Using Prediction Markets to Track Information Flows: Evidence from Google[1]

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Abstract

In the last 2.5 years, Google has conducted the largest corporate experiment with prediction markets we are aware of. In this paper, we illustrate how markets can be used to study how an organization processes information. We document a number of biases in Google's markets, most notably an optimistic bias. Newly hired employees are on the optimistic side of these markets, and optimistic biases are significantly more pronounced on days when Google stock is appreciating. We find strong correlations in trading for those who sit within a few feet of one another; social networks and work relationships also play a secondary explanatory role. The results are interesting in light of recent research on the role of optimism in entrepreneurial firms, as well as recent work on the importance of geographical and social proximity in explaining information flows in firms and markets.

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Using Prediction Markets to Track Information Flows: Evidence from Google

In the last 4 years, many large firms have begun experimenting with internal prediction markets run among their employees.[2] The primary goal of these markets is to generate predictions that efficiently aggregate many employees' information and augment existing forecasting methods. Early evidence on corporate markets' performance has been encouraging (Chen and Plott, 2002; Ortner, 1998; this paper).

In this paper, we argue that in addition to making predictions, internal prediction can provide insight into how organizations process information. Prediction markets provide employees with incentives for truthful revelation and can capture changes in opinion at a much higher frequency than surveys, allowing one to track how information moves around an organization and how it responds to external events. We exemplify this use of prediction markets with an analysis of Google's internal markets, the largest corporate prediction market we are aware of.

We can draw two main conclusions. The first is that Google's markets, while reasonably efficient, reveal some biases. During our study period, the internal markets overpriced securities tied to optimistic outcomes by 10 percentage points.[3] The optimistic bias in Google's markets was significantly greater on and following days when Google stock appreciated. Securities tied to extreme outcomes were underpriced by a smaller magnitude, and favorites were also overpriced slightly. These biases in prices were partly driven by the trading of newly hired employees; Google employees with longer tenure and more experience trading in the markets were better calibrated. Perhaps as a result, the pricing biases in Google's markets declined over our sample period, suggesting that corporate prediction markets may perform better as collective experience increases.

The second conclusion is that opinions on specific topics are correlated among employees who are proximate in some sense. Physical proximity was the most important of the forms of proximity we studied. Physical proximity needed to be extremely close for it to matter. Using data on the precise latitude and longitude of employees' offices, we found that prediction market positions were most correlated among employees sharing an office, that

[2] Apart from Google, firms whose internal prediction markets have been mentioned in the public domain include Abbott Labs, Arcelor Mittal, Best Buy, Chrysler, Corning, Electronic Arts, Eli Lilly, Frito Lay, General Electric, Hewlett Packard, Intel, InterContinental Hotels, Masterfoods, Microsoft, Motorola, Nokia, Pfizer, Qualcomm, Siemens, and TNT. Of the firms for which we know the rough size of their markets, Google's are by far the largest in terms of both the number of unique securities and participation.

[3] In Google's markets, as in many other corporate prediction markets, participants begin with an endowment of artificial currency (called "Goobles" in Google's case). Participants can use this currency to "purchase" "securities" that pay off in Goobles if a specified event occurs. While we follow the academic literature and use the terms "purchase" and "security" in describing Google's markets, it is important to note that legally Google employees are not trading securities as defined under securities laws in that they are not placing real money at risk.

correlations declined with distance for employees on the same floor of a building, and that employees on different floors of the same building were no more correlated than employees in different cities.[4] Google employees moved offices extremely frequently during our sample period (in the US, approximately once every 90 days), and we are able to use these office moves to show that our results are not simply the result of like-minded individuals being seated together.

Other forms of proximity mattered too. Google employees who reported that they had a professional association on a social network survey had significantly more correlated positions. Likewise, positions were correlated for employees on common email lists and in the same part of the organization. Most measures of demographic similarity (we checked 5 measures) were not associated with higher position correlations, but sharing a common non-English native language was.

The results about demographics not affecting information sharing significantly are especially interesting given that participants in Google's prediction markets were decidedly *not* representative of the organization as a whole. Participants were more likely to be in programming roles at Google, located on either the main (Mountain View, CA) or New York campuses, and, within Mountain View, located closer to the center of campus. In addition, participation was higher among those with more quantitative backgrounds (as evidenced by undergraduate major and current job function) and more interest in either investing or poker (as evidenced by participation on related email lists). The fact that trading positions were not correlated along most of these dimensions (physical geography being the exception) suggested that even if the market participants were not representative of Google, the people they were sharing information with might be more so.

Our findings contribute to three quite different literatures: on the role of optimism in entrepreneurial firms, on employee communication in organizations, and on social networks and information flows among investors. De Meza and Southey (1996) argue many of the stylized facts about entrepreneurship are consistent with an "entrepreneur's curse" in which firms are started by those most overly optimistic about their prospects. Evidence from experiments and the field (Camerer and Lovallo, 1999; Arabsheibani, et. al. 2000; Simon and Houghton, 2003; Astebro, 2003) suggest that entrepreneurs are indeed optimistically biased. A modest optimistic bias may be a desirable for both leaders and employees in entrepreneurial firms, however, if it generates motivation (Benabou and Tirole, 2002 and 2003; Compte and Postlewaite, 2004), leads to risk-taking that generates positive externalities (Bernardo and Welch, 2001; Goel and Thakor, 2007), or makes employees cheaper to compensate with stock

[4] As discussed below, in all data analyzed by the external researchers on this project, Google employees were anonymized and identified only by an ID# that was used to link datasets.

options. We contribute to this literature by documenting optimism among the employees of an important entrepreneurial firm, as well as by showing a strong link between optimistic bias and recent stock market performance.

Communication between managers and workers and among peers has long been viewed as an important determinant of optimal organizational structure (Bolton and Dewatripont, 1994; Harris and Raviv, 2002; Dessein, 2002), with improvements in communication technology making more efficient structures possible (Chandler, 1962 and 1990; Rajan and Wulf, 2006). While in economic research the importance of physical proximity appears to have declined with communication costs (e.g., Kim, Morse, and Zingales, 2007), many innovative firms and their employees are paying higher costs to cluster in places like Silicon Valley and New York and devoting care to the physical layout of their offices. The academic study of office layouts, communication, and innovation was pioneered by Allen (1970), who found physical location and informal relationships to be important determinants of information sharing among engineers. The lessons of the literature informed Google CEO Eric Schmidt and Chief Economist Hal Varian's (2005) third rule for managing knowledge workers: "Pack Them In." Indeed, the fact that Google employees moved so frequently during our sample period suggests that considerable thought is put into optimizing physical locations. To this literature, which has largely relied on retrospective surveys to track communication, we illustrate how prediction markets can be used as high-frequency, market-incentivized surveys to track information flows in real-time.

Finally, our work relates to a recent literature on geography, social networks and investing. Coval and Moskowitz (1999, 2001) find that fund managers overweight local firms and earn a higher return on these holdings. Hong, Kubik, and Stein (2005) find within-city correlations in the trading of fund managers. Massa and Simonov (2005) find correlations in the trading of investors with similar educational backgrounds, while Cohen, Frazzini, and Malloy (2007) find that fund managers outperform when investing in firms with board members who attended the same educational institution. Unlike many of these studies, we have much more detailed data on the extent to which any two individuals interact and can test the relative importance of physical proximity and social networks. In our setting at least, we find the former to play a significantly larger role in information sharing than the latter.

The next section describes our data and analyzes the efficiency of Google's internal markets, documenting the optimism, extremeness aversion, and favorite biases discussed above. The following section discusses our analysis of position correlations and the flow of information. A discussion follows.

Data

The data used in our analysis was collected in anonymized format from a variety of different internal Google sources. We made use of Google's data about employees' office locations and a database of office moves. For four of Google's U.S. campuses (Mountain View, CA; New York, NY; Phoenix, AZ; Kirkland, WA), the company has precise longitude and latitude data for each office. Our analysis also used the results of an internal April survey about employee backgrounds and social networks, and anonymized records of code reviews, project assignments, email list memberships, and an organizational chart from April 2007 with reporting relationships. All data we used was summarized and/or anonymized before analysis.

Google's prediction markets were launched in April 2005. The markets are patterned on the Iowa Electronic Markets (Berg, et. al., 2001). In Google's terminology, a *market* asks a question (e.g., "how many users will Gmail have?") that has 2-5 possible mutually exclusive and completely exhaustive answers (e.g., "Fewer than X users", "Between X and Y", and "More than Y"). Each answer corresponds to a *security* that is worth a unit of currency (called a "Gooble") if the answer turns out to be correct (and zero otherwise). Trade is conducted via a continuous double auction in each security. As on the IEM, short selling is not allowed; traders can instead exchange a Gooble for a complete set of securities and then sell the ones they choose. Likewise, they can exchange complete set of securities for currency. There is no automated market maker, but several employees did create robotic traders that sometimes played this role.

