IPO Information Aggregation and Underwriter Quality*

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Abstract

A key distinction between some models of IPO pricing (e.g., auctions and bookbuilding) and others (e.g., fixed-priced models) is whether price discovery occurs in the primary market or the secondary market. We show that higher investment bank reputation is associated with 1) more active filing price revisions and 2) reduced secondary market return variability. In fact, file price revisions of non-reputable banks show strong clustering on exactly zero dollars. Hence, reputable underwriters resolve a greater proportion of uncertainty before the issue goes public. Finally, the well-documented "partial adjustment" phenomenon – often attributed to information aggregation – is almost exclusively due to the behavior of reputable underwriters. Taken together, this evidence suggests that theoretical models of primary market information aggregation are better suited for reputable underwriters.

1 Introduction

IPO auction and bookbuilding models emphasize the economic importance of information flows from investors to the issuer (or underwriter) during the pre-IPO phase. The importance of these flows is motivated as follows. Information asymmetry among investors creates a winner's curse and depresses prices (Rock, 1986). A rational response, therefore, is to design a mechanism to extract private information before the price is set, thereby mitigating the winner's curse.

Any such mechanism entails costs. The question then becomes which is cheaper: designing a pre-IPO mechanism to extract and aggregate this information (e.g., Benveniste and Spindt, 1989) or simply bearing the adverse selection costs (e.g., Rock, 1986)? Equivalently: *is price discovery more efficient in the primary market or in the secondary market?*

We study primary market information aggregation by looking at price revisions, defined as the percentage change from the midpoint of the original filing price range to the final IPO offer price. In the U.S., this period fully captures the impact of the underwriter's bookbuilding efforts because soliciting investor opinions before the initial filing range is set is prohibited by the Securities Act of 1933.[1] Obviously, information revealed by investors may be either good or bad news, and so this price discovery process leads to dispersion in price movements. (Without new information, there is no reason for prices to change.) In that spirit, our primary methodology is to compare cross-sectional variability in price movements during the bookbuilding phase to that of the secondary market. By doing so, we hope to shed light on how much information is aggregated in primary markets rather than secondary markets.

Our first observation is that reputable underwriters revise their filing prices more aggressively. This is a very robust and dramatic feature of our data. For example, across IPOs underwritten by low-quality banks (Carter-Manaster ranking below 6.75) the standard deviation of observed price pre-IPO revisions (the change from the midpoint of the initial filing price range to the final offer price) is 17.0%. For reputable banks

[1] Note that this research design is not replicable for most European IPOs, for which investment banks solicit investor opinions before the initial price range is set (Jenkinson, Morrison and Wilhelm, 2005).

(Carter-Manaster ranking above 8.5) this standard deviation is 28.1%. Thus price revisions are 65% more variable for reputable banks.

Perhaps more dramatically, low-quality banks exhibit strong clustering on price changes of *exactly zero*. For underwriters of Carter-Manaster rank five and lower, a revision of zero occurs nearly half the time. For underwriters of rank nine this event occurs only 11% of the time. This frequency decreases monotonically in underwriter reputation ranking. Clearly, a price revision of zero is consistent with no important information being revealed during bookbuilding. Overall, our evidence suggests that reputable underwriters acquire information much more actively during the bookbuilding phase and incorporate that information into the price.

Price discovery in the primary market should substitute for price discovery in the secondary market. Hence, given the strong difference in primary market pattern mentioned earlier, one might expect reduced aftermarket volatility for IPOs taken public by reputable underwriters. Indeed, we find support for this hypothesis in most subperiods in our sample. (The IPO bubble is a prominent exception; this is discussed in greater detail in Section 3.2) This univariate evidence is of limited power, however, since reputable and non-reputable underwriters issue very different types of IPOs. Offerings by reputable underwriters are much more likely to be high-tech and venture capital backed, among other differences.

We control for these differences in two ways. We employ the standard firm characteristic controls (size, age, VC backing, etc.) in our regressions. These controls are insufficient, however, if the asymmetric information profile of firms approaching high and low quality underwriters is different.[2]

For our main test, we are interested in the *relative* return variability in the primary and secondary markets, i.e. not how much total information is aggregated, but rather *when* this aggregation occurs (before vs. after the issue goes public). In this spirit, we form the following ratio: cross-sectional variability of secondary market returns divided by cross-sectional variability of price movements in the primary market (i.e., percentage

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[2] In principle, this effect could go either direction. Certification reduces risk, ceteris parabus. On the other hand, firms with high ex-ante risk (but correspondingly high expected returns) have the strongest incentive to seek certification. If certification is imperfect then ex-post risk may still be higher for reputable underwriters.

change from the filing range midpoint to the offer price). This ratio functions as an additional control for unobservable differences, because heightened ex-ante asymmetric information inflates both the numerator and the denominator.

Reputable underwriters have lower variance ratios in the full sample and in every five-year subperiod. Hence, a greater proportion of this risk is resolved in the primary market rather than the secondary market when a reputable bank is employed.

While the variance ratio results indicate differences in the amount of information aggregation, they are silent on the actual price discovery mechanism employed. Here the literature offers guidance, as well as an additional testable implication. Benveniste and Spindt (1989) model predicts that IPO prices should only partially adjust to information revealed in the primary market. Their intuition is as follows. Investors realize that divulging good information leads to higher prices. Naturally, this makes it difficult to extract favorable information. To counteract the incentive to hide positive information, the underwriter adjusts prices by less than warranted when good information is revealed. Consequently, file price revisions and initial returns should be positively correlated.

In the context of our aforementioned results – high-quality underwriters are more active in the information aggregation role – this paradigm predicts more pronounced partial adjustment for reputable underwriters.[3]

We find strong support for this hypothesis. The correlation between file price revisions and underpricing is .430 for underwriters in the top tercile (Carter-Manaster rank above 8.5) but only .141 for underwriters in the bottom tercile (Carter-Manaster rank below 6.75). A correlation of .141 corresponds to an R^2 of less than 2% so that there is effectively no relation between the two variables, which is consistent with Rock's model rather than that of Benveniste and Spindt. We conclude that the partial adjustment noted by the literature in the cross-section is almost exclusively due to the behavior of reputable underwriters. Consistent with our variance ratio results, this evidence suggests the information acquisition paradigm is better suited for reputable underwriters.

One potential complication is that IPO prices tend to partially adjust to public information as well as private information. This empirical regularity is not an implication

[3] Public information is revealed during the bookbuilding period as well. In Section 2.1, we discuss how this public component is factored out in order to isolate private information.

of Benveniste and Spindt's model. Disagreement over both the magnitude and interpretation of these results constitutes one of the most active areas of current IPO research.[4] However, resolving this puzzle is outside the scope of the current analysis, which instead focuses on the extent to which *private* information is incorporated in the primary market rather than the secondary market. That is, our research question addresses the asymmetric information problem caused by investors' private information rather than the ability of a given sale mechanism to react to public information. Partial adjustment to public information therefore acts as a control variable in our analysis rather than a variable of direct interest.

