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BY

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Dedicated to my wife Cindy, my parents Franco and Robyn, and my brother Paul.

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ABSTRACT

I test whether predictable changes in the rate of information flow affect the market risk premium. Four periods of the year when the majority of firms are scheduled to announce earnings account for 70% of realized value-weighted excess returns – but only account for 50% of trading days - from 1926 to 2015. These earnings seasons have average returns of 5.3% and a Sharpe ratio of 0.61 while the remainder of the year has average returns of 2.4% and a Sharpe ratio of 0.25. Using regression-based tests to control for a variety of seasonal effects, I find the market risk premium is up to 17 basis points higher on days when large firms are scheduled to forecast earnings. I then run a series of tests related to (i) market, industry and firm volatility; (ii) cross-sectional measures of market risk; (iii) the retail industry, which delays reporting due to the holiday season; (iv) the relationship between earnings announcements, aggregate earnings and market returns; (v) the January and Wednesday effects; and (vi) economic indicators and macroeconomic cycles. The results support the information flow hypothesis linking earnings announcements to the market risk premium.

CHAPTER 1

INTRODUCTION

I test whether periods that have predictably higher rates of flow of information also have predictably higher expected market returns. Ross [1989] shows the future timing of information flows is irrelevant to the pricing of assets if cash flows are unaffected and the information flows do not affect economy-wide pricing. Whether information flows do in fact affect economy-wide pricing is an unanswered question. Savor and Wilson [2013] find that realized market returns are higher than average in a short window around the release of macroeconomic indicators and attribute this result to macroeconomic risk caused by information arrival. Lucca and Moench [2015] dispute this interpretation and find that higher returns occur only for Federal Open Market Committee (FOMC) announcements, that the higher returns occur the day before the announcement, and that there is no evidence of information leaking prior to the announcement.

Earnings announcements are a good proxy for information flows that affect the aggregate market. Earnings announcements and management forecasts of earnings have incremental information about macroeconomic indicators [Konchitchki and Patatoukas [2014a, 2014b], Gallo, Hann and Li [2016], Hann, Li and Ogneva [2017], Shivakumar and Urcan [2017]) and causally affect market returns (Kothari, Lewellen and Warner [2006], Anilowski, Feng and Skinner [2007], Cready and Gurun [2010], Bonsall, Bozanic and Fischer [2013]). The effect of earnings announcements on the market is largest for "bellwether firms" – typically large firms that are more correlated with the economy and market. While a significant portion of aggregate earnings numbers are anticipated by markets (Sadka [2007], Sadka and Sadka [2009], Ball, Sadka and Sadka [2009]), these results suggest earnings announcements provide incremental timely information related to the pricing of the market portfolio.

Earnings announcements are associated with higher firm-level returns – a result termed the earnings announcement premium (Ball and Kothari [1991], Chari, Jagannathan and Ofer [1988], Cohen, Dey, Lys, Sunder [2007], Frazzini and Lamont [2007], Barber, De George, Lehavy and Trueman [2013], Savor and Wilson [2016]). The main empirical prediction of this paper also relates earnings announcements to expected returns, but is applied at the market level. The firm-level results do not mechanically imply a market-level premium, as the earnings announcement premium is concentrated among small stocks and most studies explicitly control for market returns.

My main tests use two different measures of information arrival. My first measure is based on earnings seasons. Because the majority of firms have December year-ends, earnings announcements are clustered in certain parts of the year. I predict that the market risk premium – the expected return on the market portfolio – is higher during these earnings seasons. My second measure is based on bellwether announcements. Large firms that announce early after quarter or year-end provide relatively more information relevant to pricing the market portfolio. I predict that the market risk premium is higher when these firms are scheduled to announce earnings. Because the focus of this paper is on information flows, the main tests condition on the timing of earnings announcements, but do not condition on the sign of earnings news.

The key result of the first specification is that 67% of the market risk premium from 1927 to 2015 occurs during earnings seasons. Average value-weighted excess returns in earnings seasons are 5.25% (10.78% annualized), while non-earnings seasons have average returns of 2.38% (4.81% annualized).

The key result of the second specification is that average value-weighted excess returns are 9.53 basis points on days when bellwether firms announce earnings, and 1.98 basis points for the remainder of the year. The result is significant at the 1% level. These results are robust to controls for days with macroeconomic releases and large dividends, as well as using a day-of-year fixed effect specification that identifies the bellwether effect through variation in announcement days.

I also test whether proxies for risk and information arrival are higher during earnings seasons and bellwether announcements. Volatility is around 50% higher at the firm and industry levels during earnings seasons and bellwether announcements relative to the rest of the year. This shows that earnings seasons and bellwether announcements capture information arrival. The Sharpe ratio from 1926 to 2015 is over twice as high (0.61) during earnings seasons than quiet periods (0.25).

Retail firms tend to report one month later than the rest of the market, and the retail industry cost of capital, retail industry volatility and retail firm volatility follow a quarterly pattern that is one month later relative to the rest of the US market. The Australian market has a semi-annual reporting regime and shows semi-annual variation in the market risk premium that aligns with earnings announcements. These results show that variation in the market risk premium is aligned with the timing of earnings announcements rather than meteorological seasons, tax year-ends or the holiday season, consistent with the main hypothesis that information flows are higher in earnings seasons and these higher information flows increase the market risk premium.

I next show that investors can accurately infer aggregate earnings within thirty days of the quarter end, because the idiosyncratic component of firm-level earnings diversifies away quickly. These estimates of aggregate earnings news are correlated with signed market returns. Aggregate earnings is a better predictor of returns when firms that report late are left out of the aggregate earnings number, consistent with the result that investors infer aggregate news early in the earnings season, and consistent with earlier tests that show the relationship between earnings announcements and the market risk premium is strongest early in the reporting season.

The information flow hypothesis could explain the January and Wednesday effects. Earnings announcements tend to occur during January and on Wednesdays so may influence these effects (Rozeff and Kinney [1976], Ball and Bartov [1996]). Controlling for bellwether announcements has little effect on the January and Wednesday effects. Interactions between these effects and bellwether firms are highly negative for equal-weighted excess returns – up to negative 15 basis points per day, relative to a January effect of around 15 basis points per day and a Wednesday effect of around 5 basis points per day. A potential explanation of the negative interaction is that earnings announcements from non-bellwether firms in January and on Wednesday 'crowd out' the information from bellwether announcements by providing similar information in a timelier manner.

CHAPTER 2

BACKGROUND AND EMPIRICAL PREDICTIONS

This paper tests the hypothesis that the market risk premium is higher during periods of time when information flows are expected in advance to be relatively high.

Savor and Wilson [2013] study the arrival of information and market returns. They adapt the long-run risk model of Bansal and Yaron [2004] to include periods of high uncertainty. They find that volatility can be driven by long or short-term uncertainty, and that uncertainty related to long-run growth has a larger effect on the market risk premium per unit of volatility. However, they model information arrival as volatility of economic fundamentals. In contrast, Veronesi [2000] and Ai [2010] model aggregate information arrival independent of economic fundamentals, but do not study the effect of time-varying signal precision or information flows. An important result of these papers is that volatility related to information arrival and uncertainty about fundamentals are different constructs and do not necessarily increase the market risk premium.

Empirical evidence is also limited and contradictory. The empirical section of Savor and Wilson [2013] finds that the market risk premium is higher in a three-day window around when CPI, PPI, employment and Federal Open Market Committee announcements are scheduled to be released. They conclude that scheduled information arrival increases the market risk premium. Lucca and Moench [2016] show the results are driven by FOMC releases and that while measures of information arrival increase on the day of the announcement, the predictably high market returns occur in the day preceding the announcement. They conclude there is little evidence that the mechanism outlined in Savor and Wilson [2013] drives the result.

At the aggregate level, Rozeff and Kinney [1976] test for seasonality in aggregate returns and document the "January effect", and conjecture it may be related to earnings announcements, but do not test this theory. Penman [1987] finds that market returns are higher in the first two weeks of the quarter, when the (relatively few) firms that report earnings tend to report good firm-level news, and conjectures a causal explanation. Ball and Kothari [1991] reject the theory that the arrival of good firm-level news causes higher returns, concluding that while firms with earlier announcement dates tend to announce good news early in the season, this does not causally increase market returns early in the season. This is important for my research design as the definitions of earnings seasons and bellwether firms mainly capture early announcements.

Information arrival, risk and expected returns have been studied much more extensively at the firm level. Ball and Kothari [1991] find that firm-level unconditional returns are higher on earnings announcement dates, but the effect is concentrated among small firms so do not necessarily aggregate to the market level. Tests based on hedge portfolios confirm this result and test economic explanations for the result (Chari, Jagannathan and Ofer [1988], Cohen, Dey, Lys, Sunder [2007], Frazzini and Lamont [2007], Barber, De George, Lehavy and Trueman [2013], Savor and Wilson [2016]), but cross-sectional tests by construction cannot mechanically aggregate to the market. None of these papers investigate a premium at the market level.

A key paper relating information arrival to asset pricing is Ross [1989]. Using a no-arbitrage approach, he shows analytically that the volatility of an asset must be equal to the rate of information flow to avoid arbitrage opportunities and that the timing of information flows and the resolution of uncertainty are irrelevant for the ex-ante price of an asset. He notes on page 14 that these results are subject to the assumption "that changing the resolution of uncertainty does not alter the no-arbitrage martingale pricing operator". My results speak directly to whether this assumption holds at the aggregate level.

After the main set of tests I investigate the relationship between information arrival, volatility and risk. Koudijs [2016] provides an extensive discussion of the literature studying information arrival and volatility, while Campbell et al. [1999; section 4.6] and Scruggs [1998] provide overviews of the large empirical literature on volatility and the market risk premium and conclude the extant results are ambiguous and contradictory. More recent research by Guo and Whitelaw [2006] finds a positive relationship between volatility and the market risk premium after controlling for macroeconomic state variables in a multi-factor model. Based on recent research I include measures of industry and firm-level volatility as these may also capture market-level information and risk (Campbell, Lettau, Malkiel and Xu [2001], Ang, Hodrick, Xing and Zhang [2006]). In this paper I do not argue that volatility causally increases the market premium, because of the theoretical results discussed in the beginning of this section. Rather, I use realized volatility as a proxy for both information arrival and risk.

CHAPTER 3

EARNINGS SEASONS, BELLWETHER FIRMS, DATA AND DESCRIPTIVE STATISTICS

The main tests use two complementary tests to investigate how financial reporting impacts the market risk premium. Both test use average realized market returns on the market as a proxy for the market risk premium. The use of data from 1926 to 2015 and for 1975 to 2015 means there are sufficient observations for average returns to proxy for the market risk premium. Claus and Thomas [2001] use a "baseline" estimate of the market risk premium from 1926, citing research by Welch [2000]. The dataset from 1975 uses a longer sample than Lucca and Moench [2016] and a broadly similar regression-based analysis. Because market returns are the dependent variable in the main tests, measurement error will not bias parameter estimates, but will reduce the power of the tests.

3.1 Earnings season definitions and data sources

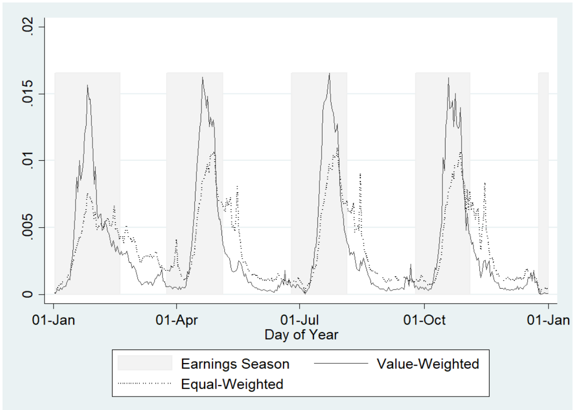
The earnings season tests split each year in the sample into four earnings seasons and four quiet periods. Earnings seasons are constructed to have the same number of days per year as quiet periods to facilitate comparison between the two groups without having to adjust for the number of days in a period.

Most listed US firms have December fiscal year-ends, and almost all of the remaining firms have fiscal year ends in March, June or September. As a result, earnings announcements are clustered in the second to fourth weeks of each calendar quarter. Figure 1 presents a histogram of earnings announcement dates through the year.

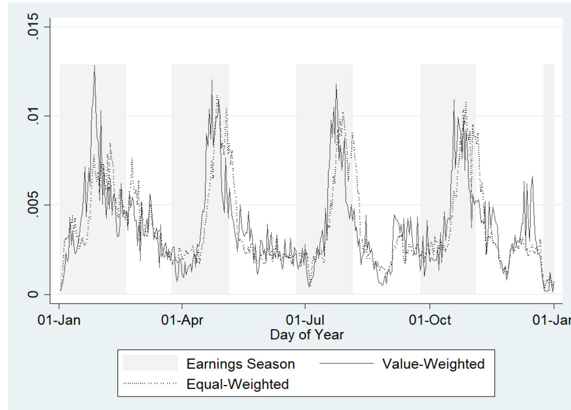
Each earnings season begins on the 24th of the month prior to the end of the quarter, to capture earnings preannouncements and leakage of private information. Before Regulation Fair Disclosure, firms could make selective disclosures of nonpublic information to financial professionals such as securities analysts or institutional investors. The ending of an earnings

Figure 1: Corporate disclosure by season

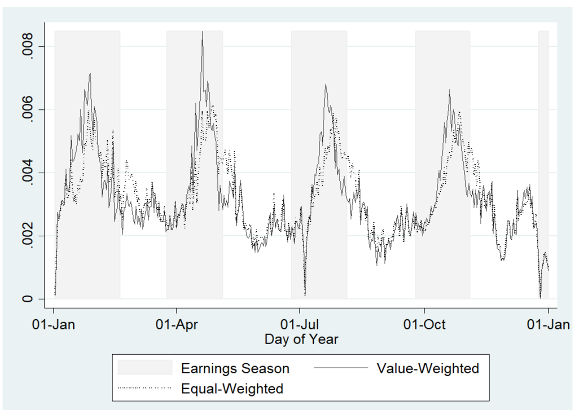
(a) Earnings announcements



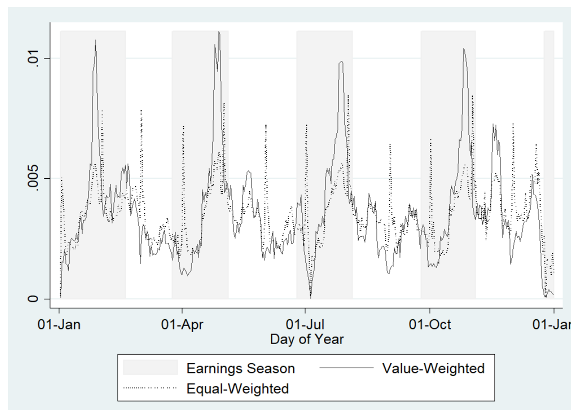
(b) Management guidance



(c) Analyst forecasts



(d) Dividends



season is set to the calendar date that captures 61% of that quarter's earnings announcements for firms with March, June, September or December year-ends. I choose 61% because this sets the number of days in an earnings season equal to the number of days in a quiet period.

Earnings seasons capture the majority of forecasts, guidance and dividend announcement dates. Table 1 and Figure 1 show the distribution of earnings announcements and these disclosures. Because annual reports have more delay between the end of the reporting period and the earnings announcement date, the 'first' earnings season (i.e. late December to mid-February) has 57 days, while the remainder have about 42 or 41. I aggregate to the annual level so differences across quarters do not affect the results.

