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The MAX effect: An exploration of risk and mispricing explanations ☆

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ABSTRACT

This paper studies the role that risk and mispricing play in the negative relation between extreme positive returns and future returns. We document a strong 'MAX effect' in Australian equities over 1991–2013 that is robust to risk adjustment, controlling for other influential stock characteristics and, importantly, manifests in a partition of the 500 largest stocks. While there is no evidence that MAX proxies for sensitivity to risk, the findings are highly consistent with a mispricing explanation. Adapting the recent methodological innovation of Stambaugh et al. (2015) to classify stocks by their degree of mispricing, we show that the MAX effect concentrates amongst the most-overpriced stocks but actually reverses amongst the most-underpriced stocks. Consistent with arbitrage asymmetry, the magnitude of the MAX effect amongst overpriced stocks exceeds that amongst underpriced stocks, leading to the overall negative relation that has been well documented.

1. Introduction

A recent study by Bali et al. (2011) suggests that extreme positive returns play a role in the cross-sectional pricing of US stocks. Measuring a stock's extreme return as the maximum daily return over the prior month (denoted MAX), Bali et al. (2011) document a pronounced negative relation between month t MAX and month $t+1$ stock returns. The MAX effect is statistically and economically significant, with a hedge portfolio taking long (short) positions in low (high) MAX stocks generating raw and risk-adjusted returns in excess of 1% per month. These findings are robust to controls for a number of other characteristics known to influence cross-sectional returns (e.g., size, book-to-market, medium-horizon momentum, short-term reversals, illiquidity and skewness). Bali et al. (2011) also document that the controversial negative relation between idiosyncratic volatility and stock returns first documented by Ang et al. (2006) is reversed after controlling for the MAX effect.

The reason why MAX predicts lower future returns is not well understood. Bali et al. (2011) note that their findings are consistent with investors having a preference for stocks with lottery-like features, whereby there is a small probability of an extreme positive payoff. Such preferences are readily observable in gambling markets, even when expected returns are low or negative. Further, there is evidence that gambling and lottery-like stocks attract very similar clienteles (Kumar, 2009). To the extent that investors believe that an extreme positive return in the recent past is likely to be repeated, low returns to high MAX stocks may reflect these lottery preferences.

Naturally, lottery characteristics are closely related to higher moments of the return distribution. A number of theoretical models motivate a preference for skewness in asset returns, with the resulting implication that various measures of skewness may be priced (e.g., co-skewness, total skewness, idiosyncratic skewness).[1] For example, the model of Mitton and Vorkink (2007) includes both traditional mean–variance optimisers and 'lotto investors' with a preference for skewness. In equilibrium, skewness-seeking investors hold underdiversified portfolios, total skewness is priced, and stocks with high idiosyncratic skewness generate negative alphas.

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[1] See Arditti (1967, 1971); Kraus and Litzenberger (1976); Simkowitz and Beedles (1978); Conine and Tamarkin (1981); Kane (1982); Harvey and Siddique (2000); Brunnermeier and Parker (2005); and Brunnermeier et al. (2007).

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Alternatively, assuming that investors have cumulative prospect theory utility functions as in Tversky and Kahneman (1992), Barberis and Huang (2008) show that low-probability extreme events are overweighted. When asset returns depart from normality, skewed securities are overpriced and generate negative excess returns, while idiosyncratic skewness is priced. To the extent that extreme positive returns are related to skewness, this may explain the observed MAX effect.

Following Bali et al. (2011), a number of studies have explored the MAX effect in settings outside the US. Using a series of multivariate regressions, Walkshäusl (2014) finds pervasive evidence of a negative relation between MAX and future returns for 11 European Monetary Union countries. Annaert et al. (2013) examine a pooled sample of nearly 8000 companies drawn from 13 European countries. Their univariate portfolio sorts detect little evidence of a MAX effect. However, after controlling for potential confounding influences using bivariate portfolio sorts and cross-sectional regressions, Annaert et al. (2013) verify the existence of a MAX effect. Curiously, Chee (2012) also finds no MAX effect using univariate portfolio sorts for the Japanese market, yet a distinct effect after controlling for firm characteristics with bivariate sorts.

Exploring an emerging stock market, Nartea et al. (2014) provide mixed out-of-sample evidence for South Korea. A MAX effect only manifests in equal-weighted portfolios, suggesting a small-firm premium may be present. Another notable feature of the South Korean evidence is that the negative relation between idiosyncratic volatility and future returns appears robust to controlling for MAX. More broadly, Cheon and Lee (2014) study 44 countries grouped into geographical regions and show that the core findings of Bali et al. (2011) generalise to many global markets. High MAX stocks generally underperform low MAX stocks, and the idiosyncratic volatility puzzle often vanishes after controlling for MAX.

Recent literature is also beginning to investigate how MAX interacts with other determinants of US cross-sectional returns. Chen and Petkova (2012) document that stocks with high MAX tend to have high R&D expenditure, which suggests that MAX may signal an abundance of growth options and investment opportunities. Consistent with the intuition of behavioural explanations of the MAX effect, Han and Kumar (2013) document that stocks with lottery-like features are heavily traded by speculative retail investors with strong gambling propensity. Motivated by Kumar (2009), Baker and Wurgler (2006), and Fong and Toh (2014) show that investor sentiment and institutional ownership influence the strength of the MAX effect. The MAX effect only exists following states of high sentiment and is strongest amongst (although not entirely restricted to) stocks with low institutional ownership.

Frazzini and Pedersen (2014) document large abnormal returns from a 'betting against beta' strategy that takes long (short) positions in low (high) beta stocks. Bali et al. (2015), however, show that these returns do not survive after controlling for MAX. Of relevance to the current paper, the abnormal returns from the betting against beta strategy are completely captured by the Fama and French (1993) and Carhart (1997) four-factor model augmented with a factor capturing lottery demand.

The current paper makes a number of contributions to this emerging literature. As a starting point, we study the existence of a MAX effect in Australian equities over the period 1991–2013. The findings are unambiguous. Using a variety of methodological approaches, the negative relation between recent extreme returns and future returns is statistically and economically significant. A hedge portfolio that takes long positions in low MAX stocks and short positions in high MAX stocks generates significant returns, irrespective of whether stocks are equal or value weighted into portfolios. These returns survive risk adjustment using an assortment of risk models and, most importantly, also manifest in a subsample comprising the 500 largest stocks. Further, using double-sorted portfolios and Fama and MacBeth (1973) regressions, the MAX effect is robust to controlling for other stock characteristics known to influence cross-sectional returns.

The second contribution of the paper relates to the idiosyncratic volatility (IV) puzzle first documented by Ang et al. (2006). While MAX and IV are highly correlated, prior work documents that the MAX effect is not a simple manifestation of the IV effect. In fact, the direction of the IV effect reverses after controlling for recent extreme positive returns (Bali et al., 2011; Annaert et al., 2013). To date, there is little Australian evidence regarding the existence of an IV puzzle. As such, before exploring the interaction between MAX and IV, we undertake a thorough investigation of the IV-return relation. For value-weighted portfolio returns, univariate sorts suggest a negative IV-return relation. When we control for MAX, however, there is little remaining evidence of an IV puzzle. In contrast, the MAX effect is strongly robust to controlling for IV.

Given the strong evidence supporting the existence of a MAX effect, our third and most important contribution is to formally study whether it is attributable to risk or mispricing. We document a high degree of persistence across time in the MAX portfolios to which stocks are assigned. This lends credence to the notion that investors may utilise MAX as a signal of lottery-like characteristics. Consistent with lottery-seeking investors being cognisant of this persistence, the implications of a recent extreme positive return for future returns diminish slowly with the passage of time. However, while these findings are necessary for a risk-based explanation, there is little further evidence that MAX proxies for sensitivity to a priced risk factor. Using portfolio sorts and cross-sectional regressions, future returns are unrelated to stock-level sensitivities to a factor-mimicking portfolio constructed around MAX. Further, the lack of commonality in co-movement between returns to US and Australian MAX spread strategies suggests that these phenomenon are not explained by an underlying economic source of risk.

In the absence of an economic risk explanation, many studies of empirical regularities default to a mispricing conclusion. In this paper, we formally test whether the MAX effect is attributable to mispricing. Our approach draws on a recent methodological innovation by Stambaugh et al. (2015) who propose a proxy for mispricing that allows stocks to be classified according to their likely degree of under/over pricing. In the spirit of Stambaugh et al. (2015), we construct a mispricing index based on seven anomalies that are well-documented in the Australian equity market. The testing for mispricing involves an examination of portfolios double sorted on MAX and the mispricing index. Noting that idiosyncratic volatility is a common proxy for the level of arbitrage risk, the strong positive correlation between MAX and idiosyncratic volatility implies that the MAX effect (i.e., negative relation between MAX and future returns) is likely to concentrate in the overpriced partition. Conversely, amongst the underpriced partition, a reverse MAX effect (i.e., a *positive* relation between MAX and future returns) is predicted. The empirical findings are strikingly consistent with these predictions. Further, the magnitude of mispricing amongst overpriced stocks far exceeds that for underpriced stocks, consistent with Stambaugh et al. (2015) notion of 'arbitrage asymmetry'. Taken together, our empirical findings provide new insight into the cause of the MAX effect, with strong evidence that it results from mispricing rather than underlying economic risk.

The remainder of the paper is structured as follows. Section 2 discusses the sources of data utilised in the paper and describes the construction of key variables. Section 3.1 commences the empirical analysis by documenting the existence of the MAX effect in raw and risk-adjusted returns and examining whether it survives after controlling for numerous other characteristics known to be associated with cross-sectional returns. The robustness of these findings is subjected to sensitivity analysis in Section 3.2. Section 4 conducts a preliminary investigation into the existence of the IV puzzle in Australian equities, before proceeding to study the interaction between MAX and IV. Whether the MAX effect is more likely to be attributable to risk exposures or mispricing is explored in Section 5. Finally, Section 6 concludes the paper.

2. Data and variable construction

2.1. Data sources

Key data are obtained from three sources. First, the Share Price & Price Relative (SPPR) file from the Securities Industry Research Centre of Asia–Pacific (SIRCA) provides monthly data for all stocks listed on the Australian Securities Exchange (ASX) since 1974. The specific variables utilised in this study include monthly stock return, closing price, market capitalization, number of shares outstanding, share type, industry code, return on the value-weighted market index (proxy for the market portfolio) and return on the 13-week Treasury note (proxy for the riskfree rate). Second, accounting data for several control variables (discussed shortly) are drawn from the Morningstar Aspect Huntley database. Financial statement data is annual and available from 1989 onwards.