The plan of the paper is as follows. In Section 2, we describe the data and the methodology. Section 3 summarizes the evidence of price revisions and variance ratios. Section 4 repeats the variance ratio analysis using each underwriter (rather than each IPO) as the unit of observation. Section 5 examines how partial adjustment to private information varies with underwriter quality. Section 6 concludes.

2 Data and Methodology

The data for this study was drawn from the Thompson SDC database and consists of initial public offerings of equity for the period 1980 through 2006. We exclude unit offers, ADRs, REITs, limited partnerships, closed-end funds and IPOs with an offer price lower than five dollars. Information for each IPO was collected regarding the initial filing range, the offer price, the number of shares sold, the identity of the underwriter, whether the firm was backed by a venture capitalist or not, and whether the firm operates in a high-tech industry or not. The above sample is supplemented with a hand-collected dataset of IPOs from 1980 to 1984, available from Jay Ritter's website. In the case of overlapping observations (e.g., an IPO in both datasets), Ritter's data enables us to backfill missing variables in SDC. Whenever there is disagreement on a variable, we use Ritter's value.

[4] Bradley and Jordan (2002) take it as evidence against the efficiency of the IPO process; partial adjustment is, after all, a literal violation of weak-form market efficiency. Loughran and Ritter (2002), Ljungqvist and Wilhelm (2005) and Ince (2007) emphasize the agency problem between issuers and banks. Edelen and Kadlec (2005) develop a tradeoff model based on the relative costs of going public and staying private, in which issuers may rationally choose higher underpricing given positive shocks to public comparables.

We supplement the dataset with the Carter-Manaster reputation rank of each underwriter and age of the firm, both of which are obtained from Jay Ritter's website. Carter-Manaster ranks range from 1 (lowest quality) to 9 (highest quality), and Ritter's website evaluates these ranks over separate time periods. When an IPO is underwritten by multiple lead underwriters, we average the reputation of all involved banks, though rank differences are typically small. In what follows, we use "high-reputation" and "high-quality" interchangeably.

We merge this database with CRSP in order to compute monthly returns, excluding those IPOs which lack data in six months or more during the first 12 months following the offering. When time-series volatility is studied, we use daily prices instead, also extracted from CRSP. Our final sample consists of 7,124 completed offerings.

In addition, we extract the deal characteristics (including underwriter identification) for 1,700 withdrawn IPOs for the same period. This inclusion is important in our study because we focus on the information revealed during bookbuilding. Clearly this information is correlated with the decision to continue or withdraw, and so our completed offering sample suffers from a censoring problem. Section 5 discusses Heckman's (1976, 1979) two-step procedure employed to address this censoring.

We order our sample by (average) underwriter rank. IPOs are grouped into one of three categories: average rank 8.5 or higher, rank between 6.75 and 8.5 and rank below 6.75. These breakpoints divide our sample into three nearly equal subsamples. (Because of integer problems in underwriter ranking, there is no other division that splits our sample more evenly.) Our results are qualitatively similar with other divisions.

2.1 Pre-IPO Price Revisions

For each IPO, we calculate the offer price's deviation from the midpoint of the filing range as follows

$$PREV = \frac{OfferPrice - MidFile}{MidFile} \tag{1}$$

where *MidFile* represents the midpoint of the initial filing price range. This is the standard definition of pre-IPO price revision (e.g., Hanley, 1993). An alternative definition uses the dollar-value filing price range width as the denominator in (1) to account for the possibility that the filing range spread is associated with ex-ante level of uncertainty (Cornelli & Goldreich 2003). Our results under this measure are significantly stronger than our reported results, although we view this difference as an artifact of low-quality underwriters' lower average offer prices rather than a true economic effect.[5]

Obviously, part of this price revision is due to public information. Following Edelen and Kadlec (2005) we calculate the average return of firms in the same Fama-French 48 industry (*COMPS*) between the filing date and the offer date as a proxy for publicly observable changes in valuation. We also employ the average underpricing of all IPOs in the 30 days preceding the offer date as a measure of overall IPO activity (*IPOHeat*) following Bradley and Jordan (2002). *IPOHeat* is orthogonalized against *COMPS* in order to isolate the information coming from the IPO market specifically rather than the overall heat of the equity markets. Finally, *PREV* is orthogonalized against both *COMPS* and *IPOHeat* to obtain a measure (*REV*) that isolates the private information revealed by bookbuilding.

Earlier drafts of this paper used raw price revisions *PREV* rather than public-information-adjusted revisions *REV*. The results are similar.

2.2 Holding Period Horizons

Our methodology requires us to specify a time by which price have incorporated pre-IPO private information. Several institutional factors contribute to the inefficiency of early aftermarket prices. First, lead underwriters engage in price support during the first month or so of trading (Aggarwal, 2000). Second, IPOs are difficult to short-sell in the immediate aftermarket (Loughran and Ritter, 1995). Third, underwriters employ a system known as the Depository Trust Company's (DTC) tracking system which aims to discourage investors from "flipping" the stock. All of these institutional features tend to impede the price discovery role of the market.

These institutional features are particularly troublesome in the current setting. Price support truncates the return distribution at zero, which tends to reduce dispersion,

[5] Note that $\frac{Offer - Mid}{Hi - Lo} = \frac{Offer - Mid}{Mid}\frac{Mid}{Hi - Lo}$, and the last fraction is smaller for low-quality underwriters. Low-quality underwriters therefore have even smaller price revisions under this alternative measure than under the reported measure.

our main variable of interest. As a result, secondary market dispersion may vary with underwriter quality *even without differences in primary market price discovery*. This reinforces the notion that very short horizons might be inappropriate for our purposes.[6]

On the other hand, estimates of long-run abnormal returns are noisy (Kothari and Warner, 1997). Moreover, much of the variation occurring at very long horizons is unrelated to ex-ante private information of IPO investors, which is the information of interest in the current study. To balance these tradeoffs, we focus on buy-and-hold returns at 3-month horizons. We also present results at 6-month horizons as a robustness check. Other drafts of the paper have employed 1-month and 12-month horizons as additional robustness checks, with broadly similar results.

2.3 Cross-Sectional Variance in Aftermarket Returns

For our cross-sectional results, we use monthly CRSP returns. The abnormal return for stock *i* at month *T* is defined as

$$BHAR_{iT} = \prod_{t=1}^{T}(1+r_{it}) - \prod_{t=1}^{T}(1+m_{it}) \qquad (2)$$

where r_{it} denotes the return on stock *i* in month *t*, and m_{it} denotes the return on the market (proxied by the CRSP stock file value-weighted market index) at time *t*. Here the implicit assumption is that the market serves as a reasonable measure of expected return for stocks in our sample. Our cross-sectional results are insensitive to the choice of benchmark, however. We note that the benchmark choice is more critical for event studies that focus on the mean rather than (as in our case) the variance, because nearly all of our cross-sectional variance is firm-specific rather than driven by the benchmark.

