Searching for Google's Value:

Using Prediction Markets to Forecast Market Capitalization Prior to an Initial Public Offering

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May 2007

Abstract

To inform theory and to investigate the practical application of prediction markets in a setting where the distribution of information across agents is critical, we conducted markets designed to forecast post-IPO valuations before a particularly unique IPO: Google. Because prediction markets allow us to infer the distribution of information before the IPO, the combination of results from our markets and the unique features of the IPO help us distinguish between underpricing theories. The evidence leans against theories which require large payments to buyers to overcome problems of asymmetric information between issuers and buyers. It is most consistent with theories where underpricing is in exchange for future benefits. This is but one of many potential applications for prediction markets in testing information-based theories.

JEL Classification Codes: C53, C93, G10, G14, G24, G32

Keywords: Initial public offering, underpricing, asymmetric information, prediction markets

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1. Introduction

Underpricing of initial public offerings is a well-documented phenomenon. Jenkinson and Ljunqvist (2001, p.27) report average underpricing of 15.3% for U.S. IPOs.[1] Smart and Zutter (2003), restricting their examination to IPOs between 1990 and 1998 for companies with dual-class shares, find a similar, though slightly lower, rate (11.9% on average). The causes of IPO underpricing have been modeled in a variety of ways including (1) information asymmetries across investors (e.g., Rock, 1986), (2) information asymmetries between issuers and investors that are overcome with large payments to investors (e.g., Chemmanur, 1993, Benveniste and Spindt, 1989, and Sherman and Titman, 2002), and (3) future benefits that result from IPO underpricing including improved secondary offerings because bad firms are driven out (Welch, 1989), ownership dispersion (Booth and Chua, 1996), and reduced potential legal liabilities (Tinic, 1988, and Hughes and Thakor, 1992).[2]

Testing many of the theories of underpricing is difficult because they rely on "unobservable" distributions of information or expectations. In this paper, we use the information aggregation properties of customized prediction markets to help us assess the "unobservable" information surrounding Google's IPO. Our markets combine the power of laboratory markets in studying financing arrangements under asymmetric information (e.g., Cadsby, Frank and Maksimovic, 1990 and 1998) with the real-world link of field studies. By linking our prediction market payoffs to Google's IPO, we are able to infer trader expectations from our market prices. Because the unusual auction process Google used for its IPO allows us to infer information about what the issuing firm knew (as discussed below), conducting a prediction

[1] Similar underpricing is found in Ritter and Welch (2002), who document an average 18.8% first day return (15.8% underpricing) in a sample of 6,249 U.S. firms between 1980 and 2001. Loughran and Ritter (2004) document that underpricing appears to change over time with average underpricing of 7% in the 1980s, 15% in the period 1990-1998, 65% in 1999-2000 (the Internet bubble), and 12% in 2001-2003.

[2] We note that there are other types of theories. For example, Loughran and Ritter (2002) discuss a role for prospect theory and Khanna, Noe, and Sonti (2005) discuss the role of labor market shortages for investment bankers. We do not discuss these models because our evidence does not address them.

market on the Google IPO in particular provides us with a unique opportunity to study the “unobservable” distribution of information surrounding an IPO.

Our evidence shows that traders were able to estimate accurately the post IPO value of Google. Further, they revealed this information for very little payment. In addition, we show that the correlation between ex ante forecasts of underpricing and the implied degree of uncertainty in traders’ forecasts runs counter to models based on asymmetric information across traders. Because this evidence does not depend on Google’s unique IPO in any way, we argue that this is general evidence against three types of asymmetric information based theories: (1) theories that rely on outsiders being relatively uninformed, (2) theories that rely on outsiders being relatively informed and revealing that information only in exchange for large payments and (3) theories that rely on significant winner’s curse problems.

The primary contribution of this paper is in providing a new kind of evidence on theories of IPO underpricing. Prediction markets extract information from outsiders and inform theory at two levels. First, market information about outsider expectations provides evidence about theories based on differential information or expectations. Second, market information about the evolution of expected underpricing and uncertainty provides evidence about theories based on the winners curse. The unique auction mechanism used in the Google IPO provides additional information. The auction mechanism rules differ from the usual bookmaking in several ways that are important to a subset of theories of underpricing. As a result, the existence of underpricing in the Google IPO provides evidence on these theories. The Google auction mechanism also provides information necessary to estimate aspects of the demand curve and, as a result, to infer information known to the issuer. This allows us to generate additional evidence about theories that are based on differential information or expectations. Though it is from a single IPO, combined, the consistent evidence from our prediction markets and the Google auction mechanism generates a particularly compelling case.[3]

[3] As we will discuss below, prediction markets have proven to be very efficient in extracting and aggregating information across traders and in showing how consensus forecasts evolve through time. As a result, we can learn a great deal from a single prediction market. While we would like to gather evidence from additional prediction markets in the long run, the particular combination of features that extend the range of implications

The markets described in this paper also have practical applications. This is a new application of prediction markets. Prediction markets have long been used for forecasting (starting with Forsythe, Nelson, Neumann and Wright, 1992). They can be used for policy analysis (Hanson, 1999) and decision support (Plott, 2000, Berg and Rietz, 2003). They have also been used to test theories like efficient markets (Camerer, 1989[4]) and theories of trader interaction (List, 2006, and Oliven and Rietz, 2004). Here, we propose another use of prediction markets: extracting information from agents to test theories that depend on otherwise unobservable information or expectations held by agents. The prediction markets reported here also show the evolution of expectations and uncertainty as an IPO develops. In this case the evolution is particularly interesting because the initial prospectuses were quite stark and much of the valuation-relevant information was given in amendments. Finally, if obvious strategic manipulation problems can be addressed, companies could use prediction market forecasts to set IPO prices that either (1) avoid underpricing when it is optimal to do so or (2) know in advance and set optimally the degree of underpricing when it is, in fact, optimal to underprice (say, in exchange for future benefits). The overall impact could be substantial. For example, Google's underpricing left more than $300 million on the table.[5] Prediction markets could help eliminate the underpricing or determine whether the amount of underpricing is optimal.

The rest of our paper is organized as follows. In Section 2, we describe prediction markets, arguing that their information aggregation properties make them particularly useful in testing theories where information differences play a key role and in the Google IPO in particular. In Section 3, we outline the history and unique features of the Google IPO. In Section 4, we describe the specific prediction markets we conducted to predict the post-IPO Google value. In Section 5, we present our results and we conclude in Section 6.

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we can draw are unlikely to be repeated in the future.

[4] Camerer's test actually uses a naturally occurring betting market instead of a prediction market per se.

[5] This statistic comes from Table II, discussed later in the text.

2. Why Prediction Markets on the Google IPO?

Since Adam Smith (1776) economists have recognized the advantage of market-based systems in efficiently organizing production, exchange and consumption. A premise underlying the Hayek Hypothesis (1945) is that markets also efficiently aggregate information, even in complex environments where individuals have very little information on their own. Laboratory tests of the Hayek Hypothesis, summarized in Vernon Smith (1982), provide support for the idea, as does field research (e.g., Roll, 1984, and Forsythe, Nelson, Neumann and Wright, 1993, among others). Here we propose using the information extraction and aggregation properties of prediction markets to infer the information held by agents from their observed behavior. This allows us to test theories of IPO underpricing that rely on the otherwise unobservable distribution of information across agents.

Prediction markets are small-scale, real-money markets designed to predict future events. They have proven accurate in aggregating and revealing the information held by traders.[6] As Surowiecki points out in The Wisdom of Crowds (2004), average forecasts from a group of individuals are frequently more accurate than individual forecasts. Like surveys, prediction markets aggregate information from groups of traders. However, they have several advantages over simple surveys. First, prediction markets give traders incentives to gather or create information. Better informed traders profit more. Second, in prediction markets, traders can express their strength of conviction through their intensity of trading. Well informed traders can trade more; less informed can abstain from trading. Thus, traders self-select. Evidence shows that traders who self select into price setting roles are more rational than average traders (Oliven and Rietz, 2004). Third, by observing current prices before trading, prediction market traders can

[6] While the evidence on prediction markets specifically is relatively recent, prediction markets are just a special form of betting markets, where evidence spans a much longer time period. In general, betting markets are accurate in predicting outcomes, except in the tails, where there is a small longshot bias. (Griffith (1949) first documented the overall accuracy of the markets. McGlothlin (1956) first identified the slight longshot bias. Many researcher since have confirmed both findings. See Thaler and Ziemba (1988) and Sauer (1998) for a complete set of references.) In pari-mutuel betting markets, win pool shares can be used as forecasts of probabilities of outcomes. Evaluating all the evidence, Sauer (1998, p. 2048) concludes: "Win pool shares w_i are good approximations to p_i, the probability that a horse i wins the race, the favorite-longshot bias notwithstanding." For IEM prediction markets in particular, Berg and Rietz (2002) show a similar accuracy of prediction markets in forecasting probabilities in the middle of the distribution, with small transient deviations in tail probabilities (though in the opposite direction of the longshot bias).

incorporate into their own forecasts the forecasts of others as summarized by prices. Finally, prediction markets can respond quickly to information events (e.g., Berg and Rietz, 2005). The end result is an extremely efficient, dynamic mechanism for aggregating information.

Plott (2000, p. 14), after summarizing the evidence on markets as information gathering tools, concludes that prediction markets have "an amazing ability to perform." Like other prediction markets, the Iowa Electronic Markets (IEM for short, markets conducted for research purposes since 1988) are also "amazing" in their ability to aggregate information. They predict well both shortly before an event (Berg, Forsythe, Nelson and Rietz, 2005) and through time (Berg, Nelson and Rietz, 2003). The markets appear to forecast better than alternative means (Berg, Nelson and Rietz, 2003) and in a variety of contexts (Wolfers and Zitzewitz, 2004). This accuracy holds not just overall or on average, but on a case-by-case, contract-by-contract basis.[7]

We chose to run the prediction market on the Google IPO in particular because it is an especially informative case for theory. Google's specific and clearly stated goal was to avoid IPO underpricing. To achieve this goal, it used an auction mechanism for gathering information, setting prices and allocating shares. Some theories of IPO underpricing rely on particular features of the usual "book building" process that were eliminated in the Google auction. Specifically, the auction severely restricted the investment bankers' discretion in issuing shares and the auction did not allow Google to pre-commit to underpricing. Because of this design, the underpricing that occurred in Google's case cannot be explained by models that rely on either of these features. The auction mechanism along with information revealed after the IPO also allows us to estimate the excess demand for Google stock at the issue price and, through this, estimate a portion of the demand curve. Thus, we can infer the pre-IPO information likely held by the issuer as a result of the bidding process. Combined, the auction process and the

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[7] For example, Figure 1 in Berg, Forsythe, Nelson and Rietz (2005) shows the forecast and actual vote shares for 237 contracts traded in 49 IEM markets designed to predict vote shares received by candidates or parties from around the world. Forecast errors were less than ten percentage points for all but four contracts, three of which were all associated with the same event: candidate performances in the 1992 Democratic primaries. Even in these cases, the markets likely aggregated trader information efficiently. Between the time of the official forecast (midnight before Election Day) and the close of voting, health questions about Paul Tsongas arose, likely changing the actions of many voters at the last second.

prediction markets allow us to infer the differences in information across the issuer and investors, which is critical for evaluating many theories of underpricing. Given the degree of excess demand at the issue price, the evidence shows that Google knew the auction mechanism was underpricing the issue.[8] Again, the evidence leans against theories that rely on asymmetric information. Along with the prediction market evidence, this makes a compelling case against asymmetric information-based theories of IPO underpricing.