Each calendar quarter from 2005Q2 to 2007Q3 about 25-30 different markets were created. Participants received a fresh endowment of Goobles which they could invest in securities. The markets' questions were designed so that they could all be resolved by the end of the quarter. At the end of the quarter, Goobles were converted into raffle tickets and prizes were raffled off. The prize budget was $10,000 per quarter, or about $25-100 per active trader (depending on the number active in a particular quarter). Participation was open to active employees and some contractors and vendors; out of 6,425 employees who had a prediction market account, 1,463 placed at least one trade.[5]

Table 1 provides an overview of the types of questions asked in Google's markets. Common types of markets included those forecasting demand (e.g., the number of users for a product) and internal performance (e.g., a product's quality rating, whether a product would leave beta on time). Much smaller scale experiments in these uses of prediction markets have

[5] By way of comparison, Google is listed in COMPUSTAT has having 5,680 and 10,674 employees at the end of calendar years 2005 and 2006, respectively. We excluded from our analyses a small number of trades that were placed after an event happened (but before the market was closed and expired) or were self-trades (which resulted from the fact that the software allowed traders to be matched with their own limit orders).

been documented at other companies (e.g., by Chen and Plott, 2002 and Ortner, 1998, respectively). Markets were also run on company news that did not directly imply performance (e.g., will a Russia office open?) and on features of Google's external environment that might affect its planning (e.g., the mix of hardware and software used to access Google).

In addition, about 30 percent of Google's markets were so-called "fun" markets – markets on subjects of interest to its employees but with no clear connection to its business (e.g., the quality of Star Wars Episode III, gas prices, the federal funds rate). Other firms experimenting with prediction markets that we are aware of have avoided these markets, perhaps out of fear of appearing unserious. Interestingly, we find that volume in "fun" and "serious" markets are positively correlated (at the daily, weekly, and monthly frequencies), suggesting that the former might help create, rather than crowd out, liquidity for the latter.

Table 2 provides summary statistics on the participants in Google's prediction markets. As noted above, participants are not representative of Google employees as a whole: on many dimensions, they are closer to the modal employee than the mean. They are more likely to be programmers, as measured by being in the Engineering department, having participated in a code review, or having majored in Computer Science. Across several measures, they are more quantitatively and stock-market-oriented (more likely to be in a quantitative role, have a quantitative-related degree, more likely to participate on investing, economics, or poker-related email lists). They are also more likely to be based in Google's Mountain View and New York campuses. Within Mountain View, they are more likely to have offices close to the center of campus. They have been employed longer, are less likely to leave after our sample ends, and are more deeply embedded in the organization across a number of measures (they subscribe to more email lists, name more professional contacts, and are more likely to have been named by someone at Google as a friend). They are also slightly more senior (as measured by levels from the CEO) than non-participants. Regressions predicting participation in Table 3 largely confirm these results in a multivariate context.

The Efficiency of Google's Markets

Google's prediction markets are reasonably efficient, but did exhibit four specific biases: an overpricing of favorites, short aversion, optimism, and an underpricing of extreme outcomes. New employees and inexperienced traders appear to suffer more from these biases, and as market participants gained experience over the course of our sample period, the biases become less pronounced.

A simple test of a prediction market's efficiency is to ask whether, when a security is priced at X, it pays X in expectation. In Figure 1, we sort trades in the Google markets into 20 bins based on their price (0-5, 5-10, etc.) and plot the average price and ultimate payoff. The standard errors for the average payoff of a bin are adjusted for clustering of outcomes within a market. The results suggest a slight (and marginally statistically significant) overpricing of favorites and underpricing of longshots. Figure 2 conducts the analysis separately for 2 and 5-outcome markets (which account for 29 and 57 percent of the markets, respectively). The two outcome markets exhibit positive returns for securities priced below 0.5, while the five outcome markets exhibit positive returns for securities priced below 0.2, confirming that a reverse favorite-longshot bias is a useful way of characterizing this predictability.

Table 4 presents regressions of returns to expiry on the difference between the transaction price and 1/N (where N is the number of outcomes). We use this functional form for two reasons: 1) the difference between price and 1/N captures the extent to which a contract is a favorite and 2) the non-parametric analysis in Figure 2 suggests that this form would describe the data well. These regressions provide statistically significant evidence of a reverse favorite-longshot bias (or favorite bias, for short). The bias is present to a roughly equal extent in subsamples of the data (2 and 5 outcome markets; fun and serious markets). Since these results could be driven by microstructure-driven noise in prices (e.g., due to bid-ask bounce), we repeat these tests using lagged prices, bid-ask midpoints, and after limiting the same to trades conducted inside the arbitrage-free bid-ask spread.[6] The favorite bias is robust to these alternative specifications.

The presence of a favorite bias is somewhat surprising in light of Ali (1977) and Manski's (2006) theoretical analysis, as well as the evidence of a longshot bias in public prediction markets (Tetlock, 2004; Zitzewitz, 2006; Leigh, Wolfers, and Zitzewitz, 2007). Ali and Manski point out that because traders can take larger positions for a given amount of downside risk when betting on longshots, when traders are liquidity constrained (and risk-neutral), we should expect the prices of longshots (favorites) to be above (below) the median probability belief. If median probability beliefs are unbiased, this should result in a longshot bias in prices. Given that these assumptions of liquidity-constraints and risk-neutrality seem more likely to hold for a corporate prediction market than for a public prediction market, especially one like *Intrade.com*

[6] In an IEM-style prediction market, one can increase one's exposure a given security by either purchasing the security or by exchanging $1 for a bundle of securities track all possible outcomes in a given market and then selling the other components of the bundle. We calculate the "arbitrage-free" ask as the cheapest way of acquiring the security, i.e. the minimum of the ask for the security and one minus the sum of the bids for the other securities. We do the analogous calculation to determine the arbitrage-free bid. The arbitrage-free mid point is the average of the arbitrage-free bid and ask. For 70 of 70,706 trades, the pre-trade arbitrage-free ask was actually below the arbitrage-free bid, implying that there was an arbitrage opportunity to either buy or sell all securities in a bundle. In these cases, we also used the midpoint as an indicator of the securities value.

where account sizes are not constrained, this makes the finding of a favorite bias in Google's markets particularly surprising. One possibility is that the favorite bias in prices reflects a larger favorite bias in the beliefs of the median trader.

Table 5 calculates returns from purchasing securities, which are negative and statistically significant on average. This suggests some traders may be adverse to short selling securities. As further evidence of short aversion, in order book snapshots collected each time an order was placed, we found 1,747 instances where the bid prices of the securities in a particular market added to more than 1, implying an arbitrage opportunity (from buying a bundle of securities for $1 and then selling the components). In contrast, we found only 495 instances where the ask prices added to less than 1 (implying an arbitrage opportunity of buying the components of a bundle for less than $1 and then exchanging the bundle). The median duration of these arbitrage opportunities was about 2 minutes.

Table 5 also calculates returns according to whether the security's outcome would be good news for Google. For some markets, such as markets on "fun" or "external news" topics, it was not clear which outcome was better for Google, so we are able to rank outcomes for 157 out of 270 markets. Of these 157, all but 11 have either 2 or 5 outcomes, and so, for simplicity, the table restricts attention to these. In two-outcome markets, the optimistic (i.e. better for Google) outcome is significantly overpriced: it trades at an average price of 46 percent but these trades earn average returns to expiry of -26 percentage points. The pessimistic outcome is underpriced by a similar margin. Five-outcome markets display a small amount of optimism bias but primarily an overpricing of intermediate outcomes; the third-best outcome out of five is priced at 30 but earns returns to expiry of -12 percentage points.[7] We refer to this bias as extreme aversion.

Table 6 measures the extent of the optimism bias in subsamples of the data. The optimistic bias exists entirely in the two categories of contracts where outcomes are most directly under the control of Google employees: company news (e.g., office openings) and performance (e.g., project completion and product quality). Markets on demand and external news with implications for Google are not optimistically biased. Optimistic bias is larger in two outcome markets, early in our sample period, and earlier in each quarter.