3. Main Results

Table 1 presents descriptive statistics for the full sample, and for the three terciles of new issues sorted by underwriter's reputation ranking. The summary statistics indicate

[6] Van Bommel, Dahya, and Shi (2006) argue that most private information is incorporated within a few days. The possibility that price support practices systematically vary with underwriter quality is irrelevant in their setting because they study information aggregation in the cross-section. On the other end of the spectrum, Ellul and Pagano (2006) employ horizons of 40 weeks and Boehmer, Boehmer and Fishe (2006) argue that private information may persist for as long as two years.

that reputable underwriters are more likely to offer IPOs that are venture capital backed and in high-tech industries. Their issues are older on average and tend to raise larger proceeds than other IPOs. Taken together, these variables have an ambiguous impact on the severity of asymmetric information across terciles: firm size and seasoning should mitigate market imperfections whereas high-tech industry affiliation may increase them.

Price revisions relative to the original filing price range, both in raw form (*PREV*) and public-information-adjusted form (*REV*), are approximately symmetrically distributed around zero in the full sample. The median value of unadjusted price revisions *PREV* is exactly zero for all three quality terciles.

The absolute value of price revision increases monotonically with bank reputation. The mean absolute value of price revision is 0.161 for firms taken public by high-quality underwriters, but only 0.110 for those by low-quality underwriters. This preliminary evidence is consistent with the notion that high-quality underwriters are more active in aggregating information in the bookbuilding period.

Consistent with Beatty and Welch (1996), Cooney, Singh, Carter and Dark (2001), Habib and Ljungqvist (2002), and Kumar, McGee and Womack (1998), we find that reputable underwriters are associated with higher average underpricing than low-quality underwriters (25.2% vs. 11.8%). Initial returns are highly skewed: median underpricing is between 5.4% and 8.7% in the three terciles.

Mean BHARs are near zero in our sample. Our three-to-six month horizons are too short to capture the long-run underperformance identified by the literature; this pattern emerges around twelve months. However, consistent with previous literature (Brav and Gompers, 1997), the aftermarket performance of IPOs with reputable underwriters is superior. The mean 6-month *BHAR* for top-tercile underwriters is 3.9% and for bottom-tercile underwriters is – 4.3%.

3.1 Variance Ratios

Our main test statistic is a "variance ratio" constructed as follows. We consider the subsample of IPOs underwritten by reputable banks, and construct *REV* and *BHAR* measures for each observation (i.e., each IPO). We then take the standard deviation across all observations in that subsample to obtain σ(REV) for high-quality banks. We compute σ (*BHAR*) in a similar manner. The variance ratio (*VR*) is defined as the ratio of these two numbers. *VRs* for the other two terciles are computed similarly.

As discussed in the introduction, we expect lower *VRs* for reputable underwriters. The reason is that price changes should be modest during periods in which no new information arrives, but highly variable during periods of significant price discovery. Ceteris parabus, therefore, primary market information aggregation will tend to inflate σ (*REV*). It will also tend to deflate σ (*BHAR*) because issue quality revealed by primary market need not be re-discovered by the secondary market. Both the numerator effect and denominator effect tend to reduce *VR*.

Our evidence strongly confirms this hypothesis. As Table 2 indicates, reputable banks have lower variance ratios in the full sample and in each 5-year subperiod. For example, during 1980-1984 the 3-month VR for reputable underwriters was 1.186, versus 2.718 for low-quality underwriters. We employ bootstrapping to measure the statistical significance of this result. Specifically, we randomly place IPOs into three terciles (regardless of their true underwriter quality). For each synthetic group we compute the variance ratios and then record the differences in variance ratio across the random groups. We repeat the above steps 1,000 times to derive an empirical distribution of differences in variance ratios between the two synthetic subsamples.

Similar results hold in the full sample and in each subperiod, though not always with significance. In particular, the gap between the *VRs* of reputable and non-reputable underwriters becomes noticeably smaller (though of the same direction) during the two periods associated with the tech boom and its subsequent collapse, that is, 1995-1999 in Panel E and 2000-2006 in Panel F. We suspect that the narrowing of this *VR* gap is driven mainly by the bubble period's anomalously high σ (*BHAR*) of tech firms, which were disproportionately underwritten by reputable banks. Table 2, Panels G and H, confirm this intuition. Removing tech firms from these two subperiods magnifies the difference between the *VR* of low-quality and high-quality underwriters.

Overall, lower variance ratios for reputable underwriters appear to be a very robust feature of our data set. We conclude that reputable underwriters resolve a greater proportion of uncertainty in the primary markets.

3.2 Is the VR Result Due to the Numerator or the Denominator?

We now consider the components of *VR*, σ(*BHAR*) and σ(*REV*), and ask which factor drives our variance ratio results.

Turning first to σ(REV), Table 2 Panel A shows a dramatic difference: in the full sample, the cross-sectional standard deviation of price revisions is 17.0% for low-quality banks and 28.1% for high-quality banks. The pattern repeats in every subperiod as well, and is always significant at the 1% level. The result also holds for a variety of untabulated robustness checks: using raw price revisions (*PREV*) rather than public-information adjustment price revisions, and partitioning the sample either into tech and non-tech offerings or into VC-backed on non-VC backed offerings.

In fact, low-quality underwriters often leave their prices literally unchanged during the course of bookbuilding. Table 3 considers the event that raw price revisions *PREV* are exactly zero. For underwriters with a Carter-Manaster rank between 2 and 3 this event occurs 50.97% of the time. This clustering on zero is very strong for underwriters of rank five and below, smoothly decreasing thereafter. For top-tier underwriters (rank nine) it is a rare event, occurring only 11.09% of the time.

Turning to σ(*BHAR*), there is a more nuanced pattern. Except for those periods overlapping the tech bubble of 1999-2000, reputable banks are associated with reduced dispersion in aftermarket return variability. For example, in the 1980-1984 subperiod, low-quality banks had σ(*BHAR*) =34.3% using the 3-month horizon, versus only 22.0% for high-quality banks. Hence the reduced *VRs* for reputable underwriters in a typical subperiod owes to both reduced numerator and inflated denominator. (Here the numerator and denominator effect happen to have roughly equal contributions.)

Despite lower σ(*BHAR*) in most subperiods, reputable banks are actually associated with *higher* σ(*BHAR*) in the full sample. This puzzling reversal is at least partly explained by a Simpson's paradox effect. To see why, note that return variability was dramatically higher during hot markets, consistent with Yung, Colak and Wang's (2008) argument that hot markets are associated with a heightened adverse selection problem. For example, for high-quality underwriters, the standard deviation of 3-month *BHARs* is 66.5% during the 1995-1999 period compared to only 25.1% a decade earlier during 1985-1989. On the other hand, there was a strong substitution towards high-quality underwriters during this hot market (compare the number of observations in each subgroup in Panel E to that of Panel B, for example). Hence, even though high-quality underwriters are associated with lower variance in most subperiods, it appears in the full sample as if they are associated with higher variance partly because they were more active during the bubble.