Table 1 Panel B shows the percentage of total earnings announcements, management

Table 1: Description of earnings seasons, including number of calendar days and summary of disclosure events

Panel A: Calendar days

	Period Start	Period End	Calendar Number of Days
Annual Report	24-Dec	18-Feb	57
Q1	24-Mar	4-May	42
Q2	24-Jun	4-Aug	42
Q3	24-Sep	3-Nov	41
Total			182
Percentage			49.7%

Panel B: Summary of disclosure events

Disclosure Type	Percent During Earnings Seasons (Count %)	Percent During Earnings Seasons (Value-weighted %)
Report dates	63	82
Management guidance	60	60
Analyst Reports	57	61
Dividends	51	57

Panel C: Summary of macroeconomic announcements

Disclosure Type	Percent During Earnings Seasons (%)
FOMC	46
CPI	47
Employment	53
Total	47

Panel A reports the period start and period ends (inclusive) used to define earnings seasons. Each period begins on the 24th of the month prior to the end of the quarter, to capture earnings preannouncements. The ending period is set to the date that captures the earliest 61% of the count of that quarter's earnings announcements. Panel B illustrates the percentage of disclosures occurring during earnings seasons. Panel C illustrates the percentage of macroeconomic announcements that occur during earnings and non-earnings seasons. Federal Open Market Committee, Consumer Price Index, Producer Price Index and Employment releases are selected based on Savor and Wilson [2013], who find these releases are associated with the market risk premium.

guidance, analyst reports and dividend announcements that fall in earnings seasons. Sixty-one percent of earnings announcements occur during earnings seasons. This increases to 82% when firms are value-weighted. Figure 1a shows that firms that report outside earnings seasons tend to report immediately after a season rather than immediately before (for example, they are more likely to report in late February than late December). Bonsall, Bozanic and Fischer [2013] and Frederickson, Lyon and Zolotoy [2012] show that early announcements have a greater effect on market returns, so I prefer to capture management pre-announcements than late earnings announcements. Fifty-nine percent of management guidance and 56% of analyst reports fall in earnings seasons. This is important because management guidance provides timely information that impacts aggregate returns (Anilowski, Feng and Skinner [2007]). Figure 1b to 1d shows value-weighted and equal-weighted histograms of management guidance, analyst recommendations and dividend announcements. Panel C shows key macroeconomic announcements. They are more likely to occur in quiet periods so controlling for these should increase the effect size in the earnings season-based tests.

No realistic definition of an earnings season can capture 100% of earnings announcements. This will understate the effect of earnings announcements on the market risk premium to the extent that earnings announcements in quiet periods reduce time-series variation in information flow. This effect is likely to be small as earnings seasons capture the vast majority of market capitalization-weighted announcements.

Because Compustat earnings announcements dates are only available in detail from 1972 onwards, it is not possible to confirm the distribution of earnings announcements in earnings seasons and quiet periods before this time. Institutional factors likely change the timing and clustering of earnings announcements before 1972, but it is not clear to what extent. Informal analysis of the Wall Street Journal from 1926 to 1950 indicates that many firms have December year ends and provides anecdotal evidence of pre-announcements and management guidance. I use quarterly definitions of earnings seasons for the entire sample period for simplicity and because many firms already reported on a quarterly basis at the start of the sample period, well before it was mandated by the SEC (Taylor [1965], Leftwich, Watts and Zimmerman [1981]). Ex-dividend dates are available from 1926 to 1970 and closely follow the quarterly pattern of ex-dividend dates from 1970 onwards. Untabulated tests show that from 1970 onwards, the average time between an earnings announcement and shares going ex-dividend is 34 days.

3.2 Bellwether definitions and data sources

The bellwether tests identify the announcement dates of firms that are expected to provide comparatively more information to investors, which I refer to as "bellwether firms". If information flows from earnings announcements increase the market risk premium, this effect should be strongest on days where earnings announcements provide relatively more information about the economy. I proxy for bellwether firms using size, as per Anilowski, Feng and Skinner [2007]. While the relative size, exposure to industries, extent of international operations and other aspects of bellwether firms have changed over the sample period, there is no research (to my knowledge) investigating the "net" effect of these changes over time on the macroeconomic news content of bellwether earnings announcements. As a result I do not make specific assumptions about whether the bellwether effect changes over time.

To select the bellwether firms, each December I select companies from 6 portfolios, based on whether they have December year-ends ($\times$ 2) and whether they are in retail, finance or remaining industries ($\times$ 3). For each of the six portfolios I select the largest 25 companies based on enterprise value, total assets, shareholders equity and market capitalization. There is considerable overlap in size metrics. Balance sheet data is based on each firm's annual report. To ensure data is available to investors at the time that bellwether firms are selected, the annual report must be for a financial year end at least six months earlier than the time of selection. As most firms have December year-ends, most firms are ranked on their financial reports from a year earlier.

For each of the six portfolios of 25 companies, I identify the first annual report and the first quarterly report announced in each calendar quarter based on the year of ranking. This creates 12 portfolios per quarter, although some portfolios are empty as, for example, no firms with December year-ends report quarterly earnings in the first calendar quarter. This creates a sample of firms based on their size at the end of the year, with report dates for that year.

To avoid look-ahead bias I then estimate the report date for each firm by taking the three nearest business days to the report date for the following year. This ensures that each estimated report date is based on actual report dates from the prior year, selected by size known by the end of the prior year. As multiple firms can be expected to forecast on a particular date, I consolidate observations resulting in a dataset of trading days and an indicator for whether a type of firm announced on that day. I then sort these indicators into a bellwether category and an alternative category. Bellwether firms are those with December year ends, that are not in finance or retail industries; plus retail firms with non-December year ends. All remaining firms all allocated to the alternative category.

3.3 Data and descriptive statistics

There are two main datasets used in the study. The first consists of returns for earnings seasons and quiet periods. The second consists of daily returns and a series of indicator variables for bellwether announcements and for various controls.

The main tests use data from the CRSP market returns files for daily raw returns and Ken French's data website for the risk-free rate and market excess return. The use of calendar dates to define earnings seasons allows me to begin my sample in 1926, well before Compustat data are available. I calculate market, industry and daily volatility measures by season following Campbell, Lettau, Malkiel and Xu [2001]. Cross-sectional data is from CRSP for beta portfolios, and from Ken French's data website for book-to-market and size decile portfolios and hedge portfolio returns.

Later tests proxy for changes in macroeconomic conditions using log payout ratios, consistent with Campbell and Shiller [1993] and Cochrane [2011]. I calculate log payout ratios as per Boudoukh, Michaely, Richardson and Roberts [2007] using Compustat data.

Table 2 outlines the descriptive statistics for the variables used in the study. Average returns during earnings seasons are higher than those of non-earnings seasons for all measures of market returns. There is practically no difference in the risk-free rate between the earnings seasons and quiet periods. The data for daily regressions show that the standard deviation of value-weighted excess returns is very high relative to the mean excess return. This is to be expected in daily data, but shows that R-squared statistics are likely to be very low. The indicator variables used in the regression tests average around 10%, so there is sufficient variation to run regression tests.

Table 2: Descriptive statistics

Panel A: Seasonal and annual variables

Variable	N	Mean	Std Dev.	Skew	Kurtosis
Return variables					
MKTRF_EARN	89	5.25	12.51	0.30	4.43
MKTRF_QT	89	2.38	13.38	−0.48	3.91
VWRETD_EARN	89	7.03	12.53	0.14	4.34
VWRETD_QT	89	4.00	13.58	−0.55	3.87
EWRETD_EARN	89	17.13	21.81	2.76	15.46
EWRETD_QT	89	8.39	22.04	1.85	11.70
RF_EARN	89	1.32	1.19	0.86	3.25
RF_QT	89	1.31	1.19	0.93	3.64
MKTRF_BELL	41	9.53	19.04	1.23	5.18
MKTRF_REMAIN	41	1.98	7.05	−1.01	4.37
Cross-sectional risk factors					
BETARET_EARN	89	0.03	0.11	2.08	12.52
BETARET_QT	89	0.01	0.08	0.84	6.47
HML_EARN	89	4.16	9.72	0.93	5.18
HML_QT	89	0.50	8.28	0.40	4.85
SMB_EARN	89	1.63	7.61	0.78	5.18
SMB_QT	89	−0.09	7.91	−0.18	4.01
Discount rate variables					
PAY_YLD	89	−3.09	0.28	−0.02	2.06
PAY_GROW	89	0.05	0.16	−0.39	3.94
PAY_YLD(t-1)	89	−3.09	0.28	−0.02	2.05

(Continued on following page)

As expected the volatility measures have very high skew and kurtosis. All tests related to volatility use test statistics that are robust to this. Volatility tends to persist over time,

Table 2, continued

Panel B: Daily variables

Variable	N	Mean	Std Dev.	Skew	Kurtosis
Daily data regressions					
MKTRF	10322	3.09	104.79	−0.59	18.74
BELL_ANN (ind)	10322	0.14			
IRR_ANN (ind)	10322	0.18			
FOMC (ind)	10322	0.12			
EMP (ind)	10322	0.11			
CPI (ind)	10322	0.12			
BIG_DIV_PAY (ind)	10322	0.10			
Daily Volatility measures					
VOL_LATE	13699	0.95	3.97	35.69	2186.44
INDVOL_LATE	13699	0.59	1.19	14.82	461.20
FIRMVOL_LATE	13699	2.90	2.58	7.25	120.71
VOL_EARLY	13799	1.13	4.91	18.82	575.29
INDVOL_EARLY	13799	0.53	4.35	61.32	4328.87
FIRMVOL_EARLY	13799	2.62	9.59	43.35	2397.42

This table presents descriptive statistics of the main variables in the paper. Panel A shows variables measured at an annual or seasonal frequency. Variables ending with EARN are measured during earnings seasons, those ending with QT are measured during quiet periods. Panel B shows variables measured at a daily frequency. (ind) refers to indicator variables. MKTRF refers to value-weighted excess returns. VWRETD refers to value-weighted returns. EWRETD refers to equal-weighted returns. RF refers to the risk-free rate. BELL and REMAIN refer to yearly averages of daily returns in basis points for days when bellwether firms announce earnings and all other days. BELL_ANN and IRR_ANN are indicator variables for days when bellwether firms and irregular bellwether announce earnings.

so all volatility tests use the ratio of earnings seasons and quiet periods. This ensures high volatility periods are compared to high volatility periods, and controls for changes over time in industry and firm volatility. The final two subsections show risk-factor and discount rate variables. These are well known datasets so I only note that they do not appear to follow normal distributions due to their skewness and kurtosis. I use standard errors that are robust to non-normality for all tests involving these variables.

CHAPTER 4

EMPIRICAL METHOD AND RESULTS: EXPECTED RETURNS

4.1 Main tests

The first main prediction of this paper is that the market risk premium is higher during earnings seasons than quiet periods.

Figure 2 Panel A shows cumulative log excess returns from investing from 1926 until 2016 in either earnings seasons or quiet periods. Cumulative log excess returns are almost three times higher for earnings seasons than quiet periods. This holds throughout most of the sample period, so the difference in mean returns is not driven by any one or two events (such as the great depression or global financial crisis). The main result is weakest for the period from around 1975 to 1985, with higher realized returns in quiet periods than earnings seasons.

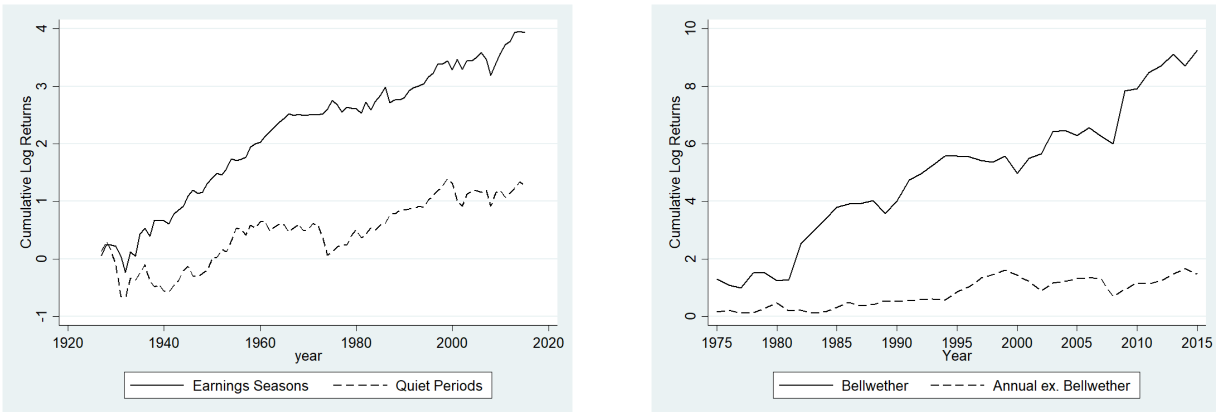
Panel B repeats the analysis using the expected earnings announcement dates of bellwether firms compared to the remainder of the year for the period 1975 to 2015. Cumulative annualized log excess returns are over six times higher for expected bellwether announcement dates. The result holds for most of the sample period, but again appears weakest between 1975 and 1985. Tests reported later in the paper show that dividend-price ratios predict the relative performance of earnings seasons to quiet periods, so the relatively weak result for 1975 to 1985 for both specifications is related to a proxy for the market risk premium and so is unlikely to be driven purely by chance.

I test for a difference in mean returns between periods that have high and low information flows. For each of the measures of the market risk premium, I run a series of difference-in-means tests. For each year I calculate the difference between earnings season and quiet periods returns. This creates an annual univariate time series. I then test whether the mean of the time series has a mean that is different from zero using Newey-West standard errors

Figure 2: Compound log returns

(a) Earnings season

(b) Bellwether announcements



with five lags. This ensures the test statistics and p-values are robust to autocorrelation and heteroscedasticity. Untabulated tests show there is a moderate amount of negative autocorrelation, implying that the error terms partially cancel out over time. Using standard errors that are robust to this autocorrelation will therefore improve the power of the tests. I also include paired t-tests for a simple reference point. In the presence of negative autocorrelation a paired t-test is conservative, because it does not adjust for the fact that errors cancel out over time.

Table 3 Panel A presents a comparison of mean returns between earnings seasons and quiet periods. The first column shows average returns for earnings seasons, the second shows average returns for quiet periods, and the third column is the difference between the two. The last two columns show p-values for the null hypothesis that the difference between earnings seasons and quiet periods is zero using Newey-West and paired t-tests.

The sign on the difference in average returns between earnings seasons and quiet periods is positive and economically significant for all definitions of the equity premium. Average six-month excess returns (MKTRF) are over twice as high for earnings seasons (5.25%) than quiet periods (2.38%). This implies that seventy percent of the equity market premium occurs during earnings seasons that comprise one half of the calendar and trading days in the year. Average raw returns on the value-weighted market portfolio are 7.03% for earnings

Table 3: Tests of difference in average returns, including robustness tests

Panel A: Tests of difference in average returns between earnings seasons and quiet periods

	Average Return (% / Season)			p-value	
	Earn	Quiet	Diff	Newey	t-test
Market risk premium					
Value-weighted excess returns	5.25	2.38	2.88	0.02**	0.07*
Value-weighted raw returns	7.03	4.00	3.03	0.02**	0.06*
Equal-weighted excess returns	17.13	8.39	8.74	0.00***	0.00***
Log value-weighted excess returns	4.42	1.43	2.98	0.02**	0.06*
Log value-weighted raw returns	6.10	3.01	3.10	0.02**	0.05*
Riskfree rate					
Riskfree rate	1.32	1.31	0.01	0.13	0.28
Log riskfree rate	1.32	1.31	0.01	0.13	0.28

Panel B: Test of difference in average returns between bellwether announcement dates and remainder of year

	Average Return (bp / day)			p-value	
	Earn	Quiet	Diff	Newey	t-test
Market risk premium					
Value-weighted excess returns	9.53	1.98	7.55	0.00***	0.02**
Value-weighted raw returns	11.32	3.73	7.59	0.00***	0.02**
Equal-weighted excess returns	15.02	7.52	7.50	0.02**	0.02**
Log value-weighted excess returns	8.94	1.43	7.51	0.00***	0.02**
Log value-weighted raw returns	10.75	3.20	7.55	0.00***	0.02**
Riskfree rate					
Riskfree rate	1.86	1.85	0.01	0.48	0.67
Log riskfree rate	1.86	1.85	0.01	0.48	0.67

(Continued on following page)

seasons and 4.00% for quiet periods. This implies 64% of raw returns occur during earnings seasons. There is no evidence of a difference between the risk-free rate across earnings seasons and quiet periods, so the risk-free rate essentially adds a constant to both seasons' returns, reducing the ratio. The difference in average raw returns across seasons is still economically significant despite the effect of the risk-free rate.