Our research complements and extends recent research on when-issued trading in German IPOs. Löffler, Panther and Theissen (2005) and Aussenegg, Pichler and Stomper (2006) both show that when-issued trading on German IPOs helps forecast post-IPO trading prices.[9] From one perspective, our prediction market evidence is similar: through a market mechanism traders reveal information in advance of the IPO that forecasts post IPO prices. However, our research provides information not available in when-issued markets. First, our markets provided valuation forecasts before the initial price ranges were set. German when-issued markets run only after initial price ranges are set, typically one week before the issue. Löffler, Panther and Theissen (2005, p. 476) report that "unbiasedness is rejected, however, for pre-IPO quotes established until the midpoint of the subscription period." That is, the prices are only unbiased forecasts in the last few days before an IPO. This is important because it severely limits the usefulness of when-issued markets in setting IPO prices. German IPO price ranges are never adjusted; IPO prices never exceed the top of the range, prices seldom fall below the bottom and more than half of the IPOs are set at the top of the range (Aussenegg, Pichler and Stomper, 2006). Thus, the relevant pricing information needs to be gathered before when-issued trading commences. In contrast, our markets ran for six weeks before the IPO and two and a half weeks before any initial price ranges or issue

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[8] We note here and later that the auction allows us and Google to infer the degree of excess demand. We do not have, nor were we able to obtain, the demand schedule from the auction. The excess demand could have resulted from deliberate pricing below market clearing (as Google's prospectus allowed them to do) or from (extreme) lumpiness in the demand schedule. Whatever the cause, we merely argue below that Google knew that the issue price was associated with excess demand and, hence, was below a true market clearing price.

[9] Löffler, Panther and Theissen (2005) find that when-issued prices are "highly informative" and Aussenegg, Pichler and Stomper (2006) find that when-issued prices are indicative but do not "fully supplant information gathering through book building."

quantities were announced. We find that our market prices were quite accurate even before initial price ranges were set.

Second, our market design allows us to build a forecast distribution of post-IPO prices, not just point estimates of the expected post-IPO price. As a result, our markets show both the amount of uncertainty surrounding the future post-IPO market price and the degree to which this uncertainty is resolved as the IPO process evolves. This is an important contribution that is left unaddressed by when-issued research. Third, since our results are on the Google IPO with its unique auction design, we provide additional evidence on what theoretical models are likely to explain underpricing.[10] Finally, prediction markets are not limited to IPOs. They are widely applicable in testing information-based economic theories.

3. The Google IPO

A. Overview

The Google initial public offering (IPO) was closely watched and unique. A search of Lexis/Nexis for the words "Google" with "IPO" or "initial public offering" within 25 words, yields 769 hits between October 24, 2003 (when the potential for an IPO was first mentioned in the *Wall Street Journal*) and August 19, 2004 (when trading in the stock began). Google's use of an auction mechanism to help set the IPO price is uncommon in the U.S., especially for an IPO of Google's size. The stated goal was to set an IPO price close to the ensuing market price. While there is debate over whether auction mechanisms mitigate underpricing (see Sherman, 2005, for example), evidence from the French stock market (Derrien and Womack, 2003) suggests an auction mechanism could have helped Google achieve its goal. Indeed, the auction mechanism did eliminate two factors that several theories of underpricing rely on: discretionary allocations of shares and pre-commitment to underpricing. However, Google's

[10] There are several other smaller distinctions as well. For example, we incorporate a variety of prediction market design features that encourage accurate price forecasts. The small size of IEM markets and evidence from other IEM markets lead us to believe that hedging and strategic manipulation are unlikely to bias prices in these prediction markets. Short selling is limited in when-issued markets. In prediction markets, synthetic short selling is constrained only by the budgets of traders.

IPO price fell short of both its opening and its closing market prices on the first day of trading by just over 15%, an amount close to the average initial underpricing of 15.3% for U.S. IPOs reported by Jenkinson and Ljungqvist (2001, p. 27) and somewhat higher than the 11.9% average underpricing reported by Smart and Zutter (2003) for IPOs of companies with dual-class shares (like Google) between 1990 and 1998.

B. Timeline of Events

Google's potential IPO was first reported by the *Wall Street Journal* on October 24, 2003. The *Journal r*eported that Google had contacted an investment banker and that an IPO was under consideration for 2004. Speculation about the IPO continued until the initial filing with the SEC on April 29, 2004 (SEC file number 333-114984). Google filed nine amended prospectuses. Its final prospectus was approved on August 18, 2004 and officially filed the next day. Table I lists the filing dates and summarizes major changes included in each amendment.

The initial filing contained little information about quantities of shares.[11] There was no initial price range and there was no target IPO date. The fourth amended filing on July 26 supplied projected share quantities, the initial price range ($108 to $135) and an August target IPO date. Issue quantities were revised in Amendment 5 on August 9 and in Amendment 9 on August 18. Amendment 9 also adjusted the initial price range down to $85-$95. The final prospectus, declared effective on August 18 and filed on August 19, set the IPO price at $85. On August, 19, Google's stock opened at $100.00 and closed at $100.34. On August 21, the San Francisco Chronicle reported that the underwriters had exercised the full over-allotment option to purchase 2.94 million more shares.[12] Google stock closed at $108.31 on August 20, even with this exercise.

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[11] Missing were the total quantity of shares expected after the offering, the number sold to the public by the company, the number sold by existing shareholders, the size of the over-allotment option and the numbers of shares subject to various lock up rules. While the joint issue of new shares and sales by existing shareholders may seem unusual, Jenkinson and Ljungqvist (2001, p. 3) point out that "many" IPOs share this feature.

[12] According to prospectus rules, these shares could be purchased by the investment bankers from pre-IPO shareholders (at a net price of $82.6161) only to cover shorts created in the IPO (sold to the public at $85).

C. Unique Features and Stated Goals of the Google IPO

Instead of using the usual bookmaking process to determine the IPO price, Google used an auction process.[13] The auction mechanism was similar to a second price auction: there would be a single market price with all bids above that price receiving shares at that price. However, unlike a second price auction, Google reserved the right to set the IPO price below the market clearing price,[14] creating excess demand. Excess demand could also come from "lumpiness" of the demand schedule, with large quantities of bids at particular prices. In such cases, bid quantities would be used to determine actual shares allocated to successful bidders using one of two pre-specified apportionment rules. This effectively limited discretion in the allocation of shares. The Google IPO auction opened on August 13, 2004 and closed on August 18.

While IPO auctions have been common in other countries[15] and the potential of using the Internet to disintermediate U.S. IPOs has been discussed (e.g., Jenkinson and Ljungqvist, 2001, p. 9), the use of an auction mechanism for an IPO of this size in the United States is novel. The major features of this process were outlined in the initial filing on April 29 and refined throughout the amended filings. The stated goal of the auction process was to set "an initial public offering price that results in the trading price for our Class A common stock not moving significantly up or down relative to the market in the days following our offering" (page 28 of the initial S-1 filing); "to have a share price that reflects a fair market valuation of Google" (page v of the initial S-1 filing); and to avoid "boom-bust cycles" (page v of the initial S-1 filing).[16] Thus, the goal was to set the IPO price near the actual market price in the days

[13] Interested readers can obtain details of the Google auction process from the prospectus available at the SEC through EDGAR (http://www.sec.gov/edgar.shtml) by searching for file number 333-114984.

[14] We note that Google defines market clearing as the bid price at which all shares, including the over allotment option, are sold. We will use the same definition. When we estimate the demand curve below, we are consistent with this, though we recognize that Google sold no shares itself in the overallotment (all shares sold in the overallotment were by prior existing shareholders).

[15] According to Jenkinson and Ljungqvist (2001) they have been common in Israel, England (in the 1980's), and Japan (in the 1990's). France uses a mixture of auctions and bookmaking. Sherman (2004) notes that IPO auctions have been tried in many countries, but have been abandoned in most.

[16] To further emphasize this objective , the prospectus and amendments also state "Our goal is to have an efficient market price—a rational price set by informed buyers and sellers—for our shares at the IPO and afterward. Our

following the IPO, avoiding the typical underpricing that characterizes most IPOs. This would be beneficial for Google. The typical 15% underpricing of IPOs in the United States and other developed countries leaves a great deal of money on the table. If companies could set IPO prices closer to eventual market prices, they would raise substantially more money and/or incur substantially less dilution on average. Given Google's stated goals, their IPO provides a natural benchmark for the performance of prediction markets: we can compare the difference between Google's IPO valuation and the post-IPO market valuation to the difference between the prediction market forecast and the post-IPO market valuation.

Though Google's auction process was used to gauge interest from potential shareholders and, with sufficient confirmation, used to generate binding orders for shares, it was not, strictly speaking, a direct auction of shares. For example, Google and its underwriters retained the right to reject bids they found manipulative or disruptive at their sole discretion without notifying bidders who submitted these bids. Moreover, the prospectus clearly states that the IPO price need not be the auction clearing price. Page 38 of the amended S-1 filing on August 13, 2004 (the day the auction began) states (emphasis added):

> The initial public offering price will be determined by us and our underwriters after the auction closes. We intend to use the auction clearing price to determine the initial public offering price and, therefore, to set an initial public offering price that is equal to the clearing price. ***However, we and our underwriters have discretion to set the initial public offering price below the auction clearing price.***

As a result, the IPO price could fall below the actual auction market clearing price. This possibility required a potential allocation mechanism in which bidders would not receive the full number of shares for which they bid. Two allocation mechanisms were described in the prospectus, with the decision about which would be used left to management discretion. Because the auction order book and clearing prices have not been made public (in accordance with prospectus rules), we do not know precisely how much "discretion" was exercised, how far the IPO price may have been set below the auction's clearing price or whether there was a lumpy demand schedule. Nor do we know exactly how

goal is to achieve a relatively stable price in the days following the IPO" (on page v of the initial S-1 filing).

close the auction market clearing price may have been to eventual trading prices.[17] However, we can estimate the excess demand at the IPO price and a segment of Google's demand curve using information from Google's prospectus and information released by investors after the IPO. This will provide evidence about whether the prices implied by our prediction market could have been realistic IPO prices for Google.

D. The Importance of the Unique Features of the Google IPO

The specific and unique auction mechanism used by Google adds further insights into IPO theories. First, it eliminates some potential causes of underpricing and, as a result, provides evidence on theories that rely on these causes. Second, the auction mechanism, combined with the allocation mechanism used and post-IPO information gathered from bidders allows us to estimate the excess demand at the issue price. Whether it was due to a lumpy demand schedule or deliberate underpricing, Google was aware of the degree of excess demand in advance of the IPO. As a result, we know something about the information held by the issuer before the issue, a critical factor in some theories of underpricing.

The unique process of information revelation followed by Google in this particular IPO is also interesting. It allows us to assess the forecasting ability of prediction markets for IPOs well in advance of the IPO and under conditions of sparse information And, the evolution of uncertainty about the post-IPO valuation of Google can be tracked by our market design allowing us to see how information revealed during the IPO process affected the uncertainty faced by traders.

[17] We note that another possible reason for using the auction mechanism is to decrease underwriting fees. According to Google's final prospectus, underwriting discounts and commissions accounted for $2.3839 of the $85 offer price. Thus, fees were 2.8% of the offer price. Only one IPO in Chen and Ritter's (2000) data set on fees in IPOs approaches Google's size. The fees on this $1.3 billion IPO were 2.97%. The next two largest IPOs had fees of 4%. So, while fees for smaller IPOs typically average 7%, the fee here seems in line after considering IPO size. The auction may have allowed Google to more accurately assess demand and avoid the costs associated with over-allotment options. However, Google's over-allotment option was exactly 15%, the "typical" amount in the U.S. according to Brealey and Myers (2003, p. 413).

4. The Iowa Electronic Markets Google IPO Markets

Though some other markets (e.g., futures markets) have a predictive component, prediction markets are designed specifically for forecasting purposes. Contracts in prediction markets have payoffs tied directly to a future event of interest (in this paper, Google's eventual market capitalization) and the markets have design features that encourage revelation of true underlying expectations. This means prices in prediction markets provide forecasts about features of the associated event, for example its probability of occurring or the consequences of its occurrence. The Iowa Electronic Markets (IEM for short, real-money small-scale prediction markets conducted for more than 18 years to forecast election outcomes, other political and economic events, prices and returns of stocks, corporate earnings and movie box office receipts) have proven remarkably accurate in the short run (Berg, Forsythe, Nelson and Rietz, 2003) and the long run (Berg, Nelson and Rietz, 2003). This accuracy holds not just overall or on average, but on a case-by-case, contract-by-contract basis. Prediction markets efficiently extract information from traders across a wide variety of environments (Wolfers and Zitzewitz, 2004). In the research described here, we use a prediction market to assess the information held by IPO outsiders and compare it to the information held by insiders (derived from the estimated demand curve as discussed above) and the ultimate post-IPO price of Google stock.