Third, estimation of MAX, idiosyncratic volatility and illiquidity requires certain data items at a daily frequency. The SIRCA Core Research Data database provides daily returns, prices and trading volume for all ASX-listed stocks over the period 1990–2013. As a starting point, this data comprises 5.5 million firm-day records. Several procedures are performed to prepare the data for use in the study. On a handful of days, the database contains *two* records for the same stock.[2] Each such occurrence is examined to determine the appropriate return. Care is also taken surrounding non-trading periods. A stock is assigned a zero return on a non-trading day. When it next trades, we estimate the cumulative return using the current and most-recent share prices. This is preferable to treating today's return a missing value, since it captures price changes across the non-trading period (Gray, 2014). As a final step, the daily returns are winsorised at the 0.1 and 99.9 percentiles.[3]

The analysis includes all stocks with the requisite data in each database, after filtering out stocks with non-ordinary share types. The intersection of time horizons spanned by the annual, monthly and daily databases is 1990–2013. As described next, several control variables require 12 months data for construction. This leaves a 23-year period spanning from 1991–2013 for the empirical analysis.

2.2. Construction of key variables

The key variable in this study is a stock's maximum daily return over the past month (denoted MAX). Specifically, for stock i in month $t, MAX_{i,t} = \max(R_{i,d}),\ d = 1, \ldots, D_t$, where $R_{i,d}$ is stock i's return on day d, and D_t is the number of trading days in month t. To be included in the sample for a given month, a stock must have at least five days in that month with non-zero trading volume with which to estimate MAX.[4]

A second important variable is a stock's idiosyncratic volatility (IV). Following Ang et al. (2006), the standard deviation of residuals from the Fama and French (1993) three-factor model proxy for IV. At the end of each month, the three-factor model is estimated for each stock using returns over the previous 252 days, subject to a minimum of at least 65 days.[5]

A raft of control variables are utilised throughout the empirical analysis. As defined in the next section, a stock's market capitalisation (*SIZE*) and book-to-market ratio (*BM*) are motivated by Fama and French (1992). The illiquidity of each stock is measured using the approach of Amihud (2002). First, on a daily basis, we calculate the ratio of the absolute return to dollar trading volume. By capturing the price response to one dollar of trading volume, this metric serves as an indicator of price impact. Second, we compute a monthly illiquidity metric for the cross-sectional analysis by averaging the daily metrics:

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R_{i,d}|}{\mathrm{Vol}_{i,d}}$$

where $R_{i,d}$ and $\mathrm{Vol}_{i,d}$ are stock i's day d return and dollar trading volume (measured in millions of dollars) respectively, and $D_{i,t}$ is the number of days for which data are available for stock i in month t.

Two measures of past return performance are utilised. First, in light of Jegadeesh (1990) and Lehmann (1990), stock i's month-t return ($REV_{i,t}$) controls for short-term reversals. The second momentum metric, which is calculated over a longer horizon following Jegadeesh and Titman (1993), is described in the next section. The systematic risk of a stock (*BETA*) is estimated using the approach of Scholes and Williams (1977) and Dimson (1979) to account for nonsynchronous trading. At the end of each month, daily excess stocks returns are regressed on the contemporaneous market risk premium, along with one lead and one lagged value. Each regression uses returns over the previous 252 days, subject to a minimum of at least 65 days of valid data.

Finally, two stock-level skewness measures are estimated. Following Harvey and Siddique (2000), systematic skewness ($SSKEW_{i,t}$) and idiosyncratic skewness ($ISKEW_{i,t}$) of stock i are estimated by fitting the following equation using daily returns over the previous 252 trading days:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \gamma_i(R_{m,d} - R_{f,d})^2 + \varepsilon_{i,d}$$

where $R_{i,d},\ R_{m,d}$ and $R_{f,d}$ are the day d returns on stock i, the value-weighted market portfolio and the riskfree rate respectively. *SSKEW* is the estimated slope $\hat{\gamma}_i$, while *ISKEW* is the skewness of daily residuals $\varepsilon_{i,d}$.

2.3. Components of mispricing index

In Section 5.2, we describe the construction of a mispricing index which is a composite rank of each stock based on a number of firm-level characteristics associated with known anomalies. This section overviews the construction of each component of the mispricing index, with the justification for inclusion of each variable deferred until Section 5.2.

Two 'anomaly' variables are readily constructed using SIRCA SPPR monthly data. $SIZE_{i,t}$ is stock i's market capitalisation at time t. $MOM_{i,t}$ is stock i's buy-and-hold return over the 5-month period

[2] There are 622 such occurrences. In some cases, they are straight duplicate records. Many cases involve a dilution event (e.g., dividend, capitalisation change), whereby one record relates to the dilution event and the other record relates to the traded price.

[3] Inevitably in a database of this size, there are some implausibly extreme daily returns (e.g., in the range of 4000–5000% on a given day). Winsorising at the 0.1 and 99.9 percentiles alters very few records yet mitigates concerns over the potential influence of data errors. Post-winsorisation, there is no stock with a daily return exceeding 100%. Further, all analysis utilises value weighting of stocks into portfolios which further mitigates the influence of extreme observations, since they are most likely to occur amongst micro cap stocks with low share prices.

[4] The results of the paper are essentially unchanged if a 10-day filter is employed. We adopt the 5-day filter with an eye towards maximising the cross-sectional sample size.

[5] Unlike the US scenario, there are no publicly-available asset-pricing factors for the Australian market at either monthly or daily frequency. The data source for and construction of our daily factors is described in Gray (2016). In brief, each December, stocks are independently sorted into 2×3 portfolios on the basis of size and BM. The constituent stocks of the S&P/ASX200 index are classified big, with the remainder classified small. Portfolio breakpoints for BM are based on the 30th and 70th percentiles of the BM distribution from the big stocks. Portfolios are value weighted and rebalanced annually.

from $t-6$ through $t-1$. The remaining five anomaly variables draw on the Morningstar-Aspect-Huntley financial accounting data. In estimating a stock's book-to-market ratio (*BM*), book value is defined as total shareholder equity, less outside equity interests, preferences shares and future tax benefits. Gross profitability (*GP*) is measured as earnings before interest, tax, depreciation and abnormals, scaled by lagged total assets.[6] Asset growth (*AG*) is the year-on-year growth rate in total assets. Accruals (*ACC*) are estimated using the direct approach via the Statement of Cash Flows. Specifically, *ACC* is proxied as earnings before interest and tax, less cashflow from operations, all scaled by lagged total assets. Finally, return-on-assets (*ROA*) is measured as the earnings before interest and taxes, scaled by lagged total assets.

Variables involving financial accounting data are estimated each December and then used for the following 12 months. Noting that over 80% of Australian companies have June balance dates, year y financials are used if the company's reporting date is June or earlier, and year $y-1$ otherwise. This provides a lag of at least 6 months between the balance date and estimation date, thus ensuring that the financial statements would have been publicly available at the time the variables are estimated.

3. Empirical analysis

3.1. Portfolio sorts and regression analysis

We begin the empirical analysis with a preliminary investigation of the existence of the MAX effect in Australian equities. The initial methodology involves univariate sorting of stocks into decile portfolios by MAX. Starting in December 1990, all stocks in the SIRCA CRD database are ranked according to their maximum single-day return in that month. Portfolio 1 (Portfolio 10) comprises stocks with the lowest (highest) MAX. The return on each portfolio over the following month is calculated on both an equal- and value-weighted basis. This procedure is repeated at the end of each month through to November 2013, generating a timeseries of 276 monthly returns to decile MAX portfolios.

Table 1 Panel A reports summary statistics that characterise the stocks within each MAX decile portfolio. For each variable, Panel A reports the time series average of the monthly cross-sectional medians. By construction, MAX increases across deciles, ranging from 0.30% for Portfolio 1 to 41.24% for Portfolio 10. The increase is approximately linear across the first seven deciles, then rises sharply across the three higher MAX deciles. The magnitude of the median MAX values, particularly for the higher MAX portfolios, must be interpreted in conjunction with the median stock prices. In general, ASX-listed stocks have prices that are significantly lower than their US counterparts. To illustrate, Fig. 1 plots the distribution of price for sample stocks, after pooling stock-month observations.[7] Across our sample period, the mean and median stock prices are \$1.66 and \$0.30 respectively. Table 1 Panel A shows that median prices are even lower for the higher MAX portfolios. Naturally, extreme single-day returns are more likely when the base price is small.

Stocks in the higher MAX deciles tend to have small market cap, low share price, high illiquidity and high beta. Since there is a vast literature that documents stocks with these characteristics tend to generate *higher* returns, the low average returns to high MAX stocks that we document shortly are all the more extraordinary. Another noteworthy feature of Panel A is the unambiguous positive relation between MAX and IV. We re-visit this issue in Section 4 and disentangle the separate effects of MAX and IV.

Table 1 Panel B corroborates this casual empiricism by reporting the cross-sectional correlation between key variables. Since market cap and BM are logged in the cross-sectional regressions to follow, the correlations are also based on natural logs of these variables. Further, all variables are winsorised at the 2.5/97.5 percentiles to mitigate the influence of outliers. Panel B documents strong correlations between MAX and size (-0.59), illiquidity (0.52) and IV (0.70). ILLIQ itself is strongly correlated with size (-0.80) and IV (0.68). Table 1 Panel B also demonstrates that MAX is highly persistent from one month to the next. On average, the correlation between a stock's month t and month $t+1$ MAX is +0.45.[8] Naturally, strong persistence in extreme positive returns is crucial to justify the argument that low returns to high MAX stocks result from lottery preferences.

Table 2 Panel A and Panel B present the average monthly return to value-weighted and equal-weighted MAX portfolios respectively, with Newey and West (1987) t-statistics in parentheses. In Panel A, the magnitude of average returns is qualitatively similar for Portfolios 1–7 (around 100 basis points), before falling dramatically for the three higher MAX deciles. The hedge portfolio that enters long (short) positions in Low (High) MAX stocks generates an average monthly return of 2.21% ($t = 5.17$). Table 2 Panel B suggests that a significant MAX effect also exists in equal-weighted portfolios. In this case, the Low MAX portfolio stands out as having the highest average return (2.37%). Portfolios 2–7 are again very similar, before average returns taper off, although not as dramatically as the value-weighted returns in Panel A.[9] Nonetheless, the hedge portfolio generates 2.64% per month ($t = 9.07$).