The results are also statistically significant. Using Newey-West standard errors, all measures are significant at the 5% level with p-values of 0.02, except equal weighted returns

Table 3, continued

Panel C: Controls

	Average Return (% / Season)			p-value	
	Earn	Quiet	Diff	Newey	t-test
Late period (1975–2015)					
No Controls	4.04	3.56	0.48	0.77	0.84
Ex. Bellwether Announcements	3.52	3.45	0.08	0.96	0.97
Full period (1926–2015)					
No Control	5.25	2.38	2.88	0.02	0.07*
Ex. Macro announcements	4.72	1.26	3.46	0.01	0.02***
Ex. January	5.08	2.38	2.71	0.06*	0.11
Ex. Wednesday	3.31	0.62	2.69	0.04**	0.12

This reports difference in means tests for a variety of measures of the market risk premium and for the risk-free rate. Panel A reports difference in mean returns between earnings seasons and quiet periods. Panel B reports difference in mean daily returns for expected bellwether announcement days and the remainder of the year. Panel C repeats the analysis of Panel A for excess value-weighted returns, using a variety of controls. p-values for tests of difference in means between earnings seasons and quiet periods are reporting based on Newey West standard errors and a paired t-test. *, ** and *** refer to $p<0.1$, $p<0.05$ and $p<0.01$ respectively.

that are significant at the 1% level. Finally, the t-test is significant at the 10% level for all regressions except equal-weighted returns, which is significant at the 1% level.

Table 3 Panel B tests the difference in expected returns between expected bellwether announcement dates and the remainder of the year. I measure average returns in basis points per day, because the number of days in which bellwether firms announce earnings is not equal to the number of days in the remainder of the year.

Average realized returns are higher during bellwether announcement days than remainder days for all definitions of the market. Bellwether announcements have average excess returns of 9.53 basis points per day, while the average expected excess return for non-announcement days is 1.98 basis points per day. These are equal to 26.9% and 5.6% on an annualized basis so the economic magnitude is large. The risk-free rate is marginally higher during bellwether announcement dates relative to non-announcement dates, but the effect is not economically or statistically significant so I drop analysis of the risk-free rate from further tests. The results for all equity specifications are significant at the 1% level using Newey-West standard errors and at the 5% level using a t-test, except equal-weighted returns which are significant at the 5% level for both p-values.

Panel C shows the main tests using value-weighted excess returns after controlling for a variety of potential variables that may affect the difference in the market risk premium across earnings seasons and quiet periods. To control for these variables I drop the observations and correct for the change in the number of days in a season.

First, I control for macroeconomic indicators. Savor and Wilson [2013] find that days with scheduled releases from the Federal Open Market Committee (FOMC), or of CPI, PPI or employment figures have higher expected returns. The result is significant at the 1% level and the difference in average returns between earnings seasons and quiet periods increases relative to tests without controls for economic releases. This is consistent with the fact that these announcements occur more often in quiet periods.

I next control for the month of January and Wednesdays. Prior research has shown January has higher returns than other months and has more earnings announcements (Rozeff and Kinney [1976]), while Ball and Bartov [1995] show the Wednesday affect is related to earnings announcements. The hypothesis that information flows can explain the Wednesday and January effects is analyzed later in the paper. This goal of this section is to show that earnings seasons are not simply proxies for January or Wednesdays – i.e. that it is a separate effect. These are very conservative tests: ideally I would control for the returns in January and Wednesdays that are not caused by information flows. As this is not possible I drop either January or Wednesdays from the sample and adjust for the change in the number of days per season.

Controlling for January lowers average six-month earnings season returns from 5.25% to 5.08%. There is no effect on quiet periods. The difference between the two periods decreases only marginally from 2.88% to 2.71%. There is a large decrease in statistics significance. The p-values using Newey-West standard errors drop from 2% to 6% after controlling for January. Given the conservatism of this test and the fact that the economic significance of earnings seasons after excluding January remains high, this is strong evidence that the earnings season premium is not driven only by January. The results after controlling for Wednesday are as follows. Both earnings season and quiet periods are reduced by about 2%, and there is a small decrease in the difference between earnings seasons and quiet periods of about 20 basis points. The difference between earnings seasons and quiet periods has a p-value of 4% using Newey-West standard errors. This result implies that the earnings season is not driven only by Wednesday returns, and that Wednesday returns are larger in earnings seasons than quiet periods. The conclusion is that while it is possible that information flows cause the Wednesday and January effects – as investigated later in the paper – earnings seasons are not simply a noisy proxy for these effects. As predicted I find that the market risk premium remains higher during earnings seasons even after controlling for these effects.

The last set of tests provides evidence that bellwether announcements and earnings season returns are economically related. If this is true, controlling for bellwether announcements will attenuate the main results. Because bellwether data is only available from 1975 onwards, I run the earnings season tests using data from 1975 to 2015. Earnings seasons are higher than quiet periods, but the effect is much weaker than the full sample. Running the tests from 1985 to 2015 shows a larger differential, so the weaker result is driven by the middle of the sample rather than the end of the sample. This is important because the persistence of the earnings season effect is evidence that it is not caused by luck or ex-ante observable mispricing that was learned by investors over the time-period.

4.2 Bellwether regressions

The next analysis provides further evidence financial reporting increases the market risk premium. For this I test I use a standard regression approach. If the information content of financial reporting increases the market risk premium, then the market risk premium should be particularly high on the days when earnings announcements are particularly informative about the economy. These tests use the report days of large firms that announce earnings early in the quarter because earnings announcements and management guidance of these firms is particularly informative about the market (Anilowski, Feng and Skinner [2007], Bonsall, Bozanic and Fischer [2015], Frederickson, Lyon and Zolotoy [2012]). The advantage of the regression approach is that I can include multiple controls simultaneously, greatly reducing the chance that omitted correlated variables drive differences in realized returns.

I test this hypothesis by regressing daily market returns on an indicator variable for bellwether announcements and controls. Bellwether announcement dates are estimated from the same quarter one year earlier. This ensures that expected earnings announcement dates are not a function of managers' private information.

The coefficient of interest is for Bellwether, an indicator variable that is equal to one for a three-day window around the expected earnings announcement dates of bellwether firms that reported early in the prior year. I use daily value-weighted market returns less the risk-free rate as the dependent variable. Irregular announcements are bellwether firms from non-standard categories, as outlined in Section 3.2. It is not clear whether announcement dates of the irregular category provide greater information flows. While these firms may provide information that others do not, or provide information during quiet periods when there is greater demand for information, they are smaller and less representative of the general economy.

Table 4 Panel A shows the main results of this section. I run five different specifications. The first is simply a regression of market returns on an indicator variable for bellwether announcements and on an indicator variable for large firms from irregular categories of firm, with year-quarter-season fixed effects to control for seasonality and variation between quarters in the market risk premium. This is a conservative approach, because controlling for seasonality will control for some of the predicted effects of bellwether announcements, which are more likely to occur during earnings seasons. The advantage of this approach is that any variation in year-quarter-season returns that is not caused by bellwether announcements will not be attributed to bellwether announcements.

Table 4: Short-window return around bellwether earnings announcement (1974–2015)

Panel A: Main specification

Dependent variable: *MKTRF*	(1)	(2)	(3)	(4)	(5)
Bellwether	7.88**	9.14***		16.63***	
	(0.02)	(0.01)		(0.00)	
Irregular	−0.18	0.02		4.01	
	(0.95)	(1.00)		(0.33)	
Bellwether					
**Earnings season*			9.11**		18.27***
			(0.02)		(0.00)
**Quiet period*			12.95		17.66***
			(0.12)		(0.01)
Irregular					
**Earnings season*			1.68		8.06*
			(0.64)		(0.10)
**Quiet period*			−7.58		−8.65
			(0.28)		(0.27)
Constant	6.74	7.10	6.13	6.96	1.72
	(0.75)	(0.74)	(0.78)	(0.42)	(0.86)
R-Squared	0.00	0.00	0.00	0.03	0.03
N	10322	10322	10322	10322	10322
Controls	No	Yes	Yes	Yes	Yes
Fixed effects	Y-Q-Son	Y-Q-Son DOW	Y-Q-Son DOW	Y-Q-Son DOW DOY	Y-Q-Son DOW DOY

(Continued on following page)

Consistent with the main prediction, the coefficient on bellwether announcements is positive and statistically significant at the 5% level with a p-value of 0.02. The coefficient of 7.88 means that a bellwether announcement increases the market risk premium by just under 8 basis points per day, or about 22 percent annualized using simple interest. This is economically significant, and large enough to explain a significant portion of the earnings announcement premium and realized annual returns as shown in Table 3 Panel C. The amount is large but not so large to be outside a credible range. It is smaller than the macroeconomic announcements effect of 11.4 basis points documented in Savor and Wilson [2013], the pre-

Table 4, continued

Panel B: Quarterly analysis

	Q1		Q2		Q3		Q4	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Announcement type								
Bellwether	3.36		18.32**		18.89***		29.89**	
	(0.60)		(0.04)		(0.01)		(0.01)	
Irregular	9.13		1.12		2.93		4.88	
	(0.18)		(0.83)		(0.68)		(0.73)	
Bellwether								
** Earnings season*		−2.23		23.07**		12.22		56.98***
		(0.77)		(0.01)		(0.14)		(0.00)
** Quiet period*		20.27*		−18.64		32.97***		−1.28
		(0.05)		(0.35)		(0.00)		(0.93)
Irregular								
** Earnings season*		8.64		4.80		−0.41		27.72*
		(0.27)		(0.43)		(0.96)		(0.08)
** Quiet period*		3.11		−3.98		9.05		−42.63
		(0.76)		(0.66)		(0.52)		(0.13)
Constant	17.64	16.44	−3.84	−4.87	1.84	1.99	−4.18	−5.63
	(0.15)	(0.18)	(0.68)	(0.59)	(0.84)	(0.83)	(0.72)	(0.62)
R-Squared	0.04	0.04	0.03	0.03	0.04	0.04	0.03	0.04
N	2537	2537	2591	2591	2607	2607	2587	2587
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	All	All	All	All	All	All	All	All

Panel A presents regressions of daily value-weighted returns less the risk-free rate on bellwether earnings announcements, irregular category bellwether announcements, interactions with these two announcement types on indicator variables for earnings seasons and quiet periods, and (optionally) controls. Panel B repeats the analysis of Panel A for each quarter separately. Controls consist of FOMC, PPI, CPI and employment releases, and days with large dividend payouts. Y-Q-S refers to Year-Quarter-Season fixed effects. DOW refers to day-of-week fixed effects. DOY refers to a separate fixed effect for each calendar date, i.e. Jan 01, Jan 02... Dec 31. *, ** and *** refer to p<0.1, p<0.05 and p<0.01 respectively.

FOMC announcement drift effect of 49 basis points documented in Lucca and Moench [2015], and the dividend payout effect of 16 basis points documented in Hartzmark and Solomon [2017]. There is no evidence that large "irregular" bellwether announcements are associated with the market risk premium.

I next add a series of controls for events that have been shown to increase the market risk premium - economic announcements, dividend payouts and indicator variables for each day of the week (excluding Friday, which is reflected in the constant term). Announcement dates are estimated from the prior year, with estimated Saturday and Sunday announcements allocated to Monday, day-of-week effects ensure any residual correlation between expected announcement dates and the day of week are controlled for, although this residual correlation is expected to be small due to randomization.

Adding these controls has very little effect on the results. The coefficient on Bellwether is slightly larger at 9.14, and is now statistically significant at the 1% level. The next specification repeats that of model 2, but splits bellwether announcements and irregular announcements into earnings seasons and quiet periods. The coefficient on bellwether announcements interacted with earnings is essentially unchanged and has a p-value of 0.02, however the interaction with quiet periods is slightly higher at 0.13 but is not statistically significant with a p-value of 0.12. Neither of the irregular measures is significant at the 10% level.

The next two specifications add day-of-year fixed effects – one for each day of the year. I keep the year-quarter-season fixed effects. This means that the effect of bellwether announcements on the market risk premium is entirely identified by variation in bellwether announcement dates, because the day-of-year fixed effects control out all predictable seasonality at the daily level. For example, assume that February 01 has a higher market risk premium due to some esoteric tax rule. Controlling for calendar days will mean that the bellwether announcement effect is calculated as the difference in expected returns on February 01 trading days when bellwether firms were scheduled to announce earnings, and expected returns on February 01 trading days where no bellwether firm was scheduled to announce earnings. This ensures the effect of the tax rule is not captured by the coefficient on bellwether announcements. An identifying assumption is that variation in bellwether announcement dates are correlated only with other earnings announcements (it acceptable for the identification strategy if other firms choose to announce on bellwether announcement days as this variation captures changes in information flows). For example, the identification strategy requires that bellwether firms announce later in the quarter when economic conditions are volatile, then the timing of the tax rule is not also delayed.

Controlling for day-of-year fixed effects increases the estimated coefficient on bellwether announcements. The coefficient remains statistically significant at the 1% level. The coefficient on bellwether announcements increases to 16.63, so a scheduled announcement has expected returns of about 16 basis points higher than the same calendar day and after adjusting for the realized returns of the same year, quarter and season. This is equal to approximately 45% per annum using simple compounding. While large, this is in line with the economic magnitude of the macroeconomic announcement, FOMC pre-announcement drift and dividend payment effects. The final specification repeats the specification of model 3 but includes day-of-year fixed effects as per model 4. The coefficients of bellwether announcements interacted with earnings seasons and quiet periods are 18.27 and 17.66 respectively, similar to the prior column, and both coefficients are statistically significant at the 1% level. Irregular announcements interacted with earnings seasons has a coefficient of 8.06 and is weakly significant at the 10% level.

The next set of tests investigates whether this result holds across all four quarters. This is important for two reasons. If the quarterly seasonality in the market risk premium is caused by information flows from earnings announcements, then the bellwether effect should also be present in all four quarters. I do not predict that the effect is higher or lower in any particular quarter. This is because the impact of information flows is a function of the information environment at the time. Bellwether announcements will have more effect when they are high quality and when information flows preceding the announcement are low. While bellwether annual earnings numbers are likely more informative than interim reports, the comparative increase in average earnings quality due to various economic incentives for high quality annual reports is likely to offset the relative importance of bellwether announcements relative to other firms. I refer to this as the ‘crowding out’ effect.

For the quarterly analysis I repeat the specifications of models 4 and 5 of the prior table for each quarter separately. The results are shown in Table 4 Panel B. The first two columns show the first calendar quarter of the year, when most firms announce annual earnings. The coefficient on bellwether announcements is 3.36, smaller than the pooled annual effect and not significant at the 10% level. This is consistent with a crowding out effect. The coefficient on Irregular announcements is larger at 9.13, but is again not significant at the 10% level. The Irregular firm definition includes large firms with a non-December year end (as long as they are not retail firms). Many of these irregular firms report interim numbers early in January, so this larger effect for Irregular announcements is consistent with a crowding out effect. The only other coefficient of interest that is significant in the first quarter is for the indicator for bellwether announcements that occur during quiet seasons. The coefficient of 20.27 is positive and has a p-value of just over 0.05. The definition of bellwether firms includes retail firms that report annual earnings in the first quarter, so this positive coefficient is as expected under the information flow hypothesis. Analysis in the next section using nonparametric estimates shows that retail firms with January year-ends tend to report late in the first quarter and that the industry has higher returns and volatility during this reporting period.