Table 7 provides tests for whether these biases are independent of one another, finding that they largely are. The final column in Table 7 interacts the four biases (optimism, favorite bias, extreme aversion, and short aversion) with a date variable (scaled to equal 0 at the

[7] All the averages in Figures 1 and 2 and Tables 4-6 are trade rather than contract-weighted. If a contract's future price path is correlated with whether it trades in the future, contract-weighted analysis of efficiency can suffer from a look-ahead bias.

beginning of our sample on April 7, 2005 and 1 at the end on September 30, 2007). The coefficients on these interactions suggest that Google's markets became significantly less biased over the course of our sample period. In the final column of Table 7, we find that weighting trades by the number of shares transacted, rather than equally, reduces the estimated magnitude of the biases.

Three of the four biases (optimism, extreme aversion, and favorite bias) could reflect ex post surprise rather than ex ante biases in beliefs: Google's outcomes during this time period could simply have been more disappointing, more extreme, and harder to predict than rational traders anticipated. Google's stock price did more than triple during our time period (April 2005 to September 2007), casting doubt on a negative ex post surprise as the explanation. Furthermore, most of the appreciation occurred during 2005, the period in which the apparent optimistic bias in Google's markets was greatest.

Further evidence that there is a behavioral component to the optimism comes from Table 8, which examines how the optimistic bias in Google's markets varies with very recent Google stock returns. The coefficient in column 1 can be interpreted as showing that, on average, optimistic securities earn returns that are 10.5 percentage points lower than neutral securities. The coefficient of 2.2 on the interaction of optimism and prior day returns implies that this pricing bias is 4.4 percentage points larger following a day with 2.0 percent higher Google stock returns (1 standard deviation during this time period). Further tests reveal that this pricing bias appears to mean revert after one day and is robust to controlling for day of the week effects and the returns on the S&P 500 and Nasdaq composite.[8] Evidence of an impact of stock price movements on the optimism bias persists when we volume-weight, rather than equal-weight, trades.

Who is driving these biases? If we predict whether a trader will trade with or against these biases using the individual characteristics in Table 9, we find several relationships. Newly hired employees are significantly more likely to take optimistic positions than other employees. In further tests omitted for space reasons, we find that this is especially true for contracts in the "Performance" and "Company News" categories in which prices are optimistically biased on average. On the other hand, newly hired employees are more likely to sell favorites and to build positions by selling rather than purchasing securities, i.e. to trade in a way that takes advantages of the reverse favorite-longshot and short aversion bias in prices. Coders are like newer employees in that they trade optimistically (which lowers their returns), but also trade in a way that takes advantage of favorite and short aversion biases. More experienced traders

[8] The underpricing of extreme outcomes and longshots, in contrast, is not statistically significantly related to the sign or magnitude of prior stock day returns.

trade in a way that profits from optimism, favorite, and short aversion biases, but contributes to extreme aversion. [9]

In summary, while Google's prediction markets grew more efficient over time, they did exhibit pricing predictabilities during our sample period. These pricing predictabilities likely arise from short aversion, as well as from optimistic, extremeness aversion, and favorite biases in the market-weighted average beliefs of Google's employees. To better understand how Google processes information as an organization, we turn to the question of whether we can use its prediction markets to understand how information moves around the organization.

Measuring the Transmission of Information

In this section we aim to understand how information is transmitted by testing whether employees who are proximate to each other in some sense trade in a correlated manner. We develop measures of geographical, organizational, and social proximity, and also measure demographic similarity.

Our analysis aims to understand which of these measures of proximity is related to correlations in opinion, as expressed in prediction market trading. In our first analysis, we take the participants in each trade to be exogenous, and attempt to predict which side of the trade the two participants will take. The exact timing of individual's trading in a low-stakes prediction market is likely to be exogenous, since it would be largely determined by when they have time available (e.g., for a programmer, while code is being compiled and tested).

Given the likely absence of hedging motives in these markets, if trader *i* buys a security from trader *j* at some price, we can infer that *i*'s subjective belief about its payoff probability is higher than *j*'s. Equally, if a third trader *k* holds a large long position in the security prior to the trade, we can infer that her subjective belief about the value of the security is higher than if she were holding a short position. Our approach will be to test whether the buyer in a particular transaction is more proximate to other traders with prior long positions.

Specifically, we will estimate *i*'s desired holdings of security *s* at prevailing market prices, $q_{is} = \sum_k w_{ik} q_{ks} + e_{is}$, where $w_{ik} = \beta s_{ik} + n_{ik}$ is the weight that *i* gives the opinion of *k*, s_{ik} is a vector of measures of the proximity/similarity of *i* and *k*, β is a vector of parameters to be

[9] One trader in Google's markets wrote a trading robot that was extremely prolific and ended up participating in about half of all trades. Many of these trades exploited arbitrage opportunities available from simultaneously selling all securities in a bundle. In order to avoid having this trader dominate the (trade-weighted) results in Table 9, we include a dummy variable to control for him or her. None of the results discussed in the above paragraph are sensitive to removing this dummy variable.

estimated, e_{is} is an error term capturing the component of *i*'s opinion about *s* that is not affected by her colleagues, and n_{ik} is an error term capturing the influence of *k* on *i* that is not affected by their proximity.[10] Given this setup, we can predict the difference in their holdings after the trade as:

$$q_{is} - q_{js} = \sum_k \beta\left(p_{ik}q_{ks} - s_{jk}q_{ks}\right) + [(e_{is} - e_{js}) + \sum_k q_{ks}(n_{ik} - n_{jk})]. \qquad (1)$$

It is convenient to rewrite this as:

$$q_{is} = \sum_k \beta(s_{ik}q_{ks}) + (e_{is} + \sum_k q_{ks}n_{ik}) + a_t, \qquad (2)$$

and a symmetric expression for q_{js}, with a_t having a natural interpretation as a trade fixed effect.

In order to estimate (2) as a regression equation, we would need to make the standard assumption that the error term (in parentheses) is uncorrelated with the independent variable (the proximity-weighted positions of colleagues). In this context, this requires assuming that the portion of the traders' opinion that is not influenced by their proximate colleagues (i.e., e_i) is uncorrelated with the positions of their proximate colleagues ($\sum_k s_{ik}q_{ks}$). In addition, it requires assuming that proximate colleagues are not unexpectedly influential in ways that are uncorrelated with their proximity (i.e., that n_{ik} is uncorrelated with s_{ik}, when weighted by the q_{ik}).

The first assumption requires that like-minded people not be proximate. This seems unlikely, given that geographical and organization proximity is optimized by the firm, that social proximity develops endogenously, and that demographical similarity may be correlated with likemindedness even in the absence of communication. Fortunately, for geographical proximity we will be able to attempt to separate causal effects from correlations by examining sharp changes in proximity (e.g., by exploiting office moves).

The second assumption requires assuming that our observed measures of proximity are not correlated with unobserved proximity. For example, if colleagues who shared an office were also friends, but failed to report in on their social network survey, we would include the effect of their being friends as part of the effect of sharing an office. The potential for such confounding effects must be kept in mind when interpreting our results.

[10] Wolfers and Zitzewitz (2007) find that traders' demand for a binary prediction market security is linear in their subjective expected returns when they have log utility and is approximately linear for most reasonable assumptions about risk aversion.

We construct our dataset for estimating (2) as follows. For each pair of our 1,463 prediction market traders, we calculate the measures of their geographical, organizational, and social proximity, as well as demographic similarity, discussed below. We recalculate geographical proximity for each week in our sample, using our dataset of office moves to reconstruct the seating chart at the beginning of the week in question.[11] Prior to each trade, we calculate the net position of each trader in each security.[12] We then construct the proximity-weighted sum of colleagues' positions for each of the two traders along each dimension of proximity.[13] We then predict the size and direction of each side of the trade using the proximity-weighted colleague positions across the different dimensions and the trader's prior position as regressors and including a trade fixed effect. Standard errors allow for clustering of errors with a given trader's trades across all securities.

Tables 10 and 11 present estimates of (2). In Table 10, the proximity-weighted sums of the pre-trade positions of a trader's colleagues are used to predict which side of a trade a trader will be on. In Table 11, the proximity-weighted sums of the signs of colleagues' pre-trade positions are used. The two tables yield similar results, with the latter approach having the advantage of reducing the influence of outliers. In Table 10, we multiply coefficients by 1,000, which is approximately the standard deviation of an individual's pre-trade position in a security.