To reinforce the notion that this effect was due more to "substitution" rather than a true change in the economic role of reputable underwriters during the bubble, consider Table 2, Panels G and H. Here we note that removing tech firms from these anomalous 1995-1999 and 2000-2006 periods restores the historical ordering of σ (BHARs) between low-quality and high-quality underwriters. For example, the cross-sectional variability of 3-month *BHAR*s during 1995-1999 was 34.5% for low-quality underwriters but only 30.9% for high-quality underwriters. With this removal, the ordering is uniform across all horizons and in all subperiods.

To summarize, reputable underwriters have lower variance ratios in every subperiod and in the full sample. Subperiod analysis indicates that this effect is typcially due both the numerator and the denominator of the variance ratio. However, a "changing composition" (or Simpson's paradox) effect plays a role in reputable underwriters being associated with higher σ (*BHAR*) in the full sample.

3.3 Time Series Volatilities

In this subsection, we conduct an analysis similar to that of Section 3.2 but using time-series volatility rather than a cross-sectional measure. Again the argument is that primary market price discovery should reduce secondary market risk.

The advantage to this approach is that it allows us to directly control for firm characteristics since each IPO has a volatility measure. (In contrast, for the section 3.2 results, each IPO has only a realized *BHAR*; the variability measure must then be computed across all IPOs in the tercile.) The disadvantage is that we do not have a time series measure of pre-market price adjustments. We are thus unable to offer a time-series analog of the variance ratio. As such, these results serve as a robustness check of our σ (*BHAR*) results, not of our main *VR* tests.

Our methodology is as follows. We use the Fama-French-Carhart four-factor model, estimating factor loadings for each IPO using the first 1200 daily observations (or as many are available, if fewer than 1200). We compute abnormal daily returns as the residuals of the non-intercept Fama-French-Carhart four-factor model. The market, size, value and momentum factor are all from Kenneth R. French's website. The first trading day is excluded.

Table 4 displays the average of aftermarket return volatility of IPOs in the top and bottom terciles of underwriter quality. The results echo our cross-sectional conclusions. That is, reputable banks are associated with reduced volatility in every subperiod except those overlapping the bubble. Yet this one subperiod reversal is so dramatic – and there is such a strong substitution toward reputable underwriters during this hot period – as to cause higher volatility in the full sample. Hence the full sample statistics appear to contradict the behavior of a typical subperiod. Panels G through I demonstrate that removing tech stocks from this subperiod reverses this anomalous result, so that both the full sample and all subperiods show a uniform relationship between reputation and secondary market risk.

Table 5 summarizes the multivariate version of this test. We regress aftermarket volatility on bank reputation and a variety of firm characteristics. The results are as expected. VC-backed and high-tech firms are riskier. Larger and older firms are less risky. The coefficients of bank reputation are significantly negative, consistent with the hypothesis that primary market information aggregation reduces secondary market risk.

4. Results Using Each Investment Bank as an Observation

This section considers a variant of the tests in Section 3.1 using each bank (rather than each IPO) as the unit of observation. Specifically, for a given bank, we measure the buy-and-hold return on each of its offerings and then compute the cross-sectional variance of these returns. We then compute the cross-sectional variance of the pre-IPO price revisions of these same offerings. Finally, we define the "variance ratio" of this bank to be the ratio of these two numbers. To ensure reasonably stable estimates we keep in our sample only underwriters with more than 5 offerings.[7] Using the same Carter-Manaster tercile cutoffs of 6.75 and 8.5 described in Section 2, we are left with 35 high-quality banks, 47 medium-quality and 129 low-quality banks. Finally, we compute the descriptive statistics of variance ratios of banks within each tercile, i.e. the average variance ratio for reputable banks, and so on.

Untabulated examination shows the variance ratios thus obtained are highly skewed. In all three terciles, the skewness of variance ratios is an order of magnitude larger than mean, median or standard deviation. Therefore, subsequent statistical analysis employs the natural logarithm of the variance ratio for each bank.

Table 6 summarizes the statistical significance of the differences in log variance ratios for the full sample. Low-quality underwriters have higher ratios than either other terciles, and this difference is significant at both horizons. Thus, the results of Section 3.2 are robust to using banks as the unit of observation.

In untabulated results, we also consider the possibility that underwriter reputation is the endogenous result of issuer firm characteristics and use a two-stage least-squares procedure to estimate the model. Again we obtain significant, negative coefficients for bank reputation.

Table 7 summarizes the results of an OLS regression estimating the determinants of banks' variance ratios. The control variables are the average of characteristics of IPOs offered by each bank. As expected, the coefficient on reputation is significantly negative.

The coefficients on the other control variables are of independent interest. Recall our argument in the introduction that variance ratios serve as an additional control for difference in firm types across underwriter terciles. Specifically, we claim that if one tercile is associated with heightened uncertainty, this risk should inflate both the numerator and denominator of the VR. It follows that firm characteristics should not load in this regression. As Table 7 shows, these coefficients are indeed typically insignificantly different from zero; firm age has only borderline significance.

[7] Far fewer observations are needed to estimate second moments than first moments. Previous drafts of the paper variously used either a cutoff of seven and/or winsorized returns at the 1% level to control for outliers. These approaches cause little qualitative change, although increasing the minimum observation threshold reduces the number of low-quality banks in the sample.

5. Partial Adjustment as a Function of Underwriter Quality

Our final hypothesis is that the partial adjustment to private information is more pronounced for prestigious underwriters. This prediction will hold provided that they act in the costly information extraction role suggested by Benveniste and Spindt (1989), while low-quality underwriters play a purely distributional role as in Rock (1986).

Note that the tests in the section involve the joint hypotheses 1) reputable banks are more effective in primary market information aggregation, and 2) Benveniste and Spindt's model is a useful description of *how* this aggregation occurs. In contrast, the evidence in Sections 3 and 4 pertains only to the first of these hypotheses.

Table 8 offers preliminary but powerful evidence on this relationship. We partition the sample according to the Carter-Manaster reputation of the underwriter. When this rank is below 5 (there are 1063 such offers) there is virtually zero correlation between price revisions and underpricing. Thus, the partial adjustment observed by Hanley (1993) is degenerate.

This zero correlation is consistent with Rock (1986) rather than Benveniste and Spindt (1989), and such an interpretation holds intuitive appeal. One might characterize low-quality underwriters as structuring a mechanism that is effectively a fixed-price sale (even if the offer might be technically classified by academic studies as bookbuilding). Without the resources to extract private information in a cost-effective way, low-quality underwriters may instead simply set an offer price based mechanically on the value of public comparables, letting the secondary market bid the issue to its true value.

As the table shows, this correlation rises in a nearly monotonic way as quality increases. For underwriters ranked nine, the correlation is .490, corresponding to a high degree of predictability. This confirms Benveniste and Spindt's prediction. In conjunction with our variance evidence, this pattern reinforces the view that reputable underwriters act in the costly information acquisition role posited by Benveniste and Spindt.

A more formal investigation of this relationship involves the regression of underpricing on REV as well as firm-specific risk proxies, as in Hanley (1993). As Edelan and Kadlec (2005) point out, this estimation needs to account for censoring of the sample. In particular, underpricing is observed only when the offer is completed, yet the decision to withdraw (or not) is correlated with the information revealed during bookbuilding, and therefore *REV*.