The coefficient on bellwether announcements is 18.32, 18.89 and 29.89 for quarters 2 to 4. The higher values are consistent with bellwether reporting being relatively more informative outside of annual reporting seasons. The coefficients are significant at the 5%, 1% and 1% levels respectively. These coefficients are economically significant. The value of 29.89 basis points is extremely large relative to macroeconomic announcements and the dividend effect, but is smaller than the pre-FOMC announcement effect. For specification (2), the interaction between bellwether announcements and earnings seasons is positive for quarters 2 to 4 and statistically significant at the 5% and 1% levels for quarters 2 and 4, while the interaction with quiet periods is positive with a coefficient of 32.97 and statistically significant at the 1% level for quarter 3. This is consistent with nonparametric tests in the next section that show that the quarterly increase in the market risk premium that occurs around the peak of each earnings season is delayed for quarter 3. Finally, the coefficient on Irregular announcements during quiet periods is -42.63 in the fourth quarter, but this is not statistically significant at the 10% level. Untabulated tests show that there is not much variation in reporting dates for irregular bellwether firms in the quiet period of the fourth quarter, so the estimated coefficient has a large standard error as there are few observations available to estimate the coefficient. However, the result is not necessarily spurious (although the point estimate is inaccurate) as there is a large spike in non-December year-end firms announcing earnings in late December.

To conclude, the analysis in this section shows that the market risk premium is particularly high during periods when bellwether firms are expected to announce earnings. This holds for a variety of specifications, including a simple regression of excess returns on an indicator variable for bellwether announcements and year-quarter-season controls, to complex specifications including year-quarter-season, day-of-week and day-of-year fixed effects. The bellwether effect on the market risk premium is weakest in the first calendar quarter, when the relative importance of bellwether announcements is likely to be low. However, there is evidence that bellwether firms that report late in the first quarter increase the market risk premium. It is possible that these are retail firms. I investigate this possibility later in the paper. Overall, the results of this section are consistent with the hypothesis that anticipated increases in information flows increase the market risk premium.

4.3 Nonparametric estimates

The last set of tests in this section of the paper use an exploratory approach to see whether the seasonality of expected returns corresponds to the quarterly seasonality in earnings announcements. I use nonparametric methods to identify variation in the market risk premium in calendar time. The advantage of this approach is it shows whether the main result is robust to alternative definitions of earnings seasons and quiet periods.

I plot a value-weighted histogram of earnings announcements by calendar date, equivalent to Figure 1a. I begin the sample in 1974 and include earnings announcements up to 2015. Next, I take daily value-weighted excess returns from 1974 to 2015, and winsorize these at the 5% level to mitigate the impact of outliers, which can be large in daily returns data. I then apply kernel smoothing to estimate expected returns by calendar date. Confidence intervals are based on estimating mean returns for each calendar date independently. The prediction of quarterly seasonality is a joint hypothesis involving all calendar dates simultaneously, so the confidence intervals do not speak directly to the "confidence" that there is a quarterly pattern.

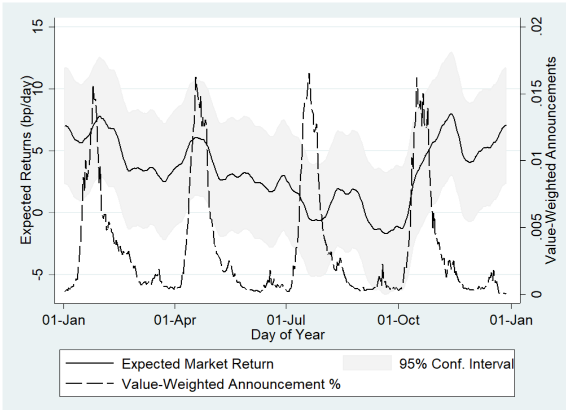
Figure 3a shows a histogram of earnings announcements and a nonparametric estimate of the market risk premium by calendar day. There are clear annual pattern in expected returns. Expected returns peak in early January and then trend downwards until early October. From October expected returns increase until mid-November, followed by a small dip over December that recovers to the early January peak.

Within this trend there is a clear series of a quarterly pattern in expected returns. A large jump occurs around the beginning of December and peaks in early January, before slowly decaying until April. This closely matches the distribution of annual earnings announcements. There is a second large jump in October and smaller, more sudden peaks at the end of April, September and October. The April and October spikes in expected returns coincide closely with the distribution of earnings announcements for quarterly reporting. Contrary to prediction, the September peak appears later, corresponding to the end of the season. There are also much smaller increases in expected returns around the last month of each quarter. While these are small relative to the 95% confidence intervals, they occur in March, June and December. Overall, I conclude there is a strong relationship between the historical distribution of earnings announcements and expected returns for three of the four earnings seasons in a year.

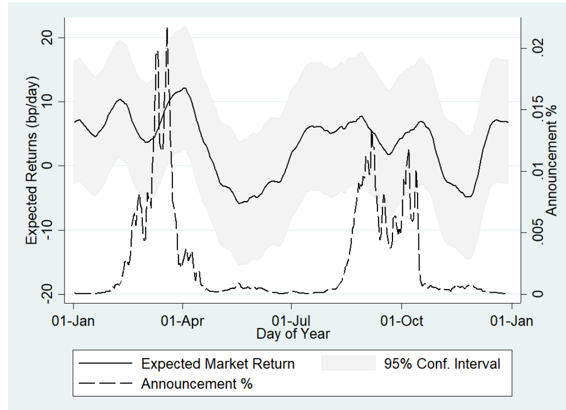
I next repeat the above analysis using Australian data. Australian firms report earnings

Figure 3: Expected market returns for equity indices by calendar day

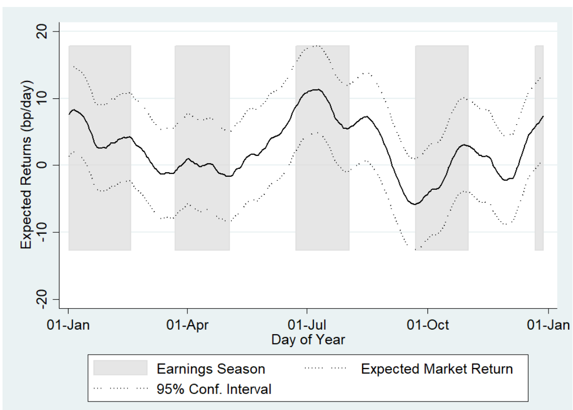
(a) US (1975 - 2015)



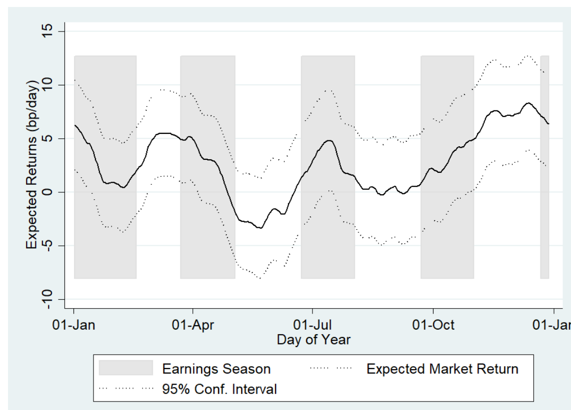
(b) Australia (2006 - 2015)



(c) US (1946 - 1974)



(d) US (1926 - 1945)



on a semi-annual basis, so if earnings announcements drive observed seasonality in expected returns then Australian markets should show semi-annual increases in expected returns. For this analysis I use value-weighted preliminary earnings announcement dates from Compustat Global, and proxy for value-weighted market returns using the ASX All Ordinaries Total Return Index from IHS Global Insight. I begin the sample in 2007 for earnings announcements because data validation shows a number of data errors in the Compustat Global database before this date. IBES earnings announcement data follows a similar pattern, with a relatively larger peak in August and a smaller peak in October. I use data from 2005 onwards for Australian returns to correspond to the Australian adoption of IFRS.

The analysis is presented in Figure 3b. Australian reporting is clustered in two distinct periods of the year, consistent with the fact that the majority of firms have June year-ends, and most of the remainder have December year ends. Australian announcements are less timely than US announcements, and do not align with the holiday season, Australian winter, calendar year ends, or fiscal-year ends. This is important because it distinguishes the main hypothesis – that the market risk premium is higher during earnings seasons due to scheduled information flows – from potential alternative hypotheses such as reduced attention during holidays, the impact of weather due to meteorological seasons, or tax-related trading.

Expected returns predominately follow a semi-annual pattern, with a large trough corresponding to the quiet periods in June and a slightly smaller trough in the quiet period in November. There are smaller peaks in late September and mid-October, which correspond to value-weighted annual announcement dates. There are also small peaks in February and early April, which correspond to the beginning and end of earnings season. Given the quarterly spikes for expected returns in the US and semi-annual patterns in Australia, both of which correspond with earnings seasons, I conclude there is reasonably strong evidence that seasonal patterns in earnings announcements correspond to patterns in expected returns.

Figures 3c and 3d show US data for the periods 1946 to 1974 and 1926 to 1945. While earnings announcement data for these periods are not available, a broad quarterly pattern is visible in both sub-samples. While quarterly reporting was only mandated by the SEC in the 1970s, Taylor [1965] and Leftwich, Watts and Zimmerman [1981] report that in response to prompting by the NYSE, 37% of NYSE-listed firms had agreed to report quarterly earnings by 1927, with another 15% agreeing to report half-yearly earnings.

The period 1946 to 1974 has a strong peak around early July, with a second large peak in early January. There are smaller peaks in late October and early August which are similar to those seen in the 1975 to 2015 subsample. The earliest sample, 1926 to 1945 again has clear peaks in January and July. There is a large peak at the end of the first calendar quarter, and expected returns increase in the fourth quarter but do not form a peak.

CHAPTER 5

EMPIRICAL METHOD AND RESULTS: INFORMATION ARRIVAL AND RISK

5.1 Volatility and Sharpe ratios

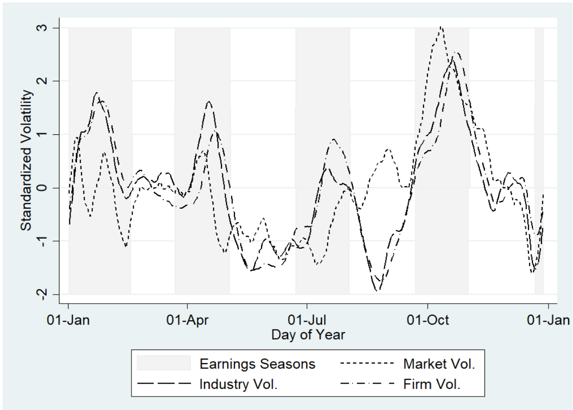
If the market risk premium is higher during periods of high information flows because information arrival increases market risk, then proxies for both risk and information arrival should be higher during earnings seasons and bellwether announcements.

Volatility is a common proxy for information, so the tests validate the selection of earnings seasons and bellwether firms. I repeat the analysis of Figure 3 using nonparametric estimates of volatility rather than returns. I measure volatility at the market, industry and firm-levels, following Campbell, Lettau, Malkiel and Xu [2001]. I standardize the seasonal estimates to allow easy comparison across volatility measures. After the nonparametric analysis I investigate differences in volatility between earnings seasons and quiet periods, as well as between bellwether announcements and the remainder of the year.

Figure 4a shows nonparametric estimates by calendar year. There is a clear quarterly pattern that corresponds to earnings seasons. The largest peak occurs during the fourth calendar quarter, consistent with the results of Figure 3a. All measures tend to move together on average. Market volatility appears to peak earlier than the other measures, which implies investors infer aggregate earnings news faster than industry (and firm) news in calendar time. A likely explanation is that the noise in aggregate earnings news diversifies away faster than industry and firm news. Market volatility is unusually high in September relative to industry and firm volatility. This corresponds to the increase in expected returns that occurs at the end of the third quarter. Finally, market volatility appears to drop off quickly at the beginning of the year and then rebound, while industry and firm volatility are high throughout the first calendar quarter (corresponding to the period the majority of firms release their annual reports).

Figure 4: Nonparametric estimates of volatility

(a) Annual



(b) Quarterly

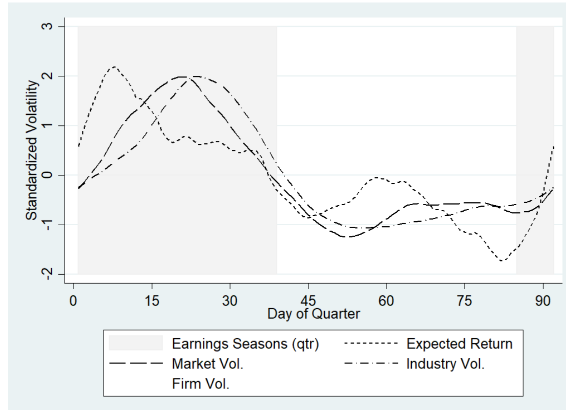


Figure 4b presents quarterly analysis of market, industry and firm volatility. There is a clear quarterly cycle, with market volatility peaking around day 15 and industry and firm volatility peaking around day 20. The earlier peak for market volatility is consistent with market news being learned faster than more idiosyncratic types of news. There is a much smaller increase in all types of volatility around day 60, which aligns with a small increase in earnings announcements.

I next analyze volatility at the market, industry and firm level using formal statistical tests. All measures use daily volatility to avoid having to divide monthly volatility between earnings seasons and quiet periods, and because bellwether announcement dates are not sequential. Aggregate industry and firm volatility are calculated following Campbell, Lettau, Malkiel and Xu [2001]. For each year I calculate the ratio of earnings season to quiet period volatility and bellwether announcement to non-announcement volatility for each of the three measures. I bootstrap the distribution of these ratios to calculate standard errors. I also include a robust estimate of the difference in market volatility which is not available for industry and firm volatility as these are averages over squared returns.

Table 5 Panel A presents the volatility results. The ratio of market volatility during earnings seasons to quiet periods is 1.02, but the robust and bootstrapped p-values are much larger than 0.1. There is no evidence that market volatility is higher in earnings seasons than quiet periods based on these tests for subsamples or for bellwether firms. The late period (1975 onwards) has a ratio of 1.07. While this is economically significant the robust and bootstrapped standard p-values are not significant at the 10% level. Taken at face value, these results suggest that the arrival of market-level information is not on average higher during earnings seasons than quiet periods. However, the nonparametric tests showed that market-level volatility peaks relatively quickly in earnings seasons and then quickly drops off, so these peaks may not persist long enough to affect season-based measures. There is also a significant peak in market-level volatility in the quiet-period of the third calendar quarter, which aligns with both the nonparametric estimates of the market risk premium shown in Figure 3a and with the bellwether analysis in Table 4 Panel B.

There is stronger evidence of differences in industry and firm-level volatility. The ratio of industry volatility across earnings seasons and quiet periods is 1.47 for the late and very late samples, and 1.67 for the early sample. These effects are weakly significant, with p-values of 0.08, 0.08 and 0.10. Firm volatility is also higher during earnings seasons, with ratios of 1.38, 1.38 and 1.52 for the full sample (1926 to 2015), late (1975 to 2015) and very late periods (1985 to 2015). The effects are significant at the 10% level, with p-values of 0.06, 0.06 and 0.02. Firm-level volatility is slightly higher during bellwether announcements but the difference is not statistically significant. I conclude there is reasonable evidence that industry and firm-level volatility are higher during earnings seasons. This is particularly important because it provides evidence that earnings seasons and expected bellwether announcement dates capture information arrival, and so help validate the choice of these proxies. Second, models incorporating investor heterogeneity and barriers to trade show that industry and firm-level volatility can be priced in equilibrium. Goyal and Santa-Clara [2003] provide empirical evidence consistent with these models, finding that average stock variance, which is largely idiosyncratic, predicts market returns while market variance has no forecasting power.