Table 2 also reports risk-adjusted portfolio returns in the form of the intercept from a risk-based factor model. Australia is a sophisticated, yet relatively small market within a global capital market. Prior literature reports mixed findings on the merit of Australian domestic versus international factors (Durand et al., 2006; Durand et al., 2016; Chiah et al., 2016). Nonetheless, a large body of international research suggests that a combination of domestic and international factors is necessary to adequately price stocks in most countries (see, for example, Brooks and Del Negro, 2006; Bekaert et al., 2009; Hou et al., 2011; Bekaert et al., 2014). As such, we adopt the four-factor asset-pricing model of Fama and French (1993) and Carhart (1997) that includes Australian domestic and global versions of each factor.[10]

Risk adjustment affects key portfolios in specific ways.[11] All MAX portfolios load significantly positively on the domestic market risk premium, with little variation across deciles. Loadings on the domestic momentum factor are predominantly negative with the largest loadings on the lower MAX deciles. The key exposure to risk factors lies on domestic *SMB*. Excluding the Low MAX portfolio, Table 1 Panel A shows that average market cap decreases

[6] Our measure of GP differs slightly from Novy-Marx (2013), since Morningstar-Aspect-Huntley does not contain a field for 'cost of goods sold'. Nonetheless, Zhong et al. (2014) have documented the existence of a *GP* effect in Australia using EBITDA in place of gross profit.

[7] The sample comprises 289,639 stock-month observations. To enhance clarity in Fig. 1, we have omitted a small number of stock-month observations with price exceeding \$20: (i) 58 observations with a price exceeding \$100, (ii) 450 observations with a price between \$50 and \$100, and (iii) 2916 observations with a price between \$20 and \$50. The distribution is even more right-skewed when these are included.

[8] When this correlation is estimated by pooling the sample across time (as opposed to averaging the monthly cross-sectional correlation estimates), the estimate is 0.35. Regressing MAX_{t+1} on MAX_t yields a slope of 0.40 ($t = 42$). These high estimates of persistence in MAX are consistent with the month-to-month transition probabilities discussed in Section 5.1.

[9] This may be attributable to the well-documented Australian size effect. Since High MAX portfolios tend to contain small stocks, equally weighting stocks into portfolios will generate higher average returns than value weighting.

[10] As was the case with daily asset-pricing factors, monthly Australian factors are also not publicly available. In this paper, risk adjustment to portfolio returns uses monthly factors constructed as per Zhong et al. (2014) and similar to the approach described in footnote 5. Global factors are sourced from Ken French's website and converted to AUD.

[11] An online appendix tabulates how each MAX portfolio loads on the risk factors.

Table 1
Summary statistics for MAX-sorted portfolios. At the end of each month, all ASX-listed stocks with ordinary share type are sorted into decile portfolios according to their maximum daily return during that month (MAX). This procedure is repeated each month from December 1990 through November 2013. Panel A presents descriptive statistics that depict the stocks within each portfolio. The reported characteristics are market capitalisation in million of dollars (*Size*), share price, book-to-market ratio (*BM*), buy-and-hold return over the 5-month period preceding the calculation of MAX (*MOM*), the short-term stock return in the portfolio-formation month (*REV*), Amihud's illiquidity measure (*ILLIQ*), beta, idiosyncratic volatility (*IV*) estimated as the standard deviation of residuals from the Fama and French (1993) three-factor model, idiosyncratic skewness (*ISKEW*) and systematic skewness (*SSKEW*) of daily stock returns over the past year, and factor loadings on MAXfactor (β_{MAX}). On average, there are 102 stocks per portfolio. Panel B reports correlations between key variables. Correlations are estimated in the cross section each month and then averaged over time. All variables are winsorised at the 2.5 and 97.5 percentiles before estimating summary statistics and correlations.

Panel A: summary statistics

MAX portfolios	Low	2	3	4	5	6	7	8	9	High
MAX (%)	0.30	2.23	3.72	5.18	6.90	9.05	11.84	15.66	22.11	41.24
Size ($m)	436	1713	1288	580	242	112	56	34	22	13
Price ($)	0.52	2.37	1.86	1.17	0.64	0.38	0.25	0.18	0.12	0.06
BM	0.84	0.59	0.57	0.58	0.62	0.64	0.69	0.74	0.80	0.86
MOM (%)	−8.28	3.39	5.34	5.45	4.04	2.42	−0.08	−2.40	−6.00	−11.91
REV (%)	−6.04	−1.68	−0.45	−0.24	−0.53	−0.39	0.14	1.68	4.23	8.33
ILLIQ	0.32	0.18	0.35	0.72	1.50	2.72	4.53	7.42	11.88	26.56
IV	1.58	1.43	1.88	2.50	3.31	4.28	5.38	6.80	9.03	15.63
Beta	0.51	0.60	0.68	0.74	0.81	0.89	0.93	0.98	1.02	1.04
ISKEW	0.95	0.40	0.33	0.42	0.51	0.58	0.64	0.68	0.77	1.31
SSKEW	−6.88	−3.13	−4.61	−7.20	−10.72	−13.34	−16.21	−18.81	−20.18	−21.86

Panel B: correlations

	MAX_t	MAX_{t+1}	Size	BM	ILLIQ	MOM	REV	IV	Beta	ISKEW	SSKEW	β_{MAX}
MAX_t	1											
MAX_{t+1}	0.45	1										
Size	−0.59	−0.50	1									
BM	0.04	0.03	−0.06	1								
ILLIQ	0.52	0.38	−0.80	0.06	1							
MOM	−0.16	−0.13	0.21	−0.02	−0.21	1						
REV	0.18	−0.09	0.11	0.01	−0.11	0.05	1					
IV	0.70	0.61	−0.84	0.05	0.68	−0.12	−0.07	1				
Beta	0.14	0.14	−0.03	0.01	−0.04	−0.02	−0.03	0.15	1			
ISKEW	0.33	0.27	−0.29	0.01	0.19	0.09	0.03	0.46	0.09	1		
SSKEW	−0.12	−0.11	0.15	0.01	−0.10	−0.02	0.01	−0.16	−0.02	−0.13	1	
β_{MAX}	−0.38	−0.35	0.36	0.01	−0.24	0.03	0.06	−0.47	−0.19	−0.26	0.14	1

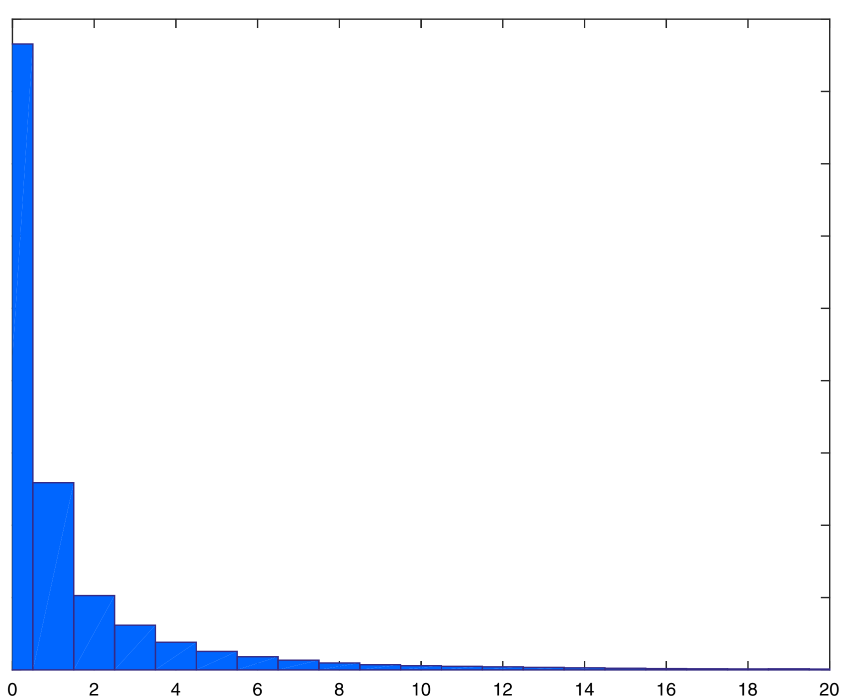

Fig. 1. Distribution of stock price within pooled sample. This figure shows the distribution of stock-month prices after pooling the sample ($N = 289,639$). To enhance clarity, we have removed 3424 stock-month observations with price exceeding $20. Specifically, there were: (i) 50 observations with price exceeding $100, (ii) 450 observations with price between $50 and $100, and (iii) 2916 observations with price between $20 and $50.

Table 2
Returns to MAX-sorted portfolios. At the end of each month, all ASX-listed stocks with ordinary share type are ranked according to their maximum daily return during that month (MAX) and sorted into decile portfolios. The return to these portfolios over the following month is calculated. This procedure is repeated each month from December 1990 through November 2013, giving a time series of 276 monthly returns to decile MAX portfolios. Panel A (Panel B) reports the average value-weighted (equal-weighted) portfolio returns. The risk-adjusted alphas are the intercept from the four-factor asset-pricing model of Fama and French (1993) and Carhart (1997) that includes Australian domestic and global versions of each factor. The *t*-statistics shown in parentheses are estimated using Newey and West (1987) standard errors.

MAX portfolios	Low	2	3	4	5	6	7	8	9	High	Low–High
	Panel A: value-weighted portfolios										
Raw return	1.02	0.76	1.07	0.85	0.80	0.95	0.99	−0.12	−0.74	−1.20	2.21
	(2.78)	(2.98)	(3.96)	(2.99)	(2.14)	(2.18)	(2.12)	(−0.25)	(−1.45)	(−2.35)	(5.17)
Alpha	0.10	−0.18	0.13	−0.04	−0.13	−0.14	−0.09	−1.42	−1.84	−1.91	2.01
	(0.40)	(−1.08)	(0.95)	(−0.25)	(−0.46)	(−0.46)	(−0.27)	(−4.63)	(−5.50)	(−5.52)	(4.95)
	Panel B: equal-weighted portfolios										
Raw return	2.37	0.83	1.04	1.24	1.09	0.95	0.65	0.25	0.07	−0.27	2.64
	(5.16)	(2.93)	(3.60)	(3.62)	(2.73)	(2.15)	(1.35)	(0.50)	(0.13)	(−0.48)	(9.07)
Alpha	1.59	0.03	0.24	0.37	0.17	−0.08	−0.36	−0.81	−0.88	−1.22	2.82
	(6.16)	(0.24)	(2.24)	(3.07)	(1.31)	(−0.50)	(−2.10)	(−3.84)	(−4.11)	(−4.78)	(10.62)

monotonically across MAX deciles. Intuitively, factor loadings on *SMB* increase across deciles. There are no distinct patterns in loadings on domestic *HML* or global factors. In terms of alphas, the overall takeaway from risk-adjusted returns is consistent with raw returns. The three highest MAX decile portfolios stand out as having the worst returns. The magnitude and economic significance of the Low–High hedge return, however, is very similar to the raw return. Overall, our preliminary findings are remarkably similar to the US findings of Bali et al. (2011), who report average returns around 1% per month for the first 7 portfolios, followed by a sharp decline in returns to stocks with higher MAX.