The coefficients can be directly compared to analyze which measures of proximity or similarity best predict correlated trading. In both tables, one of the most important predictors of correlated trading is the variable that captures the proximity of two traders' desks. The variable is 10 divided by the number of feet between the traders desks if traders are on the same floor of the same building, one if they share an office, and zero otherwise. For pairs of traders on the same floor but not in the same office, the variable ranges from 0.02 to 1 and has a mean of about 0.1.[14] The coefficients in Table 11 imply that having a colleague with a long

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[11] Ultimately we will be able to do this for organizational proximity as well, to account for reorganizations and the exact timing of overlap on projects.

[12] We calculate net positions in a security as the difference between a trader's cumulative net purchases of a security and the average of her cumulative net purchases of all securities in that market. For example, if there are two outcomes in a market, and trader X has made net purchases of 20 shares of outcome A and 10 shares of outcome B, we would calculate her positions as being +5 shares of A and -5 shares of B.

[13] For the demographic characteristics that we obtained from a voluntary survey, we are missing data for 65 percent of our traders (who account for 37 percent of the trades). For certain demographic characteristics, we are still missing data for 23 percent of traders (who account for 8 percent of trades). For traders whose demographics are unknown, we code the "same group" position as zero, and we exclude unknown-demographic traders' positions from the "same group" variables for other traders. This is equivalent to assuming that colleagues of unknown demographics have net positions of zero, i.e. the average net position across all traders.

[14] As alternative functional forms, we experimented with distance^-2 and distance^-0.5. The reciprocal of distance fit the data the best. In the next draft, we plan to estimate the effect of distance non-parametrically.

position in a security sit 10 feet away makes one makes one 12-20 percent more likely to be on the long side of a trade.

Once distance between desks is accounted for, there appears to be little additional effect from being in the same office. In the Mountain View and New York campuses where 69 and 9 percent of traders sit, respectively (and 76 and 11 percent of trades are placed, respectively), shared "offices" are typically groups of desks bounded by five-foot high walls on a large, open-plan floor. The lack of a same office effect implies that having a five foot wall between two otherwise adjacent desks does not affect trading correlations.

Another significant predictor of trading correlations is sharing the same "three-levels-below-SVP" manager. Most managers who are one level below the CEO have the title "Senior Vice President" and run one or more related departments (e.g., Engineering and Operations, Sales and Business Development, Product Management). Most of the managers two levels below CEO run functional or geographic areas within departments. Sharing a third-level manager usually implies that two traders work on the same broad set of products at Google. If same third-level manager is not controlled for, the variable that captures the positions of employees who have overlapped on the same project becomes statistically significant.

Among the variables capturing social connections at Google, the most important appears to be the one that captures self-reported professional relationships. In an April 2006 survey, employees were asked to name employees that they turned to for ideas, buy-in, technical advice, and organizational advice. They were prompted to name ten in each category; the median named was four. We coded two employees as having a professional relationship if either employee named the other in any of the four categories. Employees were also asked to name their friends at Google. In contrast to our results for professional relationships, we did not find friendships to be a strong predictor of trading correlations.

The only demographic similarity variable to predict a positive correlation in trading was sharing a common non-English native language. We coded this variable as one if neither trader was a native English speaker and both were native speakers of a common non-English language.[15] Apart from this variable, trading was if anything more correlated among demographically dissimilar employees.

As discussed above, a correlation between the trading of two proximate employees could be caused by proximity, but could also be the result of like-minded employees being

[15] In the April 2006 survey, Google employees were asked to list languages they spoke and to rate their ability from one to five, with 5 being native and 4 being fluent. Given the fact that the difference between fluency and native ability seemed likely to affect informal communication, we focused on this distinction in constructing the variable.

seated together. In Table 12, we exploit the frequency of office moves at Google to attempt to disentangle these two effects. We separately calculate the positions of each traders' currently proximate colleagues, the colleagues they were proximate to 3 month ago, and the colleagues they will be proximate to 3 months in the future. Future proximity has little estimated effect, suggesting that our results are not a result of like-minded people being seated together. Trading is correlated with the positions of one's current officemates, and also with the positions of those who sat close to one's office 90 days ago. This is consistent with relationships that lead to information sharing forming more rapidly when employees share an office than when they do not.

The analysis to this point has taken the participants in a trade as given and attempted to predict who would be the buyer and seller. An alternative approach would be to take the fact that two individuals traded at a particular time as given, and attempt to predict both which security they traded, as well as who bought and sold. This is much more data-intensive, of course, since we must calculate colleagues' pre-trade proximity-weighted positions for every available security, not just the security traded.

Table 13 compares the results from these two approaches. Due to computational constraints, we estimate models with geographical-proximity variables only. The findings about the relative importance of micro-geography are reasonably similar, although the estimate magnitude of the effect of a colleague's position is understandably smaller.

Discussion

In the past few years, many companies have experimented with prediction markets. In this paper, we analyze the largest such experiment we are aware of. We find that prices in Google's markets closely approximated event probabilities, but did contain some biases, especially early in our sample. The most interesting of these was an optimism bias, which was more pronounced for subjects under the control of Google employees, such as would a project be completed on time or would a particular office be opened. Optimism was more present in the trading of newly hired employees, and was significantly more pronounced on and immediately following days with Google stock price appreciation. Our optimism results are interesting given the role that optimism is often thought to play in motivation and the success of entrepreneurial firms. They raise the possibility of a "stock price-optimism-performance-stock price" feedback that may be worthy of further investigation.

We also examine how information and beliefs about prediction market topics move around an organization. We find a significant role for micro-geography. The trading of physically proximate employees is correlated, and only becomes correlated after the employees begin to sit near each other, suggesting a causal relationship. Work and social connections play a detectable but significantly smaller role.

An important caveat to our results is that they tell us about information flows about prediction market subjects, many of which are ancillary to employees' main jobs. This may explain why physical proximity matters so much more than work relationships – if prediction market topics are lower-priority subjects on which to exchange information, then information exchange may require the opportunities for low-opportunity-cost communication created by physical proximity. Of course, introspection suggests that genuinely creative ideas often arise from such low-opportunity-cost communication. Google's frequent office moves and emphasis on product innovation may provide an ideal testing ground in which to better understand the creative process.