A. Description of the Google IPO Markets

The IEM conducted two markets associated with the Google IPO. Both markets traded contracts with liquidation values based on the total market capitalization implied by the closing price of Google stock at the end of the first day of trading. Contracts were based on total market capitalization rather than share price so that the markets could open before initial price ranges and share quantities were announced. The market structure was the same as other IEM markets. Since descriptions of IEM markets are available elsewhere, our description here will be brief.[18]

[18] See Forsythe, Nelson, Neumann and Wright (1992), Berg, Forsythe and Rietz (1997) and Forsythe, Rietz and Ross (1999).

In IEM markets, traders invest their own money (initial investments can range from $5 to $500) and reap the real money benefits or pay the real money costs associated with their trading activities and contract holdings at liquidations.[19] Each market is organized as a continuous, electronic, multiple-unit, double auction. Traders can place limit orders (acting as endogenous market makers) or market orders at any time.[20] Bids and asks are kept in queues prioritized by price and time. Traders set their own bid and ask expiration dates and can withdraw any bids or asks that have not yet traded. Traders can buy or sell risk-free sets of contracts (one of each contract in the market at a fixed price of $1, called "fixed price bundles") from or to the exchange at any time. They can trade individual contracts purchased as parts of bundles. And, they can trade bundles at market prices (selling at the sum of the best bid prices or buying at the sum of the best ask prices). At all times traders see the best available bids and asks for all contracts, and they can retrieve histories of daily trading summaries (daily high, low, last, and average trade prices as well as volume measured in both units and dollars).

IEM Google contract liquidation values were tied to Google's market capitalization at the end of the first day of trading in its public shares. As a result, we can extract trader information and build forecasts of Google's capitalization using IEM market prices. We use these forecasts (as summaries of trader information), the quantity of stock issued, the IPO price of Google and the first-day closing price of Google to:

(1) assess the information and expectation of "outsiders;"

(2) determine the impact of announcements or news on both the forecasted level of capitalization and on the ex-ante uncertainty surrounding the forecast during the course of the prediction market;

(3) determine whether the forecasted market capitalization was closer to the actual capitalization than that implied by the IPO price;

(4) learn about how and when the price formation process aggregated information for these markets and

[19] This differs from traditional experimental markets in which the experimenter funds the subjects for money used in the experiment and other experimental prediction markets in which no real money is used at all.
[20] The Google markets were open to all traders, not just academic traders. Any person, worldwide, could become a trader by sending an investment to the IEM.

(5) analyze (using forecasts from two different markets we conduct) whether contract structure matters for prediction markets

i. *The Google Linear Market*

The Google Linear market opened on June 29, 2004 with two contracts.[21] Contract liquidation values were determined as follows:

Contract	Contract Liquidation Values
IPO_UP	= $0 if the IPO does not take place by March 31, 2005;
	= (Market Cap.)/$100 billion if $0 bil. < Market Cap. <= $100 bil;
	= $1 if Market Cap. > $100 bil.
IPO_DN	= $1 if the IPO does not take place by March 31, 2005;
	= ($100 bil.-Market Cap.)/$100 billion if $0 bil. < Market Cap. <= $100 bil;
	= $0 if Market Cap. > $100 bil.

In the absence of hedging demand, prices should equal expected values in this market.[22] Thus, the price of IPO_UP times $100 billion is the IEM's forecast of the market capitalization of Google stock after the first day of trading according to the closing market price.[23]

[21] The appendix contains the prospectus for this market.

[22] This argument can be made in numerous ways. While one might think risk aversion would lead to prices that differ from expected values, this is not the case here. Intuitively, one wants to argue that risk aversion will lead traders to price a contract below expected value to compensate for risk. This would be the case for a single contract in isolation, but fails because of the contract-bundle method of issuing claims here. If one contract in a bundle is priced below expected value, then the arbitrage restriction will force the price of at least one other contract above its expected value. This is inconsistent with the argument that contracts should be priced below expected value. In the prediction market case where all contracts are issued in risk free bundles, the only prices that support the general equilibrium are expected values (see Caspi, 1974, and Malinvaud, 1974). In asset pricing terms, modern asset pricing models (e.g., CAPM or APT) say that investors are rewarded through the risk free rate and compensation for risk. Here, the risk free rate is zero because the two risk free assets (cash and contract bundles, which can be freely exchanged between each other) both earn zero return. There is no compensation for risk because, in aggregate, the bundles always pay out exactly what is invested in them: $1. In fact, this implies that there is no systematic risk factor. We pay out the same amount to traders regardless of the state (Google's actual market value). Thus, no compensation for risk bearing and a zero risk free rate imply that prices equal expected values. In option pricing theory, these expected values would result from the risk neutral distribution, which may differ from the true distribution because of hedging demand. However, the accuracy of prices in other IEM markets suggests that hedging demands are not significant factors in determining prices.

[23] Technically, we need two further assumptions to make this the forecasting relationship. We need to assume that the probability of no IPO before the end of March 2005 is zero, which is consistent with Google's stated strong intention to issue in the summer of 2004. We also need to assume that the probability of a market capitalization greater than $100 is effectively zero. Below, we will estimate a distribution of expected market capitalizations from the other IEM market we ran. This distribution is consistent with essentially zero likelihood of a market capitalization above $100 billion.

ii. The Winner-Takes-All Market

The Google Winner-Takes-All (WTA) market opened on June 29, 2004 with six "interval" contracts.[24] Liquidation values of the initial contracts were determined as follows:

Contract	Contract Liquidation Values
IPO_0-20	$1 if market cap is less than or equal to $20 billion or if the IPO does not occur by March 31, 2005.
IPO_20-25	$1 if market cap is greater than $20 billion but less than or equal to $25 billion.
IPO_25-30	$1 if market cap is greater than $25 billion but less than or equal to $30 billion
IPO_30-35	$1 if market cap is greater than $30 billion but less than or equal to $35 billion
IPO_35-40	$1 if market cap is greater than $35 billion but less than or equal to $40 billion
IPO_gt40	$1 if market cap is greater than $40 billion.

On August 5, the IPO_gt40 contract was split into three contracts: IPO_40-45, IPO_45-50 and IPO_gt50 each with a $1 payoff in the associated capitalization range.[25] At the split, traders holding IPO_gt40 contracts received 1 share of each of the three new contracts in exchange for each IPO_gt40 contract they held (to guarantee that they incurred neither a gain nor loss in expected value from their previous portfolio position). Again, in the absence of hedging demand, prices should equal expected values in this market (see footnote 22). Expected value pricing implies that the price of each contract should equal the probability that the actual market capitalization will be in the associated capitalization range (E(value) = $p\times\$1+(1-p)\times\$0 = p$, where p is the probability of being in the range). Thus, at each point in time, prices map out discrete parts of a forecast distribution for the future market capitalization. From this distribution, we can estimate the expected post-IPO valuation of Google and obtain a direct measure of the ex ante uncertainty surrounding this forecast.

B. Fitting a Forecast Distribution with the WTA Market

The WTA markets can be used to forecast the expected distribution of future market capitalizations, not just a point estimate for the expected capitalization. In its simplest form, the WTA price vector is a vector of (risk-neutral) probabilities of six events (and after August 4, eight events).

[24] The appendix contains the prospectus for this market.

[25] This was done because of sustained high prices for the IPO_gt40 contract. It was intended to expand the price ranges covered by contracts to more closely match the apparent range of potential outcomes forecast by our traders.

Knowledge of the CDF of a random variable allows one to calculate any moments of interest. However, because the highest interval (greater than \$40 billion prior to August 4 and greater than \$50 billion afterwards) is unbounded from above, some assumption must be made about the distribution of outcomes in this range when this contract trades above a zero price. For this reason, we assume that at any point in time, *t*, the future (unknown) capitalization is distributed log normally with mean μ_t and standard deviation σ_t. We further assume that the probability of no IPO equals zero.[26]

Intuitively, we assume that the normalized contract closing prices on date *t* reflect estimates of the probabilities of observing outcomes in each range on date *t*. For given μ_t and σ_t, integrating the log normal distribution over each range yields predicted probabilities of being in each range. We derive estimates of the distribution mean and standard deviation by minimizing the distance between observed and predicted probabilities.

Formally, assume there are *K* securities traded each day and that they have a payoff, X_i, of

$$\begin{aligned} X_i \quad &= \$1 \text{ if } Z_{i-1} < \text{Market Capitalization (MC)} \leq Z_i \\ &= \$0 \text{ otherwise} \\ &\text{for } i = 1,\ldots,K \end{aligned} \tag{1}$$

For concreteness assume that Z_0=0 and that $Z_K=\infty$. The probability that market capitalization (MC) lies in interval *i* is

$$P_t(\theta_t) = F(Z_i \mid \theta_t) - F(Z_{i-1} \mid \theta_t) \tag{2}$$

where *F* is the cumulative distribution function of the random variable MC. One of these securities is redundant because both the normalized prices and actual probabilities of being in each range always sum to 1.

On date *t*, the log normal distribution parameter vector is characterized completely by the mean, μ_t and the standard deviation σ_t (i.e., $\theta_t=(\mu_t,\sigma_t)$). Because there are $K>2$ securities traded, it is possible to estimate the parameter vector θ_t for each trading date, *t*. There are several methods that could be used

[26] The log normal distribution is uncontroversial while assuming that the probability of no IPO is zero is consistent with Google's stated strong intention to issue in the summer of 2004 and the long horizon on the contracts.

to estimate θ_t. We chose a minimum χ^2 criterion as the method, although we also estimated the parameters using generalized method of moments and maximum average log likelihood criteria to see whether any significant differences existed. None were found.

Specifically, for each day, denote the objective function as $V\left(\theta_t\right)$ and solve the following for the estimates of μ_t and σ_t:

$$\hat{\theta}_t = \underset{\theta_t}{ArgMin}\, V(\theta_t) = \sum_{i=1}^{K} \frac{(p_{i,t} - P_i(\theta_t))^2}{P_i(\theta_t)} \tag{3}$$

where $p_{i,t}$ is the price of security *i* (the market based probability forecast for range *i*) on date *t* and $P_i(\theta_t)$ is its expected value according to the estimated log normal distribution. Note that this results in both an ex ante forecast of the post-IPO market capitalization and a direct ex ante measure of uncertainty surrounding this forecast.

5. Results

A. Market Performance

Figure 1 shows the normalized prices of the IPO_UP contract.[27] Trading in the Google Linear market was light.[28] From July 8, the first day after which all contracts had traded, through August 17, the day before the final registration statement was approved, 143 contracts traded. There was no discernable trend in prices. The lowest normalized closing price for the IPO_UP contract was \$0.248 and the highest

[27] Note that the price of IPO_UP should equal 1 minus the price of the IPO_DN contract. However, due to asynchronous trading and bid/ask bounce, prices of IPO_UP and IPO_DN do not necessarily sum to exactly \$1 at any given point in time. To adjust for this, we use normalized prices. The normalized price of each contract is the price of the contract divided by the sum of contract prices. The graph starts with July 8, the first day by which all contracts had traded.

[28] While these markets are thin, this does not necessarily imply an inefficient market. Prediction market research typically relies on higher volume markets with thick queues in the argument for efficiency (e.g., Berg, Forsythe and Rietz, 1996). However, experimental research suggests that even small double auction markets (e.g., with as few as four traders) can converge to efficient outcomes (e.g., Smith, Williams, Bratton and Vannoni, 1982). Further, IEM prediction markets are similar to those modeled theoretically by Milgrom and Stokey (1982). We should see no trade according to their theory if traders have concordant preferences and are risk averse (which would make holding only cash and unit portfolios a Pareto optimal distribution). In this case, shadow prices would, nevertheless, be efficient.

was $0.375, implying a forecasted market capitalization of $24.8 to $37.5 billion. On August 18, the date the prospectus was declared effective, trading volume was 228 contracts and the normalized closing price was $0.267 implying a predicted market capitalization of $26.7 billion. While the capitalization according to the August 18th IPO price was considerably below this ($23.1 billion), Google's market capitalization at the open on August 19th was $27.1 billion. It closed at a market capitalization of $27.2 billion (resulting in contract payoffs of $0.272).

