INVESTOR OPTIMISM, SALES FIXATION AND FIRM LIFE CYCLE *

Zhi Da[a]

Ravi Jagannathan[b]

Jianfeng Shen[c]

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[a] Mendoza College of Business, University of Notre Dame, Notre Dame, IN 46556-5646, United States; email: zda@nd.edu; phone: (574) 631-0354.
[b] Corresponding author: Northwestern University, NBER, Indian School of Business, and Shanghai Advanced Institute of Finance. Address: Kellogg School of Management, Northwestern University, 2001 Sheridan Road, Evanston, IL 60208, United States. email: rjaganna@kellogg.northwestern.edu; phone: (847) 491-8338; fax: (847) 491-5719.
[c] School of Banking and Finance, University of New South Wales, UNSW Sydney, NSW 2052, Australia; email: jianfeng.shen@unsw.edu.au; phone: (61) 2 9385-4581.

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ABSTRACT

We provide novel evidence supporting the view that stock prices of some firms in the early growth stage of their life cycle are set by optimistic investors fixated on sales growth. We identify these firms as those that went public during an industry IPO waves, had high sales growths but low gross margins in the first three years following the IPO. Consistent with overpricing, their stocks under-perform their peers by 0.92% per month during the subsequent four year period on a risk-adjusted basis, suggesting limits to arbitrage. This pattern is unrelated to the well documented long-run under-performance of IPOs.

Key words: firm life cycle, industry IPO wave, gross margin, growth equilibrium, limits to arbitrage

JEL Code: G02, G10, G12, G14, G17

I. Introduction

Firms go through life cycle stages such as initial growth, maturing, and aging. Firms in different life cycle stages adopt different corporate strategies. According to the popular Boston Consulting Group Model (BCG, 1968), a firm should maximize sales growth and market share early in its life cycle in order to create permanent cost and customer relationship related advantages over their competitors.

There is ample anecdotal evidence, however, that emphasis on market share by investors may lead some managers to focus excessively on short-term sales growth in their early life cycle stage without regard to costs and benefits, especially when facing intense product market competition. For example, Adizes (1988) in his classical book on corporate life cycles mentions: "… the selling orientation becomes addictive, with *more* meaning *better*… However, as they expand uncontrollably, their cost accounting becomes useless. Eventually, they might be selling more, but instead of making more profits, they might be losing money (page 35-36 op. cit.)."

Given the likely large dispersion in the prior beliefs of investors regarding which firms will be market leaders in an emerging industry, each firm is likely to develop a clientele of optimistic investors who are fixated on the reported sales growth and ignore the associated costs and sustainability of that growth. As a result, stock prices of some young firms in the initial growth stage of their life cycle are more likely to reflect the views of optimistic investors, leading to subsequent under-performance, consistent with the limits to arbitrage hypothesis of Shleifer and Vishney (1997). A relatively low gross margin turns out to be a good indicator for detecting such firms. To examine the role of optimistic investors on the relative valuation of firms in their early life cycle stage, we use a novel identification strategy by focusing on a set of firms in the same industry that went public at about the same time in a cluster, commonly referred to as an industry IPO wave. These firms are likely to be relatively homogeneous in the same early growth stage of their life cycle. In addition, there are a priori reasons to believe that firms in an industry IPO wave are likely to focus on growth. Indeed, Chemmanur and He (2011) argue that gaining market share is an important reason why these firms go public together in an industry IPO wave.[1]

ANSYS (NASDAQ: ANSS) and CSG System (NASDAQ: CSGS) help illustrate our findings. They both went public in 1996 during an IPO wave in the computer software industry that started in March 1995 and ended in January 1997. They differed in one important dimension: gross margin. During the fiscal years 1998 and 1999, ANSYS had an average gross margin of 87% and its sales grew annually at 14% on average. While CSG achieved a much higher average growth rate of 33% per year, its average gross margin was only 51%. The future stock price path of the two firms diverged. While ANSYS returned about 470% in the next four years, CSG lost more than 60% of its market value over the same period.

When we trace all U.S. IPOs in industry IPO waves from 1980 through their initial firm life cycle stages, we find that firms like CSG, i.e., those with *relatively high* sales growth and valuation but *relatively low* gross margins, are associated with poor future stock price performance on average. For each industry IPO wave, at the end of event year 3, where event year 0 denotes the year in which the industry IPO wave ended, we do a two-by-two sequential sort of firms based on their book-to-market equity ratios (BM) and the average gross margins

[1] There is also another literature on market-wide IPO waves (see Ritter (1984), Lowry and Schwert (2002), Pastor and Veronesi (2005), among others) which could be driven by different mechanisms.

(GM) in fiscal years 1 and 2.[2] We find that low-BM-low-GM IPO firms underperform their industry peers by more than 30% in the subsequent four years on average, translating to a loss of market capitalization of more than $200 million per firm. In contrast, low-BM-high-GM IPO firms, while having an average initial sales growth rate (45% per year in the fiscal years 1 and 2) and an average initial BM ratio (0.28 at the end of event year 3) that are about the same as their low-GM peers, do not underperform. This event-time comparison delivers two key observations: (1) IPO firms with high initial sales growth rates have high market valuations (lower BMs) on average regardless of their initial GMs; (2) IPO firms with low GMs but similarly high valuations (lower BMs) are initially over-valued in the market, leading to subsequent underperformance.

We confirm our findings in the event-time analysis using both calendar-time analysis and panel regressions. Calendar-time analysis suggests that, after risk adjustment, low-BM-low-GM IPO firms underperform their industry benchmarks by more than 1% per month on average. This underperformance is robust to various modifications to the empirical design of trading strategies such as sample period, portfolio formation time, holding horizon, and the definition of industry IPO waves. While replacing GM with other profitability measures such as profit margin and return on assets produces qualitatively similar results, which is not surprising given the high correlations among different measures, GM performs the best in separating the future losers from their peers among low-BM IPO firms. Further, using sales growth rate instead of BM to identify

[2] We allow for a minimum of 3-month lag for book values to be available after the end of the fiscal year. We use the stock prices corresponding to the last day of the last calendar month in event year 3. We check the robustness of our conclusions by allowing for a minimum of 12-month lag for book values to be available after the end of the fiscal year.

growth firms produces very similar underperformance (78 bps per month) of low-GM-high-growth IPO firms.

Additional analysis reveals three more interesting observations consistent with our hypothesis that investors tend to be fixated on sales growth when valuing firms in early life cycle stage, especially with more competitive product markets. First, it is crucial to condition our analysis on "industry IPO waves" that forms a cohort of homogenous firms in their initial growth life cycle stage. The underperformance of low-BM-low-GM stocks is specific to those IPO stocks in an industry IPO wave, but does not exist among their peers in the same industry over the same window. Grouping all IPOs in the same industry simply by calendar years generates a much weaker underperformance of low-BM-low-GM IPO firms (only 29 bps per month). When all CRSP/COMPUSTAT stocks are examined, the underperformance is almost economically insignificant, a mere 6 bps per month. Second, we find the underperformance of low-BM-low-GM stocks to be much stronger among industries and during times with more competitive product markets. Finally, we confirm that the stock price response for low-BM-low-GM IPO firms to changes in sales growth rates is much stronger, even after controlling for changes in earnings, but only during the first two years after the end of the wave.

We find evidence supporting the view that the investors of low-BM-low-GM IPO firms were too optimistic about the long-run growth prospects of the firms. We find that the low-BM-low-GM IPO firms do not achieve higher market share and improved profitability in the long run.

We find that low-BM-low-GM IPO firms are associated with greater uncertainty about their future. Their earnings forecasts are associated with significantly higher dispersions. Their idiosyncratic volatilities are also higher. In addition, we find that on average, low-BM-low-GM

IPO stocks are held significantly less by corporate insiders and mutual funds compared to their high-GM counterparts. Overall, greater uncertainties and lower ownership by sophisticated, better informed investors, in the presence of limits-to-arbitrage, may explain why the prices of such stocks continue to fall over three to four years in the future. Limits-to-arbitrage may arise due to direct as well as indirect short-selling costs, agency issues that make it difficult to access capital markets during margin calls, and high idiosyncratic risk that makes it less attractive to risk-averse arbitrageurs with limited capital. In addition, an industry IPO wave is likely triggered by major technological or demand shocks affecting that industry as a whole and these shocks may take several years to play out, with optimistic views prevailing for a long period of time.

Our findings are different from those in the voluminous literature on IPO long-run underperformance (see Ritter (1991), Loughran and Ritter (1995), Brav, Geczy, and Gompers (2000) among many others). One key distinction is the horizon over which IPO performance is measured and thus the potential driving force underlying the overvaluation of IPO stocks and their subsequent underperformance. The IPO long-run underperformance literature mostly focuses on the valuation at the time of IPO and the performance over the first three to five years immediately after the offering date. In contrast, we focus on the potential mispricing three years after IPO, which is likely fueled by high sales growth in the first few years after IPO, and the performance over the subsequent four-year period.[3] For example, using a clever empirical design, Purnanandam and Swaminathan (2004) find that IPOs, especially those with high sales growth forecasts and lower profitability measures, are systematically overvalued at the offer price relative to their valuations based on industry peer multiples, and the overvalued IPOs provide

[3] In fact, low-BM-low-GM stocks in our sample on average achieved abnormally high returns and sales growth relative to their peers in the first three years after IPO, which is consistent with optimistic investors' fixation on the high sales growth.

high first day returns but low long-run (over the five years following the IPO) risk adjusted returns. A direct comparison suggests that the overvalued IPOs in their paper are not driving our results. Pastor and Veronesi (2003, 2005) argue that the uncertainty associated with the IPO firms could result in high initial valuation and the subsequent learning about profitability reduces the uncertainty and valuation, thereby providing a rational explanation for the long-run underperformance of IPOs. While such a learning mechanism is consistent with the long-run underperformance of IPOs as a group, it should not drive the relative underperformance of low-BM-low-GM IPOs within an industry IPO wave as we do not observe a greater reduction in uncertainty measures over time on these low-GM firms relative to their high-GM counterparts.

In a related paper, Novy-Marx (2013) shows that firms with high gross-profit-to-asset ratio (GPA) earn higher returns going forward, even after controlling for their book-to-market ratios. Since GPA is the product of gross margin (GM) and asset turnover (AT, i.e., sales / total assets), keeping valuation and AT fixed, one should also expect GM to be positively related to average returns in the cross-section. Our paper goes further in two important ways. First, we show that GM is the key predictor of future returns among firms in their early life-cycle stages that initially receive high valuations. Second and more importantly, while Brav, Geczy, and Gompers (2000) and Brav, Michaely, Roberts, and Zarutskie (2009) argue that lower post-equity-issuance stock returns could reflect lower risks, we find that average future returns on these low-BM-low-GM firms are even below the corresponding risk-free returns.[4] Such a low return is difficult to reconcile with a positive risk premium for bearing economy-wide systematic risk in an

[4] In the event time, the buy-and-hold excess return over the risk-free rate during the 4-year holding period is -6.24% for the low-BM-low-GM portfolio.

informationally efficient market unless one can argue that realized returns were influenced by unforeseen rare events.

Our findings contribute to the literature on inefficient capital markets by identifying situations when prices of some stocks are likely to be affected by bounded rationality or biases in the way investors make decisions. Agency issues and transactions costs limit the ability of more sophisticated arbitrageurs who have to rely on other people's money from exploiting any resultant profit opportunities.

Our findings also support the theoretical predictions by Aghion and Stein (2008) who analyze a tradeoff between a growth and a margin strategy and allow two-way feedback between firms' strategies and the market's pricing rule. They show that at times investors may pay too much for growth opportunities thereby encouraging managers to focus on sales growth, and some may do so even at the expense of margins. They refer to those times as *growth equilibrium*. In the bounded rationality version of their model where investors follow a simple linear forecasting rule, they make the following prediction: "… in a growth equilibrium the market fully impounds all growth-related information, but ignores margins-related information. ... firms with weak profit margins will be overvalued (page 1051 op. cit.)."

Finally, our paper contributes to the broader literature on firm life cycle that includes Anthony and Ramesh (1992), Berger and Udell (1998), DeAngelo, DeAngelo, and Stulz (2006, 2010), and Dickinson (2011). One challenge in studying firm life cycle arises from the fact that there is no easy and objective way to classify firms into different life cycle stages. We get around this problem by focusing on industry IPO waves, which presents a model-free way to identify a sizable cohort of similar firms in the same initial growth stage of their life cycles. Over-fixation on sales growth seems to drive the overvaluation of the growth firms during the initial growth stage of their life cycle. Lakonishok, Shleifer, and Vishny (1994), La Porta (1996), La Porta, Lakonishok, Shleifer, and Vishny (1997), and Sloan (1996) also mention extrapolation of past performance and earnings fixation to explain the difference in returns between growth and value stocks. Piotroski and So (2012) show that the predictable value/growth return spreads concentrate among firms with ex ante identifiable errors in expectations about future fundamental performance. We find over-fixation on sales growth and errors in expectations about future growth and profitability are particularly prevalent for firms in the initial growth stage of their life cycle.