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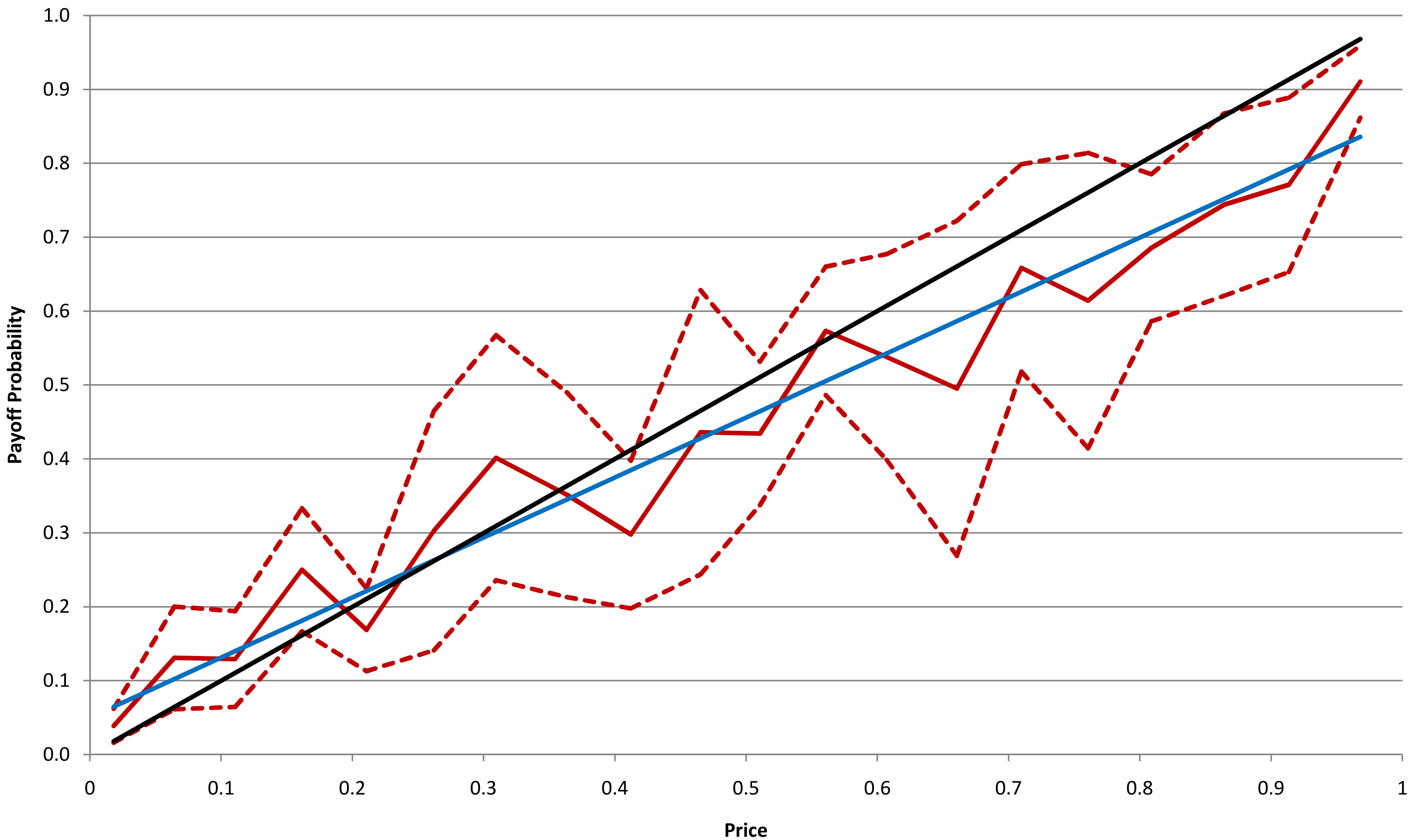
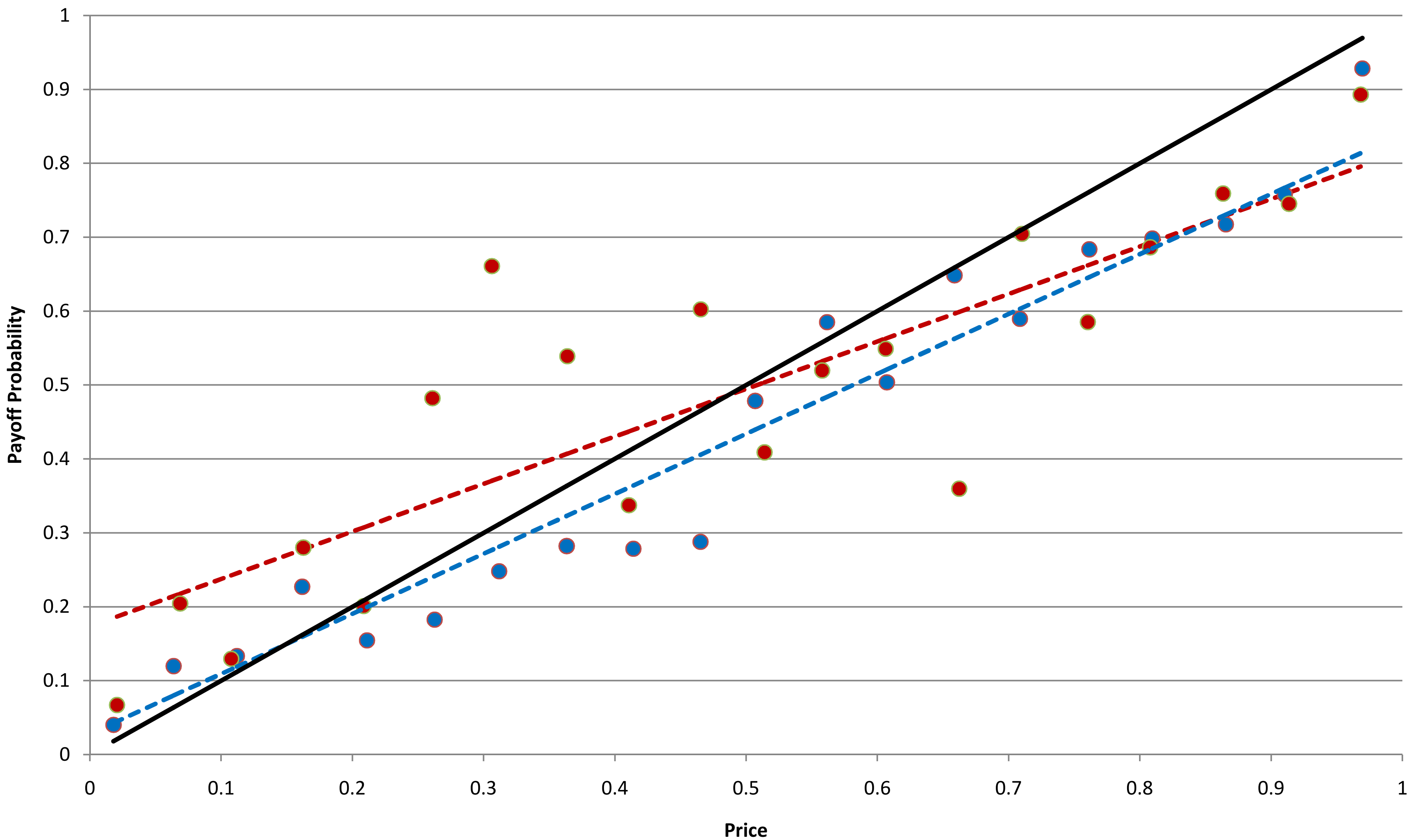
Figure 1. Prices and Payoff Probabilities in Google's Prediction Market



The 70,706 trades are sorted into 20 bins according to price (i.e., 0-5, 5-10, etc.) and then average price and payoff probability for the bin is plotted. The blue line is a regression equation obtained via OLS. Confidence intervals adjust for clustering of outcomes within market.

Figure 2. Prices and Probabilities in Two and Five-outcome Markets



Trades in two (red) and five-outcome (blue) markets (22,452and 42,416, respectively) are sorted into 20 bins according to price (i.e., 0-5, 5-10, etc.), and then average price and payoff probability for the bin is plotted. Dashed lines plot regression equations using OLS.

Table 1. Prediction markets at Google

Type	Example	Share of markets
Demand forecasting	# of Gmail users at end of quarter	20%
Performance	Google Talk quality rating	15%
Company news	Russia office to open	10%
Industry news	Will Apple release an Intel-based Mac?	19%
Decision markets	Will users of feature A users use feature B more?	2%
Fun	How many "rotten tomatoes" will Episode III get?	33%
Unique participants		1,463
Orders		253,192
Trades		70,706
Markets run (questions)		270
Securities (answers)		1,116

Table 2. Summary statistics

	Sample	All Googlers	Average for Prediction Market traders	Sign of difference with average for all employees	Odds ratio	
Job characteristics						
Department						
Engineering	A	§	§	+	1.737	***
Operations	A	§	§	+	1.324	***
Product Management	A	§	§	+	1.547	***
Sales	A	§	§	-	0.591	***
Other (Facilities, Business Operations, etc.)	A	§	§	-	0.298	***
Coder? (Participated in at least one code review)	A	§	§	+	2.554	***
Levels below CEO	A	§	§	-	-	***
Hire date (days since 1/1/2004)	A	§	§	-	-	***
Geography						
Mountain view campus (MTV)	A	§	§	+	1.379	***
MTV only: distance from center of campus (No Name Café) in miles		§	0.187	-		***
New York campus	A	§	§	+	1.639	***
Social networks and interests						
Email lists subscribed to	A	§	39	+		***
Economics list participant	A	0.02	0.08	+	3.935	***
Financial planning list participant	A	0.17	0.42	+	2.454	***
Investing list participant	A	0.03	0.09	+	3.762	***
Poker list participant	A	0.03	0.12	+	3.840	***
Coders only: times had code reviewed	A	206	354	+		***
Coders only: times reviewed code	A	204	365	+		***
Professional contacts named	B	6.65	7.07	+		***
Friends named	B	5.22	5.20	-		
Peopling naming as professional contact	B	3.95	4.01	+		
People naming as friend	B	2.53	2.71	+		***
Demographics and education						
Undergraduate major						
Computer science	B	§	§	+	1.539	***
Electrical engineering	B	§	§	+	1.133	
Other engineering/operations research	B	§	§	-	0.815	
Math/Statistics	B	§	§	+	1.438	***
Science	B	§	§	-	0.959	
Economics/Finance	B	§	§	-	0.677	*
Other Business	B	§	§	-	0.537	***
Social science/law	B	§	§	-	0.513	***
Communications	B	§	§	-	0.507	***
Humanities/other	B	§	§	-	0.558	***
Graduate degree?	B	§	§	+	1.036	

Notes:

§ - These values were withheld at the request of Google. We may be able to share more in a later draft.

Asterisks indicate the statistical significance of the difference between prediction market traders and all Google employees. Odds ratios are the share of prediction market traders in a given category (e.g., in the Engineering Department), divided by the share of all employees in the same department.