Trading in the Google WTA market was much heavier than in the linear market.[29] From July 8 through August 17, 3,021 contracts traded. Figure 2 shows prices of the WTA contracts as an area chart. Each band represents one of the contracts. The width of the band is the normalized price of the contract. Each contract price is interpreted as the probability that Google's market capitalization would be within the associated range (in billions of dollars) after the first day of trading. The sum of normalized prices (forecast probabilities) equals 1. The actual first-day, closing market capitalization of Google was $27.2 billion. Figure 2 shows that the median of the predicted distribution was in the range corresponding to the actual market capitalization from August 8 through the end of the market on August 17.

As news came out, various IEM contracts changed in price. Late in the market (around August 10), IPO_25-30 and IPO_30-35 emerged as the most likely outcomes and the median of the distribution fell in the 25-30 billion range (as shown in Figure 2). On August 18, the volume of trade on the IEM Google WTA market was 3,148 contracts. Prices collapsed to less than $0.05 for all but the IPO_20-25 and IPO_25-30 contracts and most queues were cleared.

Figure 3 shows the expected market capitalization according to the distribution estimated from the WTA prices each day. Figure 3 also includes the predicted market capitalization from the linear market for comparison. The forecasts from the WTA market follow the linear market forecasts quite closely. Their correlation is 0.71. The WTA low forecast was $23.2 billion and the high was $36.5 billion (compared to $24.8 billion and $37.5 billion from the linear market). On August 18 (the day of

[29] This trading pattern also holds in political markets, with much heavier trading in WTA contracts than in linear (vote share) contracts. See Berg, Nelson and Rietz (2003).

the final S-1 approval), several WTA contract prices fell to zero, which made identification of the two parameters imprecise without finer contract intervals.[30] However, from August 11 through August 17, the estimates of market capitalization fell between \$28.2 and \$28.9 billion and closed at \$28.3 billion on August 17.

While volumes differ considerably, forecast market capitalizations are similar across the two IEM prediction markets at any point in time. They are highly correlated even though the different contract structures and thin trading in the linear market make inter-market arbitrage difficult at best. A similar analysis of data from the 2004 WTA Presidential Election markets on the IEM shows a similar inter-market pattern. The election market analysis suggests that, while forecasts are similar, those derived from WTA markets may be more stable than those derived from the linear markets. This evidence, combined with the higher volumes in the WTA market, leads us to have more confidence in the estimates from the Google WTA market predictions. Therefore, we will focus on the WTA predictions throughout the rest of the paper.

As Figure 3 shows, the predictions were remarkably accurate. This accords with prior evidence on prediction markets (e.g., Berg, Forsythe, Nelson and Rietz, 2005; Berg, Nelson and Rietz, 2003; and Wolfers and Zitzewitz, 2004). Accuracy here, especially in the early period of the market, shows the impressive ability of prediction markets even when operating with sparse information. As noted above, there was no information about quantities of shares and price ranges in early versions of the prospectus. Even though all such information is known at the time when when-issued markets open, Löffler, Panther and Theissen (2005) document that when-issued markets are only informative in the last few days of trading. Nevertheless, from July 8 (the first day after which all contracts had traded) through July 25 (the day before the filing of Amendment 4, which contained the first estimates of share quantities and price ranges), the forecasted market capitalization from the WTA market ranged from \$23.2 to \$32.1 billion with an average of \$29.0 billion. This is higher than most independent estimates reported in the press.

[30] We cannot estimate the parameters precisely when all or nearly all of the forecast distribution lies in one interval.

While two news reports forecasted a maximum market capitalization of Google at $30 billion, typical reports forecasted a maximum of $20-$25 billion.[31] The actual market capitalization on the close of the first day of trading (August 19) was $27.2 billion, only 6.16% less than the average prediction over this early forecast period. By the next day, the market capitalization had risen to $29.4 billion, significantly closer to the early IEM forecasts. This early indication of market capitalization would be valuable in setting initial price ranges and, as a result, makes our prediction markets very different from existing when-issued markets in other countries.

After Amendment 4 was filed on July 26, the IEM forecasted market capitalization rose, likely in response to the relatively high preliminary price range ($108-$135 per share). This indicated a capitalization range of $29.3 billion to $36.6 billion with a midpoint of $33.0 billion. The IEM prices gave an average prediction of $33.9 billion from July 26 through August 8. That this is near the midpoint of the price range (instead of at or above the top of the range) contrasts with what one would expect from the when-issued market evidence. There, the eventual market capitalization of typical IPOs significantly exceeds the top of the indicated range (Aussenegg, Pichler and Stomper, 2006).

The IEM predicted market capitalization had fallen to $30.4 billion by the date of the 5th Amendment (August 9) and to $28.3 billion by the date of the 6th Amendment (August 11). From August 11 through August 17, the IEM forecasts ranged from $28.2 to $28.9 billion and averaged $28.5 billion, just 4.8% above the actual August 19 capitalization of $27.2 billion (a price of $100.34 per share). The IEM closing prices the night before the final prospectus was approved forecasted a market capitalization of $28.3 billion and, given the number of shares in the prospectus, a market price of $104.34. The actual closing market capitalization was only 3.84% less than this final IEM forecast. This degree of forecasting accuracy is not surprising given the mounting evidence on prediction markets.

[31] Wall Street Journal stories on 10/24/03, 4/23/04, 4/26/04, 4/28/04, 4/30/04 and 5/10/04 all capped the estimated market capitalization at $25 billion. A separate Wall Street Journal story on 4/30/04 stated only a $25 billion estimate. A Wall Street Journal story on 5/13/04 estimated the range to be $20 to $22 billion. Washington Post stories estimated the market capitalization at $15 to $20 billion on 1/13/04. Stories in the Wall Street Journal on 7/19/04 and the Washington Post on 5/2/04 both give a maximum of $30 billion. Later articles did not make independent capitalization estimates. Most articles simply quoted price and capitalization ranges that were derived from Google's own indicated price range and quantities as given in their prospectus.

Because the prediction market can only aggregate the information of its traders, we conclude that the traders (outsiders to the company) had accurate assessments of Google's eventual market capitalization. Further, they revealed this information for very little profit (zero profit on average by design, and an observed maximum of $241 for a single trader.) Both observations are important in evaluating theory, as discussed below.

B. The Evolution of Uncertainty Surrounding the IPO

By documenting a forecast distribution through time, we can document the degree of uncertainty and the reduction of uncertainty as the IPO unfolded. We view this direct evidence on the evolution of uncertainty during an IPO process as a significant contribution. In Figure 4, we plot the estimated (implied) volatility of the WTA market forecast ($\hat{\sigma}_t$). Implied volatility (i.e., uncertainty about the market capitalization forecast) is high, but falls dramatically as the IPO date approaches. Volatility, measured by the standard deviation of the logarithm of the forecasted market capitalization, declined by about two thirds from a high point (the day after all contracts had traded in the market) to the day before the SEC's final approval.

As one would predict from an informationally efficient market, significant changes in uncertainty follow events with significant informational content. Figure 4 shows that uncertainty peaked shortly after all contracts had traded in the markets (on July 9th and 10th). The largest reductions in uncertainty appear to occur when announcements and amendments resolved important issues. Volatility fell on every amendment filing date except one: Amendment 7, the amendment in which the potential fallout from Playboy's interview (Sheff, 2004) of Google's founders was addressed. Every other amendment seems to have reduced uncertainty, especially Amendment 4 (which outlined the initial price range and quantities expected to be offered and resulted in the largest single daily reduction in uncertainty) and Amendment 3 (which resolved uncertainty about where Google would be listed and resulted in the third largest single daily reduction in uncertainty). Also of note was the settlement of a potential Yahoo lawsuit, which was reported in newspapers on August 10th and appeared in Amendment 6 on August 11th (resulting in the 4th and 7th largest single daily reductions in uncertainty, respectively). Overall, the average change in uncertainty (change in $\hat{\sigma}_t$) on days of amendment filings was -0.066. The change on other days averaged less than 0.001. According to a Mann-Whitney two-sample rank sum statistic, this difference is significant (z=2.717, p-value=0.0066). This correspondence between the reductions in uncertainty implied by prices and what one would expect from significant information releases leads further credence to prediction market prices as efficient forecasts.

C. Estimating the Demand Curve for the Google IPO

If we knew the demand curve for Google stock, we could determine whether the IEM predicted post-IPO market price could have been a feasible market clearing price for the IPO. While Google has not released information about the bids in its auction, publicly available information combined with Google's allocation mechanism, allows us to estimate a segment of the demand curve.

Obviously, Google expected the auction to result in a market clearing price with little or no excess demand. Page 40 of the amended S-1 filing on August 13, 2004 (the day the auction began) states, "If the initial public offering price is equal to the auction clearing price, all successful bidders will be offered share allocations that are ***equal or nearly equal*** to the number of shares represented by their successful bids" (emphasis added). If the auction resulted in a lumpy demand schedule or if Google set the price lower than the auction market clearing price, the prospectus stated that Google would ration shares using one of two mechanisms (pro rata or maximum share allocation) with a goal of allocating successful bidders at least 80% of their bid quantities. Google expected significant rationing to result only from pricing the IPO below the auction market clearing price.[32] But, whatever the cause, Google

[32] This accords with theory. While one might be tempted to argue that the $85 price could result from tacit or explicit collusion among large investors to lower the price below true value in a Wilson (1979) style share auction equilibrium, free entry breaks this equilibrium. Similarly, Milgrom (2004, Chapter 7) argues that in an "N+1" auction equilibria can arise with agents bidding their true values for N units in an auction and all bidding some amount lower (even zero) for any units beyond N, where N is the number of units auctioned. While a full analysis of the equilibrium under these auction rules is beyond the scope of this paper, the pro-rata allocation

would be aware of the degree of excess demand in advance of the issue. The awareness that, in the presence of significant excess demand, free market forces would drive the price up after the IPO is all the evidence we need for our theoretical arguments below (regardless of whether it was due to a lumpy demand schedule or deliberate underpricing).

Was there excess demand at the IPO price? Yes. On August 20, a *Wall Street Journal* article (Lucchetti, Sidel and Simon, 2004) reported that Turner Investment Partners bid for 1 million shares at $85 per share and received only 700,000 shares or 70% of its bid. Internet reports (e.g., Kawamoto and Olsen, 2004, www.buygoogle.com, 8/19/04, and messages at the Google Stock discussion board at http://www.google-ipo.com) stated that small bidders were also rationed and put the percentage at up to 75%. This indicates that Google used the pro rata allocation process, which means that the quantity sold (22,545,809 shares including the over-allotment option) was 70% to 75% of the total bid quantity at the $85 price. This would imply total bids of 30,061,079 to 32,208,299 shares at or above $85 per share (i.e., an excess demand of 33.3% to 42.9% of the quantity sold).[33] These allocations show that there was significant excess demand and that the auction mechanism underpriced the shares significantly (whether it was deliberate or due to a lumpy demand schedule).

Publicly available data allows us to approximate two apparent points on the true demand function. Investors were willing to buy roughly 30 million shares at a price of $85 according to the allocation information available. The next day's opening price implied that they were willing to buy the

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mechanism without price priority appears to break such an equilibrium.