The rest of our paper is organized as follows: Section II describes our sample of industry IPO waves, Section III presents the evidence of the underperformance of growth firms with low gross margin, Section IV reports the results of additional analyses about potential driving forces, and finally Section V briefly concludes.

II. Data

Our sample consists of firms that went public in the same industry at about the same time. We collect the data for U.S. IPOs covering the period 1970 to 2010 from Thomson Financial Security Data Corporation (SDC) and keep only IPOs of only common shares with no attached units (warrants) and no accompanying issue of other types of securities. We classify IPOs into Fama and French (1997) 49 industries and drop the unclassified ones (those with missing industry classification) and those classified into the 49th industry.[5] We follow the procedure in Chemmanur and He (2011) to identify industry IPO waves based on how clustered the IPOs are

[5] We use the updated industry classifications obtained from Ken French's website.

in an industry. Specifically, for each industry *i* and each month *t*, we count the number of IPOs in the 3-month window from *t-1* to *t+1*. We then define an IPO hot month for industry *i* as one with the 3-month number of IPOs in the top quartile among all months from 1970 to 2010 with at least one IPO in industry *i*. Finally, we classify IPOs in those consecutive hot months for industry *i* as an industry IPO wave. We define the beginning month and the ending month of an industry IPO wave, for industry *i*, as the first month and the last month in an unbroken sequence of hot months for industry *i.* To avoid standalone IPOs being erroneously classified as a wave, we require a minimum of 5 IPOs in total and 1 IPO every month on average in the wave period.

For each industry IPO wave, the calendar year in which the wave ends is denoted as event year 0. We form portfolios within the wave at the end of event year 3, based on the book-to-market equity ratio at the end of event year 3 (BM) and the average of gross margins (GM) during the two fiscal years after event year 0.[6] Figure 1 plots the timeline of our portfolio formation procedure. This procedure imposes additional filters. For an IPO firm to enter our final sample, it has to: (1) exist in CRSP at the end of event year 3; (2) have positive book value at the end of event year 3; and (3) have the necessary accounting information in COMPUSTAT available during the two fiscal years after event year 0. In addition, we require at least 8 firms in an industry IPO wave at the end of event year 3 to make sure that our portfolio-level result is not

[6] The market equity is measured at the end of event year 3, and the book equity is measured from the most recent fiscal year ending at least 3 months before the end of event year 3. We also do a robustness check by defining the book-to-market equity ratio as the book equity at the end of fiscal year 2 scaled by the market equity at the end of event year 3. As can be seen from Panel B of Table 4, the results for calendar-time analysis using this alternative BM measure are stronger than those in our baseline case. For gross margin, we do not use the number in fiscal year 3 since it may not be available yet at the time of portfolio formation, the end of event year 3.

driven by a single firm.[7] These filters are based on information available by the end of event year 3 and thus do not introduce look-ahead bias. In the end, 1425 IPOs going public during 68 industry IPO waves from 1980 to 2006 satisfy our portfolio formation requirements. In other words, our final sample effectively covers the period from 1980 to 2010, including the portfolio holding period.

[Insert Figure 1 about here]

Panel A of Table 1 reports summary statistics for IPOs and industry IPO waves during the period 1980-2006. We start with 9,898 IPOs. Among them, 3,618 IPOs belong to industry IPO waves (on-the-wave). When we require IPOs to appear in COMPUSTAT until the end of event year 3, the number of IPOs drops to 8,751, and 3,069 of them are on-the-wave, among which 1,425 IPOs in 68 industry IPO waves enter our final sample. As shown in Panel B, the various characteristics of the 68 industry IPO waves in our sample are comparable to those from a larger sample reported in Chemmanur and He (2011).[8] The top 5 industries contribute 26 industry IPO waves to our sample. Panel C further shows the five biggest industry IPO waves in our sample, coming from computer software, trading, and business services industries. Altogether, 895 firms went public in these top 5 waves, among which 383 IPOs pass various portfolio formation filters and account for about 27% of our final IPO sample.

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[7] To further avoid the undue influence of outliers, we value weight stocks within each portfolio for each wave and then weight the portfolios across waves based on the number of IPOs at the end of event year 3. We also confirm that equal-weighing stocks within each portfolio and/or across waves do not change our results qualitatively.

[8] We identify a total of 184 industry IPO waves using our wave identification procedure for all IPOs in SDC from 1970 to 2006. The statistics of these waves, such as IPO volume and duration, are very close to those reported in Chemmanur and He (2011). More details are available upon request.

[Insert Table 1 about here]

Figure 2 documents the various characteristics of the industry IPO waves. In the first two sub-plots, we plot the number of IPO waves and the fraction of stocks in the sample for all Fama-French industries and all calendar years with IPO waves in our sample respectively. There are significant variations across both industries and years in terms of their representativeness in our sample, but no single industry or year dominates our sample. In the next sub-plot, we present the histogram of the number of IPOs in our sample for 68 industry IPO waves. The minimum number of IPOs in a wave is 8 as required for forming portfolios within a wave, and the maximum number of IPOs in a wave is 102. Most industry IPO waves (40 out of 68 waves) have fewer than 16 IPOs included in our sample. In the final sub-plot, we present the histogram of the wave duration. Five industry IPO waves in our sample lasted for as short as 2 months, while one wave lasted for as long as 25 months. Most industry IPO waves (54 out of 68 waves) lasted for less than 1 year, with the most common wave duration of 6 months (14 out of 68 waves).

[Insert Figure 2 about here]

III. Empirical results

A. Event-time analysis

Our analysis is first conducted in event time. In other words, we take a particular industry IPO wave at a time and trace the performance of this cohort of IPO firms over time. It is well recognized in the literature that the statistical inference based on event-time analysis is fraught with difficulty and unreliability. Therefore in the next section (Section III.B) we will verify the statistical validity of our conclusions based on event time analysis by using calendar-time analysis.

The year in which the industry IPO wave ended is denoted as event year 0. At the end of event year 3, we sort the remaining IPO firms in the wave first based on their book-to-market equity ratios (BM) into high-BM and low-BM portfolios. The BM is computed using the year-end market capitalization and the book value for the most recent fiscal year that ends at least three months before. Within each of the two portfolios, we further sort the firms into two portfolios based on their average gross margins (GM) during the fiscal years 1 and 2. We do not use the GM in fiscal year 3 since such accounting information is not available yet at the end of event year 3 for many firms when we form the portfolios. Once we construct the four portfolios, we then examine their buy-and-hold abnormal returns, in excess of the value-weighted industry portfolio returns, over holding horizons ranging from one year (event year 4) to four years (event years 4 to 7). Stocks returns are value-weighted in each portfolio and proceeds from delisting are reinvested in the same portfolio.[9]

Table 2 reports the abnormal buy-and-hold returns for each of the four portfolios, averaged across all industry IPO waves. The average returns and their t-statistics are computed across different industry IPO waves using the number of IPOs at the end of event year 3 in each wave as the weight. We follow the approach in Jegadeesh and Karceski (2009) to estimate the t-statistics of the average returns from the time-series of event-time portfolio returns. This approach allows for both heteroskedasticity and correlations in long-horizon buy-and-hold

[9] We obtain the proceeds from delisting from CRSP monthly delisting file. If the delisting payment information is not available, for performance-related delisting (delisting code in 500-599), we assume a delisting return as the average delisting return for all performance-related delistings of the listed exchange (NYSE/AMEX or NASDAQ), following the recommendation in Shumway (1997) and Shumway and Warther (1999). For delistings due to other reasons, we assume a zero delisting return when the delisting payment information is not available.

returns across event firms, and is recommended as probably "the most appropriate to reduce misspecification in tests of long-horizon event studies" by Kothari and Warner (2006) in their survey paper. However, we call for caution in making inferences from these t-statistics because of their unknown small sample distribution and lack of power as noted in Jegadeesh and Karceski (2009). Finally, we will repeat our analysis in calendar time since inference based on calendar time analysis is more robust.

[Insert Table 2 about here]

Consistent with initial overvaluation, IPOs that achieved high valuation (low BM) at the end of event year 3 with low gross margin (low GM) underperform in the next four years relative to their industry benchmark. The cumulative underperformance from event year 4 to event year 7 is more than -30% with a t-value of -1.87. The underperformance is most pronounced during the first year after portfolio formation (event year 4). It is more than -16% with a t-value of -2.28. In contrast, low-BM-high-GM stocks do not underperform, thus driving a considerable wedge between the future performances of these two portfolios of growth stocks. Table 2 also reports the stock performance of these two portfolios of growth stocks prior to the portfolio formation. Low-GM and High-GM growth stocks performed similarly both from the IPO date and from the end of event year 0, suggesting that the market was treating them similarly during the initial years after IPO. Since the number of firms declines as we increase the holding period, the statistical reliability of these observations may be low for longer horizons.[10]

[10] Our results are robust to the Winsorization of buy-and-hold returns on individual stocks at the top and bottom 1 percentile values within each BM/GM group. For example, the weighted average industry-adjusted buy-and-hold return from the end of event year 3 to the end of event year 7 is -33.01% (t-stat = -1.79) for low-BM-low-GM stocks,

When we look at the other half of our sample, we find both high-BM portfolios to outperform the industry benchmark from even year 4 to event year 7. This outperformance is stronger for the high-BM-low-GM portfolio. Importantly, we do not see a significant wedge between the future performances of these two high-BM portfolios. Overall, event-time analysis suggests that only low-BM-low-GM IPO firms are associated with underperformance in the long run.

Table 3 reports various portfolio-level characteristics of the four portfolios during the IPO (Panel A) and during the formation period (Panel B). When we examine the IPO characteristics in Panel A, we do not see much difference between the low-GM and high-GM growth stocks (see the last column for the significance test of differences). Green and Hwang (2012) document that lottery-like payoff associated with an IPO can contribute to its high first-day return and long-run underperformance, but low-GM and high-GM growth stocks have similar first-day returns. Brav and Gompers (1997, 2003) find that IPOs underperforming in the long run are more likely not backed by venture capital and with lockup restrictions. There is some weak evidence that low-GM growth stocks are more likely to have lockup restrictions in place. The only significant difference, however, is that low-GM growth firms sold more new shares (primary shares) during the IPO than high-GM growth firms, though the average offer prices are not statistically different. This is consistent with the view that existing owners of the low-GM

12.88% (t-stat = 0.68) for low-BM-high-GM stocks, 30.88% (t-stat = 1.19) for high-BM-low-GM stocks, and 29.07% (t-stat = 0.90) for high-BM-high-GM stocks. Finally, the point estimates change little if we further drop those penny stocks with the price below $1 at the time of portfolio formation, the end of event year 3. For example, the point estimate of 4-year industry-adjusted buy-and-hold return remains almost identical, with only changes in decimals, for all groups except for high-BM-high-GM group (Mean = 25.73%, t-stat = 0.85).

growth firms are less optimistic about the future prospects of their firms and are willing to dilute their ownership more at the offer price (see Myers and Majluf, 1984).

[Insert Table 3 about here]

We then examine in Panel B price-related variables measured at the formation date (the end of event year 3) and other variables measured using information during the first three event years that is available at the formation date. Comparing the high-GM growth stocks to their low-GM counterparts, the high-GM stocks not surprisingly are larger in terms of market capitalization but do not have significantly lower BMs. By construction, they have higher gross margins, and since gross margins are correlated with profitability, they also have significantly higher returns on assets (ROA) in the first two fiscal years after the wave ending year.

IPO firms in our sample in general have high sales growth rates (39%) during the first two fiscal years after the wave ending year. Among them, those classified as growth firms at the end of event year 3 are indeed associated with even higher sales growth rates in the first two years. Interestingly, low-GM and high-GM growth firms have similarly high initial sales growth rates (46% vs. 45%). These sales numbers help to make three observations: (1) an industry IPO wave contains similar firms in their initial growth stage of their life cycle; (2) market assigns high valuations (low BMs) to firms with high sales growth rate on average; (3) IPO firms with low GMs are "rewarded" with the same high valuations (low BMs) as otherwise similar IPO firms with high GMs, as long as they also achieved high initial sales growth rates.

B. Calendar-time analysis

We repeat our analysis using calendar time methods in order to adequately control for differences in systematic risk exposures and endogeneity of the firms' decisions to go public discussed in Schultz (2003) and Viswanathan and Wei (2008).[11]

As in the event-time analysis, for a particular industry IPO wave, we sequentially sort stocks in the wave into four groups at the end of event year 3, based on BM at that time first and then the average GM in the first two fiscal years after the wave ending year. Four value-weighted BM/GM wave portfolios are formed within the wave and then held during the next four years.[12] In each calendar year t, we form the four composite BM/GM portfolios at the beginning of the year by aggregating the corresponding BM/GM wave portfolios across all industry IPO waves ending in the period year t-7 to year t-4 and using the number of surviving IPOs in an industry IPO wave at the end of event year 3 as the weight for BM/GM wave portfolios in that wave. The four composite BM/GM portfolios are rebalanced at the beginning of every year t by adding stocks in industry IPO waves ending in year t-4 and dropping stocks in industry IPO waves ending in year t-8. We compute the monthly returns of these four portfolios in excess of the returns on the industry benchmark portfolio.[13]

We then regress the monthly excess returns on the Fama-French three factors (MKTRF, SMB, and HML) and the Carhart's momentum factor (UMD). The three Fama-French factors

[11] Fama (1998) and Mitchell and Stafford (2000) also recommend the use of calendar portfolio approach to adequately control for systematic risk exposures and address econometric issues underlying long-run event studies.