As noted above, MAX is correlated with some firm characteristics in ways that work against finding a significant MAX effect. Nonetheless, we undertake further analysis designed to isolate the unique influence of MAX on future returns. First, we conduct a series of bivariate sorts which examine the MAX effect after controlling for one other variable. Second, we utilise cross-sectional regressions to simultaneously control for multiple potential confounding influences.

The bivariate portfolio sorting analysis proceeds as follows. At the end of each month starting December 1990, sample stocks are sorted into five portfolios based on the desired control variable. Within each quintile, stocks are further sorted into five portfolios based on MAX, resulting in 25 double-sorted portfolios.[12] Given the large number of control variables to be considered, the reported results are an average of the returns across the quintiles of the control variable, for a given MAX grouping. This is akin to investing in stocks which have a wide range of values for the control variable, yet with similar levels of MAX. Table 3 reports the average return for each MAX grouping, thereby allowing dispersion in MAX whilst controlling for the characteristic (either SIZE, BM, MOM, REV, ILLIQ, BETA, ISKEW or SSKEW).[13]

The overwhelming takeaway from Table 3 is that the MAX effect is robust to controlling for each firm characteristic examined. For each control variable (i.e., reading down each column), there is a near monotonic relation between average returns and MAX. After neutralising portfolios to the control variable, the hedge return to a portfolio long (short) in Low (High) MAX stocks is statistically significant in all cases examined (at the 1% level or better in all but two cases). This is true regardless of whether stocks are value- or equal-weighted into portfolios, and for both raw and risk-adjusted returns.

The double-sorted results strongly suggest that the MAX effect is robust after controlling for the potential confounding influence of other variables. Naturally, a double-sorting procedure can only control for one variable at a time. To the extent that multiple variables are relevant in explaining cross-sectional return differences, and to the extent that these variables interact, the usefulness of double sorts is limited. As such, we employ Fama and MacBeth (1973) cross-sectional regressions at the individual firm level to isolate the marginal influence of MAX on returns in a multivariate context. Each month, time $t+1$ stock returns are regressed on time t values of MAX and various control variables. This regression is run in the cross section each month from December 1990 through November 2013, resulting in 276 estimates of each regression slope. The reported estimates are the timeseries average of these monthly slope estimates.

The regression results (which are tabulated in the online appendix) are highly consistent with the findings from portfolio sorts. Regressing month $t+1$ stock returns on time-t MAX, the average slope is -0.0411 ($t = -2.43$). Noting that the differential between mean MAX on Low and High deciles in Table 1 is approximately 41%, the regression coefficient implies an economically significant return spread of around 1.69% per month. Further, even after simultaneously controlling for numerous other stock-level characteristics known to influence cross-sectional returns, the strong negative relation between MAX and future returns remains intact (-0.0488, $t = -4.97$).

One final avenue of exploration involves the potential interaction of MAX with the skewness of a stock's return distribution. Section 1 highlighted a substantial theoretical literature that models investor preferences for skewed returns. A growing body of empirical work documents that various forms of skewness are priced.[14] Naturally, stocks that experience extreme positive returns are also likely to display positive skewness. Table 1 documents that MAX is positively correlated with ISKEW (0.33), yet largely uncorrelated with SSKEW (-0.12). Nonetheless, we check whether the observed MAX effect is robust to controlling for each of SSKEW and ISKEW.[15] The final two columns of Table 3 show that the MAX effect is insensitive to controlling for skewness. Similarly, the regression results

[12] On average, our sample comprises approximately 1000 stocks at each portfolio-formation point. Sequential sorting into quintile portfolios therefore places around 40 stocks in each portfolio. Clearly, double sorting into 10×10 decile portfolios would result in unacceptably sparsely populated portfolios. In any case, our use of quintile portfolios potentially biases the analysis against finding a MAX effect, given that the 'signal' provided by MAX will be dampened when only five groupings are employed.

[13] The interaction between MAX and idiosyncratic volatility (IV) is examined separately in Section 4.

[14] Harvey and Siddique (2000) and Smith (2007) show that systematic/coskewness is priced. Conrad et al. (2013) find that investors tradeoff the benefits of diversification for skewness, consistent with Mitton and Vorkink (2007); Brunnermeier et al. (2007); and Barberis and Huang (2008). Conrad et al. (2013) and Bali and Murray (2013) report that idiosyncratic risk-neutral skewness predicts future returns. Realized skewness estimated from high-frequency data is negatvely related to future returns out to one week (Amaya et al., 2015).

[15] Note that total skewness is extremely highly correlated with idiosyncratic skewness ($\rho = +0.96$). Regression results (untabulated) using total skewness are virtually identical to those reported for ISKEW.

Table 3
Double-sorted portfolios. This table reports the average monthly return for portfolios double-sorted on MAX and a given firm characteristic from 1991 to 2013. All ASX-listed stocks with ordinary share type are first sorted into quintile portfolios on the chosen characteristic. Within each quintile, stocks are further sorted into quintiles based on the stock's MAX. From the 25 double-sorted portfolios, we average across characteristic quintiles for a given level of MAX. Panel A (Panel B) reports the value-weighted (equal-weighted) portfolio returns. The risk-adjusted alphas are the intercept from the four-factor asset-pricing model of Fama and French (1993) and Carhart (1997) that includes Australian domestic and global versions of each factor. The firm characteristics adopted as control variables are market capitalisation (*Size*), buy-and-hold return over the 5-month period preceding the month in which MAX is estimated (*MOM*), short-term stock return in the portfolio-formation month (*REV*), Amihud's illiquidity measure (*ILLIQ*), book-to-market ratio (*BM*), beta, idiosyncratic skewness (*ISKEW*) and systematic skewness (*SSKEW*). Newey and West (1987) adjusted *t*-statistics are shown in parentheses.

Quintile	Size	MOM	REV	ILLIQ	BM	Beta	ISKEW	SSKEW
	Panel A: value-weighted portfolios							
Low max	2.35	0.88	1.11	1.23	1.20	0.88	0.99	0.96
2	1.61	0.76	0.95	0.93	0.99	1.00	1.04	0.99
3	1.50	0.53	0.97	0.55	0.81	0.68	0.77	0.83
4	1.11	0.30	0.51	0.34	0.69	0.47	0.51	0.60
High max	0.32	−0.01	−0.22	−0.01	−0.14	−0.07	−0.39	−0.25
Low–High	2.03	0.89	1.33	1.24	1.34	0.95	1.38	1.21
	(6.90)	(2.12)	(3.43)	(3.08)	(2.91)	(2.33)	(3.04)	(3.09)
Alpha	2.37	1.33	1.50	1.66	1.30	1.27	1.41	1.42
	(10.02)	(4.55)	(6.03)	(5.41)	(4.96)	(2.64)	(4.79)	(4.89)
	Panel B: equal-weighted portfolios							
Low max	2.63	2.57	2.63	2.47	2.64	2.28	2.25	2.32
2	1.73	1.09	1.42	1.48	1.28	1.19	1.26	1.19
3	1.59	1.22	1.18	1.40	1.31	1.12	1.09	1.38
4	1.33	1.06	1.14	1.26	1.25	1.09	0.89	0.98
High max	0.53	1.56	1.39	0.01	1.28	1.11	1.23	0.95
Low–High	2.10	1.01	1.24	1.33	1.35	1.17	1.02	1.38
	(7.14)	(2.80)	(3.71)	(3.71)	(3.34)	(3.42)	(2.78)	(4.24)
Alpha	2.46	1.41	1.36	1.86	1.56	1.49	1.17	1.68
	(10.67)	(5.28)	(5.92)	(6.41)	(5.37)	(5.85)	(4.32)	(6.35)

(see online appendix) confirm that the MAX effect is robust to inclusion of the skewness metrics.

To summarise, the empirical findings to this point provide consistent support for the existence of a negative relation between a stock's maximum daily return over the past month and its one-month ahead return. This finding manifests in univariate portfolio sorts, in double-sorted portfolios that control a given potential confounding influence, and in multivariate regressions that simultaneously control for a number of other relevant stock characteristics.

3.2. Robustness analysis

To assess the robustness of the main results, three sensitivity checks are conducted. First, we explore different definitions of MAX. While the base results sort stocks according to their highest single-day return over the ranking month, alternate definitions of MAX average the N highest daily returns over the ranking month ($N = 2, \ldots, 5$). The findings (tabulated in the online appendix) clearly demonstrate that the MAX effect documented in Table 2 is insensitive to the averaging period. Very similar patterns are documented across MAX deciles, with little discernible difference in returns across portfolios 1–7, followed by a sharp deterioration for portfolios 8–10. The Low–High hedge portfolio continues to generate statistically and economically significant returns which are marginally higher (approximately 40–50 basis points per month) than the base results in Table 2. This is the case for equal- and value-weighted portfolios, and for raw and risk-adjusted returns.

Our second robustness check relates to the possibility that the MAX effect may be driven by over-reaction to earnings events.[16] If high single-day returns are the result of investor over-reaction to an earnings announcement, and to the extent that such over-reaction is not corrected immediately, a negative relation between MAX and future returns may ensue. We explore this by examining the robustness of the MAX effect after excluding stocks with earnings events from the MAX-sorted portfolios.

The Australian Company Announcements database maintained by SIRCA provides a historical record of company disclosures commencing 1992. Earnings-related announcements include full-year results, half-year results, and for certain firms (primarily mining sector) quarterly results. In addition, firms are required to update the market whenever they become aware of circumstances that are likely to affect earnings (labelled 'price sensitive'). There are 54,265 price-sensitive earnings announcements over our sample period, each of which is time stamped to allow accurate identification of event timing.

The portfolio-sorting procedure is repeated after applying a number of alternate filters. First, any stock for which the day of the MAX return coincides with an earnings announcement date is excluded from the MAX portfolios. Notwithstanding the fact that announcements are time stamped, our second analysis excludes any stock for which the MAX day is on, or one day either side of, the earnings announcement. Third, and most conservatively, we exclude every stock that had a price-sensitive earnings announcement during the given portfolio-formation month. The results (tabulated in online appendix) are virtually unchanged from the base results in Table 2. Irrespective of the filter applied to earnings announcing stocks, the average return differential between low and high MAX stocks is approximately 2% per month. Accordingly, the MAX effect documented in this paper does not appear to be driven by earnings events.