To address this issue, we employ a Heckman (1976, 1979) two-stage procedure.[8] In the first stage, we use the full sample (including both completed and withdrawn IPOs) to run the following Probit regression,

$$I_w = \alpha_0 + \alpha_1 COMPS^+ + \alpha_2 COMPS^- + \alpha_3 WRate + \alpha_4 \operatorname{Re} pu + \alpha_5 AmtFile + \varepsilon \qquad (3)$$

where I_w equals 1 for withdrawn offerings and 0 for completed offerings. $COMPS^+$ equals *COMPS*, the equally-weighted return of listed firms in the same Fama-French 48 industry during the bookbuilding period, if *COMPS* >0, and 0 otherwise; $COMPS^-$ equals *COMPS* if *COMPS* < 0, and 0 otherwise. $COMPS^+$ and $COMPS^-$ together capture the market movement and account for potential asymmetric impact of positive and negative market movements on the IPO withdrawal/completion decision..

The IPO withdrawal rate, *Wrate*, is computed as the number of IPO withdrawals within 106 days (the median length of registration period in our sample) of filing, divided by the number of active IPOs under registration during the 30 days preceding the offer or withdrawal date. We orthogonalize *Wrate* with respect to *COMPS* and use the residual *WRate* in order to isolate the spillover information from activity in the withdrawn IPO market. *Repu* and *AmtFile* are lead underwriters' (average) reputation ranking and the issuing firm's amount filed. Finally, for each IPO we compute the inverse Mills ratio λ (sometimes called "selection hazard") implied by the above probit estimation.

Table 9 summarizes an OLS estimation of the determinants of underpricing. The control variables include the filing amount, firm age, dummy variables indicating whether the firm was VC-backed or in a high-tech industry, as well as the inverse Mills ratio λ from the first stage regression. The coefficients on these control variables, as well as the probit estimate itself, are not of direct interest and so are unreported. The key variables of interest are those involving *REV*. (We tabulate the coefficients on *COMPS* and *SPILLOVER* only to demonstrate that our sample does exhibit partial adjustment to public information, as in previous literature.)

[8] Our statistical model of the withdrawal decision, and much of the associated discussion, borrows heavily from Edelen and Kadlec (2005).

Consider specification (1). In a regression without the interaction term (price revision times reputation) partial adjustment to private information would be indicated by positive loading on REV. By contrast, here we evaluate the coefficient on REV*REPU, i.e., whether more reputable underwriters exhibit stronger partial adjustment.

The observed coefficient .137 is indeed highly significant, both economically and statistically. In Table 10, we quantify economic significance by considering a hypothetical offering, varying only underwriter quality and *REV*. For an underwriter with Carter-Manaster rank 4, for example, a one-standard deviation shock to *REV* increases underpricing by only .123 standard deviations, versus an increase of .331 standard deviations when rank is nine, corresponding to a 169% increase in economic power.[9]

In regression specification (2), we replace the interaction term with a trichotomized interaction term indicating which tercile the bank is in. The variable *Medium* (*High*) takes the value 1 if the issuer's underwriter falls in to the middle (upper) tercile, and zero otherwise.

This change enables us to identify whether the positive coefficient on (*REV*REPU*) is due to the difference between the low-quality tercile and the others, or rather due to the difference between high-quality tercile and the others. The .753 coefficient on (*REV*High*) is highly significant while the .157 coefficient on (*REV*Medium*) is insignificant. Hence the partial adjustment result of Hanley (1993) appears to be almost exclusively due to the behavior of underwriters in the top tercile rather than due to both the top and medium terciles.

Specifications (3) and (4) allow for asymmetric responses to private information. As pointed out in the literature, Benveniste and Spindt's argument is based on the difficulty of extracting *positive* information: an investor does not need to be rewarded for supplying negative information. In our context, this predicts a difference in the coefficients on (REV^+)*REPU* and (REV^-)*REPU*. In other words, not only should we observe stronger partial adjustment for reputable underwriters but this difference should be due to underadjustment to good news rather than to bad news.

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[9] In fact, this approach understates the difference somewhat because the pooled regression approach requires a uniform "one-standard-deviation" shock to REV for all underwriters. Yet as Table 2 shows, *REV* is actually 65% more variable for reputable underwriters.

Such an asymmetry is clear in Table 9. The coefficient .246 on (REV^{+})**REPU* is positive, with a high degree of both statistical and economic significance. By contrast the coefficient on (REV^{-})**REPU* is small; in fact, it is negative with borderline significance.

Finally, recognizing that our error terms may be correlated with our supposedly "independent" variables, we also employ an instrumental variables approach to address the potential endogeneity of underwriter reputation. The instrument we choose for reputation is the average reputation of the underwriters employed by offerings in the same 2-digit SIC code within the past year. In the first step we regress reputation on this instrument to obtain an expected value of reputation. We then employ this instrument in the second stage, both on its own and in the interaction items as well. The expected value of reputation is used to re-classify our IPO sample into three terciles, and the indicator variables *Medium* and *High* are then re-defined accordingly. The results are summarized in Table 11 and are qualitatively similar to those of Table 9.

In summary, the partial adjustment of reputable banks is both more pronounced and more asymmetric than that of non-reputable banks. To the extent that Benveniste and Spindt's model has support in the cross-section, we conclude that this support is due to the behavior of reputable underwriters.[10]

6. Conclusions

Our evidence suggests that reputable banks are more active in primary market information aggregation than non-reputable banks. The price revisions of underwriters in the top tercile are 65% more variable than those in the bottom tercile. In fact, low-quality banks frequently have price revisions of exactly zero dollars.

This information aggregation apparently substitutes for secondary market price discovery. In particular, both cross-sectional aftermarket return variance and time-series volatility are lower for high-quality banks in all time periods (except tech firms during the bubble period). We conclude that reputable banks have a higher relative proportion of information asymmetry resolved during the bookbuilding period rather than in the secondary market.

[10] In earlier drafts of the paper (still available online) we estimate separate underpricing regressions for low and high quality underwriters. The results are similar: the partial adjustment phenomenon occurs primarily in the top tercile.

Our analysis is silent on exactly how reputable banks achieve this superior price discovery role, although there are several natural candidates. Top-tier banks have access to a broader pool of institutional investors. Perhaps as a result they can better target investors that they suspect have value-relevant information. Even for a fixed group of investors, reputable underwriters have more established relationships, and they might leverage their standing to extract information more aggressively (Sherman, 2005).

Yet another possibility is suggested by Chen and Wilhelm (2005), who argue that the optimal sale mechanism involves non-uniform pricing. Underwriters use repeat institutional investors to stage the offering: the ultimate investors may not acquire the stock until after secondary market trading begins. This procedure effectively circumvents uniform pricing regulations and enhances the efficiency of the process. In the context of our results, low-quality underwriters are unlikely to have the "well-connected network of repeat institutional investors" posited by Chen and Wilhelm yet needed to structure such a mechanism.