I also calculate Sharpe ratios for each of the time series. I bootstrap the difference

Table 5: Volatility and Sharpe ratio tests

Panel A: Volatility ratios

	Market			Industry		Firm	
	Ratio	Robust	Boot	Ratio	Boot	Ratio	Boot
Full (1926–2015)	1.02	0.97	0.41				
Late (1975–2015)	1.07	0.14	0.18	1.47	0.08*	1.38	0.06*
End (1985–2015)	1.00	0.97	0.93	1.47	0.08*	1.38	0.06*
Early (1926–1974)	0.99	0.27	0.75	1.67	0.10*	1.52	0.02**
Bellwether (1975–2015)	1.01	0.67	0.72	1.15	0.38	1.06	0.68

Panel B: Sharpe ratios

	Full	Earn	Quiet	Diff	Boot-norm	Boot-pct
Full (1926–2015)	0.37	0.61	0.25	0.36	0.07*	0.03**
Late (1975–2015)	0.42	0.47	0.46	0.01	0.97	0.49
End (1985–2015)	0.37	0.56	0.29	0.28	0.50	0.20
Bellwether (1975–2015)	0.34	0.72	0.13	0.59	0.01***	0.00***

Panel C: Sharpe ratios - bellwether

Period	Bellwether	Static	Diff	Boot-norm	Boot-pct
Late (1975–2015)	0.48	0.41	0.07	0.26	0.14

Panel A presents tests of the difference in daily volatility between earnings seasons and quiet periods as well as between bellwether announcements and the remainder of the year. Robust refers to robust p-values for differences in volatility, Boot refers to p-values calculated using a normal approximation for the distribution of the test statistics and standard errors estimated from a bootstrap procedure of the annual ratio of the two periods. Panel B presents estimates of the Sharpe ratio between earnings seasons and quiet periods. Boot-norm refers to p-values defined as per Panel A. Boot-pct reports the percentage of bootstrap samples where low information periods have a higher Sharpe ratio than high information periods. Panel C reports Sharpe ratios for two alternative trading strategies. Static maintains a 40/60 ratio of equities to the risk-free rate, while Bellwether allocates 100% of the portfolio to equities on bellwether announcement dates and 40/60 otherwise. Boot-norm and Boot-pct are defined as per Panel B. *, ** and *** refer to $p<0.1$, $p<0.05$ and $p<0.01$ respectively.

between earnings season and quiet period Sharpe ratios. This is relatively straight-forward because both seasons have the same number of days. The analysis is more complex for the Sharpe ratios of bellwether firms. Untabulated analysis finds the results are not robust to the different ways to annualize Sharpe ratios for bellwether announcement and non-announcement periods. Instead, I calculate the Sharpe ratio for two alternative trading strategies. One invests 40% in the market and 60% in the risk-free rate. I call this the "Static" strategy. The other strategy allocates 100% of funds to the market when bellwether firms are expected to announce earnings, and follows the 40/60 rule otherwise. I call this the "Bellwether" strategy. This approach allows me to quote annual Sharpe ratios without relying on particular assumptions. Because Sharpe ratios are not affected by borrowing at the risk-free rate, the difference in Sharpe ratios is attributable to changes in average realized returns and average realized volatility across bellwether announcement dates and non-announcement dates. Industry and firm-level measures are not available for the full sample, as I use different industry definitions in the early period.

Table 5 Panel B investigates Sharpe ratios across earnings seasons and quiet periods. The first row presents results for the full sample. The Sharpe ratio from 1926 to 2015 is 0.37. The Sharpe ratio during earnings seasons is 0.61, but only 0.25 during quiet periods, so Sharpe ratios are more than twice as high during periods of high information flows. The p-value for difference in Sharpe ratios is 0.07, but only 3% of bootstrapped Sharpe ratios are less than zero, implying that the distribution of Sharpe ratios is right-skewed. I repeat the analysis for late, very late and early samples. There is no evidence of a difference in Sharpe ratios in the late sample from 1975 onwards, but average Sharpe ratios are twice as high in earnings seasons than quiet periods from 1985 onwards. Finally, the results for the pre-1975 period show that Sharpe ratios are over 5 times higher in earnings seasons than quiet periods. The last panel of Table 5 shows Sharpe ratios for bellwether and static trading strategies. The bellwether Sharpe ratio is higher than the static strategy, but the difference is relatively small at 0.07 relative to a static Sharpe ratio of 0.41 and the effect is not statistically significant at the 10% level.

The Sharpe ratio results are important for two reasons. First, they show a non-linear relationship between (expected) market volatility and the market risk premium, consistent with the theoretical results of Veronesi [1999] and Savor and Wilson [2013]. Second, the Hansen and Jagannathan Bound [1991] states that the ratio of the standard deviation of the stochastic discount factor to its mean (the risk-free rate) exceeds the Sharpe ratio of any portfolio.

5.2 Cross sectional risk factors

5.2.1 Risk factor expected returns

Asset pricing predicts that firms with greater exposure to macroeconomic or market risks have higher expected returns than firms with lower exposure to these risks. This spread in expected returns captures the difference in risk between high risk and low risk stocks. If the higher expected returns identified in earnings seasons are caused by greater risks resulting from the clustering of earnings announcements, then the spread between high and low risk firms should be higher in earnings seasons than in quiet periods.

This section tests the prediction that the increase in expected returns during earnings seasons is greater for stocks with greater exposure to macroeconomic risk. I measure exposure to macroeconomic risk using CAPM Beta as well as the size and book-to-market factors studied in Fama and French [1992, 1993]. CAPM Beta measures exposure to market risk, while Petkova [2006] and Campbell, Polk and Vuolteenaho [2010] show that the Fama and French factors proxy for innovations in variables related to risk and investment opportunities. Based on this literature I predict that risks that increase the market risk premium will also increase expected returns on hedge portfolios that reflect cross-sectional exposures to market risk.

The results of this section are reported in Table 6. Broadly consistent with prior results (Cochrane [2011]), average annual returns are higher for high Beta stocks than low Beta stocks, with the exception of the tenth decile Beta portfolio. Untabulated analysis finds that average returns for the highest and lowest Beta portfolios are not robust to changes in the definition of a financial year, so I exclude portfolios one and ten in later tests using hedge portfolios. The DIFF column is positive for all ten decile portfolios, so average realized returns are higher in earnings seasons than quiet periods for all 10 decile portfolios.

Table 6: Tests of difference in average cross sectional returns between earnings seasons and quiet periods

Panel A: Beta decile portfolios (equal weighted)

	Total	Earn	Quiet	Diff	pvalue
High Beta	51.10	25.78	10.30	15.48	0.00***
Decile 2	32.19	18.68	8.23	10.45	0.00***
Decile 3	29.09	17.04	7.85	9.20	0.00***
Decile 4	28.54	16.55	7.82	8.73	0.00***
Decile 5	26.02	14.72	8.14	6.58	0.00***
Decile 6	25.74	15.63	7.54	8.08	0.00***
Decile 7	25.24	14.70	8.00	6.70	0.00***
Decile 8	22.09	13.21	7.22	5.99	0.00***
Decile 9	19.72	12.64	5.90	6.74	0.00***
Low Beta	27.04	16.97	8.05	8.92	0.00***

Panel B: Book-to-market decile portfolios (equal weighted)

	Total	Earn	Quiet	Diff	pvalue
Value	18.19	12.37	3.66	8.71	0.00***
Decile 2	18.21	11.08	4.86	6.22	0.00***
Decile 3	16.11	9.84	4.49	5.35	0.00***
Decile 4	13.50	8.45	3.63	4.82	0.01***
Decile 5	14.12	8.71	4.15	4.56	0.01**
Decile 6	13.22	8.24	3.89	4.35	0.01**
Decile 7	12.67	7.16	4.23	2.93	0.07*
Decile 8	11.94	7.27	3.95	3.33	0.05*
Decile 9	12.00	6.83	4.62	2.21	0.21
Growth	10.99	5.53	4.72	0.81	0.66

Panel C: Size decile portfolios (equal weighted)

	Total	Earn	Quiet	Diff	pvalue
Small	20.74	13.88	3.49	10.39	0.00***
Decile 2	18.54	11.44	3.95	7.50	0.00***
Decile 3	17.30	10.69	4.37	6.32	0.01***
Decile 4	16.50	9.94	4.66	5.28	0.02***
Decile 5	15.56	9.32	4.61	4.72	0.02***
Decile 6	15.67	9.26	4.84	4.42	0.03***
Decile 7	14.62	8.60	4.59	4.01	0.03***
Decile 8	13.85	7.89	4.80	3.09	0.08*
Decile 9	12.98	7.49	4.47	3.02	0.08*
Large	11.19	6.49	3.98	2.51	0.10

(Continued on following page)

Table 6, continued

Panel D: Beta decile portfolios (value weighted)

	Total	Earn	Quiet	Diff	pvalue
High Beta	8.91	6.42	2.49	3.93	0.00***
Decile 2	10.96	7.35	3.62	3.73	0.01**
Decile 3	11.65	7.43	4.23	3.20	0.04**
Decile 4	11.50	7.38	4.13	3.25	0.05*
Decile 5	12.52	7.50	5.02	2.48	0.17
Decile 6	13.56	8.03	5.54	2.49	0.24
Decile 7	12.75	7.72	5.03	2.69	0.23
Decile 8	11.37	7.51	3.86	3.65	0.15
Decile 9	11.02	8.06	2.97	5.09	0.05*
Low Beta	9.87	7.83	2.04	5.79	0.07*

Panel E: Tests of difference in hedge portfolios

	Average Return (% / Season)			p-value	
	Earn	Quiet	Diff	Newey	ttest
Beta	3.91	0.92	2.98	0.04**	0.04**
HML	4.16	0.50	3.67	0.00***	0.00***
SMB	1.63	−0.09	1.72	0.09*	0.08*
SMB (ex 2015)	1.82	−0.21	2.02	0.04**	0.03**

This table reports difference in average cross sectional returns between earnings and non-earnings seasons. Panel A shows average returns for ten decile portfolios sorted on Beta. Panel B shows average returns for ten decile portfolios sorted on book to market. Panel C shows average returns for ten decile portfolios sorted on market equity. Panel D shows value-weighted average returns for portfolios sorted on Beta. Columns show total annual returns, returns during earning seasons, returns during quiet periods, the difference between average returns during earnings and non earnings seasons, and the p-value for a paired t-test for the difference in returns for each portfolio. Panel E shows excess returns from investing in a zero-investment hedge portfolio based on Beta, HML, SMB or SMB excluding the year 2015. p-values for tests of difference in means between earnings seasons and quiet periods are reporting based on Newey West standard errors and a paired t-test. *, ** and *** refer to p<0.1, p<0.05 and p<0.01 respectively.

The main prediction of this section is that DIFF is greater for high Beta portfolios than low Beta portfolios, with the exception of portfolio ten. The higher annual returns for portfolio ten imply that stocks in this portfolio are on average more risky than other decile portfolios, despite having a lower estimated Beta. Visual inspection indicates that DIFF decreases monotonically for deciles one to five, is roughly flat for deciles six to nine, and increases significantly at decile ten, which is broadly in line with the predicted relationship.

Panels B and C display average portfolio returns for book-to-market and size decile portfolios. Average annual returns decrease monotonically with size and increase monotonically with book-to-market, consistent with prior literature. For both book-to-market and size, DIFF also increases monotonically with the measure of risk. For both variables, this result is driven almost entirely by changes in average earnings season returns - quiet period returns are essentially flat across all deciles. Panel D tests whether the highest and lowest decile portfolio results of Panel A are caused by equal-weighting, by calculating value-weighted Beta portfolios. The relationship between Beta and returns is even worse. Fama and French [1992] find that Beta and size are highly correlated, so it is likely value-weighting removes most of the variation in Beta across portfolios.

I conclude this section by running formal statistical tests of the hypothesis that the effect of the earnings season premium is greater on stocks with greater exposure to macroeconomic or market risk. Panel E documents the results. For all hedge portfolios, the majority of returns are occur during earnings seasons. The differences for hedge portfolios formed on Beta, book-to-market and size are significant at the 5%, 1% and 10% levels respectively using Newey-West standard errors. The size hedge portfolio includes a significant outliner in the final year of the sample. For reference I remove this year and report the results in the row labelled "SMB (ex 2015)". The magnitude of the change in the earnings season and quiet period columns indicates the extent of the outliner. The difference between columns increases from 1.7% to 2%, and tests of difference between earnings season and quiet period hedge portfolio returns are now significant at the 5% level.

5.2.2 Risk factor volatility

Table 7 Panels A and B present the volatility ratios for the Fama and French [1992] high-minus-low (HML) and small-minus-big (SMB) factors. I do not include high-Beta minus low Beta as this is correlated with the market return by construction, and market returns were analyzed earlier. Petkova [2006] and Campbell, Polk and Vuolteenaho [2010] show that the

HML and SMB factors proxy for innovations in variables related to investment opportunities and risk related to future cash flows and discount rates, so factor volatility will be correlated with news arrival or uncertainty regarding investment opportunities and economy-wide risks. This uncertainty will in turn increase expected returns on hedge portfolios and the market risk premium.

Table 7: Tests of volatility ratios for cross-sectional risk factors

Panel A: High book-to-market minus low book-to-market hedge portfolio

		p-value	
	Volatility Ratio	Robust	Bootstrap
Earnings season vs quiet period			
Full (1926–2015)	1.05	0.00***	0.03**
Late (1975–2015)	1.10	0.00***	0.00***
End (1985–2015)	1.10	0.01***	0.01***
Early (1926–1975)	1.02	0.08*	0.43
Bellwether vs remainder			
Late (1975–2015)	1.14	0.01***	0.01***

Panel B: Small-minus-big hedge portfolio

		p-value	
	Volatility Ratio	Robust	Bootstrap
Earnings season vs quiet period			
Full (1926–2015)	1.09	0.00***	0.03**
Late (1975–2015)	1.21	0.00***	0.00***
End (1985–2015)	1.16	0.00***	0.00***
Early (1926–1975)	1.02	0.36	0.72
Bellwether vs remainder			
Late(1975–2015)	1.02	0.89	0.75

This table reports differences in volatility for cross-sectional measures of risk. Panel A shows results for high-minus-low hedge portfolios. Panel B shows returns for small-minus-big hedge portfolios. Robust refers to robust p-values for differences in volatility, Boot refers to bootstrapped estimates of differences in the annual ratio of the two periods. *, ** and *** refer to p<0.1, p<0.05 and p<0.01 respectively.

The results for HML and SMB factor volatility support this hypothesis. HML volatility is economically significant for the full sample. The results of both robust tests and bootstrapped tests of the volatility ratios show that the full sample is economically significant at the 1% and 5% levels respectively. This result holds for the late, very late and bellwether announcement samples, although it is much weaker in the early period (pre-1975). The result that announcements of Bellwether firms increase HML factor volatility– a proxy for macroeconomic risk – by almost 15% is particularly important given that early analysis found little relation between bellwether announcements and market volatility.

Analysis of SMB factor volatility in panel B shows that earnings seasons have higher SMB volatility for the full sample, but this effect occurs mainly in the late sample. There is no evidence that bellwether announcements drive SMB volatility. Because bellwether firms are all large, it is reasonable that these announcements do not provide much information about risks captured by differences between small and large firms.

CHAPTER 6

EMPIRICAL METHOD AND RESULTS: ACCOUNTING INFORMATION

6.1 Retail industry tests

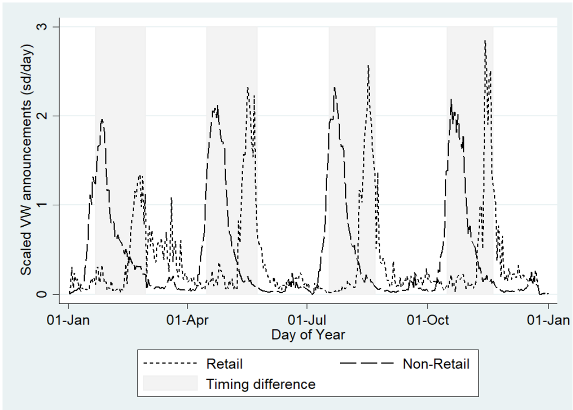
The goal of this section is to provide more evidence linking earnings announcements, measures of risk and the market risk premium. Many retail firms have January year ends due to the relative importance of the December holiday period for sales. I predict that volatility and expected returns for the retail industry will follow a quarterly seasonal pattern, but delayed one month relative to non-retail firms. Due to the importance of the fourth quarter for retail firms, I expect the effect to be strongest for annual reporting. The predictions assume macro information in retail earnings is not pre-empted by the information in the earnings of December-year end firms, which is reasonable as the retail industry has exposure to macroeconomic indicators such as consumer sentiment and employment figures.