Sample A = All permanent employees and interns employed between April 2005 and September 2007, excluding those working at remote locations

Sample B = Sample A members who responded to a Spring 2006 survey (3,139, inclduing 510 prediction market traders)

Table 3. Linear probability regressions predicting participation

Dependent variable	= 1 if ever placed trade							
Department								
Engineering	0.074	***	0.042	***	0.031	***	0.010	
	(0.003)		(0.003)		(0.003)		(0.031)	
Sales	0.053	***	0.034	***	0.026	***	-0.065	*
	(0.006)		(0.006)		(0.006)		(0.037)	
Operations	0.064	***	0.049	***	0.024	***	-0.014	
	(0.009)		(0.009)		(0.008)		(0.037)	
Product Management	0.015	***	0.022	***	0.011	***	-0.054	**
	(0.002)		(0.004)		(0.004)		(0.022)	
Coder? (Participated in code review)			0.066	***	0.025	***	-0.004	
			(0.005)		(0.005)		(0.026)	
Level (Distance from CEO)			-0.002		-0.001		0.016	**
(Range = 1 to 7)			(0.001)		(0.001)		(0.007)	
Hire date			-0.010	***	0.013	***	0.009	
(In years)			(0.001)		(0.002)		(0.006)	
NYC-based			0.021	***	0.015	*	-0.006	
			(0.008)		(0.008)		(0.027)	
Mountain View (MTV)-based			0.016	***	0.015	***	0.016	
			(0.004)		(0.004)		(0.025)	
Distance to Noname Café in miles (0 if non-MTV)			-0.031	***	-0.035	***	-0.012	
(Mean = 0.1, SD = 0.2, Max = 1.1)			(0.010)		(0.010)		(0.044)	
Email lists subscribed to (/100)					0.154	***	0.246	***
					(0.013)		(0.038)	
Economics list?					0.140	***	0.159	***
					(0.034)		(0.050)	
Financial planning list?					0.059	***	0.026	
					(0.013)		(0.022)	
Investing list?					0.108	***	0.126	**
					(0.035)		(0.053)	
Poker list?					0.155	***	0.163	***
					(0.028)		(0.045)	
Undergrad major = CS, EE, Math, or Science							0.045	**
							(0.020)	
Undergrad major = Economics or Business							0.003	
							(0.015)	
Sample	A		A		A		B	
Mean of dependent variable	0.051		0.051		0.051		0.174	
P-value of F-stat	0.0000		0.0000		0.0000		0.0000	

Notes:

Column 4 also includes controls for demographic characteristics. Standard errors are heteroskedasticity robust.

Sample A = All permanent employees and interns employed between April 2005 and September 2007, excluding those working at remote locations

Sample B = Sample A members who responded to a Spring 2006 survey (3,139, inclduing 510 prediction market traders)

Table 4. Reverse favorite-longshot bias
Dependent variable: returns to expiry

Independent variable	Sample	Obs.	Unique markets	Coeff.	S.E.	Constant	S.E.
Price	All trades	70,706	270	-0.188***	(0.072)	0.050*	(0.027)
Price - 1/N	All trades	70,706	270	-0.232***	(0.089)	-0.006	(0.005)
Price - 1/N	Fun markets	29,122	90	-0.229	(0.182)	0.000	(0.012)
Price - 1/N	Serious markets	41,584	180	-0.235***	(0.081)	-0.009**	(0.004)
Price - 1/N	2 outcome markets	22,452	79	-0.357	(0.227)	-0.005	(0.005)
Price - 1/N	5 outcome markets	42,416	155	-0.189***	(0.072)	-0.010**	(0.005)
Price - 1/N	2005 (Q2 to Q4)	17,766	73	-0.252*	(0.148)	-0.009	(0.006)
Price - 1/N	2006 (Q1 to Q4)	39,396	108	-0.292**	(0.142)	-0.002	(0.008)
Price - 1/N	2007 (Q1 to Q3)	13,544	94	-0.048	(0.065)	-0.012*	(0.007)
Price - 1/N	First month of calendar quarter	27,021	170	-0.441***	(0.167)	0.007	(0.007)
Price - 1/N	Second month	24,513	207	-0.164*	(0.089)	-0.008	(0.006)
Price - 1/N	Third month	17,614	172	-0.059	(0.066)	-0.023***	(0.005)
Price - 1/N	Trade #11 and subsequent	61,225	249	-0.213**	(0.098)	-0.005	(0.006)
Price (t-1) - 1/N	Trade #11 and subsequent	61,225	249	-0.178*	(0.099)	-0.006	(0.006)
Price (t-10) - 1/N	Trade #11 and subsequent	61,225	249	-0.160	(0.106)	-0.007	(0.006)
Price - 1/N	With quote information	57,587	201	-0.269**	(0.106)	-0.004	(0.005)
Midpoint (simple) - 1/N	With quote information	57,587	201	-0.348**	(0.170)	-0.010**	(0.004)
Midpoint (arb-free) - 1/N	With quote information	57,587	201	-0.282**	(0.129)	0.012	(0.012)
Price - 1/N	Price inside arb-free spread	15,293	201	-0.205	(0.138)	-0.013	(0.011)

Note: Each row is a regression. Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within markets. Currently quote information is not available for markets from 2007Q2 and 2007Q3, so these are excluded from the bottom panel.

Table 5. Optimistic bias in the Google markets

	Obs.	Avg price	Avg payoff	Return	(SE)
All markets	70,706	0.357	0.342	-0.015***	(0.003)
Markets with implication for Google	37,910	0.310	0.293	-0.017***	(0.004)
Two-outcome markets with implication for Google	9,023	0.509	0.492	-0.017***	(0.006)
Best outcome for Google	4,556	0.456	0.199	-0.256***	(0.063)
Worst	4,467	0.563	0.790	0.227***	(0.064)
Five-outcome markets with implication for Google	26,511	0.239	0.222	-0.017***	(0.005)
Best outcome for Google	5,592	0.244	0.270	0.027	(0.040)
2nd	5,638	0.271	0.246	-0.025	(0.066)
3rd	5,539	0.296	0.179	-0.118**	(0.053)
4th	5,199	0.206	0.178	-0.028	(0.041)
Worst	4,543	0.162	0.236	0.074	(0.056)

Notes: Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within markets.

Table 6. Optimism bias by subsample

Dependent variable: returns to expiry

Independent variable: optimism of security (scaled -1 to 1)

Sample	Obs.	Unique markets	Coeff.	S.E.	Constant	S.E.
All markets with implication for Google	37,910	157	-0.105***	(0.036)	-0.013***	(0.004)
Company News	7,430	22	-0.182***	(0.064)	-0.015**	(0.006)
Demand forecasting	12,387	51	-0.042	(0.042)	-0.022***	(0.008)
External News	6,898	42	0.100**	(0.041)	-0.011	(0.009)
Performance (e.g., schedule, product quality)	10,057	38	-0.211***	(0.077)	0.000	(0.010)
2 outcome markets	9,023	50	-0.242	(0.227)	-0.015***	(0.005)
5 outcome markets	26,511	96	-0.013	(0.032)	-0.017***	(0.005)
2005 (Q2 to Q4)	12,224	50	-0.210***	(0.065)	-0.013***	(0.005)
2006 (Q1 to Q4)	20,847	67	-0.026	(0.039)	-0.019***	(0.006)
2007 (Q1 to Q3)	4,839	44	-0.086	(0.066)	-0.007	(0.006)
First month of calendar quarter	15,397	106	-0.121**	(0.054)	-0.010*	(0.006)
Second month	14,234	120	-0.105**	(0.045)	-0.012**	(0.006)
Third month	8,279	105	-0.073**	(0.034)	-0.023**	(0.009)

Notes: Each row is a regression. Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within markets. Optimism is scaled so that the worst outcome for Google is coded -1 and the best is coded 1. I.e., (-1, 1), (-1, 0, 1), (-1, -0.33, 0.33,1), and (-1, -0.5, 0, 0.5, 1) for 2, 3, 4, and 5 outcome markets, respectively.