We also confirm that a central prediction of bookbuilding models – partial adjustment to private information – has much stronger support in the high reputation subsample. Again this evidence is consistent with a stronger price discovery role for reputable underwriters.

This finding may partially reconcile the disparate conclusions of Cornelli and Goldreich (2003), who find significant empirical support for bookbuilding models, and Jenkinson and Jones (2004), who do not. While not revealing the identity of the underwriter supplying their bookbuilding bid data, Cornelli and Goldreich do state that it is "top-tier" European underwriter. By contrast, the underwriter used by Jenkinson and Jones is classified in our middle tercile. Yet our Section 5 evidence suggests that the greater difference in primary market behavior is between top-tier banks and the others, rather than between the low-tier banks and the others.

Whatever the magnitude of this positive price discovery role of reputable banks, it ought to be traded off against their costs, which are not measured here. As a prominent example, the underwriting market appears to be less than perfectly competitive on a fee basis (Chen and Ritter, 2000).

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Table 1: Descriptive Statistics

The sample is 7,124 initial public offerings of equity between 1980 and 2006. In Panel B, the sample is divided accroding to the Carter-Manaster reputation rank of the lead underwriter, or in the case of multiple lead underwriters, the average of these values. PREV is defined as the percentage change from the midpoint of the original filing price range to the final offer price. REV is the percentage change attributed to private information rather than public information; its construction is described in more details in Section 2.1. Underpricing is defined as the percentage change from the offer price to the closing price on the first day of trading. Buy-and-hold abnormal returns are measured relative to the CRSP value-weighted index and exclude the first trading day.

Panel A: Full Sample (N=7,124)

	Mean	Median	10th percentile	90th percentile
Filing Amount ($m, 1980)	14.26	6.63	1.63	25.65
Age (years)	15.86	8	2	43
High Tech dummy	0.45	0	0	1
Venture Capital dummy	0.37	0	0	1
Bank Reputation	7.06	8	3	9
PREV	0.001	0	-0.241	0.217
REV	0.000	0.007	-0.232	0.199
Underpricing	0.176	0.074	-0.040	0.471
1-month BHAR	0.015	-0.007	-0.185	0.227
3-month BHAR	0.026	-0.029	-0.348	0.404
6-month BHAR	0.004	-0.080	-0.527	0.563

Panel B: Subsamples, Ranked By Underwriter Quality

	Low Reputation		Medium Reputation		High Reputation	
	Mean	Median	Mean	Median	Mean	Median
Filing Amount ($m, 1980)	4.09	2.41	9.66	6.78	27.51	12.77
Age (years)	7.42	7	9.01	9	10.34	9
High Tech dummy	0.36	0	0.49	0	0.48	0
Venture Capital dummy	0.23	0	0.42	0	0.43	0
Bank Reputation	4.08	4.81	7.69	8	8.93	9
PREV	-0.033	0	-0.012	0	0.043	0
REV	-0.020	0.001	-0.014	-0.004	0.031	0.023
abs(REV)	0.110	0.071	0.146	0.112	0.161	0.116
Underpricing	0.118	0.054	0.151	0.076	0.252	0.087
1-month BHAR	-0.005	-0.021	0.021	0.000	0.025	0.087
3-month BHAR	-0.010	-0.060	0.028	-0.020	0.056	-0.009
6-month BHAR	-0.043	-0.132	0.009	-0.066	0.039	-0.051

Table 2: Variance Ratios

This table considers the following statistics. REV is the percentage change from the midpoint of the original filing range to the final offer price. This measure has been orthogonalized with respect to public information proxies as described in Section 3. BHAR is buy-and-hold abnormal return using the CRSP value-weighted index as a proxy.

IPOs are then partitioned into three groups according to the reputation of their lead underwriter. Across all IPOs in a particular group, we compute the cross-sectional standard deviation of REV and BHAR observations. The variance ratio VR is the ratio of these two numbers. p-values of differences are calculated using a F-test on REV and BHAR, and in the case of variance ratios are bootstrapped (with two-tailed p-values reported).

Panel A: Full Sample

	Low Quality	High Quality	Low - High Difference (p-value)		Low Quality	High Quality	Low - High Difference (p-value)
3 Month Horizon				6 Month Horizon			
	(n=2116)	(n=2497)			(n=2116)	(n=2497)	
σ(BHAR)	0.364	0.468	0.000	σ(BHAR)	0.534	0.620	0.000
σ(REV)	0.170	0.281	0.004	σ(REV)	0.170	0.281	0.000
VR	2.150	1.670	0.000	VR	3.140	2.210	0.000

Panel B: 1980-1984

	Low Quality	High Quality	Low - High Difference (p-value)		Low Quality	High Quality	Low - High Difference (p-value)
3 Month Horizon				6 Month Horizon			
	(n=513)	(n=132)			(n=513)	(n=132)	
σ(BHAR)	0.343	0.220	0.000	σ(BHAR)	0.541	0.321	0.000
σ(REV)	0.126	0.185	0.000	σ(REV)	0.126	0.185	0.000
VR	2.718	1.186	0.000	VR	4.297	1.736	0.000

Panel C: 1985-1989

	Low Quality	High Quality	Low - High Difference (p-value)		Low Quality	High Quality	Low - High Difference (p-value)
3 Month Horizon				6 Month Horizon			
	(n=366)	(n=496)			(n=366)	(n=496)	
σ(BHAR)	0.313	0.251	0.000	σ(BHAR)	0.490	0.335	0.000
σ(REV)	0.088	0.124	0.002	σ(REV)	0.088	0.124	0.000
VR	3.543	2.036	0.000	VR	5.548	2.713	0.000

Panel D: 1990-1994

	Low Quality	High Quality	Low - High Difference (p-value)		Low Quality	High Quality	Low - High Difference (p-value)
3 Month Horizon				6 Month Horizon			
	(n=479)	(n=520)			(n=479)	(n=520)	
σ(BHAR)	0.343	0.298	0.064	σ(BHAR)	0.507	0.445	0.002
σ(REV)	0.157	0.180	0.003	σ(REV)	0.157	0.180	0.003
VR	2.180	1.656	0.008	VR	3.229	2.473	0.000

Panel E: 1995-1999

	Low Quality	High Quality	Low - High Difference (p-value)		Low Quality	High Quality	Low - High Difference (p-value)
3 Month Horizon				6 Month Horizon			
	(n=608)	(n=778)			(n=608)	(n=778)	
σ(BHAR)	0.407	0.665	0.000	σ(BHAR)	0.573	0.910	0.000
σ(REV)	0.218	0.399	0.000	σ(REV)	0.218	0.399	0.000
VR	1.867	1.667	0.284	VR	2.630	2.284	0.111

Panel F: 2000-2006

	Low Quality	High Quality	Low - High Difference (p-value)		Low Quality	High Quality	Low - High Difference (p-value)
3 Month Horizon				6 Month Horizon			
	(n=150)	(n=571)			(n=150)	(n=571)	
σ(BHAR)	0.434	0.457	0.468	σ(BHAR)	0.497	0.459	0.219
σ(REV)	0.209	0.274	0.000	σ(REV)	0.209	0.274	0.000
VR	2.078	1.664	0.114	VR	2.381	1.671	0.036