I first compare the distribution of earnings announcement days of retail and non-retail firms. Value-weighted histograms are shown in Figure 5a. As expected, retail firms follow a clear quarterly pattern but delayed approximately one month. I add a shaded "timing difference" that shows the difference between the peaks in earnings announcements for retail and non-retail firms. I add the same shading to the expected returns and volatility estimates, so I predict that peaks for these estimates will align with this shading.

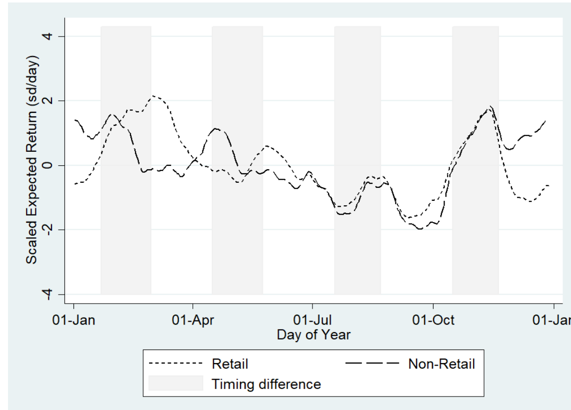
Figure 5b shows the main result. Expected returns peak for non-retail firms early in the quarter, closely in line with the peak in earnings announcements. Expected returns peak for retail firms later in the quarter, closely in line with the peak in retail earnings announcements. A similar pattern follows in the second calendar quarter, also consistent with my predictions. Expected returns for retail and non-retail firms track each other in the second half of the calendar year, although retail expected returns drop off much more than non-retail expected returns in December.

Figure 5: Retail and non-retail comparison

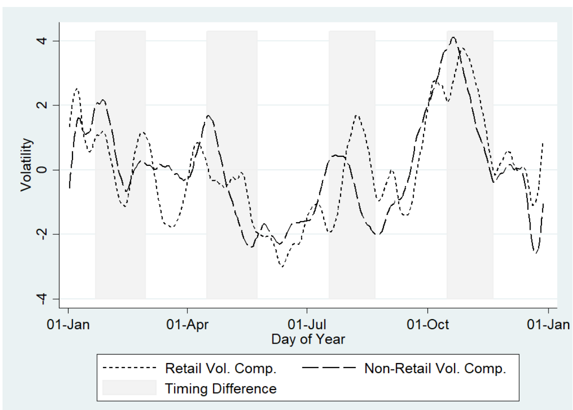
(a) Earnings announcement days



(b) Expected returns



(c) Nonparametric volatility



I next examine nonparametric volatility. Figure 5c shows estimates of retail and non-retail volatility. To facilitate comparison I combine industry and firm volatility measures into a single component using Principal Components Analysis. There is reasonable evidence of a quarterly pattern. Quarterly peaks in volatility for non-retail firms line up with non-retail earnings announcements, while peaks for retail firms are typically delayed one month. The two series are more correlated than the expected returns analysis in Figure 5b. For example retail volatility tends to increase slightly at peaks in non-retail announcements and vice-versa. This correlation is evidence of spillover effects for volatility between retail and non-retail industries.

6.2 Earnings and information arrival tests

This section investigates how the arrival of firm-level earnings corresponds to market-level information flows. I assume a simple model where (1) investors infer aggregate quarterly earnings numbers from firm-level earnings, and (2) the unexpected component of market-level earnings numbers is informative to market pricing. While a number of papers have studied (2) since Kothari, Lewellen and Warner [2006] – concluding that aggregate earnings provide incremental information used to price the market portfolio – there is less evidence regarding (1). I study (1) here, estimating the rate investors learn about aggregate earnings as more firms announce earnings during the quarter.

Evidence that investors learn about aggregate earnings early in the quarter would support the predicted link between earnings announcements, market-level information flow and the market risk premium. First, it implies information flows are concentrated early in the season, consistent with the nonparametric tests that find volatility and the market risk premium increase relatively early in the quarter. Second, it helps validate the empirical definitions of earnings seasons and bellwether announcements, which prioritize early announcements. Third, evidence that investors rapidly infer aggregate earnings from earnings announcements also provides direct evidence of a credible channel from firm-level reporting to aggregate information flows. Finally, it provides further evidence linking earnings announcements to variation in the rate of information flow using signed tests of the relationship between firm-level and aggregate earnings. Earlier tests in this paper used variation in the timing of earnings announcements to identify the effect of earnings announcements, so finding similar results using a different research design would be strong evidence that earnings announcements causally drive changes in information flows.

6.2.1 Firm level earnings and aggregate earnings

The first set of tests investigates quarterly time-series variation in the rate of information flow about aggregate earnings. I am interested in the information available about end-of-quarter aggregate earnings at each point in time during the quarter. I proxy for this with the R-Squared statistic of aggregate earnings regressed on earnings available at that point in time. This is similar to "diversification" graphs used in portfolio theory – the idiosyncratic component of earnings will diversify away as the number of earnings that have been reported increases, improving the estimate of aggregate earnings and increasing the R-Squared statistic.

For each quarter from 1975 to 2015, I calculate two measures of earnings numbers – return on assets and return on book equity. I deflate earnings before interest and tax by total assets less cash and equivalents. I label this variable ROA. I also deflate earnings before tax by shareholders' equity. I label this variable ROE. I winsorize both firm-level ROA and ROE at the 5% level.

To capture the arrival of firm-level information, I form portfolios every day after the end of the quarter until 90 days after the quarter end. These portfolios are composed of all firms that have announced from the first day of the quarter up until a specific number of days after the quarter. For example, the DAYS=25 portfolio is a portfolio of all firms that announce earnings within 25 days of quarter end. By construction, the DAYS=90 portfolio is essentially identical to the change in aggregate earnings as defined above. This process creates 90 portfolios per quarter per year. I then calculate the value-weighted earnings for each of these 90 portfolios.

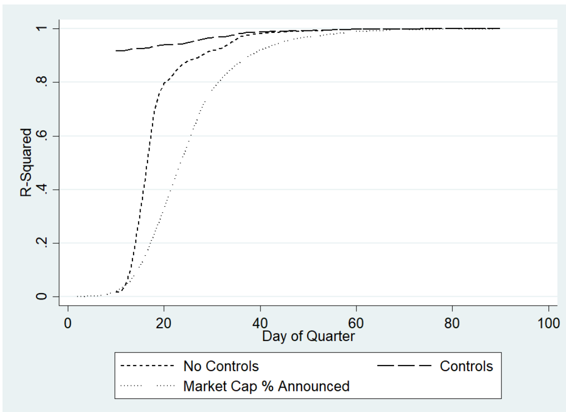
The test consists of the R-Squared from 85 separate regressions for each of the four fiscal quarters separately and combined (5×85 regressions). The R-Squared values are from regressions of value-weighted earnings of the DAYS=90 portfolio on each of the value-weighted earnings of the DAYS=5 portfolio through to the DAYS=90 portfolio. The idea is to test the extent that idiosyncratic earnings diversifies away over the reporting season. The faster that idiosyncratic earnings diversifies away, the faster the R-Squared will approach one. Because investors can anticipate earnings numbers before they are announced, I control for investor expectations using first and fourth lags of earnings. I also include regressions with controls to compare the systematic and idiosyncratic components of earnings independent of their time-series properties.

Figure 6 presents the results. The first tests show information arrival pooled across quarters. R-Squared regressions for ROA on portfolio ROA as well as the cumulative market capitalization of firms that have announced to each day are shown in Figures 6a and 6b. For ROA, portfolios diversify quickly as more firms are added to the portfolio as the quarter progresses. The R-Squared begins at approximately 0.9 when controls are included, while it begins at zero and climbs quickly to about 0.8 before day 20. R-Squared value for both groups then increase smoothly to just under 1.0 by day 40. I next look at regressions for ROA for each quarter separately. Figure 6c shows the first calendar quarter, corresponding to annual reporting. The cumulative market capitalization rises more slowly than other quarters. The R-Squared begins at 0.85 when I include controls. Both R-Squared series climb monotonically to 1 over the first 50 days of the quarter, but most of the information arrival occurs around day 20 without controls and from days 21 to 30 without controls. Figures 6d, 6e and 6f show results for calendar quarters 2 to 4, corresponding to interim reporting. Cumulative announcements rise much faster than the first quarter, and the R-Squared when including controls begins at over 0.9 for second and third quarter reporting and nearly 0.95 for the calendar quarter 4. R-Squared values without controls rise rapidly from about day 15 to day 20, then approach 1 from days 21 to 40 for calendar quarters 2 to 4. R-Squared values with controls rise more evenly from about day 15 to day 40, but similar to the uncontrolled series, the gradient is higher earlier in the quarter.

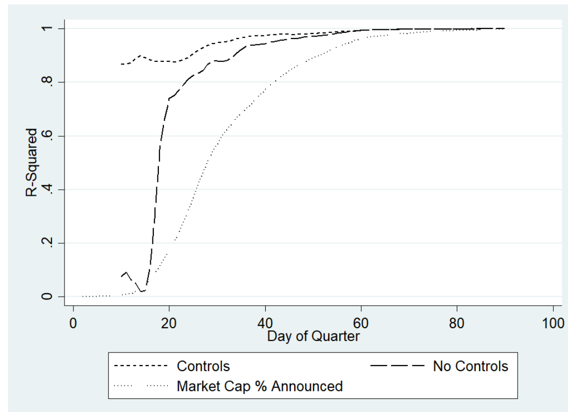
I repeat the analysis for ROE. For brevity I only include the combined quarterly results, because tests based on market returns indicate the ROE measure is not a good proxy for earnings news. The results for ROE are similar, although including controls accounts for

Figure 6: Earnings diversification

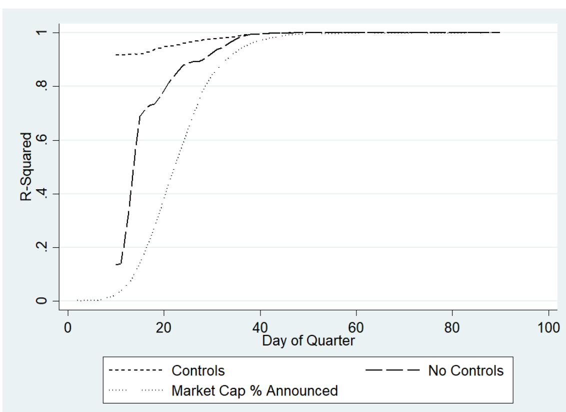
(a) ROA - all quarters



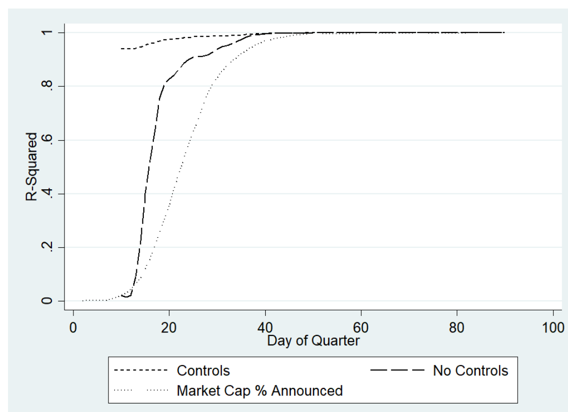
(b) ROA - quarter 1



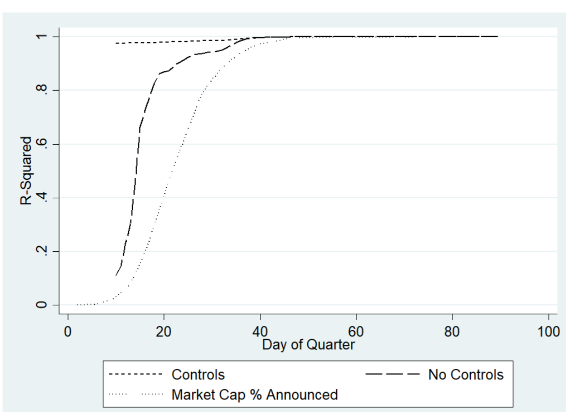
(c) ROA - quarter 2



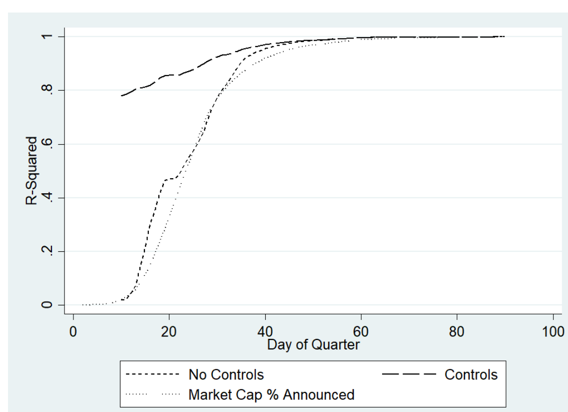
(d) ROA - quarter 3



(e) ROA - quarter 4



(f) ROE - all quarters



less variation in aggregate ROE with a starting R-Squared of about 0.8. The R-Squared for ROE without controls approaches 1 more slowly than ROA, staying ahead of the cumulative market capitalization but then briefly stalling at around day 20. Untabulated analysis finds that the R-Squared in calendar quarter 1 (annual reports) climbs much faster than other quarters. The R-Squared without controls for calendar quarters 2 to 4 climbs almost in line with cumulative market capitalization of announcing firms.

The results in this section are consistent with the hypothesis that earnings has a systematic component across firms, and that investors rapidly infer end-of-quarter earnings at the start of earnings seasons because the firm-specific components of earnings rapidly diversifies away. This is consistent with the earlier nonparametric tests of volatility, which conclude information flows are particularly high early in the quarter, and is consistent with the bellwether, Australian market and retail industry analyses that provide evidence that earnings announcements causally increase market-level information flows and the market risk premium. The results also provide evidence of a credible channel from earnings announcements to market-level information, via the information in firm-level earnings numbers about aggregate earnings. Overall, the results of this section are consistent with the hypothesis that earnings announcements that occur relatively early in the reporting season cause an economically significant increase in market-level information flows.

6.2.2 Firm level earnings and aggregate returns

This section tests and validates the interpretation of incremental R-Squared as aggregate earnings news. Because the information set available to investors is not observable, I have to use proxies for news based on proxies for expectations and proxies for the signal extracted by investors from aggregate earnings. I verify these proxies for news arrival by showing that these proxies are associated with market returns. If the incremental variance of end-of-quarter aggregate earnings explained by cumulative earnings captures news arrival, then cumulative earnings will also predict quarterly excess market returns. The tests in this section repeat those of the prior section, but with quarterly excess returns rather than end-of-period aggregate earnings as the dependent variable.

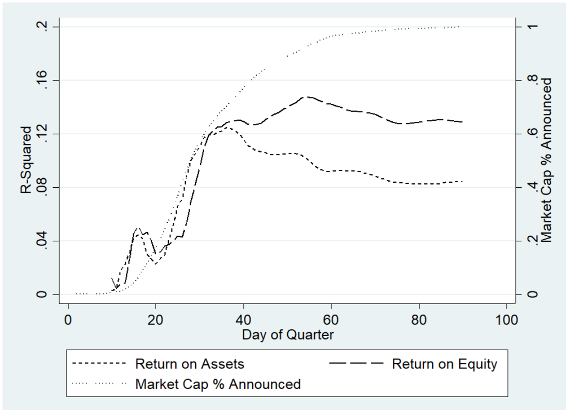
Figure 7a shows the R-Squared for the first calendar quarter (annual reporting). The R-squared for regressions of market returns on cumulative ROA and ROE increases from near zero early in the quarter to a peak of 0.15 for ROE and 0.12 for ROA. This relationship is not monotonic over the entire quarter. After each peak, the R-Squared value decreases as more firms are included in the earnings portfolio. Because investors can infer aggregate earnings for both measures by around day 30, including firms after day 30 does not add much new information about aggregate earnings, but potentially adds noise to aggregate accounting earnings as a measure of aggregate economic earnings or changes in the economic value of the market portfolio.

