the market and 31 industries over the period 1973 to 2002 whereas we analyze the excess returns on both market and 37 industries over the period 1990 to 2009. Our basis of industry classification also differs from Hong et al.'s (2007), we use the Datastream updated Industry Classification Benchmark (ICB) that was effective from 2008. Secondly, they do not control their Australian analyses for well-known market predictors, while we do. Thirdly, they adopt the growth rate of Industrial Production Index as the proxy for market fundamentals while we use the growth rate of the Westpac–Melbourne Institute Coincident Index of Economic Activity — a broad coincidental measure of economic activity. In contrast to Hong et al. (2007) who find that the ability of an industry to predict the market is closely related to its propensity to forecast market fundamentals for the U.S. market, we do not find significant evidence in favor of this proposition for the Australian market. Our findings open up possible avenues for future research into potential sources of the observed industry—market lead–lag relationships, especially in markets outside the U.S., and also make our investigations as set out in the next section more interesting.

4.2. Investor attention effects

In this section, we investigate the hypothesis that the ability of an industry to lead the market is moderated by investor attention. As set out in Eq. (3), the incremental effect of investor attention on industry i is determined by the sign and magnitude of the investor attention parameter, δ_i and the level of investor attention, $I_{i,t-1}$. In the last section, we have proposed industry size, industry liquidity and analyst

Table 4Joint industry predictive regression of market return, January 1990 to December 2009.
This table presents the results from the regression of excess market returns on the lagged excess returns of all industry portfolios and lagged market fundamentals — the excess market return, market volatility, dividend yield on the market portfolio, term premium and rate of change in the USD/AUD exchange rate. The p-values are based on heteroskedasticity and autocorrelation consistent standard errors.

Lagged regressors	Estimate	Lagged regressors	Estimate
Intercept	-0.071**	Industrial Transportation	0.079
Aerospace & Defense	0.023*	Leisure Goods	-0.083
Alternative Energy	-0.058**	Life Insurance & non-life insurance	-0.114*
Automobiles & Parts	-0.030	Media	-0.006
Banks	0.106	Mining	-0.035
Beverages	-0.193**	Mobile Telecommunications	0.021
Chemicals	-0.014	Oil & Gas Producers	-0.086
Construction & Materials	0.080	Oil Equipment & Services	0.131**
Electricity	0.046	Personal Goods	-0.149**
Electronic & Electrical Equipments	0.029	Pharmaceuticals & Biotechnology	0.011
Financial Services (Sector)	0.106**	Real Estate Investment & Services	-0.140
Fixed Line Telecommunications	0.071	Real Estate Investment Trusts	0.246**
Food & Drug Retailers	0.045	Software & Computer Services	-0.041
Food Producers	0.002	Support Services	-0.065
Forestry & Paper	0.130**	Technology Hardware & Equipment	0.030*
Gas, Water & Multi-utilities	0.074	Travel & Leisure	-0.166**
General Industrials	-0.037	Lagged market fundamentals:	
General Retailers	0.126*	Excess market return	-0.088
Health Care Equipment & Services	-0.035	Conditional market volatility	- 13.675**
Household Goods & Home Const.	-0.092	Dividend yield	2.581**
Industrial Engineering	0.139**	Term premium	0.883**
Industrial Metals & Mining	0.054	Rate change in the exchange rate	-0.150
R^2	0.569		
Adjusted R ²	0.345		

Notes: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

Table 5 Industry portfolio returns and future economic activity: results of individual regressions, January 1990 to December 2009. This table presents the results from the regression of economic growth rate on lagged excess returns of individual industry portfolios and lagged values of market fundamentals — the excess market return, market volatility, dividend yield on the market portfolio, term premium and rate of change in the USD/AUD exchange rate. The coefficients of the lagged market fundamentals are not presented in this table. The p-values are based on heteroskedasticity and autocorrelation consistent standard errors.

Lagged industry returns	Estimate	R^2	Lagged industry returns	Estimate	R^2
Aerospace & Defense	0.002	0.081	Industrial Engineering	0.005*	0.172
Alternative Energy	-0.001	0.144	Industrial Metals & Mining	-0.002	0.163
Automobiles & Parts	0.000	0.162	Industrial Transportation	-0.005	0.169
Banks	0.014**	0.185	Leisure Goods	-0.001	0.083
Beverages	-0.004	0.166	Life Insurance & non-life insurance	-0.001	0.163
Chemicals	0.001	0.163	Media	0.000	0.162
Construction & Materials	0.004	0.165	Mining	-0.010**	0.176
Electricity	0.004**	0.180	Mobile Telecommunications	0.001	0.163
Electronic & Electrical Equipments	-0.001	0.164	Oil & Gas Producers	0.001	0.162
Financial Services (Sector)	0.004	0.165	Oil Equipment & Services	0.000	0.082
Fixed Line Telecommunications	0.001	0.084	Personal Goods	0.002	0.165
Food & Drug Retailers	-0.001	0.078	Pharmaceuticals & Biotechnology	-0.003	0.171
Food Producers	-0.009**	0.176	Real Estate Investment & Services	0.003	0.163
Forestry & Paper	0.003	0.058	Real Estate Investment Trusts	0.007	0.168
Gas, Water & Multi-utilities	0.005	0.167	Software & Computer Services	-0.001	0.163
General Industrials	0.000	0.162	Support Services	-0.009*	0.173
General Retailers	0.001	0.162	Technology Hardware & Equipment	0.000	0.162
Health Care Equipment & Services	0.000	0.162	Travel & Leisure	0.003	0.165
Household Goods & Home Const.	0.005	0.170			

