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Private Firm Valuation in the Technology Sector: Illuminating the Interaction Between Multiple Performance and Peer Pool Setting

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Abstract: Prior research, investigating the absolute performance of multiples as well as the relative superiority of different types of multiples, yields contradictory results that might be attributed to varying peer pool settings. This paper emphasizes on the technology sector and extends existing research, in its entirety being limited to trading multiples on listed companies, to transaction multiples on private firms. Employing a set of 22,967 observations on private market transactions of technology firms collected from 2000 until 2018, I examine the systematic impact of peer pooling on (i) the relative superiority of cross-sectoral multiples, (ii) the absolute superiority of sectoral multiples and, (iii) the absolute superiority of cross-sectoral multiples being segmented by various country-specific high-tech indicators. The multiples employed capture both, enterprise value and equity value multiples. The performance of the multiples in the various peer pool settings is evaluated according to bias as well as accuracy, utilizing the standard holdout routine on the transactions. The results indicate that (i) contradictory results in prior research on multiple's bias may be strongly attributed to the varying peer pools employed, (ii) the enterprise value to total assets multiple clearly dominates across all peer pools on a cross-sectoral basis, indicating that contradictory results on multiple's accuracy may not be attributed to the varying peer pools employed and, (iii) the performance of sectoral multiples depends on the value driver employed, showing only a weak relationship with the peer pool setting. Therefore, valuation analysts are recommended to utilize larger peer pools when employing cross-sectoral multiples, to emphasize on the enterprise value to total assets multiple, to further break down the high-tech sector into sub-sectors and, to employ sectoral multiples or multiples segmented according to country-specific high-tech indicators alternately.

Keywords: Peer Pool, Peer Group, Multiple Performance, Transaction Multiples, Market Approach, Private Firms, Business Valuation, Technology Sector

1. Introduction

Over the years, numerous studies have been conducted, elaborating upon the absolute performance of multiples as well as on the relative superiority of a variety of multiple's definitions. These studies are subject to at least two limitations. First, they are built upon varying samples that might be responsible for result's variations. Second, they are in its entirety limited to trading multiples generated from capital market data on listed companies. Since transactions on the market for corporate takeovers of private firms differ from stock deals on the public market on various characteristics, we cannot be sure if the results found for listed companies similarly hold for private firms. This study is – to my best knowledge – the first that discusses the impact of the peer pool (sample) employed on multiple's performance in the context of private firm valuation. Highlighted by the fact that the market for corporate takeovers of private firms is at least as important as the public market, utilizing the most appropriate peer pool in private firm valuation is a question of interest to valuation analysts, investors as well as the academic community.

This study contributes to existing research in threefold ways. First, it examines the systematic impact of peer pooling on (i) the relative superiority of cross-sectoral multiples, (ii) the absolute superiority of sectoral multiples and, (iii) the absolute superiority of cross-sectoral multiples being segmented by various country-specific high-tech indicators. Second, since transactions on the market for corporate takeovers differ from stock deals on the public market on various characteristics, it extends existing research (in its entirety being limited to listed companies) to transaction multiples emphasizing on private firms. Finally, since multiples are not stable over time, existing results are simply updated.

The results on bias indicate that the composition of the peer pool (i) impacts the least biased multiple, but generally the enterprise value multiples to outperform equity value multiples, (ii) impacts the level of superiority of sectoral multiples against the cross-sectoral multiple and, (iii) is not clearly related to the bias of multiples segmented according to country-specific high-tech indicators. The results on accuracy indicate that (i) cross sectoral multiples are unaffected by the peer pool setting (with the enterprise value to total assets multiple dominating), (ii) cross sectoral multiples estimates generally improve with an increase in peer pool size, (iii) sectoral multiples generally outperform the cross-sectoral multiple regardless of the peer pool setting and, (iv) segmenting multiples according to country-specific high-tech indicators offers no material improvement over sectoral multiples across all peer pools. All results are robust on both, according to the valuation error employed and the size of the peer group.