The analysis for the first calendar quarter supports the conclusion of the earlier analysis. The amount of market-level news in cumulative earnings increases rapidly from around day 20 to day 40 of the calendar quarter. This is in line with the incremental R-squared from regressions of end-of-quarter aggregate earnings on cumulative earnings. This is reasonable evidence that my proxies for expected earnings and the signal extracted from realized earnings correspond to those used by investors.

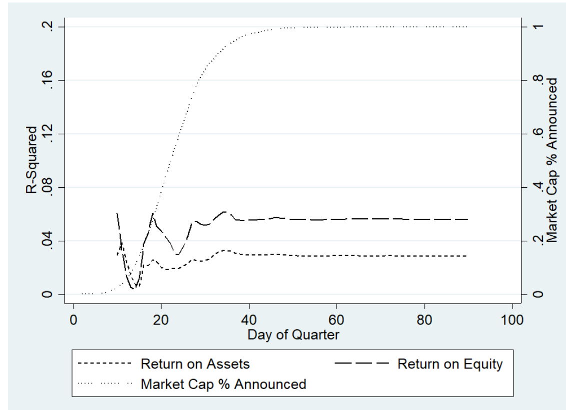
Figures 7b to 7d repeat the analysis for the second to fourth calendar quarters. The R-Squared for both ROA and ROE are lower than annual reporting. R-Squared values are largely flat after day 40, with some volatility early in the quarter. The relatively low R-Squared values, in the range of 0.05, are consistent with research investigating aggregate earnings and returns (Kothari, Lewellen and Warner [2006]). ROA increases from about day 15 to day 35 for calendar quarters 2 and 4. ROA has a peak just before day 20 for quarter 3, and is largely flat from day 20 onwards. In interpret the peak before day 20 as driven by random chance or noise as it seems unlikely that earnings announcements after day 20 have no market-level news considering less than 40% of firms by market capitalization have announced earnings by that point. ROE is highly volatile for calendar quarters 2 to 4.

Figure 7: Information content of aggregate earnings

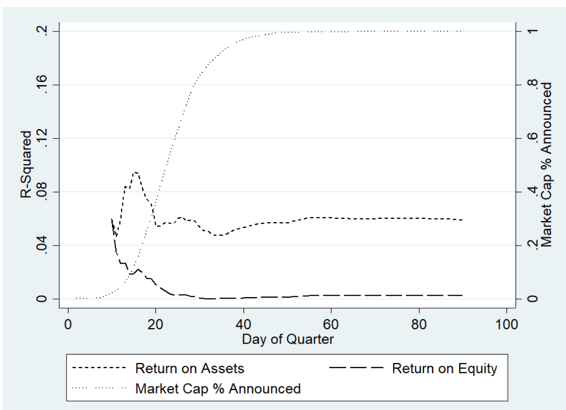
(a) Quarter 1



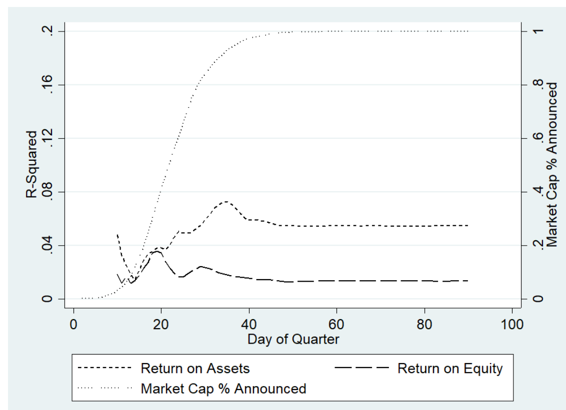
(b) Quarter 2



(c) Quarter 3



(d) Quarter 4



The results for the second to fourth calendar quarters are weaker than the first calendar quarter, but remain broadly in line with expectations. The amount of market-level news in cumulative earnings increases from day 20 to day 40 for quarters 2 and 4 when using the ROA measure. This follows a similar pattern to the tests in the previous section, providing reasonable evidence that the estimates of information flows in the prior section are based on reasonable proxies for news arrival. However, the model does not capture information flows for in the third calendar quarter for either ROA or ROE, or for interim reporting using the ROE measure.

The results of this section are in line with the prediction that investors learn about end-of-quarter aggregate earnings early in the quarter, because the idiosyncratic component of earnings rapidly diversify away as firms announce earnings through the quarter. This is important because it shows that earnings announcements increase market-level information flows relatively early in the quarter, and information flow hypothesis predicts that predictable increases in information flows will correspond to higher market-based measures of risk and a higher market risk premium. Consistent with this prediction, earlier nonparametric tests find that volatility and the market risk premium these also increase relatively early in the quarter.

This section provides additional evidence that variation in the rate of market-level information studied in this paper is caused by earnings announcements. The results provide evidence of a credible channel linking earnings announcements to market-level information flows, and validate this channel using market-based measures of news. Finally, the results are consistent with earlier tests linking earnings announcements to information flows. The fact that tests based on variation in earnings numbers produce similar results to tests based on variation in bellwether announcement dates, Australian semi-annual reporting and US retail industry announcement dates is strong evidence that earnings announcements causally increase market-level information flows.

CHAPTER 7

EMPIRICAL METHOD AND RESULTS: SEASONALITY AND ECONOMIC RISK

7.1 January and Wednesday effects

In this section I test the hypotheses that information flows from earnings announcements drive the January and Wednesday seasonal effects. Controlling for information flows will attenuate these season effects if they are driven by information flows. I use bellwether firms to control for information flows. These tests are similar to the earlier bellwether announcement analysis, with two main differences. First, I include equal-weighted returns, as both January and Wednesday effects are larger for small firms. Second, I interact bellwether announcements with indicators for January and Wednesday.

Table 8 shows the analysis of bellwether announcements and the January effect. I first look at January returns. The first specification is value-weighted returns on an indicator for January. The coefficient is 0.78, but is not statistically significant at the 10% level for the period 1975-2015 for any of the specifications. However, the effect is economically significant, as mean returns for months other than January are 1.97. I next add in an indicator variable for expected bellwether announcement dates. The coefficient on January becomes slightly negative. The third specification adds an interaction between January and bellwether announcements. January reverts to a positive coefficient on 3.12. The coefficient on bellwether announcements is slightly smaller, and the interaction term is economically large at -15.46, and significant at the 10% level with a p-value of 0.07.

For the equal-weighted results, the first specification shows the January effect is economically and statistically significant. Average January equal-weighted returns are almost four times larger than the rest of the year. Adding a control for bellwether announcements attenuates this effect – the coefficient on January drops to 12.15. Return for other months drop marginally to 4.04. While it is tempting to conclude that the January effect is at least par-

Table 8: January effect tests

	Value-Weighted			Equal-Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
January	0.78	−1.20	3.12	16.37∗∗∗	12.15∗∗∗	14.51∗∗∗
	(0.84)	(0.79)	(0.54)	(0.00)	(0.00)	(0.00)
Bellwether		8.42∗∗∗	10.63∗∗∗		5.40∗∗	6.61∗∗
		(0.01)	(0.00)		(0.03)	(0.01)
*Bell*Jan*			−15.46∗			−8.45
			(0.07)			(0.22)
Constant	1.97	1.02	0.69	4.36∗∗∗	4.04∗∗∗	3.86∗∗∗
	(0.14)	(0.46)	(0.62)	(0.00)	(0.00)	(0.00)
R-Squared	0.00	0.00	0.00	0.00	0.00	0.00
N	10322	10322	10322	10322	10322	10322
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Y-Q-S DOW	Y-Q-S DOW	Y-Q-S DOW	Y-Q-S DOW	Y-Q-S DOW	Y-Q-S DOW

This table presents regressions of daily value-weighted and equal-weighted excess returns on indicator variables for the month of January, bellwether announcements and controls. Controls consist of FOMC, PPI, CPI and employment releases, and days with large dividend payouts. Y-Q-S refers to Year-Quarter-Season fixed effects. DOW refers to day-of-week fixed effects. *, ** and *** refer to $p<0.1$, $p<0.05$ and $p<0.01$ respectively.

tially caused by Bellwether announcements (and earnings announcements more generally), the final specification shows a more complex story.

Adding an interaction between January and bellwether announcements for equal-weighted results again slightly increases the coefficient on January (14.51), marginally increases the coefficient on bellwether announcements, and the interaction term itself has a negative coefficient that is not statistically significant. These changes are in line with the value-weighted results. There are two ways to interpret the negative coefficient on the interaction between January and bellwether announcements. One is that cause of the January effect and of the bellwether effect are unrelated, and that bellwether announcements cause negative returns or near-zero returns in January due to random chance or biased investor expectations of bellwether earnings. The second interpretation is the "crowding out" effect, that is also discussed in the discussion of the quarterly bellwether analysis (Table 4 Panel B). According to this interpretation, the January effect is caused by higher information flows resulting from announcements of annual earnings numbers. If non-bellwether earnings announcements that occur earlier or concurrently with bellwether announcements pre-empt or attenuate the signal that investors would typically extract from bellwether reports, then the coefficient for interactions between bellwether announcements and January will be negative. Put differently, if the bellwether and non-bellwether earnings announcements are close substitutes in terms of providing market-level information, days with both types of announcement will not provide incremental information to the market so will not increase the market risk premium, resulting in positive coefficients on January and bellwether, and a negative coefficient on the interaction term.

I next analyze the Wednesday effect. Table 9 shows the results of this analysis. The first column of both equal- and value-weighted specifications shows the Wednesday effect is economically significant. Adding controls for bellwether announcements has little impact on the coefficient. Including an interaction term has a similar result to interacting with January – the coefficient on Wednesday increases slightly to 5.81 and 6.38 for equal and value-weighted excess market returns respectively. The coefficients on the interaction terms are negative and roughly the same size as the coefficient on bellwether announcements. The interactions are statistically significant at the 5% and 10% levels respectively. This pattern is remarkably similar to the January results and has a similar interpretation – either the Wednesday effect is caused by something other than information flows and bellwether announcements that occur on Wednesdays cause negative returns for some reason, or the greater information flows that occur on Wednesday ‘crowd out’ the effect on bellwether announcements.

To test the “crowding out” effect further I add an additional interaction term with earnings seasons. Wednesdays should “crowd out” bellwether announcements mainly during earnings seasons if the effect is because more firms announce earnings on Wednesdays. The results are consistent with the crowding out hypothesis but not statistically significant. The coefficient for Wednesdays interacted with earnings seasons increases, offset by negative in-

Table 9: Wednesday effect tests

Panel A: Value weighted

Dependent variable: value-weighted excess returns	(1)	(2)	(3)	(4)	(5)
WED	3.35	3.38	5.81**	2.87	3.57
	(0.20)	(0.20)	(0.04)	(0.43)	(0.34)
BELL_ANN		14.37***	17.84***		18.93**
		(0.00)	(0.00)		(0.04)
*WED*BELL_ANN*			−17.15**		−19.56
			(0.02)		(0.37)
*WED*EARN*				0.98	5.21
				(0.85)	(0.35)
*BELL_ANN*EARN*					−0.86
					(0.94)
*WED*BELL_ANN*EARN*					−0.05
					(1.00)
Constant	6.28	4.13	3.35	6.28	3.22
	(0.35)	(0.54)	(0.62)	(0.35)	(0.63)
R-Squared	0.00	0.00	0.00	0.00	0.00
N	10322	10322	10322	10322	10322
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Y-Q-S	Y-Q-S	Y-Q-S	Y-Q-S	Y-Q-S

(Continued on following page)

teractions between (i) bellwether announcements and earnings seasons; and (ii) three-way interactions between Wednesdays, bellwether announcements and earnings seasons.

The results of both the Wednesday and January tests are inconclusive. Controlling for bellwether announcements – days with high information flows – will (all else equal) attenuate the Wednesday and January effects if these effects are driven by information flows. I find no evidence this is the case. I also test for interactions between bellwether announcements and the Wednesday and January effects to see if these effects are independent of information flows. For all specifications the coefficient is large and negative, although not always statistically significant. I conjecture this is caused by a "crowding out" effect, but leave further investigation of this conjecture to future research.

Table 9, continued

Panel B: Equal weighted

Dependent variable: equal-weighted excess returns	(1)	(2)	(3)	(4)	(5)
WED	4.92**	4.94**	6.38***	4.56	5.10*
	(0.02)	(0.02)	(0.01)	(0.13)	(0.09)
BELL_ANN		12.63***	14.70***		13.65*
		(0.00)	(0.00)		(0.07)
*WED*BELL_ANN*			−10.20*		−14.82
			(0.09)		(0.40)
*WED*EARN*				0.72	3.00
				(0.86)	(0.51)
*BELL_ANN*EARN*					1.78
					(0.84)
*WED*BELL_ANN*EARN*					3.48
					(0.85)
Constant	12.93**	11.05**	10.58*	12.93**	10.55*
	(0.02)	(0.04)	(0.05)	(0.02)	(0.06)
R-Squared	0.00	0.00	0.00	0.00	0.00
N	10322	10322	10322	10322	10322
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Y-Q-S	Y-Q-S	Y-Q-S	Y-Q-S	Y-Q-S

This table presents regressions of daily value-weighted and equal-weighted excess returns on indicator variables for trade on Wednesdays, bellwether announcements, earnings seasons and controls. Panel A shows value-weighted excess returns. Panel B shows equal-weighted excess returns. Controls consist of FOMC, PPI, CPI and employment releases, and days with large dividend payouts. Y-Q-S refers to Year-Quarter-Season fixed effects. *, ** and *** refer to p<0.1, p<0.05 and p<0.01 respectively.

7.2 Economic risk and information tests

7.2.1 News components of earnings season and quiet period returns

This section tests the hypothesis that signed returns during earnings announcements convey different macroeconomic news to quiet periods. I use a modified version of the Campbell and Ammer [1993] decomposition. The idea is that the average amount of cash flow news and discount rate news is different during earnings seasons and quiet periods.

The main tests consist of a vector autoregression with the variables VWRET_EARN, VWRET_QT, PAY_YLD and PAY_GROWTH. I include one lag based on an untabulated

Table 10: Information environment in earnings seasons and quiet periods

Panel A: Vector autoregression coefficient estimates

	VWRET_EARN	*VWRET_QT*	*PAY_YLD*	*PAY_GROW*
VWRET_EARN	-0.25*	0.06	0.07	-0.14
	(0.06)	(0.71)	(0.71)	(0.45)
VWRET_QT	0.14	0.16	-0.18	0.13
	(0.18)	(0.19)	(0.22)	(0.39)
PAY_YLD	0.01	0.14**	0.81***	-0.06
	(0.81)	(0.01)	(0.00)	(0.35)
PAY_GROW	-0.04	-0.02	0.15	0.11
	(0.72)	(0.89)	(0.28)	(0.44)
CONS	0.07***	0.02	0.00	0.00
	(0.00)	(0.24)	(0.94)	(0.84)
p-value (coef)	0.01			
AIC	-862.32			
BIC	-812.77			

Panel B: Covariance matrix of vector autoregression residuals

	VWRET_EARN	*VWRET_QT*	*PAY_YLD*	*PAY_GROW*
VWRET_EARN	1.39	0.57	-0.87	1.11
VWRET_QT	0.57	1.85	-1.28	1.18
PAY_YLD	-0.87	-1.28	2.72	0.49
PAY_GROW	1.11	1.18	0.49	2.79

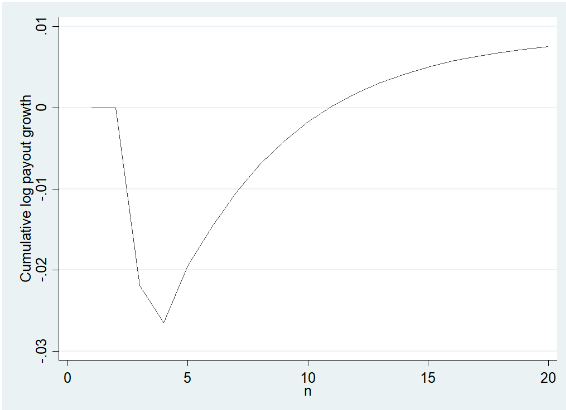
This table reports a vector autoregression (VAR) for value-weighted returns during earnings and non-earnings seasons. Panel A presents coefficient estimates. p-value refers to a test of equality of the constants across the VWRET_EARN and VWRET_QT equations. PAY_YLD and PAY_GROW are demeaned so they do not affect the constant terms for the VWRET_EARN and VWRET_QT regressions. The difference in constants across equations corresponds to the average difference between earnings and non-earnings season returns after controlling for time-series correlation. Panel B presents the correlation matrix of the residuals from the VAR. *, ** and *** refer to $p<0.1$, $p<0.05$ and $p<0.01$ respectively.

model selection procedure. Table 10 shows the VAR for the sample from 1926 to 2015.