The key to Milgrom style equilibrium is that the price on all shares rises when a marginal trader raises his or her bid, but the allocation of shares does not change, resulting in a net loss for the trader. With the pro-rata allocation rule without price priority, the allocation also changes, breaking the equilibrium. To see why, work with a simple case. Assume 15 million bidders each submit a bid for 1 share at $100 and 1 share at $85. This is similar to Milgrom's example on p. 260 and corresponds to the apparent quantities and values in the Google auction. This would lead to a market clearing price of $85, rationing at approximately 70% and net profits of 2x0.7x(100-85)=$21 per trader if $100 per share were the true value. But, it is not an equilibrium. If a trader increased his bid on his second share to $85.01, it would increase the clearing price to $85.01, but he would receive a full allocation of shares, making for a profit of 2x1x(100-85.01)=29.98. So, unlike the equilibrium in Milgrom, the traders here each have an incentive to raise the bid on the marginal share. Further, Sherman (2005, p. 629) argues that such an equilibrium is unlikely even in the N+1 clearing case with no rationing (which Google could have used as a pricing and allocation rule) and any coordination on a collusive equilibrium difficult given the large numbers of bidders potentially involved in large IPO auctions.

[33] 22,545,809/0.75=30,061,079 and 22,545,809/0.70=32,208,299. (30,061,079-22,545,809)/22,545,809=33.3% and (32,208,200-22,545,809)/22,545,809=42.9%.

actual 22.5 million shares (including the over-allotment option that had been issued) at about $100. Assuming overnight information changed the demand curve little, we can estimate the demand curve. We note that exercise of the overallotment option left Google's revenues unchanged because all overallotment shares were committed by other existing shareholders.[34] As a result, Google had no direct interest in selling the overallotment. Because of this, we ask whether Google could have expected to sell the originally committed 19.6 million shares at the IEM suggested price of $104.34. Solving for a linear demand curve (as an approximation) given the two points ($85, 30 million shares) and ($100, 22.5 million shares) gives a demand curve of Q^D (in millions) = 72.5 – 0.5P. Using the IEM suggested price of $104.34 yields a predicted sales quantity of 20.33 million > 19.6 million. A constant elasticity demand curve (fit to the same data points) gives a predicted sales quantity of 20.10 million > 19.6 million. The estimated demand curves are shown in Figure 5. Overall, the information available suggests that the IEM implication of foregone revenues of greater than $300 million (see Table II below) is reasonable. Because we do not know the demand schedule for the auction, we do not know whether Google deliberately underpriced or whether the auction rules forced them to underprice. We do know that they were aware of the degree of excess demand before the IPO. Thus, both outsiders (IEM traders) and Google appeared to know that the $85 issue price was below a true market clearing price. As a result, the players appeared symmetrically informed about the underpricing in advance. Further, as we will discuss below, IEM traders revealed this information for little or no profit.

[34] Also note that whether the over-allotment option was exercised or not also has no effect on the total market capitalization (the benchmark forecast by IEM traders). Market capitalization depends on total shares, not the number shares sold to the public.

D. Evidence on Theories of IPO Underpricing

1. Asymmetric Information I: Evidence on Theories Where Issuers Know More than Investors

Many theories suggest that IPO underpricing is a means of making payments to IPO purchasers to counter problems caused by asymmetric information. Some theorize that issuers have more information than outsiders and large payments to investors are required to provide incentives for them to acquire costly information that overcomes the asymmetry (e.g., Chemmanur, 1993). Accuracy of the prediction markets is evidence against such models. The information necessary to determine the value of the IPO appears to have been in the hands of the traders and aggregated by the prediction markets. Further, the traders generated these accurate forecasts in exchange for very small profits. The mean profit in the market was zero (by construction) and the most any trader earned was $241.

2. Asymmetric Information II: Evidence on Theories Where Investors Know More than Issuers

Other researchers theorize that outsiders have more information than issuers and that they require large payments to reveal their information (e.g., Benveniste and Spindt, 1989). Accuracy of the prediction markets could be consistent with the informational assumption of such models. However, we obtained the information nearly costlessly in the prediction markets. Further, the evidence from the excess demand and demand curve estimates above suggests that Google also knew that the true demand would have supported a higher price. Thus, the overall evidence is against such models.

3. Asymmetric Information III: Evidence on Theories with Information Asymmetry across Investors

The evidence is more consistent, though not entirely so, with asymmetric information across investors. For example, Rock (1986) argues that uninformed investors will demand a high average initial

IPO return to overcome adverse selection problems. Informed investors will only participate in an IPO if they know that the IPO is by a "good" company. In this case, uninformed investors receive partial allocations of shares. However, when the IPO is by a "bad" company, the informed investors do not participate and uninformed investors receive full allocations. This creates an adverse-selection-based winner's curse that must be overcome by underpricing on average to get uninformed investors into the IPO market.

Google's auction process may have been prone to such a winner's curse. If so, uninformed auction participants would need to expect Google to underprice on average to create sufficient returns (again, on average) to overcome the winner's curse. In contrast, Reny and Perry (2006) show that, under the right conditions, double auction markets (like prediction markets) are not prone to the winner's curse and converge to the fully revealing rational expectations equilibrium (explaining our accurate prices). Finally, differences of opinion (between investors) can also drive the observed trading in prediction markets (e.g., Harris and Raviv, 1993). This evidence is consistent with asymmetric information across investors.

However, several pieces of evidence run counter to Rock's (1986) winner's curse model. First, given Google's stated goals and IPO mechanism, it is unclear whether investors could have reasonably expected underpricing as an outcome even if Google was a "good" company. Second, according to this model "good" companies should have a higher than expected actual IPO return ex post and "bad" companies should have a lower than expected actual IPO return ex post (because the information about the company is revealed through the IPO process).[35] In neither case will the actual IPO return ex post equal the ex ante expected IPO return. For Google, the ex post return (derived from first day NASDAQ closing prices) and the ex ante expected return (derived from IEM prices) were approximately equal. Further, Rock (1986) argues that the ex ante level of uncertainty will be positively correlated with predicted underpricing. While we cannot estimate a cross-sectional correlation, we can estimate the

[35] In Rock's, 1986, model, this would be revealed by the presence of informed investors. Uninformed investors can infer the quality of the issue by seeing whether they were allocated the full number of shares for which they bid.

correlation for this IPO through time. We estimate the ex ante expected degree of underpricing as

$U_t = \frac{mid_t - \hat{\mu}_t}{\hat{\mu}_t}$, where mid_t serves as a estimate of the expected issue price and is defined to be the market capitalization computed from the midpoint of the announced price range and the announced share quantities[36] and $\hat{\mu}_t$ is the ex ante market forecast of the post-IPO market value estimated from equation (3). We correlate this with $\hat{\sigma}_t$, the ex ante market uncertainty estimated from equation (3). From the date that the first initial price ranges and share quantities were announced (with Amendment 4 on 7/26/04) through the IPO date (8/18/04), the correlation coefficient was -0.62 (t = -2.56, p-value = 0.018). While this result is not strictly counter to Rock's (1986) prediction,[37] it is indicative of a relationship between underpricing and uncertainty that would go in the opposite direction of his model.

4. Evidence on Theories that Involve Discretionary Allocations of Shares or Pre-commitment to IPO Prices

Further evidence on theory comes from Google's unique auction mechanism. Benveniste and Spindt (1989) and other models (e.g., Loughran and Ritter, 2002) rely on discretionary allocations of shares by the investment banker. Some models rely on pre-commitment to underprice (e.g., Benveniste and Spindt, 1989). Others rely on pre-commitment to a price, after which investors gather information (e.g., Chemmanur, 1993). Because the auction mechanism severely restricted discretion in allocating shares and determined the allowable maximum IPO price after bids were submitted, underpricing here is evidence against models that rely on such factors. If these factors alone explained underpricing, we should not have observed underpricing in Google's case.

[36] Whether we use the midpoint, the upper end or the lower end makes no substantive difference to the results that follow.

[37] Again, his model would predict a positive cross-sectional correlation between ex ante uncertainty and average levels of ex post under pricing. Here, we show a positive time series correlation between ex ante uncertainty and ex ante forecasts of underpricing.

5. Evidence on Theories Where there are Future Benefits to Underpricing

In contrast, the evidence is consistent with symmetric information models when there is a future benefit to underpricing. We discuss three such models here. In these models, both the issuers and the investors know the degree of underpricing in advance, which is consistent with our evidence. For each model, there is one additional piece of corroborating evidence. First, in Booth and Chua's (1996) model, issuers deliberately underprice to achieve ownership dispersion. This creates more market liquidity and future benefits from the resulting lower required return of investors. Consistent with this model, Google's prospectus states that, counter to its primary goal of price stability, it may have chosen to underprice its shares deliberately to "achieve a broader distribution of our Class A common stock" (final prospectus, p. 38). Second, Tinic (1988) and Hughes and Thakor (1992) model underpricing to avoid potential future lawsuits that may result if prices fall dramatically after the IPO. Consistent with this model, Google's prospectus goes on to state that it may have chosen to underprice its shares deliberately to "potentially reduce the downward price volatility in the trading price of our shares in the period shortly following our offering relative to what would be experienced if the initial public offering price were set at the auction clearing price" (final prospectus, pp 38-39). Finally, Welch (1989) argues that high quality firms will underprice IPO's deliberately to signal firm quality and drive bad firms from the market in a fully revealing separating equilibrium. They will recoup their losses in subsequent secondary offerings. The evidence that both Google (from the estimated demand curve) and outsiders (from the prediction markets) knew that Google would be underpriced is consistent with the fully revealing equilibrium. Also consistent with this model, Google made a secondary offering on September 14, 2005 at a price of $295 per share, raising more than $4.18 billion. Thus, while we will never know whether Google deliberately underpriced, they reserved the right to for reasons consistent with these theories involving future benefits. Further, these theories argue that all agents will know the degree of underpricing in advance. This is also consistent with the IEM predictions and excess demand evidence. Overall, the evidence is consistent with

Ritter and Welch's (2002) sentiment that underpricing is not caused by asymmetric information between the issuer and investors.

6. Summary of the Evidence on Theory

Some of the results above are driven only by the outcomes of the IEM prediction markets. In particular, the fact that the prediction markets aggregated trader information, creating an accurate forecast at little cost drives results 1 and 2 above. Evidence on the correlation of uncertainty and underpricing (part of result 3 above) is also independent of the auction mechanism. Combined, this evidence leans against IPO underpricing theories that rely on asymmetric information. Further, since the evidence is independent of the unique features of Google's IPO, we argue that these results should apply to IPO's in general. Some of the results shown above arise because of the Google auction mechanism, but shed light on all IPO's. The auction mechanism eliminates some factors that lead theorists to predict underpricing. Specifically, the auction eliminates pre-commitment to prices or pre-commitment to underpricing and discretionary allocations of shares as sources of underpricing (result 4 above). Since underpricing still occurs, this casts doubt on these as reasons for underpricing in general. Some results depend on the combination of the prediction markets and the unique features of the Google IPO. In particular, the combination drives part of the mixed evidence on winner's curse models in result 3 above and the evidence for models of underpricing in exchange for future benefits in result 5 above. This constellation of results highlight why Google is a particularly informative IPO to study.

E. Practical Implications

Results from the IEM Google markets illustrate the value of prediction markets in extracting information from groups of traders to test theories where information held by various groups is important for theory. In addition, the evolution of uncertainty in these markets is consistent with the information revealed in prospectuses being used by traders to more accurately assess the value of an IPO. Prediction markets might also help determine whether it is optimal to underprice or not in setting the IPO price.

Setting IPO prices according to our prediction market forecasts would have made a substantial difference in funds raised. Table II shows the difference it might have made. Google actually set an IPO price of $85, implying a market capitalization of $23.1 billion. The closing market price and market capitalization were 18% above this after the first day of trading. According to the final prospectus, Google sold 14,142,135 shares and existing shareholders sold 5,462,917 shares for a total of 19,605,052 shares at a net price of $82.6161. At the IPO price, Google raised $1,168.4 million for itself and selling shareholders received $451.3 million (Table II, column 1). Had Google managed to set the price equal to the closing price on the first day, sold the same number of shares and paid the same percentage spread to investment bankers, Google would have raised $1,379.2 million (or $210.9 million more) for itself and Google's existing shareholders would have received $532.8 million (or $81.5 million more), without the exercise of the over-allotment option.[38] Adding the difference in investment bank proceeds brings the total difference to $300.7 million that was clearly "left on the table" (see calculations in Table II, column 4). Had Google set its IPO price at the IEM forecast and managed to sell the same number of shares, including the overallotment option, the total foregone proceeds increases to $379.19 million (calculations in Table II, column 5).[39]

There are two possible explanations for this underpricing: First, Google deliberately left this much money on the table by setting their IPO price below market clearing. They would do this to achieve future benefits. If it is indeed an equilibrium to underprice by a given amount, prediction markets can serve a valuable role as low cost mechanisms for forecasting post-IPO market prices. These forecasts could be used to set IPO prices to achieve desired levels of underpricing. Alternatively, Google may have been forced to effectively underprice by the rules of their auction mechanism and an extremely lumpy demand schedule. Here, if obvious strategic manipulation problems could be over come, the double-

[38] The entire over-allotment option was sold by existing shareholders. Had they sold the full over-allotment at the IEM predicted net price (assuming the same spread) instead of the actual $82.6161, existing shareholders would have made $158.0 million more than they actually did.