Table 7. Pricing of securities by optimism, extremeness, and favorites

Dependent variable: Returns to expiry

Optimism (-1 = Worst outcome, 1 = Best)		-0.105 ***	-0.106 ***	-0.104 ***	-0.210 ***	-0.043
		(0.036)	(0.036)	(0.036)	(0.068)	(0.027)
Optimism*Date					0.272 **	
					(0.121)	
Extremeness (-1 = Least extreme, 1 = Most extreme)			0.052 **	0.043 *	0.041	0.045 *
			(0.023)	(0.024)	(0.038)	(0.025)
Extremeness*Date					0.005	
					(0.073)	
Favorite (Price - 1/N)				-0.211 **	-0.368 **	-0.103 *
				(0.084)	(0.181)	(0.060)
Favorite*Date					0.365	
					(0.330)	
Constant (captures Short Aversion)	-0.015 ***	-0.013 ***	-0.032 ***	-0.022 **	-0.024	-0.014
	(0.003)	(0.004)	(0.009)	(0.010)	(0.019)	(0.008)
Date (scaled 0 to 1)					0.002	
					(0.030)	
Trades	70,706	37,910	37,910	37,910	37,910	37,910
Weighting of trades	Equal	Equal	Equal	Equal	Equal	Volume
Unique markets	270	157	157	157	157	157

Notes: These regressions predict returns from a given trade's price to expiry. Optimism is scaled -1 (worst outcome for Google) to 1 (best outcome for Google). Extremeness is the demeaned absolute value of optimism, scaled -1 to 1. The date variable is scaled to be zero at the beginning of the sample (4/1/2005) and one at the end (9/30/2007). Standard errors are heteroskedasticity robust and account for clustering of outcomes within the same market.

Table 8. Returns, optimism, and Google stock returns
Dependent variable: Returns to expiry

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
Optimism (-1 = Worst outcome, 1 = Best)	-0.105	***	-0.104	***	-0.096	***	-0.097	***	-0.133	***	-0.129	***	-0.068	**
	(0.036)		(0.036)		(0.034)		(0.027)		(0.037)		(0.036)		(0.034)	
Extremeness (-1 = Least extreme, 1 = Most extreme)			0.043	*	0.042	*	0.041		0.041		0.042		0.047	*
			(0.024)		(0.024)		(0.027)		(0.027)		(0.027)		(0.025)	
Favorite (Price - 1/N)			-0.211	**	-0.222	***	-0.222	***	-0.225	***	-0.225	***	-0.103	*
			(0.084)		(0.081)		(0.066)		(0.065)		(0.065)		(0.059)	
Constant	-0.013	***	-0.022	**	-0.022	**	-0.022		-0.021		0.045		0.006	
	(0.004)		(0.010)		(0.010)		(0.023)		(0.036)		(0.035)		(0.028)	
Optimism*Google log stock return (t+1)					-0.831		-0.906	*	-1.033	*	-1.173	**	-0.863	*
					(0.651)		(0.538)		(0.554)		(0.584)		(0.510)	
Optimism*Google log stock return (t)					-1.417	**	-1.430	***	-1.302	***	-1.132	**	-0.956	*
					(0.687)		(0.486)		(0.469)		(0.513)		(0.547)	
Optimism*Google log stock return (t-1)					-2.209	***	-2.156	***	-2.065	***	-1.512	**	-0.722	
					(0.791)		(0.623)		(0.576)		(0.658)		(0.562)	
Optimism*Google log stock return (t-2)					-0.034		-0.081		-0.260		0.017		-0.491	
					(0.676)		(0.543)		(0.531)		(0.626)		(0.332)	
Google stock returns (t+1, t, t-1, t-2)					X		X		X		X		X	
Interactions of Google stock returns (t+1, t, t-1, t-2) with extremeness and favorites							X		X		X		X	
Day of week fixed effects and interactions with optimism									X		X		X	
S&P and Nasdaq returns (t+1, t, t-1, t-2) and interactions with optimism											X		X	
Unique markets	157		157		157		157		157		157		157	
Unique securities	612		612		612		612		612		612		612	
Obs	37,910		37,910		37,910		37,910		37,910		37,910		37,910	
Weighting of trades	Equal		Equal		Equal		Equal		Equal		Equal		Volume	

Notes: Current-day stock return refers to the stock/index return for the same stock market close-to-close period. The daily standard deviation of Google's log stock return during the sample period is 2.0%. Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within markets.

Table 9. Regressions predicting trade characteristics from traders' attributes
Dependent variable: Security characteristic*(1 if buy, -1 if sell)

Dependent variable	Optimism (scaled -1 to 1)		Favorite Price - 1/N		Extreme Abs(Optimism)		Buy		Return	
Relationship with returns	Neg.		Neg.		Pos.		Neg.			
Coder? (Participated in code review)	0.033		-0.102	***	-0.284	***	-0.404	***	0.072	***
	(0.049)		(0.022)		(0.081)		(0.139)		(0.023)	
Level (Distance from CEO)	0.006		0.004		0.066	**	0.102	**	0.023	**
	(0.019)		(0.007)		(0.029)		(0.040)		(0.009)	
Hire date (in years)	0.051	**	-0.032	***	-0.093	***	-0.224	***	0.005	
	(0.021)		(0.008)		(0.034)		(0.041)		(0.009)	
NYC-based	-0.169		-0.050	*	0.028		0.014		0.017	
	(0.105)		(0.029)		(0.086)		(0.121)		(0.024)	
Mountain View (MTV)-based	-0.119		-0.101	***	0.161	*	-0.005		0.045	
	(0.105)		(0.031)		(0.096)		(0.122)		(0.029)	
Distance to Noname Café in miles (0 if non-MTV)	0.032		0.085	*	-0.161		-0.597	**	0.069	
	(0.125)		(0.047)		(0.179)		(0.294)		(0.043)	
Experience [Ln(1 + previous trades)]	-0.014		-0.044	***	-0.049	***	-0.094	***	0.026	***
	(0.011)		(0.004)		(0.019)		(0.031)		(0.003)	
Trades	37,910		70,706		37,910		70,706		70,706	
Unique traders	1,126		1,463		1,126		1,463		1,463	

Note: Each observation is a side of a trade. Regressions use trader chatacteristics to predict security characteristics, multipled by -1 if the side in question is a sell. Regressions include trade fixed effects and a dummy variable for one particular extremely prolific trader. Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Table 10. Determinants of trading correlations
Dependent variable: = 1 if buying, -1 if selling
Independent variables: Proximity-weighted sums of colleagues' pre-trade positions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Geographical proximity							
Same city	-0.009				-0.008	-0.012	-0.013 ***
	(0.011)				(0.010)	(0.009)	(0.005)
Same building	0.032				0.024	0.020	0.012
	(0.021)				(0.017)	(0.016)	(0.010)
Same floor	-0.033 *				-0.042 **	-0.029	-0.020 *
	(0.020)				(0.019)	(0.018)	(0.012)
Same office	0.002				0.031	0.024	0.018
	(0.022)				(0.033)	(0.030)	(0.023)
Proximity on floor (10/distance in feet)	0.178 ***				0.135 ***	0.132 ***	0.143 ***
	(0.047)				(0.046)	(0.050)	(0.034)
Organizational proximity							
Same SVP		0.012			0.006	0.007	-0.004
		(0.010)			(0.010)	(0.010)	(0.004)
Same "Level-below-SVP"		-0.021 **			-0.020 **	-0.025 ***	-0.023 ***
		(0.011)			(0.011)	(0.009)	(0.006)
Same "2 Levels-Below-SVP"		0.087 ***			0.053 ***	0.047 ***	0.039 **
		(0.021)			(0.020)	(0.017)	(0.017)
Overlapped on project?		0.006			0.001	-0.010	-0.004
		(0.012)			(0.012)	(0.011)	(0.006)
Social connection							
# of overlapping email lists			0.0005		0.0012	0.0013 *	0.0014 ***
			(0.0006)		(0.0009)	(0.0008)	(0.0005)
Self-reported professional relationship?			0.054		0.040	0.098 **	0.049
			(0.046)		(0.041)	(0.042)	(0.034)
Self-reported friendship?			0.011		-0.082	-0.050	-0.026
			(0.051)		(0.055)	(0.057)	(0.031)
Reviewed each other's code			0.0010 *		0.0006	0.0005	0.0004
			(0.0006)		(0.0006)	(0.0006)	(0.0004)
Demographic overlap							
Demographic Control #1				-0.110 *	-0.118 **	-0.074 *	-0.072 *
				(0.057)	(0.050)	(0.045)	(0.039)
Same undergrad school				0.041	0.014	0.048	0.002
				(0.062)	(0.067)	(0.065)	(0.053)
Same coder status				0.016 *	0.022 **	-0.002	0.013 *
				(0.009)	(0.009)	(0.009)	(0.007)
Same undergrad major				0.009	0.011	0.025 *	0.026 ***
				(0.015)	(0.014)	(0.013)	(0.007)
Demographic Control #2				0.006	0.011 *	0.020 ***	0.009
				(0.008)	(0.006)	(0.008)	(0.007)
Demographic Control #3				-0.032 ***	-0.043 ***	-0.047 ***	-0.059 ***
				(0.008)	(0.009)	(0.010)	(0.009)
Both native English speakers				0.016	0.004	0.002	-0.005
				(0.013)	(0.011)	(0.011)	(0.007)
Common non-English native language				1.071 **	1.066 **	0.549 **	0.872 ***
				(0.419)	(0.423)	(0.256)	(0.286)
Other controls							
Trade fixed effects	X	X	X	X	X	X	X
Initial position	X	X	X	X	X	X	X
Trader characteristics						X	
Trader fixed effects							X
Observations	141,412	141,412	141,412	141,412	141,412	141,412	141,412
R-squared	0.0609	0.0612	0.0566	0.0614	0.0733	0.1346	0.2307