The remainder of this article is organized as follows: Section 2 discusses the literature on the performance of multiples. Section 3 defines the high-tech sector and reports descriptive statistics on sample data. Section 4 describes the research methodology. Section 5 reports the results on bias and accuracy of multiples across varying peer pool settings cross-sectoral, sector-related as well as according to country high-tech indicator segmentations. Section 6 reports the results on robustness tests. Finally, section 7 concludes.

2. Literature Review

Empirical evidence on the performance of multiples reveals contradictory results that may be attributed to varying peer pool settings (sampling). Evaluating the performance of enterprise value as opposed to equity value multiples, studies for the U. S. market generally conclude that enterprise value multiples outperform equity value multiples on both, accuracy and bias [1, 2]. In contrast, for emerging markets, studies conclude superiority of equity value multiples, explaining the inferiority of enterprise value multiples by the noise being incorporated when the book value of debt is used as a proxy for its market value [3, 4]. For European markets, the results are somewhat inconsistent, on the one hand concluding superiority of enterprise value multiples [5] and, on the other hand, finding equity value multiples do dominate [6, 7].

Examining the relative superiority of multiples according to the value driver employed, studies on European markets conclude earnings multiples to yield highest prediction accuracy [e. g. 6, 8, 9]. A similar result is found in an international setting [10]. In contrast, the results for the U. S. market yield somewhat contradictory results. While some studies similarly conclude earnings multiples to generate superior prediction accuracy [e. g. 11-16], other studies conclude asset multiples to generate more accurate and less biased estimates [1, 2, 17]. Furthermore, sales are found to be more value relevant than reported negative earnings in the valuation of high-tech loss firms [18].

On a sectoral basis, results of prior research are consistent in that different multiples are most accurate across industry sectors (for the U. S. market [13, 15, 19], for the European market [5, 20] and, for emerging markets [3, 4, 21]), but with varying relative superiorities that may be again attributed to peer pool sampling.

Finally, varying peer pool settings (the respective country itself, European Union member countries, OECD countries and, the U. S. market) are found to dominate when investigating optimal peer pools yielding minimum valuation errors of synthetic peer group multiples for European Union member countries [22].

3. Sample Data

I segment the high-tech sector into eight industry groupings based on five industry groupings widely used [23] as well as an extension adding two more industry groupings [24] and, by additionally adding an Automotive industry grouping. Since prior research reveals that the sectoral classification system employed impacts multiple's accuracy due to varying firms being assigned to industries [e. g. 25-31], and documents limitations as well as deficiencies of the widely used SIC codes to select and segment samples [25, 32, 33] due to its treatment of conglomerates [34], its emphasis on manufacturing operations [35] and, its product-based view not capturing vertical relationships among firms [36, 37], I employ the NACE Rev.2 industry classification.

Along with the findings on the optimal code combinations assigned to the various industries [25] as well as the succus on sampling employed in prior studies [e. g. 18, 23, 38-49], I convert SIC codes into NACE Rev.2 codes and assign the respective code combinations to the eight predefined high-tech industry groupings as reported in table 1.

Table 1 reports the SIC code combinations recommended by literature and the converted NACE Rev.2 code combinations assigned to the eight predefined high-tech industry groupings.

The data is compiled from two sources. First, the information on transactions, pricing data and company data is obtained from ZEPHYR M&A database, adding company data from ORBIS database to gain additional information on incomplete datasets to assure maximum data. Second, the data on country high-tech indicators is obtained from The World Bank (Science and Technology Indicators).

Table 1. *High-tech industry groupings and assigned industry classification code combinations.*

High-Tech Industry	SIC code combination recommended	NACE Rev.2 code combination converted
Computer Hardware and Electronics Manufacturing	35, 367	261, 262, 264, 265, 268, 951
Communications	366, 48	263, 60, 61
Software Development	73	582, 62, 631, 742, 802, 951
Medical Technology	28, 38, 87	204, 21, 266, 325, 721
Electrical Manufacturing	173, 36	27, 33, 432
Internet & IT-Services	596, 641, 73, 870, 873, 874	479, 581, 732, 822
Automotive	-	29, 309, 452
Other High-Tech Industries	261, 272, 28, 29, 34, 35, 37, 381, 387, 491, 492, 493, 573, 762, 781, 783, 791, 871	192, 201, 202, 203, 205, 25, 28, 301, 302, 303, 35, 383, 39, 712