Panel G: 1995-1999 (without Tech firms)

	Low Quality	High Quality	Low - High Difference (p-value)		Low Quality	High Quality	Low - High Difference (p-value)
3 Month Horizon				6 Month Horizon			
	(n=355)	(n=320)			(n=355)	(n=320)	
σ(BHAR)	0.345	0.305	0.025	σ(BHAR)	0.602	0.402	0.000
σ(REV)	0.157	0.195	0.000	σ(REV)	0.157	0.195	0.000
VR	2.203	1.567	0.125	VR	3.846	2.065	0.000

Panel H: 2000-2006 (without Tech firms)

	Low Quality	High Quality	Low - High Difference (p-value)		Low Quality	High Quality	Low - High Difference (p-value)
3 Month Horizon				6 Month Horizon			
	(n=76)	(n=232)			(n=76)	(n=232)	
σ(BHAR)	0.326	0.229	0.000	σ(BHAR)	0.379	0.332	0.158
σ(REV)	0.133	0.162	0.000	σ(REV)	0.133	0.162	0.000
VR	2.455	1.413	0.015	VR	2.854	2.044	0.059

Panel G: Full Sample (without Tech firms)

	Low Quality	High Quality	Low - High Difference (p-value)		Low Quality	High Quality	Low - High Difference (p-value)
3 Month Horizon				6 Month Horizon			
	(n=1345)	(n=1301)			(n=1345)	(n=1301)	
σ(BHAR)	0.336	0.250	0.000	σ(BHAR)	0.540	0.362	0.000
σ(REV)	0.141	0.162	0.000	σ(REV)	0.141	0.162	0.000
VR	2.383	1.543	0.000	VR	3.830	2.235	0.000

Table 3: Offer Price Revisions of Exactly Zero

The sample is 7,124 initial public offerings of equity between 1980 and 2006. The sample is divided according to the Carter-Manaster reputation rank of the lead underwriter, or in the case of multiple lead underwriters, the average of these values. *PREV* is defined as the percentage change from the midpoint of the original filing range to the final offer price. The table summarizes the frequency of this percentage change being exactly zero.

Panel A

Reputation Partition	Reputation	Total number of observations	Observations with *PREV* = 0	Proportion of observations with *PREV* = 0
1	[0,2)	188	87	46.28%
2	[2,3)	257	131	50.97%
3	[3,4)	346	159	45.95%
4	[4,5)	272	115	42.28%
5	[5,6)	579	127	21.93%
6	[6,7)	486	84	17.28%
7	[7,8)	874	137	15.68%
8	[8,9)	2239	244	10.90%
9	9	1885	209	11.09%

Panel B

Reputation Tercile	Reputation	Total number of observations	Observations with *PREV* = 0	Proportion of observations with *PREV* = 0
1	[0, 6.75]	2116	701	33.13%
2	(6.75, 8.5)	2511	314	12.50%
3	[8.5, 9]	2497	278	11.13%

Table 4: Time-Series Volatility Comparison

This table presents the mean of aftermarket daily return volatility of 7,124 IPOs issued between 1980 and 2006. Abnormal returns are computed as the residual from a Fama-French-Carhart four-factor model. Firms are classified into terciles according to the Manaster-Carter reputation ranking of their underwriters and comparisons are made between those underwritten by low-reputation banks and those by high-reputation banks. The Pr>t column shows the T-test results indicating whether the differences in the mean volatility are statistically significant.

Panel A: Full Sample	Low (n=2116)	High (n=2497)	Pr > t
3 months	0.0170	0.0200	0.000
6 months	0.0190	0.0200	0.021

Panel B: 1980-1984	Low (n=513)	High (n=132)	Pr > t
3 months	0.0009	0.0007	0.000
6 months	0.0009	0.0007	0.000

Panel C: 1985-1989	Low (n=366)	High (n=496)	Pr > t
3 months	0.0011	0.0009	0.000
6 months	0.0013	0.0010	0.000

Panel D: 1990-1994	Low (n=479)	High (n=520)	Pr > t
3 months	0.0017	0.0011	0.000
6 months	0.0020	0.0012	0.000

Panel D: 1995-1999	Low (n=608)	High (n=778)	Pr > t
3 months	0.0025	0.0028	0.255
6 months	0.0027	0.0027	0.749

Panel F: 2000-2006	Low (n=150)	High (n=571)	Pr > t
3 months	0.0028	0.0033	0.020
6 months	0.0031	0.0033	0.001

Panel G: 1995-1999, w/o tech firms	Low (n=355)	High (n=320)	Pr > t
3 months	0.0022	0.0012	0.000
6 months	0.0024	0.0012	0.000

Panel H: 2000-2006, w/o tech firms	Low (n=76)	High (n=232)	Pr > t
3 months	0.0021	0.0011	0.000
6 months	0.0024	0.0012	0.000

Panel I: 1980-2006, w/o tech firms	Low (n=1345)	High (n=1301)	Pr > t
3 months	0.0015	0.0009	0.000
6 months	0.0017	0.0010	0.000

Table 5: Determinants of Time-Series Return Volatilities

The sample is 7,124 IPOs issued between 1980 and 2006. The table shows the results of regressing a firm's aftermarket daily return volatility on firm characteristics and underwriter reputation. Fixed year effects are taken into account. High-tech firms during the 1990-2000 bubble period are not included in the sample. All other explanatory variables are scaled down by a factor of 1000 to secure proper magnitudes for estimated coefficients. Enclosed in parenthesis are heteroscedasticity-consistent standard errors of estimated coefficents above. Statistical significance at the 1%, 5% and 10% level are denoted by ***,** and *, respectively.

	3-month	6-month
Bank Reputation	-0.034***	-0.061***
	(0.012)	(0.011)
Filing Amount	-0.260***	-0.280
	(0.021)	(0.021)
Age	-0.104***	-0.088***
	(0.015)	(0.015)
VC-Backed	0.249***	0.318***
	(0.042)	(0.039)
Hi-Tech	0.399***	0.404***
	(0.042)	(0.037)
Year Dummies	Included	Included
Adj. R^2	0.232	0.282

Table 6: Variance Ratios Using Each Bank as an Observation

This table presents the folowing statistic. For each underwriter in our sample with at least 5 IPOs, we compute the cross-sectional variance of secondary market returns of IPOs underwritten by that bank, employing 1-, 3-, and 6-month holding periods. We also compute cross-sectional variance of pre-IPO price revisions, again for IPOs underwritten by that bank. The variance ratio is defined as the ratio of these two statistics. The high-quality subsample consists of underwriters with Carter-Manaster rank 8.5 or higher, and the low-quality subsample consists of underwriters with Carter-Manaster rank below 6.75.