[39] We have already discussed how the excess demand information can be used to judge the likelihood that the same number of shares could have been sold at the IEM predicted price. In addition, Google closed above the IEM forecasted price on the second day of trading and has risen above this level even after the exercise of the over-allotment option had been made public.

auction nature of a prediction market could serve as a viable alternative to a one-sided auction in helping to determine an effective market clearing price.

In neither case would we argue that prediction markets should replace road shows, book building and other means of gathering information. Instead, we argue that prediction markets can supplement other mechanisms. This mirrors observations from political markets. Election prediction markets do not replace polls. Instead, they provide an additional information aggregation mechanism. Given the stakes involved, any mechanism that provides additional information about IPO valuations would be extremely valuable.

6. Conclusion and Discussion

Economic situations in which results may be driven by the distribution of information across agents is of great theoretical and practical interest. IPO underpricing is one such situation where the distribution of information is both critical and difficult to observe. The distinctive features of the Google IPO and the IEM prediction markets run in advance of the IPO provide unique evidence on underpricing theories that rely on the distribution of information. Some evidence comes from conducting the prediction markets alone. Our markets indicate that the information necessary to forecast the post-IPO price of Google's stock existed in traders information sets and could be aggregated cheaply well in advance of the IPO. Since this evidence does not depend on the specific features of the Google IPO, we argue that it should generalize to other IPOs. Some evidence comes from the unique features of the Google IPO including the allocation restrictions that the auction mechanism imposed on discretionary allocations of shares and the inability to pre-commit to prices. As a result, underpricing in Google's case is inconsistent with models that rely on pre-commitment and/or discretionary allocations of shares. Further, evidence about the likely auction demand curve suggests that the degree of excess demand and, hence, underpricing was predictable to Google (whether deliberate or as an unavoidable result of the auction rules). Combined, the evidence is particularly compelling because it allows us to compare expectations likely held by both insiders and outsiders. In both cases, the evidence leans against theories of IPO underpricing that rely on asymmetric information. The evidence is consistent with theories that rely on future benefits of underpricing.[40]

From a practical point of view, we show how prediction markets can be used to test theories that rely on differential, otherwise "unobservable," information. We also show how uncertainty evolves throughout the IPO process. Finally, there are a number of mechanisms that may help firms set IPO prices closer to market values or set them closer to optimal underpricing. We introduce the idea of using a prediction market to do so. Our evidence suggests that such markets can be successful in forecasting post-IPO values of stocks. The forecasts were quite accurate for Google even before many aspects of the issue (e.g., the number of shares, initial price range indications, etc.) were revealed.[41]

What can explain the accuracy of these markets? At one level, given the pervasive underpricing, one might argue that prediction markets perform well by simply forecasting a market capitalization higher than that indicated using preliminary price ranges from the prospectus. However, two pieces of evidence run counter to this assertion. First, IEM prices predicted well even before preliminary price ranges and share quantities were available. Second, shortly after the initial ranges were announced, the IEM prices predicted a market capitalization near the average of the price range, not above the range, and the prediction fell long before the price range was revised downward. Thus, the prediction market traders did more than simply "mark up" preliminary price ranges from the prospectus. Why might this be possible? Recent evidence suggests that the degree of underpricing may be predicted from publicly available

[40] One might argue that the results here are weakened because Google is a single IPO. We believe this is not the case for three reasons. First, we argue that unique features of the Google IPO strengthen the results. Both the unique features of the Google IPO alone and the outcomes of the prediction market alone provide interesting evidence on theories of IPO underpricing. When combined, the evidence is particularly compelling. For example, the ability to estimate the demand curve through information about the auction allows us to determine whether both Google (the issuer) and outsiders (our market participates) were both informed about the degree of underpricing, allowing for a more complete analysis of asymmetric information models. Second, we argue that the evidence here is interesting in spite being generated by a single IPO because the evidence comes from the evolution of prediction market prices through the entire IPO process. For example, the evolution of ex ante uncertainty through time and the correlation of uncertainty with ex ante forecasts of underpricing can shed light on theory even from a single IPO prediction market. Third, we argue that Google's unique goals and mechanism make it an interesting IPO to study in its own right. Google provides a natural and conservative benchmark for evaluating the efficiency of IPO prediction markets because of their stated intentions of avoiding large post-IPO price changes and their auction mechanism.

[41] Of course, to use these markets in practice, obvious strategic manipulation problems will need to be resolved.

information that underwriters and/or companies do not build into prices (e.g., Bradley and Jordan, 2002, Loughran and Ritter, 2002, and Lowry and Schwert, 2004). Participants in prediction markets may be able to incorporate this information without the biases and conflicts frequently hypothesized to affect firms, investment bankers and investors.

Researchers have a long history of studying the properties of prediction markets (e.g., their efficiency as markets, their information aggregation properties and their predictive power). Here, we show how they can be used to inform economic theory regarding other phenomenon. They can be used to extract information from sets (or subsets) of agents who may otherwise not reveal their information to test theories that depend on the information held by agents. In the case of IPO underpricing, they inform theory by providing evidence about the validity of assumed information distributions. Given the apparent success of this market and the high stakes involved in IPOs, we suggest that the CFTC should allow more research on IPO Prediction Markets or that Investment Bankers run private prediction markets as a supplementary means of gathering information before an IPO.

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Tables

Table I: Filing Dates and Major Changes Included In Amendments during the Google IPO Process

Date	Filing	Major Changes
4/29/2004	Initial Prospectus	
5/21/2004	Amendment 1	Filled in some warrant and option information Added underwriters Some adjustment in financial data
6/21/2004	Amendment 2	Modified some auction details Modified warrant and option information Some modifications to Risk Factors
7/12/2004	Amendment 3	Some additional details of auction mechanism Small change in purpose of offering Stock plan approved and reclassification of insider shares Applied for NASDAQ listing
7/26/2004	Amendment 4	Estimate 268,519,643 shares after offering Estimate 24,636,659 shares for sale, offering 14,142,135 by company, 10,494,524 shares by selling stockholders, with over-allotment option of 3,695,498 shares Range $108-$135 per share Approved for listing on NASDAQ, ticker GOOG Target date set for August Adjustment to warrant and option information Lock up period details revealed Some modifications to auction process June financial information available Change in underwriter list Added "road show" presentation
8/9/2004	Amendment 5	Increased shares for sale to 25,697,529 (increase from selling shareholders) Some modification to the auction process Yahoo settlement discussed
8/11/2004	Amendment 6	Slight changes in auction process and relationships with underwriters Added notes to financial statements regarding settlement with Yahoo
8/13/2004	Amendment 7	Adds potential fallout from Playboy interview to risk factors Entire text of interview added to notes Slight changes in auction process
8/16/2004	Amendment 8	Minor changes only
8/18/2004	Amendment 9	Reduced shares for sale to 19,605,052 (reduction from selling shareholders) Reduced over-allotment option to 2,940,757 Reduced range to $85-95 per share and changed some example and pro-forma numbers accordingly Small adjustment in number of shares in lock-up Changed insider share distributions
8/19/2004	Final Prospectus	Set price at $85 finalizes pro-forma statements and examples accordingly Some changes in lock up periods Allocations to underwriters set Declared effective

Table II: Potential Google IPO Prices and Proceeds

	Google Share Prices					
	Actual IPO (Column 1)	1st Day Close (Column 2)	IEM Prediction (Column 3)	1st Day Close - IPO Price (Column 4)	IEM Prediction - IPO Price (Column 5)	IEM Prediction - 1st Day Close (Column 6)
IPO Price	$85.0000	$100.3400	$104.3416	$15.3400	$19.3416	$4.0016
Spread (@ 2.8%)	$2.3839	$2.8141	$2.9264	$0.4302	$0.5425	$0.1122
Per Share Proceeds to Google & Existing Shareholders	$82.6161	$97.5259	$101.4152	$14.9098	$18.7991	$3.8894
Quantities and Total Proceeds without Exercise of Over-Allotment Option (x1 mil.)						
Quantity Sold by Google	14.142	14.142	14.142	14.142	14.142	14.142
Quantity Sold by Existing Shareholders	5.463	5.463	5.463	5.463	5.463	5.463
Total Proceeds to Google	$1,168.3680	$1,379.2241	$1,434.2279	$210.8561	$265.8598	$55.0038
Total Proceeds to Existing Shareholders	$451.3249	$532.7758	$554.0230	$81.4509	$102.6981	$21.2472
Total Proceeds to Investment Bankers	$46.7365	$55.1710	$57.3713	$8.4346	$10.6348	$2.2002
Total Proceeds	$1,666.4294	$1,967.1709	$2,045.6222	$300.7415	$379.1927	$78.4512
Quantities and Proceeds with Exercise of Over-Allotment Option (x1 mil.)						
Quantity Sold by Google	14.142	14.142	14.142	14.142	14.142	14.142
Quantity Sold by Existing Shareholders	8.404	8.404	8.404	8.404	8.404	8.404
Proceeds to Google	$1,168.3680	$1,379.2241	$1,434.2279	$210.8561	$265.8598	$55.0038
Proceeds to Existing Shareholders	$694.2788	$819.5757	$852.2605	$125.2969	$157.9818	$32.6849
Proceeds to Investment Bankers	$53.7470	$63.4467	$65.9770	$9.6997	$12.2300	$2.5303
Total Proceeds	$1,916.3938	$2,262.2465	$2,352.4654	$345.8527	$436.0716	$90.2189

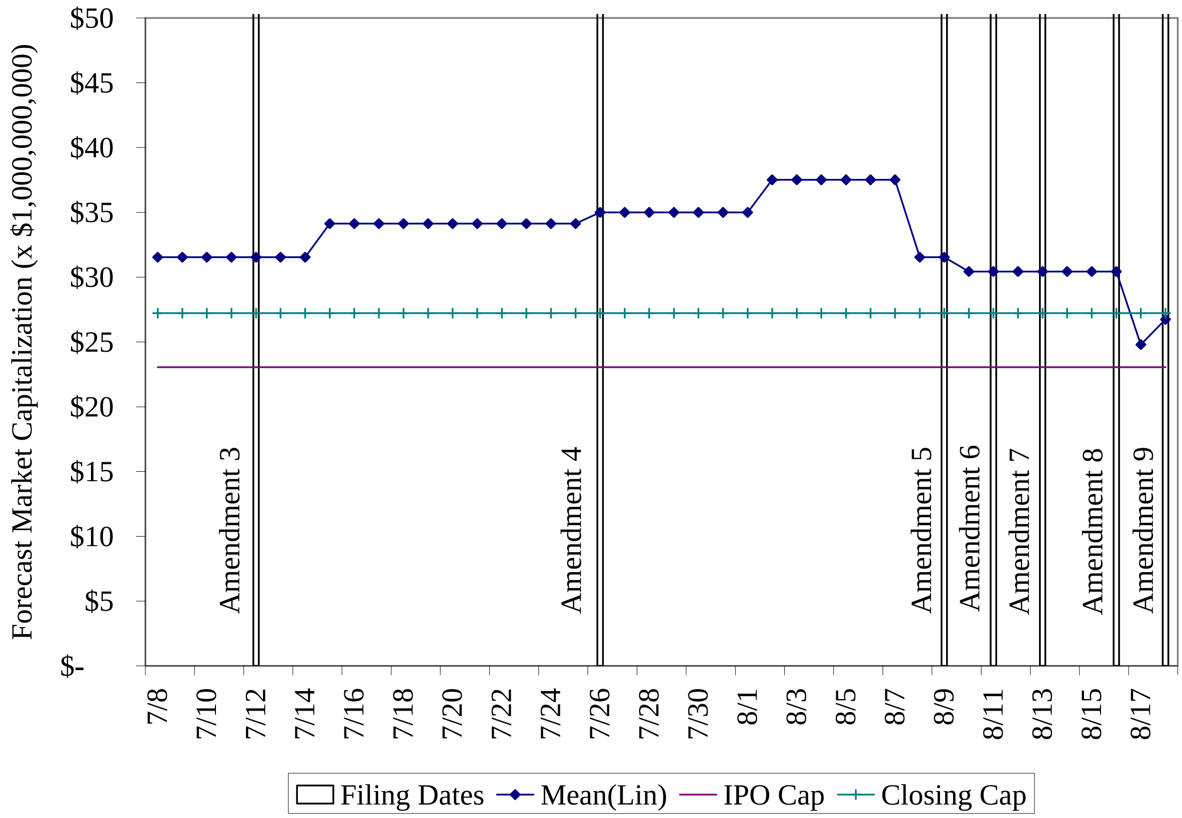

Figure 1: Predicted Google market capitalization from normalized closing prices in the IEM Google Linear Market (Mean(Lin)). For comparison the actual market capitalization according to the IPO price (IPO Cap) and first-day closing price (Closing Cap) are shown. For context, S1 amendment filing dates are also shown.