[12] In the case of delisting, the proceeds from delisting are reinvested in the affiliated portfolio.

[13] For BM/GM wave portfolios in an industry IPO wave, we use the returns on the value-weighted industry portfolio as the return benchmark. We use the same weighting scheme across industry IPO waves in forming the composite BM/GM portfolios to aggregate corresponding industry benchmark returns for individual industry IPO waves.

represent economy wide pervasive risk. We use the Carhart factor in addition, to ensure that any mispricing according to the Fama-French three factor model is not due to the well known momentum anomaly. Panel A of Table 4 reports the regression results for the four calendar-time BM/GM double sorted portfolios. Confirming the results from event-time analysis, we find low-BM-low-GM stocks to significantly underperform their industry benchmarks on a risk-adjusted basis during the four-year holding period by more than 1% per month with a t-value of 4.36. Interestingly, none of the other three portfolios is associated with abnormal returns after risk adjustment. As a result, we see a significant risk-adjusted spread between the high-GM and low-GM growth stocks, but not between high-GM and low-GM value stocks.

[Insert Table 4 about here]

As we follow Chemmanur and He (2011) to define IPO waves based on the full-sample IPO distribution, our calendar-time portfolios are not tradable in real time. Though having a profitable trading strategy is not the main objective of our study, we also examine an alternative approach to form portfolios using only the IPO information available at the time of portfolio formation. Specifically, for each industry i and each year y, we define a month t in that year as an IPO hot month if the number of IPOs in the 3-month window from $t-1$ to $t+1$ is in the top quartile among all months from 1970 to year y+3 with at least one IPO in industry i.[14] We then classify IPOs in those consecutive hot months for industry i as an industry IPO wave. We define the beginning month and the ending month of an industry IPO wave, for industry i, as the first month and the last month with at least one IPO in an unbroken sequence of hot months for

[14] We require a minimum of 10-year data and a minimum of 12 months with IPOs to obtain the distribution of the number of IPOs. We also exclude the December in year y+3 from the estimation of distribution to avoid the use of IPO information in January of year y+4.

industry *i*. To avoid standalone IPOs being erroneously classified as a wave, we require a minimum of 5 IPOs in total and 1 IPO every month on average in the wave period. Finally, once we identify an industry IPO wave ending in year *y*, we follow our baseline trading strategy to form and hold portfolios of stocks in this newly-defined industry IPO wave at the end of year y+3.[15] The untablulated results are almost identical to those reported in Table 4. Only low-BM-low-GM stocks significantly underperform their industry benchmarks on a risk-adjusted basis during the four-year holding period (alpha = -1% per month with a t-value of -4.11). Further, there is a significant risk-adjusted spread between the high-GM and low-GM growth stocks (alpha = 0.83% per month with a t-value of 2.84), but not between high-GM and low-GM value stocks. Since the results from our baseline portfolio construction do not seem to be driven by any forward-looking bias, we continue to rely on the baseline strategy in the rest of the paper.

B.1 Robust checks: Sub-periods and alternative portfolio formation methods

Next we focus on IPO firms with high initial valuation and low gross margins that are associated with poor long-run performance. In our first set of additional analyses, we conduct a battery of robustness checks to examine whether our main finding is driven by specific time periods or the specific way we form and hold our portfolios. We report our findings in Panel B of Table 4. First, when we divide the time series of portfolio returns into two halves: 1985-1997 and 1998-2010, we find significant underperformance for the low-BM-low-GM IPOs in both sub-periods. The underperformance is slightly stronger in the first half (-1.14% with a t-value of -

[15] The only minor modification is that for industry IPO waves ending exactly in December, year *y*, we treat them as ending in year *y* +1 and start to include stocks in these waves in portfolios since year *y* +5 to avoid the look-ahead bias. Knowing these waves actually ending in year *y* requires the knowledge of January, year *y* +1 not being a hot month, which requires the information of IPOs in year *y* +4.

3.33) than in the second half (-0.87% with a t-value of -2.59). This sub-period analysis further confirms that our findings are not driven by a few big industry IPO waves. As is shown in figure 2.2, the second sub-period witnesses more industry IPO waves than the first one. Panel C of Table 1 also shows that that the top five industry IPO waves in our sample all ended in years after 1994 with the holding periods starting in years after 1998.

Second, we value weight all stocks both within and across waves to make sure that our results are not driven by penny or micro-cap stocks and those thin waves with very few stocks. We continue to find a significant underperformance of low-BM-low-GM stocks relative to both their industry benchmarks and their low-BM-high-GM peers.[16] Third, when we vary the holding horizon from one year (event year 4) to seven years (event years 4 to 10), the underperformance of low-BM-low-GM stocks is significant in all holding horizons. For simplicity we only report the results of 1-year and 7-year holding horizons. The underperformance is stronger in the first year after portfolio formation. Fourth, when we change the portfolio formation date to the end of event year 2 or 4, the results do not change significantly. Fifth, when we combine waves in the same industry with a gap less than 6 months in between into one wave, this coarser definition of industry IPO waves does not change our main finding.[17] Finally, to make sure that our sorting variables do not introduce look-ahead bias, we measure the book-to-market equity ratio alternatively as the ratio of book equity at the end of fiscal year 2 to the market equity at the end

[16] When we weight all stocks equally both within and across waves, the alpha of low-BM-low-GM portfolio is actually smaller (alpha = -0.61%, t-stat = -2.27), which provides further evidence that our results are not driven by penny or micro-cap stocks or thin waves.

[17] We also tried to combine waves with a shorter gap (3-month) or a longer gap (12-month). The underperformance is presented in both analyses, though further longer gaps produce less precise industry IPO waves and weaker results.

of event year 3, and then form portfolios accordingly. The underperformance of low-BM-low-GM stocks is even stronger than that in our baseline case.

B.2 Robust checks: Alternative sorting variables to form portfolios

In the second set of additional analyses reported in Panel A of Table 5, we repeat our portfolio formation procedures and the calendar-time trading strategies but base on firm characteristics other than BM and GM. We first replace GM with other measures related to profitability such as profit margin (PM), asset turnover (AT), gross-profit to-asset ratio (GPA), return on assets (ROA), and return on equity (ROE). Given that low gross margin is highly correlated with low profitability, it is not surprising that low-BM-low-profitability firms also significantly underperform their industry benchmarks. However, when we examine the risk-adjusted return spreads between high- and low-profitability growth stocks, we find them to be much smaller and less significant compared to that between high- and low-GM growth stocks. In other words, if we want to separate out future losers from their peers among the current growth IPO firms, the recent gross margin seems to be a better predictor than other measures of profitability.

[Insert Table 5 about here]

In a related paper, Novy-Marx (2013) shows that firms with high gross-profit-to-asset ratio (GPA) earn higher returns going forward, even after controlling for their book-to-market ratios. Since GPA is the product of gross margin (GM) and asset turnover (AT), the results in Panel A show that a lower GM, not a lower AT, is driving the future underperformance of firms that initially received high valuations in their early life-cycle stage. More importantly, our paper differs from Novy-Marx (2013) in that we find average future returns on low-BM-low-GM firms to be even below risk-free rates, but positive loadings on the three Fama-French factors that capture economy wide pervasive risk. In the calendar time, the average excess return over the risk-free rate during the 4-year holding period is -29 bps per month for the low-BM-low-GM portfolio. Such a low return is difficult to reconcile with a positive risk premium for bearing economy-wide systematic risk.

Instead, our finding is consistent with the view that that low-margin-induced high sales growth fuels higher initial valuation under investor bounded rationality as modeled in Aghion and Stein (2008), resulting in long-run underperformance. As a direct check, we conduct a sales growth / GM double sort instead of the usual BM / GM double sort. As shown in the bottom of Table 5 Panel A, we again observe a significant future underperformance (from event years 4 to 7) among stocks that experienced high sale growth but low gross margin during the first two fiscal years after event year 0. The underperformance is 78 bps per month with a t-value of -2.88. The smaller magnitude in underperformance is to be expected since we did not control for market valuation (BM) explicitly.

B.3 Robust checks: Industry competition

Our hypothesis posits that some firms, in the face of product market competition, are induced to sell their products at a lower margin in order to keep up the high sales growth rates. Naturally, one would expect to see a bigger effect among industries with more intense product market competition. We use two proxies for the degree of product market competition: Herfindahl index of sales and the advertisement intensity in an industry. Herfindahl index of sales is the sum of squared market shares across all firms in an industry. Industries with a lower Herfindahl index of sales are generally viewed as being more competitive because market shares are less concentrated. Advertisement intensity is measured as the industry total advertising expenses scaled by the industry total sales. Industries with higher advertisement intensity are normally expected to be more competitive as their products are more likely to be homogeneous.

In our third set of additional analyses, we partition all industry IPO waves in our sample into two groups based on the median value of the average industry competition measure in the first two fiscal years after the industry IPO wave ending year. Waves with above-median competition measures are classified into the High-group. For each of the two competition measures, we repeat the calendar-time portfolio analysis for the High- and Low-groups separately and report the results in Panel B of Table 5. Indeed we find the magnitude of future underperformance of the low-BM-low-GM stocks to be much stronger in more competitive industries, as indicated by a lower Herfindahl index of sales and a higher advertisement intensity. Further, the underperformance of low-BM-low-GM stocks also exists among industry IPO waves in less competitive industries, albeit in a smaller magnitude.

B.4 Robust checks: The role of initial growth lifecycle stage

Our hypothesis applies to a cohort of similar firms in the same initial growth stage that are facing product market competition. Industry IPO wave is a particularly useful way to identify such firm cohorts since product market competition is one important driving force behind why these firms went public together in the first place (Chemmanur and He, 2011). As a result, we conjecture that if we do not condition our analysis on industry IPO waves, we should expect to find weaker or no results. This is the fourth set of additional analyses whose results are reported in Panel C of Table 5.

First, if we define industry IPO waves by simply grouping IPOs in the same industry and the same calendar year and repeat our portfolio formation procedures and calendar-time trading strategies, we find a much weaker underperformance among low-BM-low-GM stocks. Under such a pseudo industry IPO wave definition, low-BM-low-GM IPO stocks underperform less than 30 bps per month, a significant drop from 103 bps per month in the case where we use a more precise procedure to identify industry IPO waves (Table 4, Panel A). Second, if we replace stocks in each wave by all other stocks in the same industry and existing in CRSP/COMPUSTAT at the end of wave year and then replicate our baseline trading strategy, we find no evidence of underperformance of low-BM-low-GM stocks. We check the robustness of this result by further including those stocks on the wave or further excluding stocks listed in the most recent 3-year period preceding the wave in the portfolios, and find almost identical results. Finally, when we repeat our portfolio formation procedures and calendar-time trading strategies for all CRSP/COMPUSTAT stocks, the underperformance of low-BM-low-GM stocks becomes economically insignificant, at a mere 6 bps per month.

Overall, using both event-time and calendar-time analyses, we find strong empirical support for our hypothesis that low-margin-induced high initial sales growth fuels optimism among investors, resulting in overpricing of some growth firms in the initial growth stage of their life cycle and leading to the long-run underperformance of these firms. We find that this key result is robust to various modifications to our empirical design and that conditioning on industry IPO waves is crucial to identify similar firms in an initial growth stage.

C. Panel regression analysis

In Table 6, we confirm our event-time and calendar-time portfolio results using panel regressions which allow us to simultaneously control for other firm / IPO characteristics that could potentially explain the abnormal performance.

(1) $EXRET_{i,t} = a_0 + b_1 BM_{Low,i} * GM_{High,i} + b_2 BM_{High,i} * GM_{High,i} + a_1 SIZE_{i,t-1} + a_2 BM_{i,t-1} + a_3 EXRET_{i,t-1} + a_4 TURNOVER_{i,t-1} + c_1 INITIAL\_RETURN_i + c_2 VC_i + c_3 LOCKUP_i + c_4 PRIMARY\_SHARES_i + \sum_j d_j WAVEDM^j_i + e_{i,t}.$

In regressions, we include the industry IPO wave fixed effects, and calculate the standard errors from two-way clustering on both industry and year (Petersen, 2009).[18] Our key variables of interest are the two interaction terms of GM_{High} with BM_{Low} and BM_{High}. BM_{Low} (BM_{High}) is the dummy variable for low (high) initial BM group, based on sorting all IPO stocks in an industry IPO wave on BM at the end of event year 3. Consistent with our portfolio analysis, we measure GM as the average gross margin in the first two fiscal years after the industry IPO wave ending year. GM_{High} is the dummy variable for high initial GM group, based on sorting all IPO stocks in an industry IPO wave on GM within each BM group at the end of event year 3. Our dependent variables are annual industry-adjusted stock returns in percentage points during event years 4 to 7.