Panel A: Full Sample			
	Average Log Variance Ratio		
	Low (n=129)	High (n=35)	Low vs. High Pr > t
3-month VR	1.746	1.097	0.003
6-month VR	2.592	1.681	0.001

Table 7: Determinants of Investment Banks' Variance Ratios

This table presents the the coefficient estimates, and heteroscedasticity-consistent standard errors in parentheses, of OLS regressions. The dependent variable is the observation for each underwriter (with at least 5 IPOs) of the following statistic: the log of the cross-sectional dispersion in secondary market returns divided by the cross-sectional standard deviation of price revisions. Statistical significance at the 1%, 5% and 10% level are denoted by ***,** and *, respectively.

	Dependent Variables (N=211)			
Independent Variables	VR3	VR6	VR3	VR6
Bank Reputation	-0.203***	-0.265***	-0.179**	-0.159**
	(0.038)	*(0.039)*	*(0.070)*	*(0.069)*
IPOHeat			-2.682	-2.200
			(2.697)	*(3.308)*
Filing Amount			-0.001	-0.239
			(0.996)	*(0.154)*
Age			-0.285*	-0.316*
			(0.171)	(0.176)
VC-backed			-0.557	-0.588
			(0.623)	(0.648)
Hi-Tech			0.737	0.450
			(0.608)	(0.566)
R^2	0.130	0.195	0.194	0.279

Table 8: Correlation Coeffecients between *REV* and Underpricing

This table presents the correlation coefficients between *REV* and underpricing for IPOs underwritten by investment banks of different reputation rankings. The sample is partitioned in two ways, into 9 subsamples as shown in Panel A, and into three terciles as shown in Panel B, respectively. The last column reports ρ , the correlation coefficient.

Panel A			
Reputation Partition	Reputation	No. of Obs.	ρ
1	[0,2)	188	-0.030
2	[2.3)	257	0.006
3	[3,4)	346	0.125
4	[4,5)	272	-0.002
5	[5,6)	579	0.218
6	[6,7)	486	0.288
7	[7,8)	874	0.328
8	[8,9)	2239	0.308
9	9	1883	0.490
Panel B			
Reputation Tercile	Reputation	No. of Obs.	ρ
1	[0,6.75]	2,116	0.141
2	(6.75, 8.5)	2,511	0.368
3	[8.5,9]	2,497	0.430

Table 9: Partial Adjustment and Underwriter Quality - OLS Estimation

This table presents the coefficient estimates, and heteroscedasticity-consistent standard errors in parentheses, of OLS regressions in which the dependent variable is IPO underpricing. Control variables include *AmtFile*, *Age*, *VCBack*, *HiTech* and λ, the inverse mills ratio from Heckman's method. REV^+ equals REV if $REV > 0$, and 0 otherwise; REV^- equals REV is $REV < 0$, and 0 otherwise. Dummy variables *Medium* and *High* indicate an IPO is in the middle underwriter quality tercile and high underwriter quality tercile, respectively. Statistical significance at the 1%, 5% and 10% level are denoted by ***,** and *, respectively.

	Symmetric Response		Asymmetric Response	
	(1)	(2)	(3)	(4)
REV	-0.196	0.438***		
	(0.165)	(0.126)		
REV^+			-0.837***	0.160
			(0.134)	(0.151)
REV^-			0.821***	0.690***
			(0.160)	(0.083)
REPU	0.011***	0.009***	-0.007*	-0.005
	(0.003)	(0.003)	(0.004)	(0.004)
REV*REPU	0.137***			
	(0.023)			
REV*Medium		0.157		
		(0.133)		
REV*High		0.753***		
		(0.155)		
REV^+*REPU			0.246***	
			(0.028)	
REV^-*REPU			-0.042*	
			(0.023)	
REV^+*Medium				0.597***
				(0.163)
REV^+*High				1.283***
				(0.210)
REV^-*Medium				-0.273***
				(0.104)
REV^-*High				-0.081
				(0.114)
COMPS	0.154***	0.158***	0.159***	0.166***
	(0.045)	(0.045)	(0.046)	(0.046)
SPILLOVER	0.827***	0.829***	0.791***	0.794***
	(0.046)	(0.046)	(0.044)	(0.044)
Adjusted R^2	0.405	0.412	0.419	0.422

Table 10: Impact of Pre-Offering Price Revision on Underpricing

This table shows the changes in underpricing corresponding to a positive, one-standard-deviation change in pre-offering price revision by underwriters of different Carter-Manaster reputation ranking. The first column gives the reputation ranking, the second column displays the systemetric response of underpricing to changes in REV, and columns 3 and 4 show the changes in underpricing given changes in positive REV and negative REV, respectively.

Reputation	A one-standard-deviation change in		
	REV	REV^{+}	REV^{-}
	causes change in underpricing		
1	-0.002	-0.139	0.167
2	0.039	-0.091	0.151
3	0.081	-0.043	0.134
4	0.123	0.005	0.118
5	0.164	0.053	0.102
6	0.206	0.101	0.085
7	0.248	0.149	0.069
8	0.289	0.197	0.052
9	0.331	0.245	0.036

Table 11: Partial Adjustment and Underwriter Quality - IV Estimation

This table presents the coefficient estimates, and heteroscedasticity-consistent standard errors in parentheses, of IV regressions in which the dependent variable is IPO underpricing. The Instrument for *REPU* is the average underwriter reputation ranking for all IPO firms in the same 2-digit SIC industry in the same year. Control variables include *AmtFile*, *Age*, *VCBack*, *HiTech* and λ, the inverse mills ratio from the Heckman's method. REV^{+} equals *REV* if *REV* > 0, and 0 otherwise; REV^{-} equals *REV* is *REV*<0, and 0 otherwise. Dummy variables *Medium* and *High* indicate an IPO is in the middle underwriter quality tercile and high underwriter quality tercile, respectively, classified according to the predicted *REPU* in the first step estimation. Statistical significance at the 1%, 5% and 10% level are denoted with ***,** and *, respectively.

	Symmetric Response		Asymmetric Response	
	(1)	(2)	(3)	(4)
REV	-0.247	0.400***		
	(0.222)	(0.121)		
REV^{+}			-0.874***	0.119
			(0.202)	(0.130)
REV^{-}			0.966***	0.610***
			(0.194)	(0.104)
REPU	0.025***	0.025***	0.007**	0.009
	(0.009)	(0.009)	-0.003	(0.010)
REV*REPU	0.145***			
	(0.031)			
REV*Medium		0.350***		
		(0.128)		
REV*High		0.698***		
		(0.152)		
REV^{+}*REPU			0.256***	
			(0.036)	
REV^{-}*REPU			-0.063**	
			(0.027)	
REV^{+}*Medium				0.844***
				(0.147)
REV^{+}*High				1.268***
				(0.201)
REV^{-}*Medium				-0.119
				(0.113)
REV^{-}*High				-0.103
				(0.129)
COMPS	0.137***	0.140***		0.133***
	(0.046)	(0.046)		(0.046)
SPILLOVER	0.842***	0.833***		0.800***
	(0.047)	(0.046)		(0.044)
Adjusted R^2	0.400	0.403	0.414	0.416