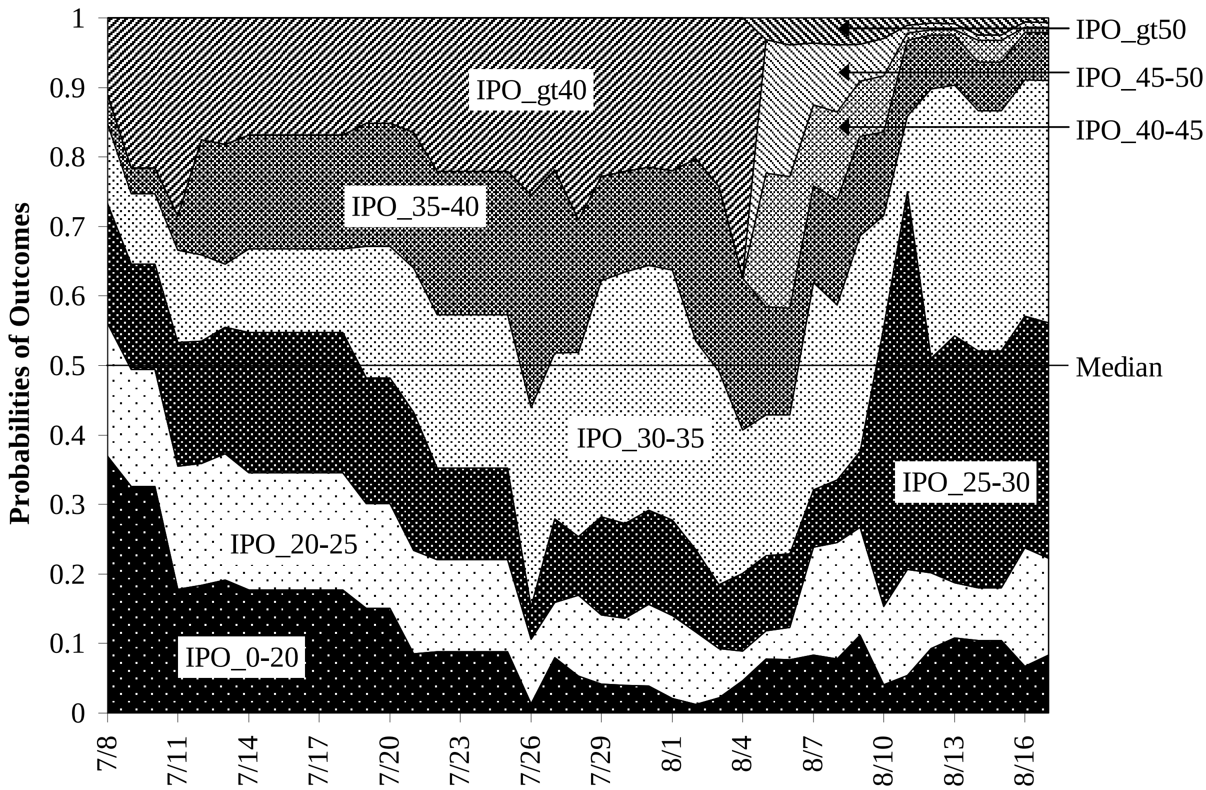

Figure 2: Prices of IEM Google WTA Contracts. This is an area chart. Each band corresponds to the price of one contract. The width of the band is the normalized price of the contract. Each contract price is interpreted as the probability that Google's market capitalization will be within the associated range (in billions of dollar) after the first day of trading. The sum of normalized prices (probabilities) equals 1.

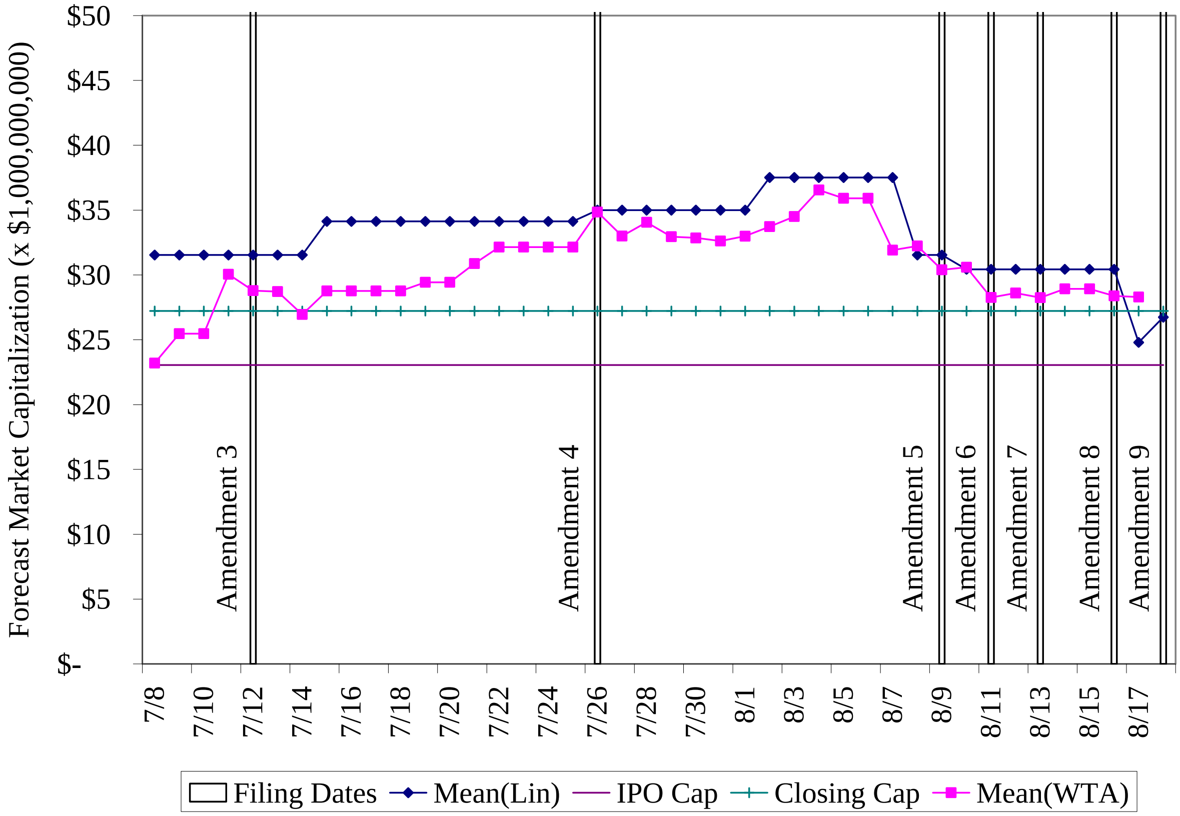

Figure 3: Predicted Google market capitalization from normalized closing prices in the IEM Google Winner-Takes-All Market (Mean(WTA)). For comparison, the prediction from the IEM Google Linear Market (Mean(Lin)), the actual market capitalization according to the IPO price (IPO Cap) and the first-day closing price (Closing Cap) are shown. For context, S1 amendment filing dates are also shown.

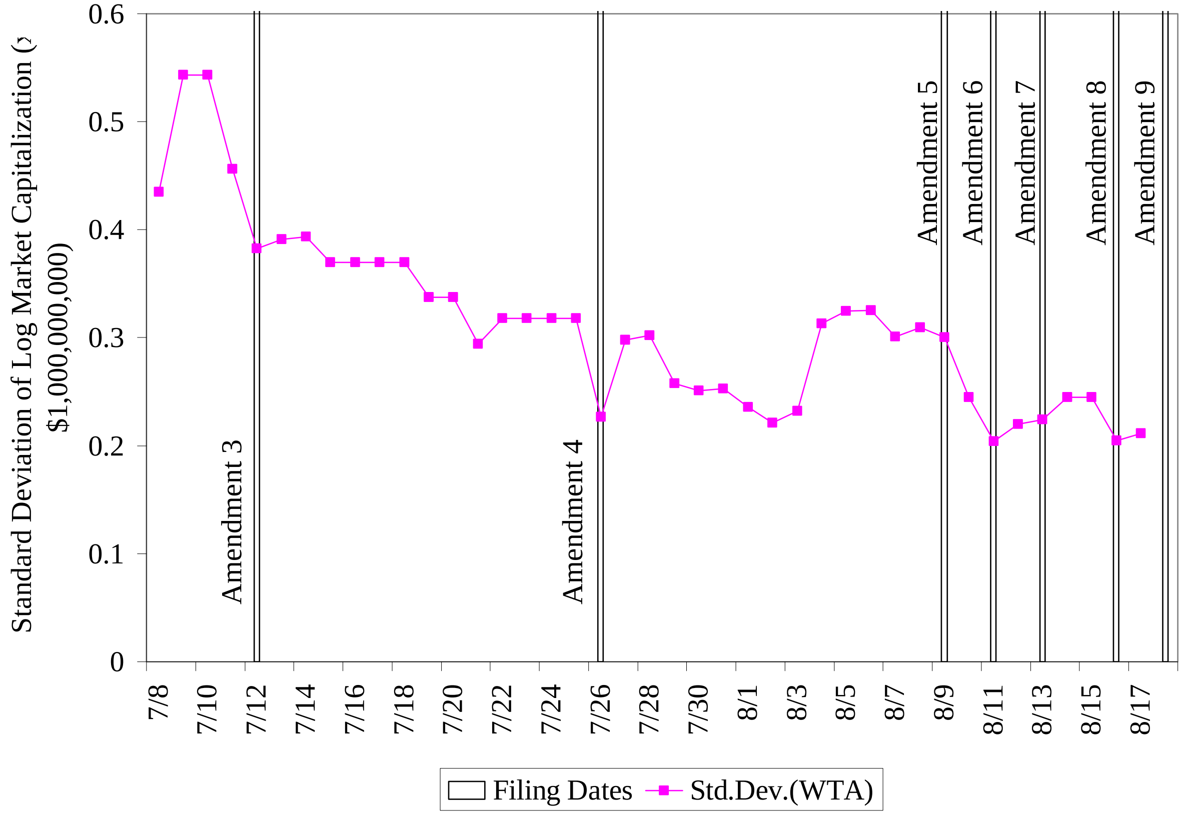

Figure 4: Estimated (log) Google market capitalization forecast volatility from the IEM Google Winner-Takes-All market.