I started by identifying all private market transactions according to their deal type and extracted all acquisitions of minority as well as majority stakes (and simultaneously excluded all transactions of the deal types mergers, demergers, joint ventures, management buyouts and, institutional buyouts). The sample comprises all private market transactions observed in countries being categorized into the four cultural regions English origin, French origin, German origin and, Scandinavian origin [50]. Additionally, I introduced a fifth category capturing (post) communist countries. I collected all private market transactions, being confirmed or at least being assumed confirmed, occurring from 2000 until 2018, for which a complete dataset was available. Employing the method of static sampling ensures that similarities as well as differences across the various multiples and peer pool settings are not attributable to sampling. Although there is considerable debate upon the exclusion of negative value indications and/or negative value drivers in forming peer groups, I follow general practice (empirically concluding that the elimination of negative multiples improves valuation accuracy [10, 51, 52]) and employ only private market transactions providing both, positive value (pricing) indications and positive value driver metrics in order to ensure only positive multiples. The original sample population was 24,347 observations on private market transactions.

I limited the sample using only private market transactions indicating direct sales of common stock, as they can be considered as arm's length transactions representing fair market value. Therefore, I dropped all transactions of convertible preferred stock, stock options, or warrants, as they usually do not involve actual arm's-length negotiations that may cause a significant bias on the multiples. This reduced the sample by 562 observations. Furthermore, I dropped all transactions of firms with (i) sales below one million Euro, (ii) an EBITDA and/or an EBIT below 500,000 Euro and, (iii) total assets below two million Euro. This further reduced the sample by 818 observations. The final sample population is 22,967 observations on private market transactions (thus, representing 94.3 percent of the original sample), being distributed across countries of origin (indicating a concentration by a GINI coefficient of 0.776), peer pools (geographical/political as well as cultural regions) and, high-tech industry groupings as reported in table 2.

Table 2. *Sample population by country, peer pool and, high-tech industry grouping.*

Panel A: Sample population by country

Country	count	Country	count
Argentina	1	Kenya	1
Australia	1,639	Luxembourg	22
Austria	49	Malaysia	238
Belgium	276	Malta	4
Bosnia and Herzegovina	13	Montenegro	8
Brazil	9	Netherlands	1,405
Bulgaria	7	New Zealand	172
Canada	179	North Macedonia	2
Chile	5	Norway	298
China	375	Pakistan	6
Colombia	3	Philippines	59
Croatia	32	Poland	314
Cyprus	3	Portugal	148
Czech Republic	10	Romania	85
Denmark	136	Russia	137
Egypt	5	Serbia	38
Estonia	13	Singapore	50
Finland	285	Slovak Republic	16
France	1,632	Slovenia	33
Germany	1,872	South Africa	10
Greece	40	South Korea	4,666
Hong Kong	1	Spain	825
Hungary	84	Sri Lanka	11
Iceland	2	Sweden	500

Country	count	Country	count
India	579	Switzerland	383
Indonesia	2	Taiwan	237
Ireland	38	Thailand	74
Israel	6	Turkey	1
Italy	1,108	Ukraine	62
Japan	1,689	United Kingdom	1,522
Jordan	2	United States	1,545
		Total	22,967

Panel B: Sample population by peer pool and high-tech industry grouping

Peer pool	Geographical/Political Regions			
	European Union	Europe	OECD	World
Total (by countries)	10,459	11,403	20,913	22,967
Computer Hardware and Electronics Manufacturing	1,477	1,597	3,413	3,707
Communications	1,285	1,466	2,413	2,677
Software Development	2,844	3,053	5,860	6,228
Medical Technology	987	1,127	2,501	2,703
Electrical Manufacturing	1,268	1,338	2,203	2,422
Internet & IT-Services	842	950	1,572	1,689
Automotive	764	774	1,436	1,589
Other High-Tech Industries	3,418	3,817	7,066	7,915
Total (by industry groupings)	12,885	14,122	26,464	28,930