[Insert Table 6 about here]

In the first regression (Model 1), we control for annual stock characteristics such as size, BM, past return, and turnover that have been shown to have predictive power about future returns in the literature. Size is measured as the log market capitalization at the end of the previous year,

[18] Alternative ways to control fixed effects, such as industry fixed effects only or both industry and year fixed effects, produce qualitatively similar results.

and BM is the ratio of book equity to market capitalization at the end of the previous year, where book equity precedes the year end by at least 3 months. Turnover is the sum of monthly share turnover in the previous year. We find a positive and significant coefficient on BM_{Low}* GM_{High} (7.62 with a t-value of 2.03), suggesting that among growth IPO stocks, those with a low gross margin in the initial years after IPO subsequently underperform their high gross margin peers by 7.62% per annum in the period event years 4 to 7, consistent with our hypothesis. Interestingly, GM has no predictive power among IPO firms with relatively high book-to-market equity ratios in the initial years after IPOs, consistent with earlier results in both event-time and calendar-time portfolio analyses.

In the second regression (Model 2), we further control for a list of IPO characteristics that may predict long-run IPO performance, including the IPO first-day return, a dummy variable that equals 1 if the IPO has venture capital backing, a dummy variable that equals 1 if there is a lock-up condition, and the percent of primary (new) shares sold in the IPO. Consistent with Brav and Gompers (2003), IPOs with lockup restrictions are associated with significantly lower long-run excess returns. There is very weak evidence that IPOs backed by venture capital are associated with better long-run performance, which is also consistent with Brav and Gompers (1997) although the coefficient is not statistically significant. After controlling for these IPO characteristics, the coefficient on BM_{Low}*GM_{High} is almost unchanged and still significant. To conclude, the panel regressions confirm that the underperformance of the low-BM-low-GM IPO firms is significant both economically and statistically.

We further check whether the performance predictability of GM in low BM firms in our sample is driven by the relation between gross-profit-to-asset ratio (GPA) and future return documented in Novy-Marx (2013). In the third regression (Model 3), we interact the BM dummies with a dummy variable indicating high asset turnover (AT) instead of GM. Interestingly, while higher AT predicts higher future performance, this predictive power is stronger among high-BM IPOs, although the regression coefficient on neither interaction term is statistically significant.

Finally, in the fourth regression (Model 4), we interact the BM dummies with both high GM and high AT dummy variables. The regression highlights the differential roles played by GM and AT. AT is a significant predictor of future performance among high-BM IPOs. This relation could be mechanical. To the extent that high-BM firms are associated with less growth options, the utilization rate of their current assets, as measured by AT, is a good indicator of their future cash flows. Holding valuation ratio (BM) constant, firms with higher ATs (thus higher future cash flows) should then be associated with higher expected returns.

In contrast, lower GM is a stronger indicator of poor future performance among low-BM IPOs. This result is unlikely to be mechanical. Untabulated results suggest that low-BM-low-GM stocks have future average raw returns close to or even below the risk-free rates. Such a low average return is difficult to reconcile with a positive risk premium for bearing economy-wide systematic risk. Instead, a low GM could be associated with a risky pricing strategy for gaining market share in the initial growth stage of a firm's life cycle. Our findings thus suggest that the prices of such firms may reflect the unfulfilled optimistic views of investors.

D. Relation to IPO overvaluation in Purnanandam and Swaminathan (2004)

What differentiate our findings from the typical IPO long-run underperformance are the nature of overvaluation and the horizon over which IPO performance is measured. The IPO long-run underperformance literature focuses on the overvaluation at the time of IPO and thus the underperformance of IPO firms over the initial period, mostly three to five years, immediately after the offering date. For example, according to Purnanandam and Swaminathan (2004), IPOs that are overvalued at the offer price relative to their valuations based on industry peer multiples provide high first day returns but low long-run (over the five years following the IPO) risk adjusted returns. They further show that overvalued IPOs have lower profitability and higher analyst growth forecasts than undervalued ones, but fail to deliver the expected high growth ex-post.

In contrast, we focus on firms listed during an industry IPO wave, experiencing high sales growth at the expense of a low gross margin in the initial three-year period after IPO, but valued highly by the market at the end of the third year after IPO. We find an underperformance of these firms' stocks over the following four years, which suggest that investors may be over-optimistic about these firms' growth opportunities, over-extrapolating the high post-IPO sales growth rates without paying sufficient attention to profitability. Despite these important differences in the horizons over which overvaluation and subsequent underperformance are measures, could the overvalued IPOs in Purnanandam and Swaminathan (2004) empirically drive our results? We examine this possibility directly.

We obtain the price-to-value (PV) ratios of IPOs, which are the ratios of the offer price to the "fair/intrinsic value" computed from comparable firms' price-to-EBITDA ratio and the IPO *firm's EBITDA.[19] We first check whether those underperforming stocks - low-BM-low-GM ones - were relatively overvalued at the time of offering compared with their peers based on PV

[19] We are grateful to Amiyatosh Purnanandam for generously sharing their data. For each IPO, they choose a non-IPO industry peer with comparable sales and EBITDA profit margin that did not go public within the past three years to compute the benchmark price-to-EBITDA ratio.

ratios. We are able to obtain valid PV ratios for only 516 out of 1425 stocks in our sample.[20] We test the difference in the natural log PV ratio between low-GM and high-GM stocks within each B/M group and present the results in Table 7, Panel A. There is no evidence that low-GM stocks are relatively overvalued at the offering price compared with their high-GM peers in both B/M groups. To the contrary, low-GM stocks actually have a lower average PV ratio than their high-GM peers, though the difference is not statistically significant. We further check the robustness of our main findings - the underperformance of low-BM-low-GM stocks - by removing 516 stocks with matched PV ratios and replicating both calendar-time portfolio analysis and panel regression analysis with the remaining 909 stocks. The calendar-time portfolio results presented in Table 7, Panel B confirm the underperformance of low-BM-low-GM stocks over the 4-year holding period, with an even more negative Fama-French four-factor alpha of -1.12% (T-statistics = -3.54) compared with the number reported in Table 4, Panel A. Similarly, unreported panel regression results suggest that the coefficient on $BM_{Low}*GM_{High}$ is significantly positive and qualitatively similar to those reported in Table 6.

[Insert Table 7 about here]

To summarize, the overvalued stocks in our sample do not overlap with those overvalued IPOs identified in Purnanandam and Swaminathan (2004). Further, the underperformance of low-BM-low-GM stocks in our sample persists even if we remove all stocks with PV ratios at the time of offering (which include those overvalued IPOs with high PV ratios) from our analysis. More generally, the overvaluation of those underperforming stocks in our sample should be driven by investors' over-optimism about growth opportunities fueled by initial high growth after

[20] Purnanandam and Swaminathan (2004) apply various filters to their IPO sample, one of which requires the IPO to have valid sales and positive EBITDA available in Compustat industrial files for the prior fiscal year.

IPO, rather than by the unrealistic optimism at the time of IPO which is typically cited as the driving force for IPO overvaluation in the typical IPO long-run underperformance literature.

IV. Additional analysis

So far we have provided strong evidence that among firms in their initial growth life cycle stage with high current valuations and historical sales growth rates, those with low gross margins are over-valued relative to firms with high gross margins. In this section, we investigate a comprehensive list of characteristics on these firms and their high-GM counterparts over time since IPO, aiming to shed further light on the underlying economic mechanism that generated the initial overpricing and why this overpricing could persist. These analyses also help to rule out several alternative explanations for our results.

A. Price sensitivity to sales growth

We have argued that optimistic investors over-fixate on sales growth numbers. We provide direct supporting evidence for such an over-fixation by examining the market price response to surprises in earnings and sales growth. Specifically, we run the following regressions following Anthony and Ramesh (1992):

(2) $$EXRET_{i,q} = a_0 + b_1 \Delta SG_{i,q} + b_2 \Delta IB_{i,q} + b_3 \Delta CAPX_{i,q} + e_{i,q},$$

where $EXRET_{i,q}$ is the quarterly industry-adjusted return over the 3-month period from the end of the first calendar month of quarter q to the end of the first calendar month of quarter q+1. ΔSG_q is the change in sales growth rate from calendar quarter q-1 to q, where the sales growth rate in quarter q is calculated as $(Sales_q - Sales_{q-4}) / Sales_{q-4}$. ΔIB_q is the year-over-year change in quarterly earnings, calculated as $(IB_q - IB_{q-4}) / MV_{q-4}$, where IB_q is the income before extraordinary items in quarter q and MV_q is the market capitalization at the end of quarter q. $\Delta CAPX_q$ is the year-over-year change in quarterly capital expenditure, calculated as ($CAPX_q$ - $CAPX_{q-4}$)/ MV_{q-4}, where $CAPX_q$ is the capital expenditure in quarter q. The regression specification is for evaluating whether stock prices are responding to sales growth news after controlling for earnings news and investment news. We run the regressions separately for each BM/GM portfolio in each year during the 7 years after event year 0. Our hypothesis is that the slope coefficient b_1 should be positive and larger for low-BM-low-GM stocks when compared to low-BM-high-GM stocks in the initial years after IPO as the investors who follow those stocks are more likely to over-fixate on sales growth.

In Table 8, we report these sales growth response coefficients, which are the regression coefficients on ΔSG_q, and associated t-statistics. We also report the difference in the coefficients between high and low GM groups and the associated t-statistics. All t-statistics are calculated based on the standard errors clustered by industry. To obtain the industry benchmark of the sales response coefficient, we run similar regressions for a sample of all stocks in the industry which were listed at least 3 years before the ending year of the current industry IPO wave.

[Insert Table 8 about here]

Consistent with the market's over-fixation on sales, stock prices react significantly to sales growth rates among all industry IPO wave stocks during the first two years after the wave ending year, even after controlling for contemporaneous earnings surprises. This is more so for the low-GM stocks. In the first year after the industry IPO wave, a 1% increase in quarterly sales growth rate translates to 8 basis points in the quarterly stock return. Interestingly, after event year 3, the low-GM stocks no longer have significant sales growth response coefficients, which is consistent with the notion that the market starts to notice the overpricing among the low-GM stocks and the market price adjusts itself downward.

B. Future operating performance

Observing the initial high sales growth rates on the low-GM firms, investors might over-estimate the firm's earnings power in the future. Over time, correction in these errors-in-expectation leads to long-run underperformance. In this subsection, we provide direct evidence for the initial investor optimism and detailed analysis of the price correction process.

Table 9 shows additional portfolio-level characteristics over years after the industry IPO wave ending year for the high-GM and low-GM growth portfolios, their differences, and the same characteristics for the industry benchmark. Panel A reports the post-formation annual frequencies for performance-related delisting. Consistent with the return results, low-BM-low-GM IPO firms experience significantly more delisting than their high-GM counterparts. More than 18% of them were delisted by the end of event year 7 whereas less than 9% of the low-BM-high-GM firms were delisted during the same period, confirming that growing sales at the expense of profitability is indeed not a sustainable strategy.

[Insert Table 9 about here]

Firms may deliberately keep prices and GM low in the early stages of their life cycle with the expectation that it will help them gain market share and greater future profits via increased pricing power and/or permanent cost advantages arising from economies of scale. Our findings suggest that such expectations, if they were there to start with, were not fulfilled in our sample. In Panel B, when we examine the market share of low-BM-low-GM IPO firms, it only grows from 0.12 to 0.17 from event year 3 to 7. In contrast, the low-BM-high-GM IPO firms actually grow their market share faster in the same period from 0.14 to 0.23. The lower market share, coupled with a low GM, not surprisingly leads to a subpar operating performance of low-BM-low-GM IPO firms. Return on assets (ROA) of low-BM-low-GM firms is significantly worse than their high-GM peers throughout the seven event years after the IPO wave ending year. Overall, evidence in Panels A and B suggests that low-BM-low-GM firms have deteriorating operating performance in the long-run relative to low-BM-high-GM firms, and investors who use simple linear extrapolation in forecasting, are likely to be too optimistic at the beginning.

C. Uncertainty measures

Firms in their initial growth life cycle stage, as identified as those in industry IPO waves, are especially prone to optimism bias. These firms have short tracking records. Due to the resulting uncertainty associated with their future earning power, investors are more likely to over-fixate on sales numbers in valuation at least initially.