coverage as measures of the industry level investor attention. The overall level of attention of investors to the stock market is measured by a dummy variable of economic recession. The detailed regression results for each industry are not presented here but are available upon request.

4.2.1. Effect of industry size and liquidity

We find that, except for the Insurance industry, the six industries which individually lead the market lose their significance when the interaction term between industry excess returns and industry liquidity or size is added to the regressions. The interaction term pertaining to industry size is statistically significant at the 10% level in twelve cases (in which six are significant at the 5% level), while the interaction term pertaining to turnover is statistically significant at the 5% in eight cases and at the 10% level in four cases. The interaction term between industry return and value traded is statistically significant at the 5% level in seven cases and at the 10% level in two cases. Most interaction terms have the sign opposite to that of the corresponding industry return coefficient, and they drive out the explanatory power of industry returns. The results indicate that the information contained in the returns of those small, illiquid industries, such as Alternative Energy and Industrial Engineering, is slowly incorporated into market return, while the information content of large and liquid industries, such as Banks and Mining, is contemporaneously captured by the market. Our findings provide evidence in support of the gradual-information-diffusion hypothesis that the slow information diffusion from industries to the market may result from delayed investor recognition of information contained in the neglected industries. Our finding that small and illiquid industries are apparently more informative in leading the market is also consistent with that of Naes et al. (2011), who investigate the informativeness of U.S. stock market liquidity for the real economy across stocks and find that small and less liquid stocks are more informative.

4.2.2. Effect of financial analyst coverage

It may be controversial whether the moderation effects of industry size and liquidity on the predictive power of industry returns is indicative of gradual information diffusion due to investor attention or market frictions as size and liquidity are closely related to both of them. Thus, we interact the lagged industry return with two direct measures on investor attention absolute analyst coverage and relative coverage.

The slopes of these interaction variables are statistically significant at the 10% level in two cases and at the 5% level in five cases. Similar to the industry size and liquidity effects, we also observe that the sign of the coefficient of the interaction variable is opposite of that of the lagged industry return in 34 out of 37 industries. The industries of Alternative Energy and Oil & Gas Producers remain significant in leading the market; the other four industries that individually lead the market lose their significance. Three industries (Industrial Engineering, Oil Equipment & Services, and Pharmaceuticals & Biotechnology) have a positive coefficient for both the interaction term and industry return. However, Industrial Engineering and Oil Equipment & Services industries lose their statistical significance in leading the market when the interaction terms enter the regressions.

Therefore, the results of this section confirm the findings of the last section and provide more direct evidence in support of the gradual information hypothesis. The results suggest that the information of those industries that are well covered by financial analysts, such as Banks, Mining, and Construction & Materials, is incorporated into the market more quickly, and the predictive power of industries is substantially moderated by financial analyst coverage.

4.2.3. Effect of business cycle

We construct a business cycle dummy variable that takes a value of one during periods of economic recession and zero otherwise, and test whether the predictive power of industry portfolio returns is moderated by business cycle, a proxy for the overall investor attention to the stock market. We find that the coefficient of the interaction term has a negative sign for all industries, nine of which are statistically significant at the 5% level. Three industries (Alternative Energy, Insurance, and Oil & Gas Producers) lose their statistical significance in leading the market when the interaction term is introduced. For these industries, the coefficient for the industry return has the same sign as that for the interaction term, implying that the industry effect is subsumed by the investor attention effect. Nine industries can significantly lead the market at the 10% level (of which four are significant at the 5% level) when the interaction term is included in the regression. The results suggest that the predictive power of industries is significantly moderated by business cycle, the information contained in industry stock returns is incorporated into the market return more slowly during economic recession. This finding is consistent with the related literature reporting that both the quantity and quality of information decrease during periods of economic contraction (Veldkamp, 2005; Brockman et al., 2010), and investors attend to information less actively when the markets are flat or falling (Karlsson et al., 2009). Therefore, when the overall investor attention decreases during the economic recessions, the information contained in industry returns diffuses across the market with more delay. Our finding alludes to the time-varying predictive ability of industries, which is of interest to future researchers.

