Online Appendix B

Gratton, Holden, and Kolotilin (2017) "When to Drop a Bombshell"

1 Description of Data

We gather data on all original initial public offerings (IPOs) from the Thomson Reuters SDC Platinum database, during 1983 to 2016, and match them with stocks in the Wharton Research Data Service (WRDS). The initial total number of observations is 963. For each IPO i, the SDC Platinum database reports $launch\,date_i$ and $trade\,date_i$, which we use to calculate $time\,gap_i = trade\,date_i - launch\,date_i$. For 244 IPOs, the variable $time\,gap$ is zero and we drop these observation.[1] We also drop 6 observations for which $time\,gap$ is greater than 365 days and 20 observations for which the WRDS price variable runs for less than 12 months. As a result, we remain with 693 observations with time gaps ranging from 1 to 353. The average $time\,gap$ is 79.7 days, the median is 70, and the standard deviation is 52.5.

We use the WRDS price variable to calculate IPO returns, and we use Ken French Data Library to calculate CRSP daily market returns. For each IPO i and year $y \in \{3, 5\}$, we calculate $return_i^y$ from the trade date closing price until the y-year anniversary of the IPO. We then compare each $return_i^y$ with $market\,return_i^y$ calculated as the value-weight return of all CRSP firms over the same period. We define the dummy variable $good_i^y = 1$ if $return_i^y \geq market\,return_i^y$ and $good_i^y = 0$ otherwise.

[1] We verified that, for the 10 most recent of these 244 IPOs, the actual launch date preceded $trade\,date$; so it appears that the database replaces $launch\,date$ with $trade\,date$ when $launch\,date$ value is missing. In any case, we run our test on the whole sample including these 244 observations. Due to the large number of observations for which $time\,gap = 0$, we can form only $k \leq 3$ equiprobable intervals. So we run the test with $k = 3$ equiprobable intervals, and the results are qualitatively similar to those in Table 1. In particular, for both 3 and 5 years performance, we reject H_0 in favor of H_1 at the 1 percent significance and we cannot reject H_1 in favor of H_2 at all standard significance levels. We also run the test with $k = 7$ intervals, out of which only the last 6 are equiprobable, and the results are qualitatively the same to those in Table 1.

2 The Test

We test our main prediction using an approach developed by Dardanoni and Forcina (1998), comparing the distributions of *time gap* conditional on $good = 1$ and $good = 0$. We now briefly summarize this approach. For a given number of intervals k, we express the distributions as a two-way contingency table with ordered margins. Dardanoni and Forcina consider three hypothesis.

H_0**:** The conditional distributions are identical.

H_1**:** The distribution conditional on $good = 1$ dominates the distribution conditional on $good = 0$ in the likelihood ratio order.

H_2**:** The conditional distributions are unrestricted.

For each hypothesis H_0, H_1, and H_3, the test computes the maximum likelihood estimates under multinomial sampling, subject to the hypothesis. It then computes log-likelihood ratio statistics for H_0 *vs.* H_1 and H_1 *vs.* H_2. Dardanoni and Forcina derive asymptotic distributions of these statistics and use a simulation method to compute p-values. In the paper, as well as in here, we report these p-values. The test accepts the hypothesis of interest H_1 if it rejects H_0 in favor of H_1 and fails to reject H_1 in favor of H_2.

For an asymptotic distribution to be a good approximation of our finite sample distribution, the number of intervals k should be sufficiently small. Following Roosen and Hennessy (2004), we divide *time gap* into k intervals that are equiprobable according to the empirical unconditional distribution of *time gap*. In our benchmark specification, we use $k = 7$.

3 Alternative Specifications

We now explore how our results change or do not change under alternative specifications. First, not all stocks are listed for $y \in \{3, 5\}$ years. Instead of omitting delisted stocks from the analysis, following Ritter (2003), we define $good_i^y$ by comparing the return of IPO i with the market return at the earlier of the delisting date or the y-year anniversary of the IPO. We then run the Dardanoni and Forcina test on this modified dataset. We report our results in row S1 in Table 1. The results are in line with our main specification.

Second, we explore a different way to tell good from bad firms, namely defining good (bad) firms as those with $y \in \{3, 5\}$ years performance relative to market $return_i^y / market\ return_i^y$ above (below) the median IPO over the whole sample from 1983 to 2016. We report our

Table 1: Dardanoni and Forcina test for likelihood ratio order. Alternative specifications.

		3 years	5 years
S1	*H0 vs H1*	0.045	0.003
	H1 vs H2	0.002	0.315
	obs.	693	693
S2	*H0 vs H1*	0.029	0.001
	H1 vs H2	0.000	0.000
	obs.	529	403
$k = 5$	*H0 vs H1*	0.001	0.000
	H1 vs H2	0.001	0.549
	obs.	529	403
$k = 9$	*H0 vs H1*	0.003	0.000
	H1 vs H2	0.000	0.319
	obs.	529	403

results in row S2 in Table 1. In this case, while the test continues to reject the hypothesis H_0 in favor of H_1, it also rejects the hypothesis H_1 in favor of the unrestricted hypothesis H_2.

Finally, we check whether our results are robust to different choices of the number of equiprobable intervals k. We report our results in rows $k = 5$ and $k = 9$ in Table 1.

References

Dardanoni, Valentino and Antonio Forcina, "A unified approach to likelihood inference on stochastic orderings in a nonparametric context," *Journal of the American Statistical Association*, 1998, *93* (443), 1112–1123.

Ritter, Jay R., "Investment Banking and Securities Issuance," in George M. Constantinides, Milton Harris, and Rene M. Stulz, eds., *Handbook of the Economics of Finance*, Vol. 1A: Corporate Finance, Elsevier, 2003, chapter 5, pp. 255–306.

Roosen, Jutta and David A Hennessy, "Testing for the monotone likelihood ratio assumption," *Journal of Business & Economic Statistics*, 2004, *22* (3), 358–366.