We examine two measures of uncertainty using the analyst forecasts and stock prices after the IPO. Diether, Malloy and Scherbina (2002) find that stocks with higher analyst forecast dispersion are likely to underperform in the future, compared with their peers with lower forecast dispersion. They interpret their results as consistent with the argument proposed in Miller (1977) that higher difference-of-opinion, combined with short-sales constraints, could lead to temporary overvaluation. In light of the recent finding in Cheong and Thomas (2011) that analyst forecast dispersion does not vary with scale, we measure the dispersion as the standard deviation of analyst forecasts of current fiscal year's earnings per share as reported by IBES. In Table 10, we report the statistics on the measure of analyst earnings forecast dispersion. Low-BM-low-GM IPO firms are consistently associated with greater dispersion in their earnings forecasts, especially during the early years after the IPO, which is consistent with the notion that the significant degree of uncertainty concerning these growth firms could acerbate the initial overvaluation for firms pursuing unsustainable business strategies.[21]

[Insert Table 10 about here]

We also report the idiosyncratic volatility of firms in this table. To estimate a firm's idiosyncratic volatility in year t, following Ang, Hodrick, Xing and Zhang (2006), we first regress its daily stock returns in year t on Fama-French three factors (MKTRF, SMB and HML) and Carhart's momentum factor (UMD), and then calculate the standard deviation of the residuals. To mitigate the skewness in the distribution, we take the natural log of the estimated idiosyncratic volatility. Overall, low-GM growth firms are associated with much higher idiosyncratic volatilities and these volatilities gradually decline over time after the IPO. Pastor and Veronesi (2003) argue that the uncertainty associated with the IPO firms could result in high initial valuation and the subsequent learning about profitability reduces the uncertainty and valuation, explaining the IPO long-run underperformance. While such a learning mechanism could be consistent with the long-run underperformance of IPOs as a group, it should not drive the relative underperformance of low-BM-low-GM IPOs within an industry IPO wave as we do

[21] Hanley and Hoberg (2010) argue that the Risk Factors section is "the only section that has significant loadings on both positive and negative tone" and thus describes "the second moment of the outcomes (high and low)". When conducting textual analysis of the Risk Factor sections in the IPO prospectus available for a subset of IPO firms in our sample, we find that low-BM-low-GM IPOs indeed witness more mentions of "Cost(s)" and "Profitability", suggesting greater uncertainty associated with their earnings prospects. To save space, these results are not tabulated but available upon request.

not observe a greater reduction in idiosyncratic volatility over time for the low-GM growth firms relative to their high-GM counterparts.[22]

D. Investor type and limits to arbitrage

We obtain further insights about the overpricing of low-BM-low-GM IPO stocks by examining the holdings by corporate insiders and mutual funds over years after IPO. Table 11 reveals some interesting patterns about the holdings of these potentially better informed / sophisticated investors on the two groups of growth IPO stocks. On average, low-BM-low-GM IPO stocks are held significantly less by insiders and mutual funds (including those with a growth-style) when compared to their high-GM peers, especially during earlier years.[23] The low-BM-low-GM growth IPO firms seem to have developed a clientele for relatively more naïve investors who are more likely to suffer from over-reliance on sales growth.

[Insert Table 11 about here]

Overall, greater uncertainties and lower ownership by sophisticated / potentially better informed investors, in the presence of limits-to-arbitrage such as direct or indirect short-selling constraints and high idiosyncratic risk, may explain why it takes three to four years for the initial over-valuation to disappear. Our findings are consistent with Stambaugh, Yu and Yuan (2012)

[22] The untabulated test shows that the reduction in log idiosyncratic volatility from event year 3 to event year 7 does not differ significantly across two groups of firms.

[23] We obtain the holdings of corporate insiders via Thomson Reuters Insiders Filing database and include the holdings of insiders with relationship to firms up to level 3 (senior executives). We obtain the mutual fund holdings via Thomson Reuters Mutual Fund Holdings database (S12), and classify mutual funds into different styles according to their investment objective codes in S12, supplemented by the style information from CRSP mutual fund data. Funds with a growth or aggressive growth style are classified as growth funds.

who find that asset pricing anomalies are generally stronger following high levels of investor sentiment, and in long-short strategies that exploit anomalies, the short leg of the strategies is more profitable following high investor sentiment.

V. Conclusion

The predictability of stock returns based on valuation ratios, like E/P, P/B, and C/P etc., is well documented in the literature. More recent evidence supports the view that some of the predictability may reflect psychological biases built into the way investors make decisions, and agency issues limit the ability of more sophisticated arbitrageurs who have to rely on other people's money from exploiting any profit opportunities that may arise from such predictability. Our findings contribute to this literature by identifying situations when prices of some stocks are likely to be affected by investor optimism and narrow framing due to fixation on sales growth.

Our findings support the hypothesis in Aghion and Stein (2008) that there are time periods when market conditions are more favorable to growth firms, and during those times firms with strong growth but weak margins will be over priced. Taking advantage of industry IPO waves as a natural setting for studying a homogenous group of firms in the same growth stage of their life cycles, we find that among firms that went public during an industry IPO wave, those with relatively high valuations and historical sales growth rates, but low gross margins during the first three years after the wave under-perform their industry peers by more than 1% per month during the subsequent four-year period, after adjusting for risk differentials. Greater uncertainties and lower ownership by sophisticated, better informed investors associated with these firms, in the presence of limits-to-arbitrage such as direct or indirect short-selling constraints and high idiosyncratic risk, may explain why it takes so long for the initial over-valuation to disappear.

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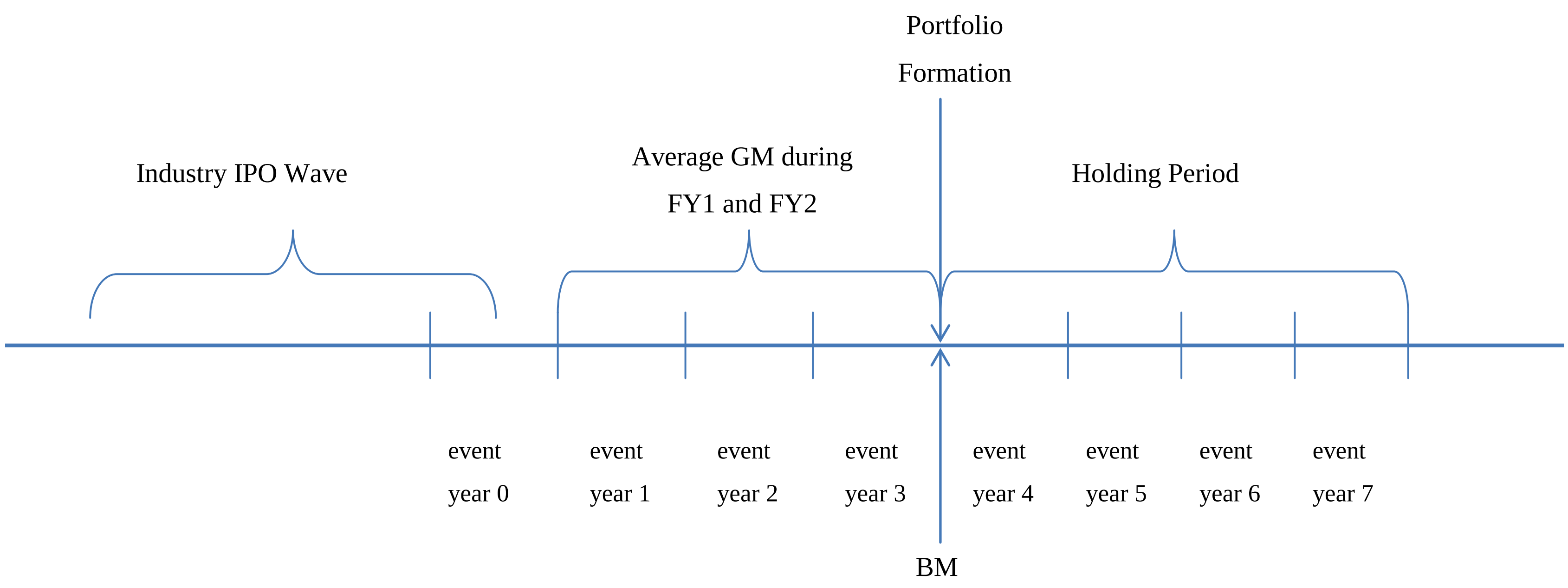

Figure 1

Timeline of our portfolio formation procedure

We follow the procedure in Chemmanur and He (2011) to identify industry IPO waves based on how clustered the IPOs are in an industry. For each industry IPO wave, the calendar year in which the wave ended is denoted as event year 0. We form portfolios within the wave at the end of event year 3, based on the book-to-market equity ratio (market price at the end of event year 3 and book equity preceding the market price by at least 3 months) and the average of gross margins (GM) during fiscal years 1 and 2. We do not use the GM in fiscal year 3 since such accounting information is not yet available at the end of event year 3 for many firms when we form the portfolios. In addition, we require at least 8 firms in an industry IPO wave at the end of event year 3 to ensure that our portfolio-level result is not driven by a single firm. The portfolios are then held for four years from event year 4 to event year 7.

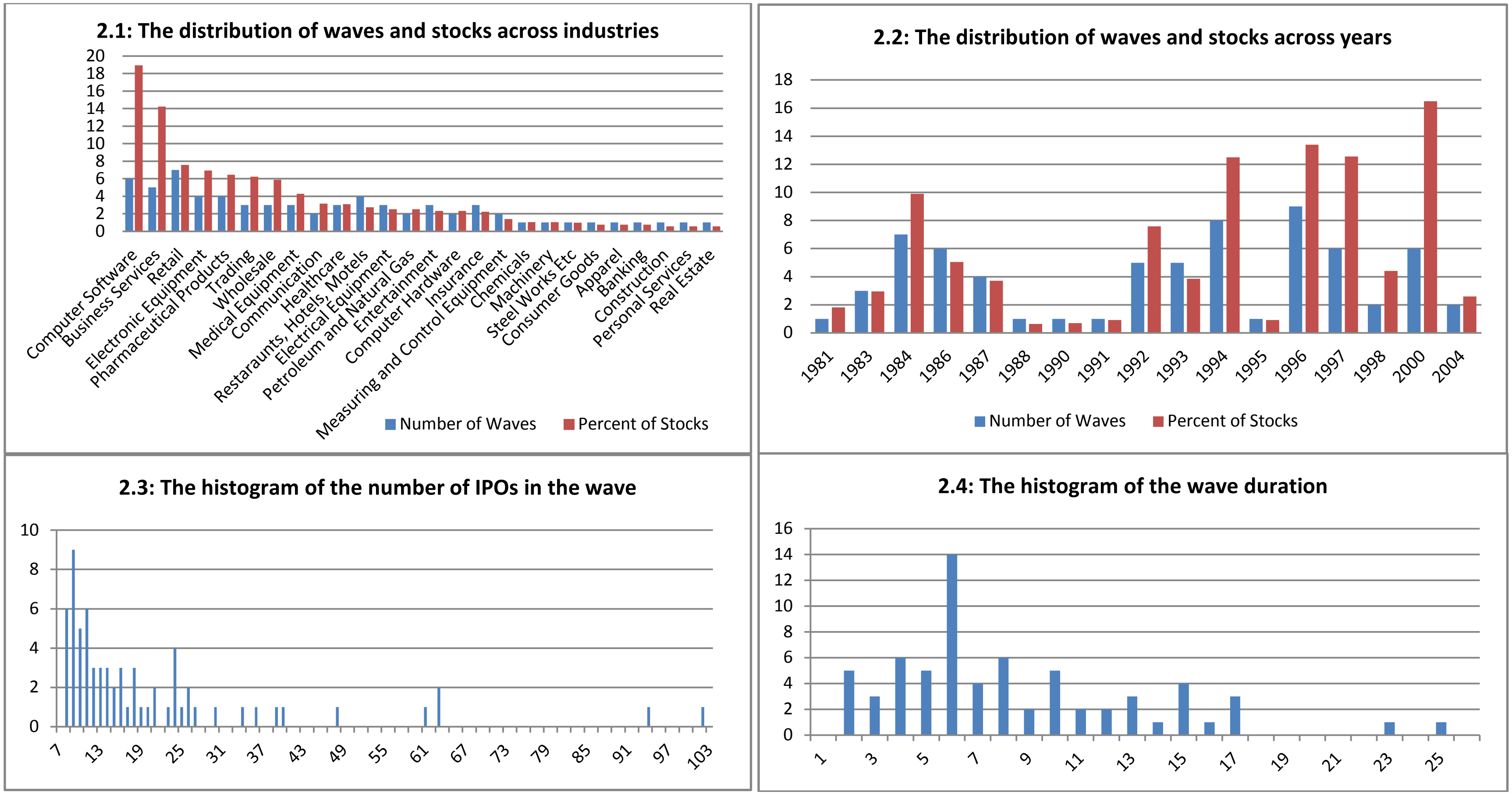

Figure 2

Selected statistics of industry IPO waves

Figures 2.1 and 2.2 plot the number of IPO waves and the fraction of sample stocks by industry and year respectively. Figures 2.3 and 2.4 plot the histograms of the number of IPOs in the wave and the duration of the wave in months. In these two plots, the numbers on the horizontal axis are possible values for the plotted variable, and those on the vertical axis are the frequencies of the corresponding values in our sample.