The third, and most critical, robustness check relates to the 'investability' of the hedge portfolio implied by the Low–High MAX strategy. Table 1 Panel A reports the mean market cap and Amihud illiquidity of stocks within each MAX decile. It is readily apparent that the three portfolios with highest MAX are populated with relatively small, illiquid stocks, on average. In particular, the High MAX portfolio has the smallest average market cap.[17] In practice, it is unlikely that all of the requisite short positions in High MAX stocks could be entered. Since the profitability of the Low–High

[16] We are grateful to Geert Bekaert (Editor) for suggesting this line of enquiry.

[17] For perspective, note that as at December 2013, the mean and median market cap of ASX-listed stocks were \$865 m and \$20 m respectively. For the top 500 stocks, the mean (median) market cap was \$3.5bn (\$595 m).

MAX strategy derives in large part from the poor returns to the High MAX portfolio, it is possible that the apparent profits may not be genuinely exploitable.

We explore whether the MAX profitability is vulnerable to potential barriers to short selling by restricting the analysis to the top 500 stocks by market capitalisation as at each portfolio-formation point. This ensures that portfolios contain stocks that could be readily traded (in particular, the short positions in High MAX stocks).[18] Table 4 reports the value- and equal-weighted returns to decile MAX portfolios after restricting the sample to the top 500 stocks. Compared to Table 2, the magnitude of average returns to the Low–High hedge portfolios is approximately 50–60 basis points lower. Nonetheless, the hedge returns of 1.68% and 2.10% to value- and equal-weighted portfolios respectively are both economically and statistically significant. As with the base results, the profits remain after risk adjustment. Further, Table 4 displays patterns across deciles that are similar to those observed in both Table 2 and Bali et al. (2011) – average returns are relatively constant across low-to-medium MAX portfolios, before declining sharply for the highest MAX deciles.

To summarise, the MAX effect documented in Section 3.1 is strongly robust to a number of methodological variations. The findings are not dependent on the averaging period over which MAX is estimated, nor are they driven by earnings announcement events. The fact that a pronounced MAX effect remains amongst a partition of the largest ASX stocks alleviates legitimate concerns over the illiquidity and ability to enter short positions in high MAX stocks. As such, the robustness findings enhance confidence that the MAX effect could be successfully implemented in practice.

4. The interaction of MAX and idiosyncratic volatility

Empirical evidence suggests that investors have a preference for lottery-type assets. Kumar (2009) documents a correlation between individuals' propensity to gamble and their investment decisions. In fact, state lotteries and lottery-type stocks attract very similar socioeconomic clienteles. Kumar (2009, p. 1902) conjectures that investors may use one or more salient stock characteristics to identify lottery-like stocks. A stock's idiosyncratic volatility is one candidate characteristic. When idiosyncratic volatility is high, investors might believe that extreme return events observed in the past are more likely to be repeated (Kumar, 2009, p. 1900). Consistent with high idiosyncratic volatility signaling potential lottery payoffs, there is considerable international evidence that average returns are negatively related with stock level idiosyncratic volatility (Ang et al., 2006; Ang et al., 2009).

Given the high correlation between MAX and IV (+0.70; see Table 1), it is possible that the observed MAX effect is simply capturing a relation between IV and the cross-section of returns. To date, however, there is little evidence on the existence of an IV puzzle in Australian equities.[19] In this section, we investigate several issues surrounding IV and its potential interaction with MAX. As a starting point, we undertake a thorough examination of the existence of the IV puzzle in Australian equities. Building on the existing work of Liu and Di Iorio (2016), our data facilitates analysis over a considerably longer time series and broader cross section of stocks. We then proceed to investigate the extent to which IV and MAX have stand-alone influence on cross-sectional returns.

Table 4
Profitability of MAX effect: top 500 stocks. At the end of each month, the top 500 ordinary stocks on the ASX by market capitalisation are sorted into decile portfolios based on their maximum daily return in the current month. The return to these portfolios over the following month is calculated. This procedure is repeated each month from December 1990 through November 2013, giving a time series of 276 monthly returns to decile MAX portfolios. The table reports the average value- and equal-weighted portfolio returns. The risk-adjusted alphas are the intercept from the four-factor asset-pricing model of Fama and French (1993) and Carhart (1997) that includes Australian domestic and global versions of each factor. Newey and West (1987) adjusted *t*-statistics are shown in parentheses.

	VW portfolios		EW portfolios	
	Raw return	Alpha	Raw return	Alpha
Low MAX	1.13	0.20	1.13	0.30
2	0.96	0.03	1.26	0.47
3	1.04	0.16	1.04	0.25
4	0.91	0.08	1.12	0.30
5	0.76	−0.12	1.26	0.40
6	0.91	−0.19	1.16	0.21
7	0.89	−0.22	0.92	−0.07
8	0.48	−0.43	0.57	−0.46
9	1.04	−0.28	0.17	−0.94
High MAX	−0.56	−1.51	−0.97	−2.00
Low–High	1.68	1.71	2.10	2.30
t-Stat	(3.82)	(4.39)	(5.90)	(8.96)

To study the IV-return relation, IV is estimated for each stock as described in Section 2.2. Quintile portfolios are formed and held for one month, after which the procedure is repeated.[20] This generates a time series of 276 monthly returns to IV-sorted portfolios spanning 1991–2013. Table 5 Panel A reports average returns and risk-adjusted alphas to quintile IV portfolios formed on both value- and equal-weighted basis. For value-weighted portfolios, the well-known IV puzzle is evident – average returns decrease monotonically with IV, from 0.96% for the Low IV portfolio to −0.48% for the High IV portfolio. A hedge portfolio that enters long (short) positions in high (low) IV stocks generates a highly significant −1.43% per month ($t = -2.99$). When stocks are equal-weighted into portfolios, the monotonicity disappears and the hedge return is statistically insignificant. The tenet of these findings is identical to U.S. findings of Ang et al. (2006); Bali et al. (2011); and Bali and Cakici (2008).

Reconciling the current findings with the prior Australian work is more difficult.[21] For equal-weighted portfolios, Liu and Di Iorio (2016) report average monthly returns of 3.80% (0.53%) to the High (Low) IV deciles, yielding a spread of *positive* 3.27% per month. Further analysis shows that the divergent findings are not attributable to the use of decile versus quintile portfolios. Rather, it appears to be attributable to a combination of time period studied and the assumed holding period. First, applying our method to Liu and Di Iorio's shorter time series (2002–2010), the IV puzzle in value-weighted returns vanishes, while equal-weighted portfolios generate a positive IV-return relation (albeit a more modest spread of 1.37%, $t = 1.89$). Second, whereas we follow Bali et al. (2011) and Ang et al. (2006) and others by using a one-month holding period and re-forming portfolios monthly, Liu and Di Iorio (2016) rank stocks by IV each December and form portfolios that are held for the following year. When we adopt this methodological variation, the results from equal-weighted sorts again suggest a positive IV-return rela-

[18] In their study of momentum profitability, Demir et al. (2004) have similar concerns over the ability to short past loser stocks. Accordingly, they restrict their analysis to securities approved for short selling. At that time, they report that close to 500 stocks were on the approved securities list.

[19] Liu and Di Iorio (2016) study whether there is a risk factor associated with idiosyncratic volatility. In doing so, they document a *positive* relation between IV and average returns. It is pertinent to note that their study is confined to a relatively short time horizon (2002–2010), which Liu and Di Iorio (2016) attribute to limitations in their Datastream data.

[20] Quintile portfolios are utilised for consistency with the double-sorting procedure that follows next. The key findings and inferences on the IV puzzle are virtually unchanged when decile IV portfolios are employed (documented in the online appendix).

[21] The online appendix contains detailed tables of results illustrating our attempt to reconcile the current findings to Liu and Di Iorio (2016) by way of different time periods studied and methodological choices.

Table 5
Interaction between MAX and IV effects. This table reports average monthly returns to quintile portfolios based on univariate sorts by IV (Panel A) and MAX (Panel C). The portfolios are formed each month and held for the subsequent month. Panel B (Panel D) represent double sorts to examine the IV (MAX) effect after controlling for MAX (IV). Each month, stocks are first sorted into quintiles on the basis of the control variable. Then, within each quintile, stocks are sorted into quintiles on the primary variable. The sample period spans from 1991 to 2013. *t*-Statistics based on Newey and West (1987) standard errors are reported in parentheses.

Panel A: Univariate IV Effect			Panel B: Controlling for MAX			Panel C: Univariate MAX Effect			Panel D: Controlling for IV		
	VW	EW		VW	EW		VW	EW		VW	EW
Low IV	0.96	1.05	Low IV	0.67	0.70	Low MAX	0.78	1.60	Low Max	1.40	2.29
2	0.69	0.72	2	0.42	0.84	2	0.96	1.14	2	0.94	1.64
3	0.19	0.32	3	0.54	1.08	3	0.90	1.02	3	0.60	1.18
4	0.05	0.55	4	0.65	1.55	4	0.66	0.46	4	0.30	1.09
High IV	−0.48	0.71	High IV	1.19	2.54	High MAX	−0.87	−0.12	High Max	0.10	0.63
High–low	−1.43	−0.34	High–low	0.52	1.83	Low–High	1.65	1.72	Low–High	1.29	1.66
	(−2.99)	(−0.78)		(1.28)	(4.81)		(3.94)	(5.96)		(5.22)	(9.47)
Alpha	−1.61	−0.52	Alpha	0.16	1.70	Alpha	1.65	1.88	Alpha	1.22	1.88
	(−5.71)	(−1.83)		(0.61)	(6.53)		(4.83)	(9.03)		(4.90)	(11.12)

tion. This apparent sensitivity of findings to assumed holding period is consistent with Chen and Petkova (2012), who report that the negative relation between IV and stock returns vanishes seven months after portfolio formation point. Further, Bali and Cakici (2008) show that the existence of an IV effect is sensitive to the weighting scheme employed to average stocks into portfolios; specifically, they find no evidence of a negative IV effect in equal-weighted portfolios. While Liu and Di Iorio (2016) do not explicitly describe their weighting scheme, it is highly likely that stocks are equally weighted into their portfolios.

Returning to Table 5, Panel B isolates the stand-alone influence of IV on cross-sectional returns, after controlling for the influence of MAX. Each month, we first sort stocks into quintile portfolios based on MAX (the control variable). Second, within each MAX grouping, stocks are assigned to quintile portfolios based on IV. For each IV grouping, Panel B reports returns averaged across the five corresponding MAX groupings. Controlling for the MAX effect, the IV puzzle documented in Panel A no longer exists. For value-weighted portfolios, the High–Low spread is a statistically insignificant 0.52% per month ($t = 1.28$). For equal-weighted portfolios, the IV puzzle is reversed (+1.83% per month, $t = 4.81$). As such, Table 5 Panel B corroborates the findings of Bali et al. (2011). After controlling for MAX, there is no evidence of Ang et al.'s (2006) IV puzzle. Rather, average returns appear to be positively related to IV, consistent with a reward for holding idiosyncratic risk.