4.2.4. Industrial Engineering: an illustration

As an example from a large set of results, Table 6 reports the results of regressing the excess market returns on lagged excess returns on Industrial Engineering, lagged control variables and the interaction terms between industry return and proxies for investor attention. The Industrial Engineering portfolio consists of 25 actively traded stocks, while both its market capitalization and value traded constitute about 0.1% of the whole market on average, and average financial analyst coverage is about 0.53% of all industry coverage over the sample period. As indicated in specification 1 of Table 6, Industrial Engineering portfolio excess return leads the market significantly at the 1% level, while the lagged excess market return has little explanatory power. The result in specification 2 of Table 6 suggests that market volatility, market dividend yield, and term premium are good predictors of the market; however, their predictive power is driven out once the lagged Industrial Engineering excess return enters the regression, as reported in specification 3 of Table 6. The lagged Industrial Engineering portfolio excess return remains significant at the 1% level in the presence of well-known market predictors. Specifications 4 to 6 present the results with an interaction term between lagged Industrial Engineering return and a proxy for industry size and liquidity. The coefficient on the lagged Industrial Engineering excess return loses its significance while all three interaction terms significantly lead the market with an increased adjusted-R². The results suggest that the information contained in Industrial Engineering excess return is essentially captured by industry size and liquidity. Similarly, when an interaction term between industry return and a proxy for financial analyst coverage enters the regression of specification 3, the industry excess return loses its significance in leading

Table 6Predictive ability of Industrial Engineering: an illustration, January 1990 to December 2009. This table presents the results from a regression of the excess market return on lagged excess return on Industrial Engineering portfolio, market fundamentals and a set of interaction variables pertaining to investor attention. The measurements of variable are discussed in Section 2. The p-values are based on heteroskedasticity and autocorrelation consistent standard errors.

Lagged regressors	1	2	3	4	5	6	7	8	9
Intercept	0.001	-0.017	-0.014	-0.012	-0.011	-0.012	-0.012	-0.013	-0.015
Excess market return $(R_{M,t-1})$	-0.030	0.065	-0.019	-0.055	-0.045	-0.043	-0.052	-0.059	-0.023
Excess Industrial Engineering return (R_{t-1})	0.120**		0.100**	0.017	0.022	0.041	0.031	0.042	0.146**
Market volatility $_{t-1}$		-5.902**	-4.615	-3.634	-4.186	-4.468	-4.074	-3.876	-3.808
Dividend yield $_{t-1}$		0.651*	0.555	0.466	0.457	0.496	0.480	0.488	0.577
Term premium $_{t-1}$		0.485**	0.362	0.330	0.319	0.330	0.357	0.350	0.323
Rate of change in the exchange rate _{$t - 1$}		0.058	0.024	0.005	0.018	0.022	0.018	0.017	0.012
$R_{t-1} \times size_{t-1}$				0.730*					
$R_{t-1} \times \text{turnover}_{t-1}$					1.487**				
$R_{t-1} \times \text{value traded}_{t-1}$						0.480**			
$R_{t-1} \times \text{absolute analyst}$ coverage_{t-1}							0.035		
$R_{t-1} \times \text{relative analyst}$ coverage_{t-1}								7.855	
$R_{t-1} \times \text{economic}$ recession dummy									-0.085
R^2	0.056	0.044	0.075	0.091	0.091	0.093	0.086	0.089	0.081
Adj-R ²	0.048	0.024	0.051	0.064	0.064	0.065	0.058	0.061	0.053

Notes: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

the market, as reported in specifications 7 and 8. Specification 9 of Table 6 includes an interaction term between the lagged Industrial Engineering excess return and the dummy variable for economic recession. The coefficient of the interaction term has a negative sign but is not statistically different from zero, and the lagged Industrial Engineering return remains significant in leading the market.

In summary, we find that a few industries significantly lead the market; however, we do not find evidence that the ability of an industry to predict the market is closely related to its propensity to forecast economic growth. Instead, we find that the predictive power of an industry is significantly moderated by the proxies for investor attention, which provides empirical evidence in support of the gradual-information-diffusion hypothesis.

5. Conclusion

In this study, we empirically investigate two issues. First, we investigate whether Australian industries lead the market and whether the ability of an industry to predict the market is closely related to its ability to forecast market fundamentals. Using monthly data of 37 industry portfolios consisting of 1720 ASX-listed stocks over the period of January 1990 to December 2009, we find that the excess returns of six industry portfolios significantly lead the excess market return in the individual industry analyses, and 13 industries significantly lead the market when all industries simultaneously enter the regression. However, we do not find evidence that the ability of an industry to predict the market is closely related to its capacity to forecast economic growth. Instead, we find that the returns of the largest and most liquid industries that are also most followed by financial analysts, such as Banks and Mining industries, can significantly predict future economic growth, while the information contained in these industries is captured by the markets contemporaneously.