Table 1
Descriptive statistics of industry IPO waves

Panel A: Number of IPOs

Year	All IPOs: All	All IPOs: On-the-wave	All IPOs: Off-the-wave	IPOs appearing in COMPUSTAT within 3 years after IPO year: All	IPOs appearing in COMPUSTAT within 3 years after IPO year: On-the-wave	IPOs appearing in COMPUSTAT within 3 years after IPO year: Off-the-wave	IPOs in the sample
1980-1993	5,138	1,676	3,462	4,320	1,233	3,087	608
1994-2006	4,760	1,942	2,818	4,431	1,836	2,595	817
Total	9,898	3,618	6,280	8,751	3,069	5,682	1,425

Panel B: Distributions of industry IPO waves in the sample across the Fama-French 49 industries

Industries name	Number of waves	Duration of the wave (months): Mean	Duration of the wave (months): Median	Duration of the wave (months): Std.	Number of IPOs in the wave – all IPOs: Mean	Number of IPOs in the wave – all IPOs: Median	Number of IPOs in the wave – all IPOs: Std.	Number of IPOs in the wave – filtered sample: Mean	Number of IPOs in the wave – filtered sample: Median	Number of IPOs in the wave – filtered sample: Std.
Retail	7	5.83	4	6.46	23.14	23	7.60	15.43	18	5.26
Computer Software	6	2.82	2	1.83	96.17	39	100.85	45.00	23.5	41.52
Business Services	5	4.20	2	3.97	74.80	77	46.43	40.60	40	22.52
Pharmaceutical Products	4	3.80	2	4.13	29.00	28	17.42	23.00	22	12.41
Electronic Equipment	4	4.10	4	2.73	37.50	38	18.14	24.75	25	11.93
All others	42	5.20	4	4.14	29.93	18	35.38	15.55	12	10.73
Total	68	4.91	3	4.16	38.76	22	46.47	20.96	14	18.66

Panel C: Five of the Industry IPO waves with most number of IPOs in the sample

Industries name	Number of IPOs in the wave - all IPOs	Number of IPOs in the wave – filtered sample	Beginning month	Ending month
Computer Software	230	102	Mar. 1995	Jan. 1997
Computer Software	222	94	Feb. 1999	Apr. 2000
Trading	211	63	Jul. 1992	Jul. 1994
Business Services	97	63	Aug. 1995	Dec. 1996
Business Services	135	61	May 1999	Sep. 2000

Note: This table presents the descriptive statistics of industry IPO waves. We define industry IPO waves by Fama-French 49 industries based on how clustered the IPOs are in an industry. For each industry i and month t, we count the number of IPOs in the 3-month window from t-1 to t+1. We then define a hot IPO month as a month with the 3-month number of IPOs in the top quartile of all IPO months from 1970 to 2010 in the industry. Finally, we classify IPOs in those consecutive hot months as a wave. We define the beginning month and the ending month of a wave as the first month and the last month with IPOs in that wave. To avoid the problem that standalone IPOs are erroneously classified as a wave, we require a minimum of 5 IPOs in total and 1 IPO every month on average in the wave period. Our empirical analyses involve forming four portfolios within each industry IPO wave three years after the wave ending year (event year 0), based on the book-to-market equity ratio at the end of event year 3 and the average profitability in the first two fiscal years after event year 0. We require a minimum of 8 IPOs with non-missing sorting variables at the portfolio formation time for a meaningful sort. After imposing these filters, 1425 IPOs going public during 68 industry IPO waves in the period 1980 to 2006 enter our sample.

Panel A presents the distribution of IPOs on and off waves during our sample period. Columns 2-4 present the distribution for all IPOs in SDC, excluding those in the 49th Fama-French industry or those not classified into any industry. Columns 5-7 present the distribution for those IPOs appearing in COMPUSTAT within 3 years after the listing year. And the final column presents the number of IPOs in our sample. Panel B presents the distribution of 68 industry IPO waves in our sample across Fama-French 49 industries, and the summary statistics for some wave characteristics such as the duration of the wave, the number of all IPOs in the wave, and the number of IPOs in the wave entering our final sample. Panel C presents the statistics for the five biggest waves in our sample.

Table 2

Industry-adjusted buy-and-hold returns of event-time portfolios of stocks in industry IPO waves formed on book-to-market equity ratio and gross margin

		Formation period: return to the end of event year 3 (%)		Holding period: adjusted return since the end of event year 3 (%)			
Portfolio	Stat.	Raw return since IPO date	Adjusted return since the end of event year 0	Event year 4	Event year 5	Event year 6	Event year 7
Low BM	Mean	471.35	167.35	-16.53	-22.53	-26.06	-31.04
Low GM	t-stat.	1.16	1.53	-2.28	-2.12	-2.02	-1.87
Low BM	Mean	481.50	190.09	-2.96	0.61	-4.65	19.59
High GM	t-stat.	1.30	1.66	-0.46	0.07	-0.41	0.80
Low BM	Mean	10.15	22.74	13.56	23.14	21.41	50.63
H-L GM	t-stat.	0.12	1.33	2.12	1.81	1.64	1.48
High BM	Mean	-5.34	-54.75	8.13	27.14	21.98	36.99
Low GM	t-stat.	-0.38	-1.43	0.80	1.17	0.84	1.23
High BM	Mean	-2.31	-61.87	9.18	13.12	19.94	29.39
High GM	t-stat.	-0.17	-1.64	1.12	1.03	0.87	0.91
High BM	Mean	3.03	-7.13	1.05	-14.03	-2.04	-7.60
H-L GM	t-stat.	0.40	-1.55	0.13	-0.71	-0.09	-0.28

Note: This table presents the industry-adjusted buy-and-hold returns of event-time portfolios of stocks in industry IPO waves in 7 years after the wave ending year (denoted as event year 0). For each industry IPO wave, we conduct a two-by-two sequential sort for IPOs in the wave on the book-to-market equity ratio (BM) at the end of event year 3 and the average gross margin (GM) in fiscal years 1 and 2. Four event-time BM-GM portfolios are formed across all industry IPO waves. We first calculate buy-and-hold returns for each IPO stock in both the portfolio formation period and the portfolio holding period, then calculate the value-weighted average returns within a wave, and finally obtain the wave-size-weighted average returns across all waves. For consistency of comparison, we use the market capitalization of individual stocks and the number of IPOs in a wave at the time of portfolio formation, the end of event year 3, as weights for individual stocks and waves respectively. The industry adjusted buy-and-hold returns are calculated as the buy-and-hold returns in excess of the buy-and-hold value-weighted average industry returns over the corresponding horizon. We report the average returns (%) and their heteroskedasticity-and-correlation consistent t-statistics, calculated using the approach proposed by Jegadeesh and Karceski (2009), for four BM-GM portfolios and the difference between high GM and low GM portfolios within each BM group.

Table 3
Summary statistics of IPO and firm characteristics for IPO stocks

Panel A: IPO characteristics

Variable	All IPOs in SDC (Mean/Std.)	All IPOs in sample (Mean/Std.)	Low BM low GM (Mean/Std.)	Low BM high GM (Mean/Std.)	High BM low GM (Mean/Std.)	High BM high GM (Mean/Std.)	Low BM H-L GM (Mean/t-stat.)
Offer price ($)	11.45	12.11	11.93	12.38	11.93	12.19	0.44
	(5.80)	(5.18)	(5.26)	(5.27)	(5.27)	(4.95)	(1.08)
Initial return (%)	14.78	21.88	24.24	23.33	17.42	22.48	-0.90
	(28.75)	(37.58)	(38.76)	(38.29)	(36.03)	(37.01)	(-0.30)
IPO proceeds ($ million)	73.42	54.36	55.27	63.91	51.49	47.04	8.64
	(272.23)	(134.99)	(119.65)	(217.14)	(79.91)	(71.53)	(0.63)
Primary shares (%)	90.82	91.16	93.27	89.91	91.92	89.70	-3.36
	(17.38)	(15.91)	(14.40)	(16.52)	(15.18)	(17.07)	(-2.75)
Age	15.28	12.15	11.83	11.99	12.50	12.27	0.16
	(21.00)	(15.88)	(16.21)	(16.02)	(16.24)	(15.13)	(0.13)
VC-backed IPOs (%)	28.05	39.02	45.07	41.44	32.48	37.40	-3.64
	(44.92)	(48.80)	(49.83)	(49.33)	(46.90)	(48.45)	(-0.97)
IPOs with lockup period (%)	46.88	54.32	56.42	50.00	56.98	54.11	-6.42
	(49.90)	(49.83)	(49.66)	(50.07)	(49.58)	(49.90)	(-1.70)

Panel B: Firm characteristics in the portfolio formation period

Variable	All firms in sample (Mean/Std.)	Low BM low GM (Mean/Std.)	Low BM high GM (Mean/Std.)	High BM low GM (Mean/Std.)	High BM high GM (Mean/Std.)	Low BM H-L GM (Mean/t-stat.)
Log of market cap	4.49	5.02	5.34	3.74	3.89	0.32
	(1.86)	(1.73)	(1.77)	(1.73)	(1.70)	(2.40)
BM	0.96	0.30	0.28	1.56	1.64	-0.01
	(2.35)	(0.26)	(0.23)	(2.56)	(3.63)	(-0.72)
Turnover	1.69	1.79	1.88	1.46	1.62	0.09
	(1.63)	(1.47)	(1.96)	(1.47)	(1.55)	(0.69)
Gross margin	0.30	0.04	0.54	0.06	0.53	0.50
	(0.45)	(0.51)	(0.27)	(0.44)	(0.24)	(15.85)
ROA	-0.08	-0.14	-0.04	-0.11	-0.04	0.10
	(0.19)	(0.22)	(0.19)	(0.18)	(0.16)	(6.19)
Sales growth rate	0.39	0.46	0.45	0.33	0.34	-0.01
	(0.49)	(0.57)	(0.44)	(0.50)	(0.44)	(-0.21)

Note: This table presents the summary statistics of variables for our sample. Columns 2-7 in panel A present the mean and standard deviation of IPO variables for all IPOs in SDC, IPOs in our sample, and IPOs in the four BM-GM portfolios respectively. The last column reports the difference between high GM and low GM stocks in the low BM group and the t-statistics. Initial return is the return on the first trading date. Age is the number of years since the founding year at the time of IPO. Panel B presents the statistics of firm characteristics in the portfolio formation period. Denoting the industry IPO wave ending year as event year 0, market capitalization and BM are measured at the end of event year 3. Turnover is the average annual share turnover in event years 1 to 3. Gross margin, ROA, and sales growth rate are measured as the average value of the corresponding variable in fiscal years 1 and 2. We skip fiscal year 3 for accounting variables to avoid the potential overlapping with the portfolio holding period.

Table 4

Monthly returns of calendar-time portfolios of stocks in industry IPO waves formed on book-to-market equity ratio and gross margin

Panel A: The average monthly industry-adjusted returns, alphas and betas of BM-GM portfolios

Portfolio	Avg. Ret	Alpha	MKTRF	SMB	HML	UMD	Adj. Rsq
Low BM	-0.87	-1.03	0.20	0.83	0.04	-0.11	0.36
Low GM	(-3.03)	(-4.36)	(3.66)	(11.17)	(0.52)	(-2.30)	
Low BM	0.11	-0.11	0.23	0.49	0.00	0.03	0.20
High GM	(0.40)	(-0.46)	(4.22)	(6.39)	(-0.05)	(0.61)	
Low BM	0.97	0.92	0.04	-0.34	-0.05	0.14	0.05
H-L GM	(3.46)	(3.25)	(0.56)	(-3.86)	(-0.47)	(2.44)	
High BM	0.12	-0.06	0.01	1.08	0.27	-0.04	0.31
Low GM	(0.36)	(-0.20)	(0.10)	(11.82)	(2.71)	(-0.73)	
High BM	0.39	0.34	-0.01	0.85	0.23	-0.17	0.12
High GM	(0.90)	(0.80)	(-0.14)	(6.35)	(1.55)	(-1.93)	
High BM	0.27	0.40	-0.02	-0.23	-0.04	-0.13	0.00
H-L GM	(0.59)	(0.83)	(-0.18)	(-1.48)	(-0.25)	(-1.26)	

Panel B: Robust checks of the four-factor monthly alphas of low BM portfolios

Low GM		High GM		H-L GM	
Alpha	t-stat.	Alpha	t-stat.	Alpha	t-stat.
Holding period: 1985-1997					
-1.14	-3.33	-0.42	-1.09	0.72	1.58
Holding period: 1998-2010					
-0.87	-2.59	0.15	0.51	1.02	2.85
Value-weighting across all stocks					
-0.88	-3.44	-0.05	-0.16	0.83	2.45
Holding IPO stocks for 1 year from the end of event year 3					
-1.08	-2.88	0.13	0.38	1.20	2.50
Holding IPO stocks for 7 years from the end of event year 3					
-0.60	-3.11	0.24	1.16	0.85	3.26
Forming portfolios at the end of event year 2					
-0.87	-3.57	0.03	0.13	0.90	3.26
Forming portfolios at the end of event year 4					
-0.70	-2.99	-0.38	-1.50	0.32	0.99
Combining waves in the same industry with a gap less than 6 months in between					
-0.82	-3.79	-0.11	-0.45	0.72	2.59
Measuring BM as BE_FYear2/ME_Year3					
-1.12	-4.64	-0.12	-0.49	1.00	3.50

Note: This table presents the industry-adjusted monthly returns on calendar-time portfolios of stocks in industry IPO waves in the holding period, event years 4 to 7, after the wave ending year (event year 0). For each industry IPO wave, at the end of event year 3, we do a two-by-two sequential sort for IPOs in the wave on the book-to-market equity ratio (BM) at that time and the average gross margin (GM) in the fiscal years 1 and 2, and then hold these stocks during the subsequent four years. In each calendar year t, four calendar-time BM-GM portfolios are formed at the beginning of the year across all industry IPO waves ending in years t-7 to t-4. Within each BM-GM portfolio, stocks in the same industry IPO wave are value-weighted first to form the wave portfolio, and then wave portfolios are weighted by the number of IPOs at the end of event year 3 for all waves entering into the trading strategy. The portfolios are rebalanced annually at the beginning of each year.