The two remaining panels in Table 5 consider whether the MAX effect documented throughout this paper is robust to controlling for IV. Whereas Table 2 documents the MAX effect using decile portfolios, Panel C generates essentially the same findings with quintile portfolios. Panel D then isolates the stand-alone MAX effect after controlling for IV. Stocks are first sorted into quintiles based on IV, and then sequentially into MAX quintiles. Table 5 Panel D shows that the negative relation between recent past extreme returns and future returns exists independent of any IV effect. Consistent with Bali et al. (2011), controlling for IV reduces the magnitude of Low–High spread compared to univariate MAX sorting. However, irrespective of whether stocks are value- or equal-weighted into portfolios, or whether raw or risk-adjusted returns are considered, Low MAX stocks significantly outperform High MAX stocks.

Each of these findings from the portfolio analysis is corroborated using cross-sectional regressions at the individual stock level (see online appendix). When IV is employed as the sole explanatory variable for one-month ahead returns (Appendix Table A2 model b), there is no evidence of an IV puzzle ($\beta = -0.0375, t = -0.80$). The absence of an IV puzzle is consistent with the equal-weighted univariate IV sorts in Table 5 Panel A. Similarly, when the influence of MAX is controlled (model c), the regression findings mimic Table 5 Panel B. There is a significant positive relation between IV and returns ($\beta = 0.1143,\ t = 2.46$) and a significant negative relation between MAX and future returns ($\beta = -0.0706,\ t = -6.50$). That is, the IV puzzle reverses after controlling for MAX. In the final 'kitchen sink' specification (model h), the negative relation between MAX and future returns remains robust, while the positive IV relation becomes statistically insignificant.

To summarise, while MAX and IV are highly correlated, the MAX effect documented in this paper is not simply a manifestation of the IV effect. The negative relation between MAX and future returns is consistently strong and robust after controlling for IV and other stock-level characteristics. In contrast, the IV puzzle appears highly sensitive to the time period studied, which other variables are controlled for and how stock-level data are averaged. Univariate portfolios sorts and regressions document the familiar (but contentious) negative relation between IV and future returns. However, this finding either reverses or vanishes depending on which other variables are included in the analysis.

5. Risk, mispricing and the MAX effect

Our findings support the existence of a statistically and economically significant MAX effect in Australian equities. The negative relation between MAX and future returns is robust to methodological variations and survives after controlling for various other characteristics known to influence cross-sectional returns. Importantly, the MAX effect exists amongst the largest market cap stocks. As such, it is natural to question whether the observed cross-sectional pattern reflects underlying risk or mispricing. The following sections explore the risk and mispricing explanations for the observed MAX effect.

5.1. Does MAX proxy for sensitivity to risk?

The Australian MAX effect documented in this paper is strikingly similar to that found in the US (Bali et al., 2011; Bali et al., 2015). This raises the possibility that negative returns to high MAX stocks reflect exposure to underlying risk. This conjecture is explored with several avenues of investigation.

A number of explanations for the relation between past extreme returns and future returns have been proposed. Investors may regard stocks that experience high MAX as having a desirable lottery-like feature (Kumar, 2009; Bali et al., 2011). Alternatively, investors may have distorted views on the likelihood of future extreme returns (Barberis and Huang, 2008; Brunnermeier et al., 2007). Naturally, the plausibility of each explanation is enhanced if recent extreme positive returns have a tendency to be repeated. To this end, we compile estimates of the persistence/transition of stocks between MAX deciles at varying time intervals (full details appear in the online appendix). Consistent with the high positive month-to-month correlation between MAX reported in Table 1, stocks assigned to the High MAX decile in month t have a 38% likelihood of falling in the High MAX decile in month $t+1$, and a 64% likelihood of being assigned into one of the three highest MAX deciles. This persistence diminishes only marginally with the passage of time. The likelihood that a stock assigned to the High MAX decile at time t falls in that same decile in month $t+3,\ t+6$ or $t+12$ is 33%, 30% and 27% respectively.

Such high persistence in extreme positive returns out to intermediate horizons lends support to the notion that investors may utilise recent past MAX as a signal of future lottery-like behaviour. To the extent that investors are cognisant of this persistence, a recent extreme return may have a lingering influence on future returns. Table 6 examines the influence of MAX estimated at time $t-k,\ k \in \{0,1,2,5,11\}$ on $t+1$ returns.[22] For brevity, we only report the value-weighted portfolio returns. Panel A re-produces the baseline result from Table 2. Time-t MAX has clear implications for one-month-ahead returns, with the raw and risk-adjusted spread between Low and High MAX portfolios exceeding 2% per month. Consistent with a high degree of persistence in MAX, Panel B shows that MAX estimated at month $t-1$ also has implications for month $t+1$ returns. However, the magnitude is approximately half the baseline result, potentially reflecting the increased uncertainty that a stock with high MAX in $t-1$ will have a similar extreme event two months ahead. Panel C and Panel D consider the implications of MAX for returns three and six months ahead respectively. Over short to intermediate horizons, there is little dropoff in the likelihood of a High MAX stock experiencing another extreme positive return (see online appendix). As such, the magnitude of the MAX effect documented in Table 6 Panel C and Panel D is very similar to Panel B. Finally, even for a twelve-month-ahead horizon, time $t-11$ MAX generates a significant, albeit diminished, spread in $t+1$ returns. Clearly, the influence of an extreme positive return is not short lived.

To summarise, we document non-trivial persistence in extreme positive returns, which may re-enforce the perception of a lottery. The fact that the implications of high MAX for future returns diminish only marginally with the passage of time suggests that investors are conscious of the likely persistence of MAX. It is important, however, to recognise that these stylised facts are necessary but not sufficient conditions for the risk story. If there was little persistence in the MAX portfolio to which stocks are allocated, investors would be unlikely to regard MAX as a signal of lottery-like characteristics. Having documented strong persistence in MAX, we proceed to formally test whether MAX proxies for sensitivity to a priced risk factor.

First, we briefly consider whether there is co-movement between the MAX effect in Australia and the US. To the extent that there is commonality in MAX spread returns across countries, it is possible that the MAX effect is driven by a broad, not easily diversifiable factor.[23] Using CRSP daily data for US stocks, we form decile portfolios at the end of each month based on the maximum single-day return during that month. The sample includes all common stocks on the NYSE, AMEX and NASDAQ which have a month-end share price of at least \$5. The US MAX effect (denoted MAX^{US}) reflects a strategy that enters long (short) positions in stocks with low (high) MAX and holds for the following month. This procedure is repeated each month spanning 1991–2013 to generate a time series of 276 monthly returns to MAX^{US} coinciding with the sample used throughout this paper.[24] In the spirit of Ang et al. (2009) and Amihud et al. (2015), and with all returns denominated in Australian dollars, we regress monthly returns to the Australian long-short MAX strategy on MAX^{US}. Table 7 reports the results.

The first set of results (Model I) replicate the value-weighted Low–High alpha from Table 2. Specifically, a risk-based model that incorporates both domestic and global risk factors cannot explain the return premium earned by low MAX stocks over high MAX stocks $(2.01\%, t = 4.95)$. In Model II, the co-movement between the US and Australian MAX returns is statistically significant (0.17, $t = 2.87$), yet economically modest. For example, the mean MAX^{US} over our sample period is 0.53% per month. If it were to double, the Australian MAX return would increase by a mere 9 basis points. Model III casts further doubt over the notion that there is a commonality in returns to the MAX strategy across the US and Australia. When Australian domestic and global risk factors are included as independent variables, there is no co-movement evident $(0.06, t = 0.83)$ and $\bar{R}^2$ is unchanged.[25]

To summarise, the findings in Table 7 provide little support for the existence of co-movement in Australian and US MAX spread returns. The abnormal returns generated by the Australian MAX spread strategy are robust to adjustment for local and global risk factors, and do not appear to be driven by commonality between MAX spread returns across countries. While the Australian MAX spread return is statistically correlated with MAX^{US}, the economic importance of the relation is negligible. Given that MAX^{US} is correlated with global asset-pricing factors, the apparent co-movement (Model II) may be more indicative of the exposure of Australian spread returns to global factors than to an underlying economic source of risk related to MAX. Nevertheless, we round off the analysis with a formal test whether MAX proxies for underlying risk.

In order to examine whether MAX proxies for sensitivity to a priced risk factor, we construct a factor-mimicking portfolio around MAX (denoted MAXfactor). Each month, stocks are assigned to three portfolios using the 30th and 70th percentiles of the cross-sectional distribution of MAX as cutoffs. In a similar fashion, stocks are independently sorted into two size groupings. Following Brailsford et al. (2012b) and Zhong et al. (2014), stocks inside (outside) the S&P/ASX200 are denoted big (small). This procedure generates six portfolios double sorted on MAX and firm size. The value-weighted return to each portfolio is estimated for the following month. The MAXfactor is the average return on the two low MAX portfolios less the average return on the two high MAX portfolios. Over 1991–2013, the mean monthly return to the MAXfactor is positive and statistically significant (1.14% per month, $t = 3.10$).

Having estimated returns to the factor-mimicking portfolio, we calculate the sensitivity of each stock to MAXfactor (denoted β_{MAX}). Each month, excess stock returns over the prior 60 months are regressed on MAXfactor, subject to a minimum time series of 24 valid returns. The procedure generates stock-level sensitivities to MAXfactor spanning 1992–2013 which are the basis for the following empirical analysis.

First, we utilise univariate portfolio sorts to examine whether there is a relation between MAXfactor sensitivity and future stock

[22] We are grateful to an anonymous referee for suggesting this approach to characterising the ongoing influence of MAX on future returns.

[23] Similar ideas are presented in: (i) Ang et al. (2009) who document that returns to a trading strategy taking long (short) positions in foreign stocks with high (low) idiosyncratic volatility have large exposure to a similar US-based strategy, and (ii) Amihud et al. (2015) who document a commonality in illiquidity return premiums across countries.

[24] Our construction of the US MAX spread generates returns that reconcile closely with prior work. Bali et al. (2015) report a mean monthly equal-weighted return to their MAX^{US} strategy of 0.95% ($t = 3.91$) over the period July 1963–December 2012 ($MAX(1)$ in Table A3 of their paper). Extending our analysis of US stocks to span the same period, we generate a near-identical mean monthly equal-weigthed return of 0.96% ($t = 4.16$) and value weighted return of 0.67% ($t = 2.42$).