⁸ We cannot reject the null hypothesis that the parameters of Industry Engineering Return and the interaction terms in specifications 7 and 8 are jointly zero at the 90% confidence level based on both F and Wald tests.

Second, we examine whether the gradual information diffusion from industries to the aggregate stock market results from investors' attention constraints. We construct three sets of variables as proxies for investor attention: industry size and liquidity, industry financial analyst coverage, and dummy variable of economic recession. The first two sets of variables represent investor attention at the industry level, while the third one indicates the overall investor attention to the stock markets. We then interact these variables with industry portfolio excess returns to test whether the predictive power of industry excess returns is moderated by the proxies for investor attention.

We find that the predictive power of industry return is significantly moderated by the proxies for investor attention. The information contained in the industry portfolio returns is mostly captured or offset by the proxies of investor attention at the industry level. Small and illiquid industries are more informative in leading the markets due to delayed investor attention to information content of these industries. The information of industries followed by more financial analysts is captured by the market more quickly. We also find that an industry's ability to lead the market is sensitive to business cycle. In general, the information contained in industry portfolio returns is incorporated into the market return more slowly during the economic recession when the overall investor attention is lower. Our research provides new empirical evidence in support of the gradual information hypothesis from a market that is significantly different from the U.S. in terms of the industry composition.

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References

Aggarwal, R., Klapper, L., Wysocki, P.D., 2005. Portfolio preferences of foreign institutional investors. J. Bank. Financ. 29, 2919–2946. Barber, B., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Finan. Rev. Stud. 21, 785–818.

Bodnaruk, A., Ostberg, P., 2009. Does investor recognition predict returns? J. Financ. Econ. 91, 208-226.

Brockman, P., Liebenberg, I., Schutte, M., 2010. Comovement, information production, and business cycle. J. Financ. Econ. 97, 107–129.

Campbell, J., Shiller, R., 1988. The dividend–price ratio and expectation of future dividends and discount factors. Rev. Financ. Stud. 1,

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. J. Financ. 63, 1977-2011.

Fama, E., French, K., 1989. Business conditions and expected returns on stocks and bonds. J. Financ. Econ. 25, 23-49.

Fang, L., Peress, J., 2009. Media coverage and the cross-section of stock returns. J. Financ. 64, 2023–2052.

Grullon, G., Kanatas, G., Weston, J.P., 2004. Advertising, breadth of ownership, and liquidity. Rev. Financ. Stud. 17, 439–461.

Hirshleifer, D., Teoh, S.H., 2003. Limited attention, information disclosure, and financial reporting. J. Account. Econ. 36, 337–386.

Hodrick, R., Prescott, E.C., 1997. Postwar U.S. business cycles: an empirical investigation. J. Money Credit Bank. 29, 1–16.

Hong, H., Stein, J., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. J. Financ. 54, 2143–2184.

Hong, H., Torous, W., Valkanov, R., 2007. Do industries lead the stock market? J. Financ. Econ. 83, 367–396.

Hou, K., 2007. Industry information diffusion and the lead-lag effect in stock returns. Rev. Financ. Stud. 20, 1113–1138.

Hou, K., Moskowitz, T., 2005. Market frictions, price delay, and the cross-section of expected returns. Rev. Financ. Stud. 18, 981–1020. Kahneman, D., 1973. Attention and Effort. Prentice-Hall, Englewood Cliffs, New Jersey.

Karlsson, N., Loewenstein, G., Seppi, N., 2009. The ostrich effect: selection attention to information. J. Risk Uncertain. 38, 95-115.

Menzly, L., Ozbas, O., 2010. Market segmentation and cross-predictability of returns. J. Financ. 65, 1555–1580.

Merton, R., 1987. A simple model of capital market equilibrium with incomplete information. J. Financ. 42, 483–510.

Naes, R., Skjeltorp, J.A., Odegaard, B.A., 2011. Stock market liquidity and business cycle. J. Financ. 66, 139-176.

Pashler, H., Johnston, J., 1998. Attentional limitations in dual-task performance. In: Pashler, Harold (Ed.), Attention. Psychology Press, East Essex. UK

Peng, L., Xiong, W., 2006. Investor attention, overconfidence, and category learning. J. Financ. Econ. 80, 563-602.

Veldkamp, L., 2005. Slow boom, sudden crash. J. Econ. Theory 124, 230-257.

Yao, J., Gao, J., Alles, L., 2005. Dynamic investigation into the predictability of Australian industrial stock returns: using financial and economic information. Pac. Basin Financ. J. 13, 225–245.