In panel A, we report the average monthly industry-adjusted returns, the slope coefficients (factor betas) for the three Fama-French factors and Carhart's momentum factor, the four-factor alphas and their t-statistics (below in parentheses). We consider four BM-GM sorted portfolios and the long-short portfolios (long high gross margin stocks and short low gross margin stocks within each BM group). In panel B, we present the four-factor monthly alphas for the two low-BM portfolios and the long-short portfolio with various modifications to the baseline trading strategy: 1) splitting the whole holding period into two sub-periods; 2) value-weighting stocks both within and across waves; 3) having alternative holding periods; 4) forming portfolios at alternative time points, such as at the end of event year 2 based on BM at that time and GM in fiscal year 1, and at the end of event year 4 based on BM at that time and the average GM in fiscal years 1 to 3; 5) combining those waves in the same industry with a gap less than 6 months in between to form a bigger wave, and then forming portfolios based on our baseline trading strategy with the re-defined waves; and 6) measuring BM alternatively as the ratio of book equity at the end of fiscal year 2 to the market equity at the end of event year 3.

Table 5
Other results on monthly returns of calendar-time portfolios of growth stocks

Panel A: Alternative sorting variables using the industry IPO wave sample

Low		High		High-Low	
Alpha	t-stat.	Alpha	t-stat.	Alpha	t-stat.
Sorting on BM and profit margin (PM)					
-0.93	-3.20	-0.26	-0.97	0.66	1.95
Sorting on BM and asset turnover (AT)					
-0.85	-2.96	-0.42	-1.63	0.43	1.23
Sorting on BM and gross-profit-to-asset (GPA)					
-0.81	-2.42	-0.46	-1.97	0.35	0.97
Sorting on BM and return on assets (ROA)					
-1.00	-2.86	-0.46	-1.82	0.54	1.38
Sorting on BM and return on equity (ROE)					
-0.94	-2.68	-0.53	-2.20	0.41	1.06
Sorting on sales growth rate and gross margin					
-0.78	-2.88	-0.23	-0.87	0.55	1.68

Panel B: Industry competition and the four-factor monthly alphas of low BM portfolios sorted on BM and GM

	Low GM		High GM		High-Low GM	
	Alpha	t-stat.	Alpha	t-stat.	Alpha	t-stat.
Industry competition measure: Herfindahl index of sales						
Low	-1.03	-2.98	0.24	0.77	1.27	3.11
High	-0.58	-1.67	-0.29	-0.98	0.29	0.68
Industry competition measure: Advertisement intensity						
Low	-0.72	-2.41	0.12	0.42	0.84	2.22
High	-1.20	-3.69	-0.40	-1.29	0.79	2.04

Panel C: Forming portfolios among non-IPO-wave samples based on BM and GM

Low GM		High GM		High-Low GM	
Alpha	t-stat.	Alpha	t-stat.	Alpha	t-stat.
All IPOs in the same industry offered in the same year					
-0.29	-1.84	-0.09	-0.70	0.20	1.03
All stocks in industry-years with an IPO wave, excluding those stocks in the wave					
-0.01	-0.13	-0.12	-1.26	-0.11	-0.78
All stocks in CRSP/COMPUSTAT in the same industry					
-0.06	-2.19	0.05	1.71	0.12	2.57

Note: This table presents the four-factor monthly alphas in the 4-year holding period of portfolios of growth stocks formed differently than our baseline trading strategy. In panel A, we form portfolios of growth stocks among our industry IPO wave sample based on alternative sorting variables. The first five sub-panels present the results of two-by-two sequential sorts on BM at the end of event year 3 and the average value of other operating performance measures, such as profit margin (PM), asset turnover (AT), gross-profit-to-asset (GPA), return on assets (ROA) and return on equity (ROE), in fiscal years 1 and 2. The last sub-panel presents the result of a two-by-two sequential sort on the average sales growth rate and the average gross margin in fiscal years 1 and 2. Similar to our baseline trading strategy, all these trading strategies form portfolios at the end of event year 3 and hold them during the next four years.

In panel B, we partition the industry IPO waves into two groups based on competition measures of their affiliated industries. For each selected industry competition variable, we take the average value of the variable in the first two fiscal years after event year 0 as the proxy of industry competition. The High-group (Low-group) refers to industry IPO waves with the value of the industry competition measure above (below) the median value of the measure across all waves in our sample. We then form BM-GM portfolios separately among IPOs in these two groups of industry IPO waves, following the method in our baseline trading strategy. Herfindahl index of sales is the sum of squared market shares across all firms in an industry. Advertisement intensity is measured as the industry total advertising expenses scaled by the industry total sales.

In Panel C, we form BM-GM portfolios among non-IPO-wave samples, following methods similar to that in the baseline trading strategy on our IPO wave sample. The first sub-panel presents the results of forming portfolios among all IPOs in the same industry which were listed in the same year. First, IPOs in an industry-year IPO cohort are assigned into four groups at the end of the third year after the offering year based on a two-by-two sequential sort on the most recent BM and the average GM in the first two fiscal years after the offering year. Then in each calendar year t, we form four BM-GM portfolios at the beginning of the year across all industry-year IPO cohorts going public in years t-7 to year t-4. We first value-weight stocks within an industry-year IPO cohort to form cohort portfolios and then weight cohort portfolios across all industry-year IPO cohorts by the number of IPOs in each IPO cohort at the end of the third year after the offering year. The portfolios are rebalanced annually at the beginning of each year. The second sub-panel presents the results of forming portfolios among all stocks in those industry-years with an IPO wave included in our sample, excluding those stocks in the wave. For each wave, we replace stocks in the wave by all other stocks in the same industry and existing in CRSP/COMPUSTAT at the end of wave year, and then replicate our baseline trading strategy. The third sub-panel presents the results of forming portfolios among all stocks in CRSP/COMPUSTAT in the same industry. First, at the end of each year t, we do a two-by-two sequential sort within each industry based on the most recent BM and the average GM in the previous two fiscal years. Then we form four BM-GM portfolios across all industries, value-weighting stocks within each industry to form industry portfolios and weighting industry portfolios across all industries by the number of stocks in each industry, and hold portfolios during the next four years. Each month in the holding period, the overlapping BM-GM portfolios formed in the previous four years are equally weighted to calculate the final portfolio returns.

Table 6

Panel regression of annual industry-adjusted returns in the holding period on the average GM in the portfolio formation period

	Model 1		Model 2		Model 3		Model 4	
Variable	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
$BM_{Low}*GM_{High}$	7.62	2.03	7.18	1.96			9.98	2.65
$BM_{High}*GM_{High}$	-0.64	-0.41	-1.22	-2.28			-2.89	-0.97
$BM_{Low}*AT_{High}$					2.05	0.67	-0.54	-0.18
$BM_{High}*AT_{High}$					7.49	1.22	10.43	1.73
$SIZE_{t-1}$	-7.13	-3.33	-7.70	-3.46	-6.76	-3.15	-7.30	-3.30
BM_{t-1}	1.70	0.82	1.63	0.78	1.56	0.74	1.64	0.78
$EXRET_{t-1}$	-0.03	-2.22	-0.03	-2.22	-0.03	-2.27	-0.03	-2.28
$TURNOVER_{t-1}$	-1.51	-1.96	-1.58	-2.01	-1.56	-2.07	-1.60	-2.08
INITIAL_RETURN			0.05	0.73	0.05	0.79	0.06	0.82
VC			5.63	1.19	6.30	1.38	6.42	1.38
LOCKUP			-8.27	-1.81	-8.63	-1.91	-8.55	-1.86
PRIMARY_SHARES			-0.10	-0.80	-0.07	-0.58	-0.07	-0.59
Fixed effects	wave		wave		wave		wave	
Rsq (%)	4.48		4.61		4.59		4.75	

Note: This table presents the result of the following panel regression for our industry IPO wave sample,

$$EXRET_{i,t} = a_0 + b_1BM_{Low,i}*GM_{High,i} + b_2BM_{High,i}*GM_{High,i} + b_3BM_{Low,i}*AT_{High,i} + b_4BM_{High,i}*AT_{High,i} + a_1SIZE_{i,t-1} + a_2BM_{i,t-1} + a_3EXRET_{i,t-1} + a_4TURNOVER_{i,t-1} + c_1INITIAL\_RETURN_i + c_2VC_i + c_3LOCKUP_i + c_4PRIMARY\_SHARES_i + \sum_j d_jWAVEDM^j_i + e_{i,t}.$$

$EXRET_t$ is the annual industry-adjusted return in year t in the holding period, the fourth to the seventh years after the wave ending year (event year 0). BM_{Low} is a dummy variable, equaling 1 if the IPO stock is classified into the low BM group within an industry IPO wave based on the BM at the end of event year 3, and zero otherwise, and BM_{High} is the dummy variable for those IPO stocks in high BM group in an industry IPO wave. *GM* and *AT* are the average values of gross margin and asset turnover in the first two fiscal years after event year 0. GM_{High} is a dummy variable, equaling 1 if the IPO stock is classified into the high GM group within its BM group in an industry IPO wave, and zero otherwise. AT_{High} is a dummy variable, equaling 1 if the IPO stock is classified into the high AT group within its BM group in an industry IPO wave, and zero otherwise. $SIZE_{t-1}$ is the log of market capitalization at the end of year t-1. BM_{t-1} is the book-to-market equity ratio at the end of year t-1, calculated as the book equity of the fiscal year ending at least 3 months before the end of year t-1 to the market capitalization at the end of year t-1. $TURNOVER_{t-1}$ is the annual share turnover in year t-1. *INITIAL_RETURN* is the first day return of IPOs. *VC* is a dummy variable, equaling 1 if an IPO has venture capital backing, and zero otherwise. *LOCKUP* is a dummy variable, equaling 1 for IPOs with a lockup condition, and zero otherwise. *PRIMARY_SHARES* is the percentage of primary (new) shares offered in the IPO. $WAVEDM^j$ is a dummy variable for the j^{th} industry IPO wave in our sample.

The first two models include only interactions between BM dummies and high GM dummy, controlling only annual stock characteristics in model 1 and further controlling IPO characteristics in model 2. Model 3 includes only the interactions between BM dummies and high AT dummy, controlling both the annual stock characteristics and IPO characteristics. Model 4 include all the interaction terms. T-statistics are calculated based on two-way clustered standard errors by the Fama-French 49 industries and the calendar years.

Table 7
Relation to IPO overvaluation in Purnanandam and Swaminathan (2004)

Panel A: The comparison of Ln(PV) between high and low GM stocks

	Low GM			High GM			H-L GM	
	N	Mean	Std.	N	Mean	Std.	Mean	t-stat.
Low BM	103	0.68	1.36	129	0.74	1.40	0.06	0.33
High BM	133	0.50	1.28	151	0.64	1.27	0.15	0.97

Panel B: The average monthly industry-adjusted returns of low-BM portfolios, excluding stocks with valid PV ratios

Portfolio	Avg. Ret	Alpha	MKTRF	SMB	HML	UMD	Adj. Rsq
Low BM	-0.96	-1.12	0.14	0.98	0.05	-0.08	0.27
Low GM	(-2.66)	(-3.54)	(1.90)	(9.74)	(0.49)	(-1.18)	
Low BM	0.35	0.10	0.20	0.58	0.09	0.07	0.16
High GM	(1.15)	(0.35)	(2.95)	(6.35)	(0.85)	(1.13)	
Low BM	1.31	1.23	0.06	-0.39	0.03	0.14	0.03
H-L GM	(3.47)	(3.19)	(0.65)	(-3.24)	(0.24	(1.83)	

Note: This table presents the results of tests relating the underperformance of low-BM-low-GM stocks in industry IPO waves to the underperformance of overvalued IPOs in Purnanandam and Swaminathan (2004). PV is the ratio of the offer price to the fair value for an IPO as defined in Purnanandam and Swaminathan (2004), where the fair value is computed from the IPO firm's EBITDA and the price-to-EBITDA ratio of the benchmark firm - a non-IPO industry peer with comparable sales and EBITDA profit margin and listed more than three years ago. Panel A presents the mean and the standard deviation of ln(PV) for BM-GM groups and the results of t-tests for the difference in ln(PV) between high and low GM groups, for the 516 out of 1425 stocks in our sample with valid PV values. Panel B presents the average monthly industry-adjusted returns, the slope coefficients (factor betas) for the three Fama-French factors and Carhart's momentum factor, and the four-factor alphas, along with their t-statistics (below in parentheses), for the low-BM portfolios formed on our industry IPO wave sample according to our baseline trading strategy, while excluding those stocks with valid PV values.