[25] Further investigation reveals that MAX^{US} has non-trivial correlations with global SMB (0.56) and global MRP (−0.38).

Table 6
Influence of MAX on future returns. At the end of each month t, all ASX-listed stocks with ordinary share type are ranked according to their maximum daily return (MAX) estimated during month $t-k$, $k \in \{0,1,2,5,11\}$. The value-weighted returns to decile MAX-sorted portfolios are estimated for month $t+1$. This procedure is repeated each month from December 1990 to November 2013. Panel A presents the baseline results from Table 2 where MAX is estimated during the most-recent month ($k=0$). Panels B through E then document the longevity of the MAX effect by increasing the lag k between when MAX is estimated and the portfolio-formation date. Each panel reports the average value-weighted portfolio returns. The risk-adjusted alphas are the intercept from the four-factor asset-pricing model of Fama and French (1993) and Carhart (1997) that includes Australian domestic and global versions of each factor. The t-statistics shown in parentheses are estimated using Newey and West (1987) standard errors.

MAX portfolios	Low	2	3	4	5	6	7	8	9	High	Low–High	*t*-Stat
	Panel A: month t + 1 returns based on MAX estimated during month t (baseline results)											
Raw return	1.02	0.76	1.07	0.85	0.80	0.95	0.99	−0.12	−0.74	−1.20	2.21	(2.35)
Alpha	0.10	−0.18	0.13	−0.04	−0.13	−0.14	−0.09	−1.42	−1.84	−1.91	2.01	(4.95)
	Panel B: month t + 1 returns based on MAX estimated during month t − 1											
Raw return	1.27	0.82	1.04	0.79	0.68	0.89	0.29	0.15	−0.16	0.14	1.13	(2.65)
Alpha	0.61	−0.15	0.11	−0.45	−0.43	−0.16	−0.59	−1.01	−0.99	−0.87	1.48	(3.21)
	Panel C: month t + 1 returns based on MAX estimated during month t − 2											
Raw return	1.04	0.77	0.88	0.74	0.92	1.07	0.42	0.42	0.36	−0.10	1.14	(2.65)
Alpha	0.38	−0.01	−0.16	−0.42	−0.15	0.11	−0.39	−0.71	−0.82	−1.15	1.52	(3.77)
	Panel D: month t + 1 returns based on MAX estimated during month t − 5											
Raw return	0.96	0.94	1.25	0.63	0.83	0.45	1.14	0.03	0.56	−0.18	1.14	(2.61)
Alpha	0.25	0.09	0.24	−0.29	−0.22	−0.80	0.04	−1.38	−0.35	−1.19	1.45	(3.34)
	Panel E: month t + 1 returns based on MAX estimated during month t − 11											
Raw return	0.87	0.94	0.93	0.76	0.93	0.90	0.51	0.44	0.23	0.08	0.79	(1.71)
Alpha	0.12	0.16	−0.11	−0.18	0.02	0.17	−0.21	−0.39	−0.40	−0.93	1.05	(2.61)

Table 7
Commonality in MAX effect. This table reports estimates of the co-movement between Australian and US MAX portfolios. The dependent variable is the monthly return to a portfolio that enters long (short) positions in Australian stocks with low (high) MAX during the most-recent month. The key independent variable is a similarly defined long-short portfolio constructed from US stocks (MAX^{US}). Other independent variables include Australian domestic and global versions of the common asset-pricing factors (MRP, SMB, HML, UMD). All returns are denominated in Australian dollars. The regressions utilise a time-series of 276 monthly returns spanning January 1991 through December 2013.

	I	II	III
Intercept $\times 10^2$	2.01	2.11	1.54
	(4.95)	(5.19)	(2.59)
MRP (AUS)	0.19		0.17
	(1.06)		(1.31)
SMB (AUS)	−0.66		−0.67
	(−5.47)		(−5.57)
HML (AUS)	0.19		0.19
	(1.05)		(1.05)
UMD (AUS)	−0.17		−0.18
	(−1.14)		(−1.19)
MRP (global)	−0.07		−0.17
	(−0.45)		(−0.74)
SMB (global)	−0.26		0.35
	(−1.29)		(1.66)
HML (global)	0.44		0.15
	(2.49)		(1.25)
UMD (global)	0.16		1.97
	(1.35)		(0.96)
MAX^{US}		0.17	0.06
		(2.87)	(0.83)
adj R^2	0.22	0.04	0.22

returns. Each month, stocks are sorted into decile portfolios according to their β_{MAX}. Table 8 Panel A reports the average value-weighted return and risk-adjusted alpha to the β_{MAX}-sorted portfolios. By construction, β_{MAX} increases monotonically from −1.87 for portfolio 1 to 0.37 for portfolio 10. On average, returns to high β_{MAX} portfolios exceed returns to low β_{MAX} portfolios. However, the return differential between extreme portfolios is statistically insignificant (0.81% per month, $t = 1.11$). Similarly, risk-adjusted alphas exhibit no obvious relation with β_{MAX}.

Second, we adopt the Fama and MacBeth (1973) cross-sectional regression approach to compare the ability of MAX and β_{MAX} to predict one-month-ahead stock returns. Each month, time $t+1$ stock returns are regressed on time t values of MAX, β_{MAX} and a number of other variables known to influence cross-sectional returns:

$$R_{i,t+1} = b_0 + b_1 MAX_{i,t} + b_2 \beta_{MAX,i,t} + \sum_{j=1}^{9} \gamma_j X_{j,i,t} + \varepsilon_{i,t+1},$$

where the vector of control variables comprises $\ln(Size)$, $\ln(BM)$, MOM, REV, $ILLIQ$, $BETA$, IV, $ISKEW$ and $SSKEW$ as defined in Section 2.2. All variables are winsorised at the 2.5/97.5 percentiles to mitigate the potential influence of outliers. The regression is estimated using the cross-section of stocks each month from January 1992 through November 2013, resulting in 263 estimates of each slope. The reported estimates are the time-series average of these monthly estimates. All statistical inference utilises Newey and West (1987) standard errors.

Consistent with the univariate portfolio analysis, Table 8 Panel B shows no evidence that future returns are influenced by β_{MAX}. The time-series average of monthly estimates of b_1 are economically and statistically insignificant. In contrast, there is a significant negative relation between MAX and future stock returns. The full model documents familiar negative (positive) relations between stock returns and firm size, short-term performance and skewness (book-to-market, medium horizon momentum, and illiquidity). Even after controlling for these other influential variables, time t MAX retains a strong ability to predict $t+1$ returns ($b_1 = -0.0411, t = -4.64$).

To summarise, while stocks exhibit the strong persistence in MAX necessary to re-enforce the perception of lottery-like characteristics, the empirical testing provides little support for the notion that the observed negative relation between MAX and future returns reflects exposure to underlying risk. The commonality in co-movement between Australian and US MAX spread returns is economically modest. Significant abnormal returns remain after controlling for common risk factors and MAX^{US} returns. Stock-level sensitivities to a factor-mimicking portfolio designed around the MAX effect exhibit no ability to predict future returns. This lack of findings motivates a closer examination of whether the MAX effect represents mispricing.

Table 8
Predictive ability of β_{MAX}. This table examines whether stock-level sensitivity to MAXfactor (denoted β_{MAX}) predicts future returns. At the end of each month, the sensitivity of each stock to MAXfactor is estimated by regressing excess stock returns over the prior 60 months on MAXfactor, subject to a minimum of 24 valid observations. In Panel A, stocks are sorted monthly into decile portfolios according to β_{MAX}. Value-weighted raw returns for each portfolio are estimated for the following month. This procedure is repeated each month from January 1992 through November 2013. For each portfolio, Panel A reports the average β_{MAX}, the average one-month-ahead portfolio return and the risk-adjusted alpha. The risk-adjusted alphas are the intercept from the four-factor asset-pricing model of Fama and French (1993) and Carhart (1997) that includes Australian domestic and global versions of each factor. Panel B reports estimates from monthly Fama and MacBeth (1973) cross-sectional regressions. *t*-Statistics using Newey and West (1987) standard errors are shown in parentheses.

Panel A: univariate portfolios sorted on β_{MAX}											
β_{MAX} portfolios	Low	2	3	4	5	6	7	8	9	High	High–Low
β_{MAX}	−1.87	−1.19	−0.87	−0.63	−0.44	−0.29	−0.15	−0.03	0.10	0.37	
Raw return	0.13	0.12	0.04	0.08	0.48	0.75	0.91	1.30	0.70	0.93	0.81
	(0.16)	(0.17)	(0.06)	(0.14)	(1.10)	(1.72)	(2.46)	(3.76)	(2.55)	(2.91)	(1.11)
Alpha	−0.28	−0.34	−0.89	−0.63	−0.08	−0.41	−0.05	0.17	0.12	0.02	0.31
	(−0.70)	(−0.81)	(−2.28)	(−1.88)	(−0.27)	(−1.57)	(−0.21)	(0.99)	(0.89)	(0.06)	(0.59)
Panel B: Fama and MacBeth (1973) regressions											
β_{MAX}	MAX	ln(Size)	ln(BM)	MOM	REV	ILLIQ	BETA	IV	ISKEW	SSKEW	adj R^2
0.0036											0.02
(1.20)											
0.0017	−0.0356										0.03
(0.71)	(−2.36)										
0.0018	−0.0411	−0.0009	0.0030	0.0052	−0.0393	0.0001	−0.0010	0.0338	−0.0013	−0.0001	0.06
(1.08)	(−4.64)	(−1.37)	(3.32)	(2.42)	(−6.20)	(2.64)	(−1.36)	(0.82)	(−2.62)	(−0.50)	

5.2. Exploring a mispricing explanation

Empirical work has traditionally explored whether cross-sectional patterns between stock characteristics and average returns can be explained by differential exposures to risk factors. In the absence of a risk-based explanation, the documented anomaly is often attributed to mispricing. In studying the idiosyncratic volatility puzzle, Stambaugh et al. (2015) develop a more-formal approach to assessing whether cross-sectional return patterns are likely to be the result of mispricing. Using a composite rank of numerous characteristics known to be associated with anomalous returns, they build a simple proxy for mispricing that allows the classification of stocks by the direction and degree of mispricing. Consistent with their mispricing hypotheses relating to arbitrage risk and arbitrage asymmetry, Stambaugh et al. (2015) demonstrate that the degree of mispricing plays a role in determining the strength and direction of the IV-return relation.