Notes: Independent variables are the sum of the pre-trade position of a trader's colleagues, weighted by the variable given (e.g., an indicator for whether the two traders are in the same city). Coefficients are multiplied by 1,000. Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Table 11. Determinants of trading correlations

Dependent variable: = 1 if buying, -1 if selling

Independent variables: Proximity-weighted sums of signs of colleagues' pre-trade positions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Geographical proximity							
Same city	-0.141 ***				-0.110 ***	-0.103 ***	-0.085 ***
	(0.021)				(0.019)	(0.019)	(0.022)
Same building	0.021				0.011	0.013	0.025 **
	(0.024)				(0.018)	(0.018)	(0.013)
Same floor	-0.029				-0.022	-0.005	-0.009
	(0.023)				(0.019)	(0.018)	(0.014)
Same office	-0.021				-0.037	-0.031	-0.019
	(0.042)				(0.049)	(0.046)	(0.045)
Proximity on floor (10/distance in feet)	0.416 ***				0.245 ***	0.295 ***	0.247 ***
	(0.085)				(0.080)	(0.086)	(0.072)
Organizational proximity							
Same SVP (one level below CEO)		-0.083 ***			-0.025	-0.028	-0.034 **
		(0.013)			(0.017)	(0.018)	(0.017)
Same "2-Levels-below-CEO" manager		-0.006			-0.019	-0.027	-0.029
		(0.019)			(0.020)	(0.020)	(0.018)
Same "3-Levels-below-CEO" manager		0.141 ***			0.089	0.108 **	0.109 **
		(0.055)			(0.055)	(0.054)	(0.051)
Overlapped on project?		0.048 ***			0.033 **	0.010	0.013
		(0.015)			(0.014)	(0.014)	(0.013)
Social connection							
# of overlapping email lists			-0.004 ***		0.007 ***	0.006 ***	0.005 **
			(0.001)		(0.002)	(0.002)	(0.002)
Self-reported professional relationship?			0.075 **		0.102 ***	0.101 ***	0.042
			(0.032)		(0.033)	(0.032)	(0.048)
Self-reported friendship?			-0.058		-0.141 **	-0.100 *	-0.033
			(0.057)		(0.059)	(0.055)	(0.054)
Reviewed each other's code			0.0012 ***		0.0001	0.0003	0.0001
			(0.0003)		(0.0002)	(0.0002)	(0.0002)
Demographic overlap							
Demographic Control #1				-0.050 *	-0.069 ***	-0.054 **	-0.029
				(0.026)	(0.025)	(0.022)	(0.018)
Same undergrad school				-0.050	-0.068	-0.047	-0.036
				(0.052)	(0.058)	(0.053)	(0.051)
Same coder status				-0.021	-0.003	-0.039 **	-0.020
				(0.014)	(0.015)	(0.018)	(0.014)
Same undergrad major				-0.006	-0.012	-0.011	-0.008
				(0.017)	(0.015)	(0.014)	(0.010)
Demographic Control #2				-0.046 ***	-0.035 ***	-0.008	-0.012
				(0.012)	(0.011)	(0.008)	(0.008)
Demographic Control #3				-0.115 ***	-0.113 ***	-0.116 ***	-0.114 ***
				(0.025)	(0.023)	(0.023)	(0.019)
Both native English speakers				-0.030 **	-0.036 ***	-0.019	-0.012
				(0.014)	(0.013)	(0.013)	(0.011)
Common non-English native language				0.340 **	0.378 ***	0.298 ***	0.197 **
				(0.133)	(0.110)	(0.099)	(0.080)
Other controls							
Trade fixed effects	X	X	X	X	X	X	X
Initial position	X	X	X	X	X	X	X
Trader characteristics						X	
Trader fixed effects							X
Observations	141,412	141,412	141,412	141,412	141,412	141,412	141,412
R-squared	0.0806	0.0609	0.049	0.0908	0.1193	0.1621	0.2858

Notes: Independent variables are the sum of the signs of the pre-trade positions of a trader's colleagues, weighted by the variable given (e.g., an indicator for whether the two traders are in the same city). Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Table 12. Timing of geographical proximity effects
Dependent variable: = 1 if buying, -1 if selling
Independent variables: Proximity-weighted sums of signs of colleagues' pre-trade positions

	(1)		(2)		(3)	
Geographical proximity (beginning of week of trade)						
Same city	-0.003		-0.024		-0.053	
	(0.062)		(0.060)		(0.053)	
Same building	0.051	**	0.035		0.039	**
	(0.023)		(0.022)		(0.018)	
Same floor	-0.116	***	-0.102	***	-0.059	***
	(0.031)		(0.030)		(0.021)	
Same office	0.233	***	0.200	***	0.103	
	(0.078)		(0.076)		(0.066)	
Proximity on floor (10/distance in feet)	-0.114		-0.098		-0.098	
	(0.123)		(0.112)		(0.091)	
Geographical proximity (13 weeks before trade)						
Same city	-0.109	*	-0.063		0.005	
	(0.059)		(0.055)		(0.047)	
Same building	-0.026		0.009		0.012	
	(0.027)		(0.028)		(0.022)	
Same floor	0.066	*	0.060	**	0.023	
	(0.034)		(0.030)		(0.018)	
Same office	-0.311	***	-0.262	***	-0.166	***
	(0.101)		(0.082)		(0.064)	
Proximity on floor (10/distance in feet)	0.522	***	0.336	***	0.397	***
	(0.127)		(0.098)		(0.084)	
Geographical proximity (13 weeks after trade)						
Same city	-0.030		-0.025		-0.038	
	(0.040)		(0.037)		(0.032)	
Same building	-0.024		-0.045	*	-0.034	**
	(0.031)		(0.026)		(0.016)	
Same floor	0.067	*	0.062	*	0.048	**
	(0.039)		(0.032)		(0.024)	
Same office	0.077		0.039		0.076	
	(0.131)		(0.110)		(0.103)	
Proximity on floor (10/distance in feet)	0.166		0.065		0.075	
	(0.109)		(0.104)		(0.086)	
Controls						
Trade fixed effects	X		X		X	
Initial position	X		X		X	
Org, social, demographic similarity			X		X	
Trader fixed effects					X	

Notes: Independent variables are the sum of the signs of the pre-trade positions of a trader's colleagues, weighted by the variable given (e.g., an indicator for whether the two traders are in the same city). Standard errors are heteroskedasticity robust and adjust for clustering of outcomes within person.

Table 13. Regressions predicting which security a pair of traders will trade based on positions of geographically proximate colleagues

Dependent variable: = 1 if buying, 0 if not trading, -1 if selling

Independent variables: Proximity-weighted sums of colleagues' pre-trade positions

	(1)		(2)	
Net positions of proximate colleagues				
Same city	-0.0093		-0.0009	
	(0.0105)		(0.0007)	
Same building	0.0320		0.0000	
	(0.0206)		(0.0005)	
Same floor	-0.0330	*	-0.0002	
	(0.0195)		(0.0005)	
Same office	0.0016		-0.0009	
	(0.0223)		(0.0008)	
Proximity on floor (10/distance in feet)	0.1780	***	0.0181	*
	(0.0466)		(0.0105)	
Observations included				
Buys	X		X	
Securities not bought by buyer			X	
Sells	X		X	
Securities not sold by seller			X	
Fixed effects	Trade		Trade*security	
Observations	141,412		8,438,033	
R-squared	0.1304		0.0846	

Note: Column 1 replicates Column 1 from Table 10, and predicts which of side of the trade the two traders were on. Column 2 predicts which of the available securities the buyer-seller pair traded, as well as which side of the trade each trader was on. Coefficients and standard errors are multiplied by 1,000. Standard errors are heteroskedasticity robust and adjust for correlations. Regressions control for traders' initial positions.