Table 8
Sales growth response coefficients over time

Portfolio	b_1	Event year 1	Event year 2	Event year 3	Event year 4	Event year 5	Event year 6	Event year 7
Low GM	Coef.	0.08	0.05	0.01	0.01	0.01	0.01	0.01
	t-stat.	2.07	3.03	0.84	0.58	0.50	0.31	0.54
High GM	Coef.	0.04	0.05	0.04	0.07	0.07	0.03	0.07
	t-stat.	1.23	1.98	1.76	2.46	2.70	1.60	1.93
Industry benchmark	Coef.	0.02	0.02	0.03	0.02	0.03	0.02	0.03
	t-stat.	4.71	3.97	4.88	4.37	3.31	4.59	2.80
H-L GM	Coef.	-0.04	0.00	0.03	0.05	0.06	0.03	0.06
	t-stat.	-1.47	0.05	1.03	1.28	1.97	0.99	1.40

Note: The sales growth response coefficients are computed using the following regression,

$EXRET_{i,q} = a_0 + b_1 \Delta SG_{i,q} + b_2 \Delta IB_{i,q} + b_3 \Delta CAPX_{i,q} + e_{i,q}$,

$EXRET_q$ is the industry-adjusted quarterly return over the 3-month period from the end of the first month of calendar quarter q to the end of the first month of calendar quarter q+1. ΔSG_q is the change in sales growth rate from calendar quarters q-1 to q, where the sales growth rate in quarter q is calculated as ($Sales_q$ - $Sales_{q-4}$)/ $Sales_{q-4}$ and $Sales_q$ are the sales in quarter q. ΔIB_q is the year-over-year change in quarterly earnings, calculated as (IB_q - IB_{q-4})/ MV_{q-4}, where IB_q is the income before extraordinary items in quarter q and MV_q is the market capitalization at the end of quarter q. $\Delta CAPX_q$ is the year-over-year change in quarterly capital expenditure, calculated as ($CAPX_q$ - $CAPX_{q-4}$)/ MV_{q-4}, where $CAPX_q$ is the capital expenditure in quarter q. We run the regressions separately for the low-BM-low-GM group and the low-BM-high-GM group by event years in the 7-year period after event year 0 (the industry IPO wave ending year). We report the sales growth response coefficient, which is the regression coefficient on ΔSG_q, and its t-statistics for both low and high GM growth firms. We also report the difference in the coefficient between high and low GM groups and its t-statistics. We obtain the industry benchmark of the sales response coefficient by running the same regression for a sample of all stocks in the same industry as those in industry IPO waves which were listed at least 3 years before event year 0. All t-statistics are calculated based on standard errors clustered by industry.

Table 9
Operating performance over time

Panel A: Fraction of stocks delisted due to poor performance (%)

Portfolio	Stat.	Event year 4	Event year 5	Event year 6	Event year 7
Low GM	Mean	4.78	5.37	3.68	4.96
	Std.	21.36	22.58	18.85	21.75
High GM	Mean	1.38	1.79	2.93	2.29
	Std.	11.69	13.26	16.90	14.99
Industry benchmark	Mean	4.41	4.21	4.03	4.30
	Std.	14.42	12.34	10.75	9.90
H-L GM	Mean	-3.39	-3.58	-0.74	-2.67
	t-stat.	-2.57	-2.40	-0.50	-1.59

Panel B: Operating performance

Portfolio	Stat.	Event year 1	Event year 2	Event year 3	Event year 4	Event year 5	Event year 6	Event year 7
Market share (%)								
Low GM	Mean	0.12	0.15	0.14	0.17	0.20	0.22	0.21
	Std.	0.57	0.71	0.58	0.64	0.78	0.95	0.53
High GM	Mean	0.14	0.17	0.18	0.22	0.24	0.25	0.26
	Std.	0.46	0.57	0.52	0.58	0.65	0.77	0.62
Industry benchmark	Mean	0.61	0.64	0.68	0.74	0.79	0.81	0.87
	Std.	1.86	1.97	1.98	1.81	1.74	1.51	1.42
H-L GM	Mean	0.02	0.02	0.04	0.05	0.04	0.02	0.05
	t-stat.	0.53	0.39	0.95	0.97	0.68	0.32	0.95
Return on assets (%)								
Low GM	Mean	-12.76	-13.28	-9.53	-8.26	-4.67	-4.35	-3.78
	Std.	32.07	33.29	32.87	32.35	23.78	24.87	22.88
High GM	Mean	-0.58	0.41	1.87	1.33	1.51	1.58	1.74
	Std.	26.01	25.47	24.05	24.37	22.09	20.98	19.99
Industry benchmark	Mean	-0.73	-0.16	0.56	1.51	2.44	2.96	3.65
	Std.	33.70	27.81	28.77	23.02	18.67	15.53	12.73
H-L GM	Mean	12.18	13.70	11.40	9.59	6.18	5.93	5.52
	t-stat.	5.43	6.04	5.15	4.14	3.19	2.87	2.72

Note: This table presents characteristics of low-BM IPO stocks by event years in the 7-year period after the industry IPO wave ending year (event year 0).

Panel A reports the fraction of stocks delisted due to poor performance, as indicated by the delisting code between 500 and 599 in CRSP. Panel B reports the operating performance measures including market share and return on assets (ROA). A firm's market share in year t is calculated as its sales divided by the industry's total sales in year t. A firm's ROA in year t is calculated as its operating income after depreciation and amortization (OIADP) in year t divided by the average of total assets (AT) in years t and t-1. For each variable, we report its mean and standard deviation for low-GM and high-GM growth firms. We also report the difference between high and low GM groups and its t-statistics. We also report the industry benchmark for each variable. For each industry IPO wave, we select those stocks in the industry which were listed at least 3 years before the ending year of the current industry IPO wave, and then take the mean value of a specific variable among these firms as the industry benchmark for stocks in the wave. We then weight these industry benchmarks by the number of IPOs in the corresponding industry IPO waves, and report the weighted mean and standard deviation.

Table 10
Measures of uncertainty over time

Portfolio	Stat.	Event year 1	Event year 2	Event year 3	Event year 4	Event year 5	Event year 6	Event year 7
Analysts' earnings forecast dispersion								
Low GM	Mean	0.09	0.10	0.09	0.09	0.10	0.09	0.08
	Std.	0.11	0.11	0.12	0.11	0.12	0.14	0.10
High GM	Mean	0.07	0.07	0.06	0.07	0.08	0.08	0.07
	Std.	0.09	0.08	0.08	0.08	0.10	0.12	0.10
Industry benchmark	Mean	0.12	0.11	0.11	0.11	0.10	0.09	0.09
	Std.	0.24	0.24	0.22	0.23	0.22	0.20	0.16
H-L GM	Mean	-0.02	-0.03	-0.03	-0.02	-0.02	-0.02	-0.01
	t-stat.	-2.16	-3.53	-2.97	-2.77	-1.85	-1.23	-0.89
Idiosyncratic volatility								
Low GM	Mean	1.46	1.47	1.45	1.45	1.36	1.30	1.23
	Std.	0.53	0.55	0.53	0.55	0.52	0.52	0.56
High GM	Mean	1.35	1.36	1.34	1.33	1.27	1.22	1.15
	Std.	0.51	0.50	0.49	0.49	0.52	0.58	0.52
Industry benchmark	Mean	1.28	1.27	1.24	1.23	1.14	1.11	1.05
	Std.	1.65	1.64	1.55	1.39	1.25	1.22	1.05
H-L GM	Mean	-0.11	-0.11	-0.11	-0.12	-0.09	-0.08	-0.08
	t-stat.	-2.71	-2.70	-2.76	-2.95	-2.27	-1.72	-1.53

Note: This table reports other uncertainty measures including the dispersion of analyst earnings forecasts and idiosyncratic volatility by event years in the 7-year period after the wave ending year (event year 0). The dispersion of analyst earnings forecasts for a firm in year t is measured as the average value of the standard deviation of annual earnings per share forecasts reported in IBES monthly summary file in year t. To estimate a firm's idiosyncratic volatility in year t, we first regress its daily stock returns in year t on Fama-French three factors (MKTRF, SMB and HML) and Carhart's momentum factor (UMD), and then calculate the log value of the standard deviation of the residuals. For each variable, we report its mean and standard deviation for low-GM and high-GM growth firms. We also report the difference between high and low GM groups and its t-statistics. We also report the industry benchmark for each variable. For each industry IPO wave, we select those stocks in the industry which were listed at least 3 years before the ending year of the current industry IPO wave, and then take the mean value of a specific variable among these firms as the industry benchmark for stocks in the wave. We then weight these industry benchmarks by the number of IPOs in the corresponding industry IPO waves, and report the weighted mean and standard deviation.

Table 11
Stock ownership over time

Portfolio	Stat.	Event year 1	Event year 2	Event year 3	Event year 4	Event year 5	Event year 6	Event year 7
Percentage of shares outstanding held by insiders (%)								
Low GM	Mean	4.09	3.40	3.26	3.67	3.36	3.23	2.65
	Std.	9.17	7.27	7.52	9.19	8.22	7.79	6.02
High GM	Mean	6.41	5.70	6.26	5.57	4.26	4.95	4.41
	Std.	12.66	11.97	11.96	11.59	9.70	11.11	9.82
Industry benchmark	Mean	3.21	3.13	3.16	3.40	3.23	3.31	3.27
	Std.	6.01	7.01	7.10	7.01	7.10	6.68	6.02
H-L GM	Mean	2.31	2.30	3.00	1.90	0.90	1.72	1.76
	t-stat.	2.56	3.01	3.96	2.38	1.26	2.18	2.45
Percentage of shares outstanding held by mutual funds (%)								
Low GM	Mean	8.66	10.00	12.10	13.07	13.86	14.59	14.64
	Std.	9.33	10.38	11.74	13.02	13.38	13.87	14.58
High GM	Mean	10.27	11.86	13.42	14.61	13.93	14.64	15.80
	Std.	10.51	11.65	12.10	13.51	13.02	13.63	13.52
Industry benchmark	Mean	7.37	7.98	8.76	9.67	10.48	11.11	11.92
	Std.	14.53	15.77	17.90	19.70	20.86	20.64	20.72
H-L GM	Mean	1.61	1.85	1.32	1.54	0.08	0.06	1.17
	t-stat.	2.15	2.22	1.46	1.54	0.07	0.05	0.93
Percentage of shares outstanding held by growth-style mutual funds (%)								
Low GM	Mean	6.78	7.61	9.12	9.46	10.05	10.26	9.91
	Std.	7.49	8.17	8.86	9.78	10.04	10.01	10.06
High GM	Mean	8.13	9.13	10.49	11.10	10.27	10.36	11.13
	Std.	8.80	9.38	9.84	10.74	9.99	9.99	9.87
Industry benchmark	Mean	5.44	5.76	6.12	6.66	6.97	7.22	7.50
	Std.	10.59	10.81	11.83	12.77	12.85	12.42	11.89
H-L GM	Mean	1.35	1.51	1.36	1.64	0.22	0.11	1.22
	t-stat.	2.18	2.28	1.92	2.11	0.28	0.13	1.38

Note: This table reports the fraction of shares outstanding held by insiders, all mutual funds, and the growth-style mutual funds at the end of each event year during the 7-year period after the wave ending year (event year 0). We classify all mutual funds in the Thomson Reuters Mutual Fund Holdings database into different styles based on the investment objective code, supplemented by the style information from

CRSP mutual fund historical style data. Growth funds include those funds classified as growth style or aggressive growth style. For each variable, we report its mean and standard deviation for low-GM and high-GM growth firms. We also report the difference between high and low GM groups and its t-statistics. We also report the industry benchmark for each variable. For each industry IPO wave, we select those stocks in the industry which were listed at least 3 years before the ending year of the current industry IPO wave, and then take the mean value of a specific variable among these firms as the industry benchmark for stocks in the wave. We then weight these industry benchmarks by the number of IPOs in the corresponding industry IPO waves, and report the weighted mean and standard deviation.