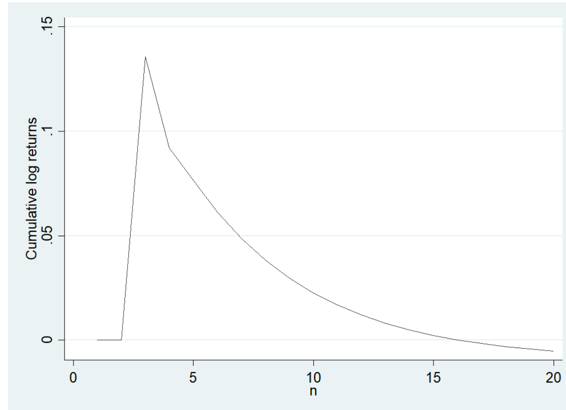
The coefficient on lagged VWRET_EARN in the VWRET_EARN equation is negative and slightly outside the 5% significance level. The coefficient of -0.25 is very large in economic terms, implying that a 10% unexpected return during an earnings season will lower the expected return in the next earnings season by 2.5%. This reversal is why the main tests use Newey-West standard errors as the main specification.

Figure 8: Impulse response function

(a) Cumulative payout growth



(b) Cumulative returns



The main results of this analysis are shown in Figure 8 using impulse response functions. Two important caveats should be noted. First, the economic magnitudes of these effects are small. Second, the results are not robust to including or excluding the period from 1926 to 1945. The analysis below excludes 1926 to 1945 as an indicative test of the directions for future research and possible analysis.

I shock the model with a 1 unit return in earnings announcement periods and an offsetting 1 unit return in quiet periods. The standard Campbell and Ammer [1993] decomposition implies there will be no effect, as returns are measured annually. In this analysis, earnings season and quiet period return are modelled separately, and can have different effects on payout yields, future returns and dividend growth. Figure 8a shows the expected effect on payout growth – a sharp drop for approximately 5 years, followed by a slow increase over the next 20 years. Figure 8b shows the effect on cumulative annual returns (earnings seasons and quiet periods combined). Prices increase over the following 4 years, but then slowly decrease over the next 20 years. These combined results are partially consistent with the hypothesized effect: earnings seasons and quiet periods returns have clearly different cash flow and discount rate implications. However, rather than earnings seasons having more cash flow news, the term structure of the news is different. Earnings seasons have long run-implications for payout growth, while quiet periods have short term-effects. Again, this analysis is subject to the caveats noted above.

In conclusion, while there is evidence from the VAR coefficient estimates, the VAR covariance matrix and the estimated impulse response functions that earnings season and quiet period returns have different implications for discount rate news and cash flow news, estimates using the current method and sample are too imprecise to reconcile Campbell and Ammer [1993] with Sadka [2007], or to explain variation in risk between earnings seasons and quiet periods.

7.2.2 Time series variation in expected returns

This section investigates whether the earnings season premium varies over time in line with proxies for the market risk premium. Two theories make opposite predictions. First, if the earnings season premium is driven by increases in macroeconomic risk caused by information, then – all else equal – the premium should increase when investors are less willing to hold assets that are exposed to this macroeconomic risk. Second, Johnson [1999] shows that earnings response coefficients and earnings persistence are lower when the economy is in recession, so the difference between earnings season and quiet period returns should decrease when the economy is depressed. This section tests these two alternative hypotheses.

The tests in this section are closely based on Fama and French [1988], Sadka [2007] and Cochrane [2011]. Each Panel runs three separate regressions: VWLRET_EARN, VWLRET_QT and VWLRET_TOT are dependent variables and LOG_PY(t-1) as the independent variable. I use logged transformations of the variables. The coefficients on the first two regressions add to the coefficient on the third regression. The third regression is included as a benchmark (it repeats the results of prior research). Consistent with prior literature, I use value-weighted returns.

Table 11 Panels A to C measure returns at the 5, 10 and 15-year periods respectively. I use Newey-West standard errors with bandwidth of 6, 11 and 16 respectively to control for the overlapping samples resulting from regressions using long-run returns. Based on the

Table 11: Macroeconomic cycles and earnings season premium

Panel A: 5-year compound returns

	Dependent variable: *VWLRET_EARN*	*VWLRET_QT*	*VWLRET_TOT*
LOG_PY(t-1)	0.20***	0.42***	0.62***
	(0.00)	(0.00)	(0.00)
CONS	0.94***	1.47***	2.41***
	(0.00)	(0.00)	(0.00)
R-Squared	0.10	0.18	0.22
N	84	84	84

Panel B: 10-year compound returns

	Dependent variable: *VWLRET_EARN*	*VWLRET_QT*	*VWLRET_TOT*
LOG_PY(t-1)	0.35***	0.69***	1.04***
	(0.00)	(0.00)	(0.00)
CONS	1.64***	2.46***	4.10***
	(0.00)	(0.00)	(0.00)
R-Squared	0.33	0.30	0.41
N	79	79	79

(Continued on following page)

Campbell-Shiller approximation I apply a discount factor of 0.95.

The three panels show the effect of aggregating returns over longer periods. Consistent with prior literature, the third column shows that the predictive power for annual returns (VWLRET_TOT) increases with the horizon. The coefficient on LOG_PY increases from 0.62 to 1.09 for the 5-year and 15-year horizons. Cochrane [2011] argues this predictability (as replicated in the third column of each Panel) is one of the most important results in finance, because it shows that the market risk premium varies over time. This variation reflects long-run cycles in the stock market and economy.

The coefficients on LOG_PY is different across the equations for VWLRET_EARN and VWLRET_QT. The coefficient for quiet periods is higher than that for earnings seasons, so the earnings season premium is lower when investors are less willing to hold equities.

Table 11, continued

Panel C: 15-year compound returns

	Dependent variable: *VWLRET_EARN*	*VWLRET_QT*	*VWLRET_TOT*
LOG_PY(t-1)	0.40***	0.69***	1.09***
	(0.00)	(0.00)	(0.00)
CONS	1.98***	2.56***	4.54***
	(0.00)	(0.00)	(0.00)
R-Squared	0.43	0.26	0.42
N	74	74	74

Panels A to C shows the regression results of each of VWLRET_EARN, VWLRET_N and VWLRET_TOT on LOG_PY(t-1), when returns are compounded 5, 10 and 15 years forward. The regressions are run separately. For example, the dependent variable in column 1 of Panel C is value-weighted log returns from year t=0 to year t=14 inclusive. All tests use Newey-West standard errors with a bandwidth of 6, 11 and 16 years respectively. VWLRET_EARN is the annual logged value-weighted return during earnings seasons. VWLRET_QT is the annual logged value-weighted return during non-earnings seasons. VWLRET_TOT is the annual logged value weighted return for the entire year. LOG_PY(t-1) is the lagged log aggregate payout yield, where payouts are defined as dividends plus share buybacks. *, ** and *** refer to p<0.1, p<0.05 and p<0.01 respectively.

Consistent with predictions, the market risk premium during earnings seasons and quiet periods varies with economic cycles. The sign is consistent with the idea that earnings are less informative during downturns. To the extent that investors require higher returns to hold assets during risky periods (i.e. the risk theory) this is effect appears to be offset by lower information from earnings numbers during downturns as per Johnson [1999].

7.2.3 Relationship between S&P500 earnings and macroeconomic indicators

In this section I document that earnings is correlated with various economic indicators, implying that anticipation of earnings (at the quarterly level as studied in the information arrival section, as well as longer timeframes) implies investors can also learn about these indicators. Testing the information content of aggregate earnings with regards to macroeconomic indicators is immensely complex, because it requires strong assumptions about the conditioning information sets of investors. Recent work in economics outside of capital markets research (Jaimovich and Rebelo [2009], Schmitt-Grohe and Uribe [2012] and Leeper, Walker and Yang [2013]) show that modelling anticipation of macroeconomic shocks can alter the predictions of a wide class of economic models. While this is likely a fruitful area of research it is outside the scope of this paper.

Table 12: Relationship between corporate profits and macroeconomic indicators

Panel A: Pre-1975 and Post-1975 correlation matrix of economic indicators and corporate profits

	Pre-1975					Post-1975				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
(1) ΔSP_EARN	1.00					1.00				
(2) ΔGDP	0.54	1.00				−0.15	1.00			
	(0.00)					(0.36)				
(3) $\Delta Consumption$	0.76	0.77	1.00			−0.16	0.89	1.00		
	(0.00)	(0.00)				(0.31)	(0.00)			
(4) *Employment*	−0.18	−0.61	−0.43	1.00		0.24	−0.45	−0.45	1.00	
	(0.37)	(0.00)	(0.02)			(0.13)	(0.00)	(0.00)		
(5) $\Delta PROF\_US$	0.67	0.80	0.73	−0.19	1.00	0.39	0.46	0.34	0.11	1.00
	(0.00)	(0.00)	(0.00)	(0.35)		(0.01)	(0.00)	(0.03)	(0.50)	

Panel B: Pre-1995 and Post-1995 correlation matrix of economic indicators and corporate profits

	Pre-1995					Post-1995				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
(1) ΔSP_EARN	1.00					1.00				
(2) ΔGDP	0.63	1.00				−0.40	1.00			
	(0.00)					(0.07)				
(3) $\Delta Consumption$	0.57	0.86	1.00			−0.37	0.93	1.00		
	(0.01)	(0.00)				(0.09)	(0.00)			
(4) *Employment*	−0.44	−0.44	−0.19	1.00		0.47	−0.70	−0.80	1.00	
	(0.06)	(0.06)	(0.43)			(0.03)	(0.00)	(0.00)		
(5) $\Delta PROF\_US$	0.61	0.71	0.64	−0.16	1.00	0.43	0.18	0.04	0.23	1.00
	(0.01)	(0.00)	(0.00)	(0.52)		(0.04)	(0.43)	(0.87)	(0.30)	

(Continued on following page)

Table 12 outlines covariance matrixes for four subsamples. The first compares economic indicators before and after 1975. I choose this cutoff because it's roughly the middle of the sample and coincides with the period where bellwether data is available. Casual inspection

Table 12, continued

Panel C: Test of change in time of correlation between S&P500 earnings and economic indicators

	Full sample			Late sample		
	Early 1946-1975	Late 1975-2016	p-value	Mid 1975-1995	End 1995-2016	p-value
Correlation between ΔSP_EARN and:						
(2)ΔGDP	0.54	−0.15	0.01***	0.63	−0.40	0.00***
(3) $\Delta Consumption$	0.76	−0.16	0.00***	0.57	−0.37	0.00***
(4) *Employment*	−0.18	0.24	0.09*	−0.44	0.47	0.00***
(5) $\Delta PROF\_US$	0.67	0.39	0.13	0.61	0.43	0.43
Full correlation matrix:						
All Indicators (1–5)			0.01**			0.01**

Panel A reports correlation matrices for 1946 to 1974 and 1975 to 2015. ΔSP_EARN is the percentage change in aggregate profits of the S&P500 index, from Robert Shiller's website. ΔGDP, ΔConsumption, Employment and ΔPROF_US refer to annual estimates from the US Bureau of Labor Statistics. ΔPROF_US is series A051RC1 'Corporate profits with inventory valuation and capital consumption adjustments'. Panel B reports correlation matrices from 1975 to 1994 and 1995 to 2015. Panel C tests for changes in correlation between ΔSP_EARN and the four economic indicators separately, except the last row which tests for changes in the full correlation matrix.

indicates the relationship between earnings and other variables has changed in the early and late samples. The correlation between earnings and the contribution of corporate profits (including unlisted firms) to GDP stays relatively constant across samples. The remaining correlations vary considerably across subsamples. The relationship between GDP and earnings is positive in the early sample and negative in the later sample, while employment has a negative correlation with earnings in the early sample and a positive correlation in the later sample. I also examine the late period divided into pre-1995 and post-1995 subperiods. Again, there is considerable variation in correlations. Earnings and GDP are positively correlated between 1975 and 1995, and negatively correlated after. The correlation goes from negative to positive between earnings and employment.

Panel C formally tests for differences in correlation. I test for changes in correlation between earnings and each of the economic indicators separately and for the full correlation matrix. I run this test for both the full sample (divided into early and late periods) and the late sample (divided as before and after 1995). The tests between change in GDP and change in either consumption or employment are significant at the 1% level for both periods of analysis. The relationship between earnings and employment has very weak evidence of changing across the full sample at 10% level, but is significant at the 1% level when dividing the late period into subsamples. There is no evidence of a statistically significant change between earnings of the S&P500 and the national contribution of corporate profits to GDP.

CHAPTER 8

CONCLUSION

This paper tests whether predictable changes in the rate of information flow affect the market risk premium. While the relationship between information, risk and the cost of capital has been studied extensively at the firm level, the impact of information arrival on uncertainty and risk and returns at the market level has received much less attention. The two papers that investigate this issue (Savor and Wilson [2013] and Lucca and Moench [2016]) find conflicting results. The empirical strategy of this paper is to instrument or proxy for information flow using (i) earnings seasons; and (ii) earnings announcements by large firms that are scheduled to report early in the season.

The main result is that the market risk premium is higher during earnings seasons than quiet periods and during scheduled bellwether announcement dates relative to the rest of the year. The effect is economically and statistically significant – for example, 70% of the market risk premium from 1926 to 2016 occurs during earnings seasons, despite earnings seasons and quiet periods having an equal number of days per year. Sharpe ratios are higher during earnings seasons than quiet periods but are essentially identical during bellwether announcements and the remainder of the year.

A battery of tests links earnings numbers, earnings announcements, market-level information flows, market-level risk and the market risk premium. I investigate market, industry and firm volatility, cross-sectional measures of market risk, and estimates of the rate that investors learn about aggregate earnings as firms announce earnings throughout the quarter. I confirm the main results for the US retail industry, that delays reporting due to the holiday season, and for of the Australian market, that follows semi-annual reporting. The results are consistent the hypothesis that predictable changes in the rate of information flow affect the market risk premium.

The results of this paper do not in themselves imply normative conclusions about disclosure or information arrival. In particular, the paper does not study the long-term implications of information arrival. The "costs" of increased volatility and increased risk in the short term (i.e. over weeks) have to be offset against long-term benefits such as more efficient resource allocation, investment efficiency, improved consumption patterns and other potential benefits of long-term information.

One caveat is the focus on macro-level effects in accounting is a relatively new research area. This paper does not investigate the potentially important roles of information intermediaries such as analysts and newspapers, incentives for private information acquisition, or interactions between earnings announcements and related disclosures such as conference calls. Further research could study how these factors affect the aggregate market reaction to earnings announcements and other forms of disclosure.

Another caveat is that the results are consistent with the hypothesis that the flow of information affecting the market risk premium, and that information arrival also increases proxies for risk. The question as to which of these proxies (if any) is the channel from information arrival to the market risk premium is an important question that is outside the scope of this paper. In particular, I do not claim, for example, that the predictable increase in firm-level volatility is causally responsible for the observed increase in the market risk premium.

The main finding of this paper is the pre-scheduled arrival of market-level information during intervals of time increases the market risk premium during these intervals. A series of results studies the relationship between earnings announcements, risk, earnings numbers, macroeconomic risk, and the market risk premium. These results support the main finding that predictable increases in the rate of information flow increase the market risk premium.

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