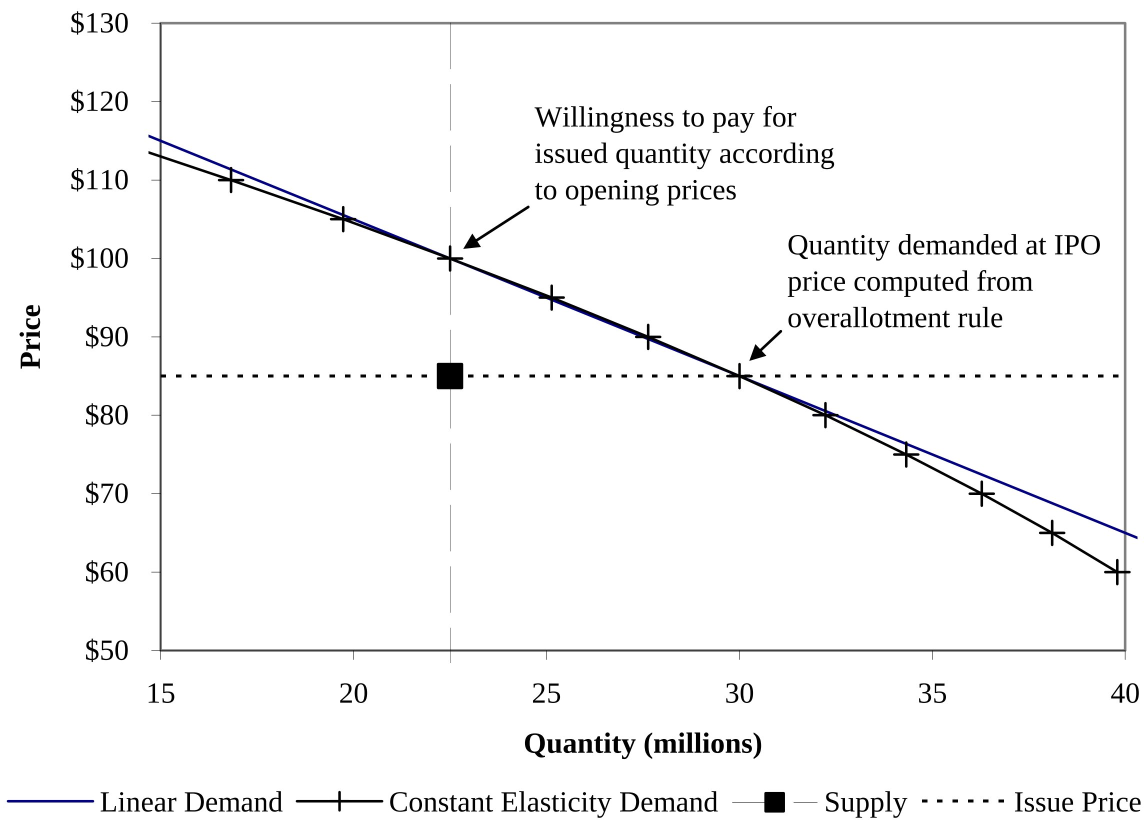

Figure 5: Estimated Demand Curves for the Google Stock Computed From the Apparent Quantity Demanded at the Issue Price According to the Allocation Rule and the Apparent Willingness to Pay for the Actual Issue Quantity According to Opening Prices

Appendix: Google Market Prospectuses

IEM PROSPECTUS: GOOGLE_LIN
GOOGLE IPO MARKET CAPITALIZATION
LINEAR MARKET

On Tuesday, June 29, 2004, at 1:00pm CDT, the Iowa Electronic Market (IEM) will open trading in a market based on the market capitalization value (closing price multiplied by the number of Class A and Class B shares outstanding) of Google Inc.'s stock at the end of the first day of trading on the stock exchange named in Google's S-1 filing.

Two contracts with linear payoff rules will trade in this market. The liquidation value of the first (up) contract will increase from $0.00 to $1.00 as Google's market capitalization increases from $0 billion to $100 billion. The second (down) contract will have a liquidation value that decreases from $1.00 to $0.00 as Google's market capitalization increases from $0 billion to $100 billion.

This document describes that market and should be viewed as a supplement to the Trader's Manual. Except as specified in this prospectus, trading rules for this market are the same as those specified in the Trader's Manual for the Iowa Electronic Market.

CONTRACTS

The contracts traded in this market have the payoff structure shown in column 2 of the following table:

Code Contract Description

Code	Contract Description
IPO_UP	= $0 if the IPO does not take place by March 31, 2005;
	= (Market Cap bil.)/100 billion if $0 bil. < Market Cap <= $100 bil;
	= $1 if Market Cap > $100 bil.
IPO_DN	= $1 if the IPO does not take place by March 31, 2005;
	= ($100 bil.-Market Cap)/100 billion if $0 bil. < Market Cap <= $100 bil;
	= $0 if Market Cap > $100 bil.

DETERMINATION OF LIQUIDATION VALUES

This is a linear market. Each security will have a liquidation value based on the exact market capitalization achieved on the first trading day on the market named in Google Inc.'s S-1 filing to the SEC. For example, if there are (hypothetically) 100 million shares of Class "A" and Class "B" stock and the closing price on the first trading day is $210.00, then market capitalization is $210 x 100 million = $21.0 billion. Each share of IPO_UP will pay $0.210 (=(21)/100) and each share of IPO_DN will pay $0.790 (=(100-21)/100).

The print edition of the Wall Street Journal will be the official source for the closing price of Google stock and the final, completed S-1 filing (that is, the last filing – including any re-filings — prior to the IPO) with the SEC will be the source for the outstanding number of shares

The judgment of the IEM Directors will be final in resolving questions of interpretation and typographical or clerical errors.

CONTRACT BUNDLES

Fixed price contract bundles, each consisting of one share of IPO_UP and one share of IPO_DN, can be purchased from or sold to the IEM system at any time. The price of each contract bundle is $1.00. The determination of liquidation values described above guarantees that the total payoff from holding a contract bundle until the market closes is $1.00.

To buy or sell fixed price contract bundles from the system, use the "Market Orders" option from the Trading Console. Select "GOOGLE_LIN (buy at fixed price)" from the Market Orders list to buy bundles. Select "GOOGLE_LIN (sell at fixed price)" to sell bundles.

Bundles consisting of one share of each of the contracts in this market may also be purchased and sold at current aggregate market prices rather than the fixed price of $1.00. To buy a market bundle at current ASK prices, use the "Market Order" option as above but select " GOOGLE_LIN (buy at market prices)." To sell a bundle at current market BID prices, select " GOOGLE_LIN (sell at market prices)."

Bundle purchases will be charged to your cash account and bundle sales will be credited to your cash account.

MARKET CLOSING

This market will remain open until contract liquidation. Liquidation values will be credited to the cash accounts of market participants.

MARKET ACCESS

Current and newly enrolled IEM traders will automatically be given access rights to the GOOGLE_LIN Market. Access to this market is achieved by logging into the IEM and choosing "GOOGLE_LIN" from the Navigation Bar.

Funds in a trader's cash account are fungible across markets so new investment deposits are not required. Additional investments up to the maximum of $500 can be made at any time. New traders can open accounts using the IEM OnLine Account Application page (http://iemweb.biz.uiowa.edu/signup). There is a one-time account registration fee of $5.00, and investments are limited to the range of $5.00 to $500.

Requests to withdraw funds may be submitted at any time by completing the IEM's Online Withdrawal Request form (www.biz.uiowa.edu/iem/accounts/withdrawalrequestform.html) or by completing and mailing the paper version of the request form. Additional information about requesting withdrawals is available at the IEM website at http://www.biz.uiowa.edu/iem/accounts/withdrawals.html.

IEM PROSPECTUS: GOOGLE_WTA
GOOGLE IPO MARKET CAPITALIZATION
WINNER-TAKES-ALL Market

On Tuesday, June 29, 2004, at 1:00pm CDT, the Iowa Electronic Market (IEM) will open trading in a market based on the market capitalization value (closing price multiplied by the number of Class A and Class B shares outstanding) of Google Inc.'s stock at the end of the first day of trading on the stock exchange named in Google's final S-1 filing.

Initially, six contracts will trade in this market, each representing one of six possible unique and exhaustive outcomes. The liquidation value of the contract which represents the actual outcome of the IPO will be $1.00. All other contracts will have a value of zero.

This document describes that market and should be viewed as a supplement to the Trader's Manual. Except as specified in this prospectus, trading rules for this market are the same as those specified in the Trader's Manual for the Iowa Electronic Market.

CONTRACTS

The initial financial contracts traded in this market are as follows:

Symbol	Description
IPO_0-20	$1 if market cap is less than or equal to $20 billion or if the IPO does not occur by March 31, 2005.
IPO_20-25	$1 if market cap is greater than $20 billion but less than or equal to $25 billion.
IPO_25-30	$1 if market cap is greater than $25 billion but less than or equal to $30 billion
IPO_30-35	$1 if market cap is greater than $30 billion but less than or equal to $35 billion
IPO_35-40	$1 if market cap is greater than $35 billion but less than or equal to $40 billion
IPO_gt40	$1 if market cap is greater than $40 billion.

The range of values in the contract symbol represent the threshold values at which that contract will pay off.

DETERMINATION OF LIQUIDATION VALUES

This is a winner-takes-all market. The contract that corresponds to the actual market capitalization according to the closing price and shares outstanding at the end of the first trading day after the IPO will have a liquidation value of $1.00; all others will have values of $0.00. For example, if there are (hypothetically) 100 million shares of Class "A" and Class "B" stock and the closing price on the first trading day is $210.00, then market capitalization is $210 x 100 million = $21 billion and a share of IPO_20-25 will pay $1.00 while all other contracts pay $0.

The print edition of the Wall Street Journal will be the official source for the closing price of Google stock and the final, completed S-1 filing (that is, the last filing – including any re-filings – prior to the IPO) with the SEC will be the source for the outstanding number of shares.

The judgment of the IEM Directors will be final in resolving questions of interpretation and typographical or clerical errors.

CONTRACT SPIN-OFFS

The Directors of the IEM reserve the right to introduce new contracts to the market as spin-offs of existing contracts. When a contract spin-off occurs, an original contract will be replaced by new contracts which divide the payoff range of the original contract into sub-intervals. No holder of the pre-spinoff contracts will be adversely affected. Traders will receive the same number of each of the new contracts as they held in the original, and the sum of the liquidation values of the new contracts will equal the liquidation value of the original. Decisions to spin-off a contract will be announced at least two days in advance of the spin-off. The new contract names, the specifications regarding liquidation values and the timing of the spin-off will be included in the announcement. This announcement will appear as an Announcement on your WebEx login screen.

CONTRACT BUNDLES

Fixed price contract bundles consisting of one share of each of the contracts in this market can be purchased from or sold to the IEM system at any time. The price of each fixed price contract bundle is $1.00. Because exactly one of the market capitalization outcomes will result from the Google IPO, the total payoff from holding a contract bundle until the market closes is $1.00.

To buy or sell fixed price contract bundles from the system, use the "Market Orders" option from the Trading Console. Select "GOOGLE_WTA (buy at fixed price)" from the Market Orders list to buy bundles. Select "GOOGLE_WTA (sell at fixed price)" to sell bundles.

Bundles consisting of one share of each of the contracts in this market may also be purchased and sold at current aggregate market prices rather than the fixed price of $1.00. To buy a market bundle at current ASK prices, use the "Market Order" option as above but select " GOOGLE_WTA (buy at market prices)." To sell a bundle at current market BID prices, select " GOOGLE_WTA (sell at market prices)."

Bundle purchases will be charged to your cash account and bundle sales will be credited to your cash account.

MARKET CLOSING

This market will remain open until contract liquidation. Liquidation values will be credited to the cash accounts of market participants.

MARKET ACCESS

Current and newly enrolled IEM traders will automatically be given access rights to the GOOGLE_WTA Market. Access to this market is achieved by logging into the IEM and choosing " GOOGLE_WTA " from the Navigation Bar.

Funds in a trader's cash account are fungible across markets so new investment deposits are not required. Additional investments up to the maximum of $500 can be made at any time. New traders can open accounts using the IEM OnLine Account Application page (http://iemweb.biz.uiowa.edu/signup). There is a one-time account registration fee of $5.00, and investments are limited to the range of $5.00 to $500.

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