We utilise a similar framework to study whether the observed MAX effect is consistent with mispricing. Central to this analysis, we construct a mispricing proxy for the Australian context similar in spirit to Stambaugh et al. (2015). There is a respectable literature documenting the existence of anomalies in the Australian stock market.[26] Many papers document size, value and momentum effects. A handful of recent papers provide preliminary evidence of profitability effects (proxied by GP and ROA), accruals and asset growth anomalies. Accordingly, our mispricing proxy is based on seven anomalies (size, BM, momentum, GP, ROA, accrual, and asset growth).[27]

Our construction of the mispricing index proceeds as follows. On a monthly basis, a percentile rank is assigned to each stock for each anomaly variable. The lowest rank is assigned to the value of the anomaly variable associated with the highest expected return (i.e., most underpriced), while overpriced stocks with the lowest expected return from an anomaly variable receive the highest rank. For example, given the expected positive relation the between BM and average returns, stocks with the highest (lowest) BM ratio receive the lowest (highest) rank. This procedure leads to seven rankings for a given stock, which are averaged to generate that stock's mispricing index for that month. Stocks with the highest (lowest) composite rank are the most overpriced (underpriced).[28] Given the mispricing index, stocks are independently double sorted into quintiles based on MAX and mispricing. Using the intersection of these quintiles, value-weighted returns to twenty-five portfolios are estimated for the subsequent month, after which the double-sorting procedure is repeated. Table 9 reports the average monthly return to each portfolio.

There are several important takeaways from Table 9. First, there is validation that the mispricing index successfully classifies under/over priced stocks. Within each MAX grouping (i.e., reading down each column), the spread between under- and over-priced stocks is positive and statistically significant. Second, the magnitude of mispricing increases with MAX, from 0.79% for the Low MAX grouping through to 3.05% for High MAX stocks. Stambaugh et al. (2015) conjecture that mispricing occurs partly because arbitrage risk deters investors from fully correcting the mispricing. Noting that idiosyncratic volatility is a common proxy for arbitrage risk, they document that the magnitude of mispricing increases with IV. Given that MAX and IV are highly correlated (+0.70; see Table 1), it is intuitive that the mispricing is greatest in the High MAX grouping since these stocks are subject to the highest arbitrage risk.

Most importantly, Table 9 provides strong evidence that the MAX effect is attributable to mispricing. Controlling for the level of mispricing (i.e., reading across a given row), and again noting that MAX and IV are highly correlated, High MAX stocks are expected to be the most-susceptible to mispricing that is not arbitraged away due to high arbitrage risk. In the case of overpriced stocks, the familiar negative relation between MAX and returns is predicted – high levels of arbitrage risk deter investors from entering the short positions in High MAX stocks necessary to correct the overpricing. Consistent with this conjecture, amongst the Most Overpriced stocks, average returns decrease near monotonically

[26] Australian evidence on anomalies is well documented in a number of recent papers (see, for example, Gharghori et al., 2009; O'Brien et al., 2010; Brailsford et al., 2012a; Dou et al., 2013; Zhong et al., 2014).

[27] To independently corroborate the existence of these anomalies, we conducted a preliminary analysis involving univariate sorts on each of the seven chosen variables. Detailed results are included in the online appendix. The appendix also tabulates the correlation between returns to the MAX strategy and each component of the mispricing index.

[28] A file containing firm-month records of the composite mispricing index and each of its components is available from the authors on request.

Table 9
The role of mispricing in the MAX effect. This table reports the average monthly returns and Fama and French (1993) and Carhart (1997) four-factor alphas for portfolios constructed by sorting independently on the mispricing index and MAX. The mispricing index is the average of the percentile rankings based on 7 anomaly variables. All ASX-listed stocks with ordinary share type are first sorted into quintile portfolios on the mispricing index at the end of each month. Stocks are also sorted into quintile portfolios on MAX independently at the end of each month. The intersection of both sorts gives rise to 25 portfolios. The figures in the parentheses represent Newey and West (1987) adjusted *t*-statistics.

	Low MAX	2	3	4	High MAX	Low–High		Alpha	
Most underpriced	1.43	1.75	1.67	1.80	2.10	−0.66	(−1.02)	−0.75	(−1.06)
2	0.90	1.21	1.36	1.36	0.75	0.15	(0.23)	−0.61	(−0.85)
3	0.82	0.68	0.73	1.03	0.57	0.25	(0.35)	0.68	(0.91)
4	0.53	0.67	0.09	0.40	0.25	0.27	(0.39)	0.04	(0.06)
Most overpriced	0.64	−0.52	−0.17	−0.77	−0.95	1.59	(2.05)	1.61	(1.87)
Underpriced less overpriced	0.79	2.26	1.85	2.57	3.05				
	(1.67)	(4.86)	(3.82)	(4.70)	(4.42)				
Alpha	1.05	2.37	1.50	2.88	3.41				
	(1.98)	(4.76)	(2.78)	(4.34)	(4.98)				

with MAX, from 0.64% to −0.95%. The Low–High spread averages 1.59% per month ($t = 2.05$).

Conversely, in the case of underpriced stocks, Stambaugh et al.'s (2015) argument works against finding the familar MAX effect – arbitrage risk deters investors from entering the requisite long positions in High MAX stocks to reduce their returns. Table 9 again supports this prediction. Amongst the Most Underpriced stocks, average returns *increase* with MAX. The Low–High spread averages *negative* 0.66%, although statistically insignificant. Taken together, the manner in which mispricing influences the MAX effect largely parallels Stambaugh et al.'s (2015) findings for mispricing and idiosyncratic volatility. In their case, a negative relation between IV and returns resides amongst overpriced stocks, since high IV stocks are likely to be the most overpriced. Amongst underpriced stocks, the IV effect is positive since high IV stocks are likely to be the most underpriced.

Table 9 is also consistent with the notion of 'arbitrage asymmetry'. Stambaugh et al. (2015, p. 1), note that 'many investors who would buy a stock they see as underpriced are reluctant or unable to short a stock they see as overpriced'. As a consequence, the activities of arbitrageurs should eliminate more underpricing than overpricing. Consistent with arbitrage asymmetry, the magnitude of mispricing amongst overpriced stocks (1.59%) far exceeds that for underpriced stocks (−0.66%), with the difference of 2.25% significant at the 1% level. In fact, the Most Overpriced grouping is the only quintile for which the MAX effect is statistically significant.

To summarise, while the empirical analysis finds no evidence that the observed MAX effect reflects underlying economic risk, there is strong support that it is due to mispricing. In particular, the negative relation between MAX and future returns is: (i) concentrated in the most-overpriced stocks, and (ii) largely driven by low returns to the High MAX partition amongst overpriced stocks. Given the high correlation between MAX and idiosyncratic volatility, this finding is highly consistent with the notion that arbitrage risk and arbitrage asymmetry deter the short positions that would be necessary to eliminate the MAX mispricing.

6. Conclusions

In recent years, a growing body of work has documented a negative relation between extreme positive returns and one-month ahead stock returns. Several explanations for the so-called MAX effect have been proposed. A number of theoretical models motivate a preference for skewness in asset returns and recent empirical work documents that various forms of skewness are priced. Alternatively, behavioural models suggest a preference for assets with lottery-like payoffs. Naturally, the extreme positive returns captured by MAX are related to both skewness and lottery characteristics.

This paper makes a number of contributions to this emerging literature. We document a strong and robust negative relation between past extreme positive returns and future returns in Australian equities over an extended time period (1991–2013). Using a variety of methodological approaches, the magnitude of this MAX effect is both statistically and economically significant. It is robust to controlling for numerous other characteristics that influence cross-sectional returns and survives risk adjustment using an assortment of risk models. Importantly, given that high MAX stocks tend to be small and illiquid, the magnitude of the MAX effect is only marginally reduced when we restrict the analysis to the largest 500 listed stocks. This finding alleviates some concerns that the low returns to high MAX stocks – which to a large degree drive MAX profitability – are illusory.

As part of our study of the interaction between MAX and IV, this paper also makes an important early contribution to the Australian evidence on the IV puzzle. To date, Liu and Di Iorio (2016) is the only prior Australian study of the relation between idiosyncratic volatility and future stock returns. With the benefit of a considerably longer time period and broader cross-section of stocks, we document the familiar negative relation between IV and stock returns consistent with most international evidence. Further, we are able to reconcile this finding to Liu and Di Iorio (2016) by showing that their positive IV-return relation is attributable partly to the 2002–2010 time period studied, and partly to methodological choices (specifically, annual portfolio formation and 12-month holding periods). While the negative IV-return relation appears strong when considered in isolation, IV is highly correlated with MAX. After controlling for MAX, there is little compelling evidence of an IV puzzle. In contrast, the negative MAX-return relation is strongly robust to controlling for IV.

Finally, and most importantly, the paper is the first research to formally explore whether the observed MAX effect is attributable to risk or mispricing. Testing whether an empirical regularity is a consequence of sensitivity to risk factors is standard practice in asset-pricing literature. However, in the absence of an economic risk explanation, many studies default to a mispricing story without formally testing its merit. An innovative contribution of our paper is to construct a mispricing index that facilitates a formal test of whether the MAX effect is attributable to mispricing.

The empirical findings emphatically favour mispricing over risk explanations. Contrary to expectations if MAX reflects a source of underlying economic risk, the commonality in co-movement between US and Australian MAX spread returns is economically negligible. Further, constructing a factor-mimicking portfolio around MAX, there is no evidence that stock-level sensitivity to the MAXfactor predicts future returns. In contrast, there is strong evidence that the MAX effect is attributable to mispricing. Our findings demonstrate that the negative relation between MAX and future returns concentrates amongst the most-overpriced stocks (where high levels of arbitrage risk deter investors from entering the short positions in high MAX stocks necessary to eliminate mispricing). For the underpriced grouping, the MAX effect actually *reverses* (since arbitrage risk deters investors from entering the requisite long positions in high MAX stocks). Further, given arbitrage asymmetry, the magnitude of the MAX effect amongst overpriced stocks exceeds that amongst underpriced, resulting in an overall negative relation that has been well documented.

Given the weight of evidence consistent with a mispricing explanation, future research may benefit from exploring the cause of this mispricing. For example, Han and Kumar (2013) show that overpriced stocks tend to have a high proportion of trading by retail investors, which they conjecture captures speculation. While the role of institutional ownership in the MAX effect has been studied by Fong and Toh (2014) and Han and Kumar (2013) show that retail trading proportion is not a simple transformation of institutional ownership. As such, the influence of retail investors' trading on the MAX effect warrants investigation. Similarly, the extent to which limits to arbitrage impede the full correction of mispricing is relevant. Our finding that the MAX effect concentrates in the most-overpriced grouping (where short selling is warranted) is suggestive of an important role for arbitrage costs. Linking the strength of the MAX effect to time series and cross-sectional variation in trading and short selling costs would augment the mispricing explanation.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbankfin.2016.01.007.

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