Peer pool	Cultural Regions				
	English	French	German	Scandinavian	(Post) Communist
Total (by countries)	6,071	5,550	8,896	1,221	1,229
Computer Hardware and Electronics Manufacturing	664	799	2,085	97	62
Communications	814	806	724	132	201
Software Development	2,135	1,572	1,765	442	314
Medical Technology	661	377	1,375	144	146
Electrical Manufacturing	525	760	881	145	111
Internet & IT-Services	583	385	510	95	116
Automotive	261	444	802	12	70
Other High-Tech Industries	1,835	1,776	3,446	380	478
Total (by industry groupings)	7,478	6,919	11,588	1,447	1,498

Panel A reports the sample population by country. No observations were reported for Albania, Belarus, Ecuador, Kazakhstan, Kosovo, Latvia, Lithuania, Mexico, Moldova, Nigeria, Peru, Uruguay, Venezuela and, Zimbabwe. Panel B reports the sample population by peer pool (geographical/political as well as cultural regions) and high-tech industry grouping. Since firms may be engaged in more than one high-tech industry grouping, the total number of observations on the industry groupings exceeds the total number of observations by country.

4. Research Methodology

Despite the superiority of forward trading multiples [1, 5, 7, 8, 10, 11, 13, 15, 53-56], since this study emphasizes on transaction multiples employing data from the market for corporate takeovers of private firms, I employ trailing multiples for at least three reasons: First, forecast value drivers are often simply not available for private firms as they are for public companies. Second, even if forecast value drivers are available, they often lack reliability or cannot be verified in a reliable manner, respectively. Third, value drivers employed in trailing multiples are less susceptible to manipulation, since the auditor's certificate ensures reliability.

I employ four enterprise value and one equity value multiple popular in valuation literature, namely the enterprise value to sales multiple, the enterprise value to EBITDA multiple, the enterprise value to EBIT multiple, the enterprise value to total assets multiple and, the equity value to EBT multiple. The sales multiple and the total assets multiple are denoted by [7, 57]

$$\lambda_i^{\delta_{i,j}} = \frac{E_i + T_i - I_i + D_i - C_i + L_i + P_i + A_i}{\delta_{i,j}} \quad (1)$$

where i is the index on firm transactions, $\delta_{i,j}$ is the value driver (with j indicating operating sales and total assets), $\lambda_i^{\delta_{i,j}}$ is the enterprise value multiple on the corresponding value driver, E_i is the market value of equity, T_i is the market value of third party (minority) shares in subsidiaries, I_i is the market value of investments in unconsolidated companies (associates and joint ventures), D_i is the market value of straight debt (interest bearing liabilities), C_i is the market value of cash and cash equivalents, L_i is the market value of finance leases, P_i is the market value of pension reserves and,

A_i is the market value of accounts payable.

The earnings multiples (EBITDA and EBIT) are denoted by

$$\lambda_i^{\delta_{i,j}} = \frac{E_i + T_i - I_i + D_i - C_i + L_i\,(+P_i)}{\delta_{i,j}} \quad (2)$$

where i is the index on firm transactions, $\delta_{i,j}$ is the value driver (with j indicating EBITDA and EBIT), $\lambda_i^{\delta_{i,j}}$ is the enterprise value multiple on the corresponding value driver, E_i is the market value of equity, T_i is the market value of third party (minority) shares in subsidiaries, I_i is the market value of investments in unconsolidated companies (associates and joint ventures), D_i is the market value of straight debt (interest bearing liabilities), C_i is the market value of cash and cash equivalents, L_i is the market value of finance leases and, P_i is the market value of pension reserves (only being added if the interest on pensions is not part of the cost of goods sold).

The Equity Value to EBT multiple is denoted by

$$\lambda_i^{\delta_{i,j}} = \frac{E_i}{\delta_{i,j}} \quad (3)$$

where i is the index on firm transactions, $\delta_{i,j}$ is the value driver (with j indicating EBT), $\lambda_i^{\delta_{i,j}}$ is the equity value multiple on the corresponding value driver and, E_i is the market value of equity.

I computed the datasets for each multiple, each peer pool as well as each high-tech sub-sample employing the standard holdout routine, once utilizing the target transaction as the transaction peers are searched for, and in all other cases serving as part of the peer group. Herewith, three fundamental methodological decisions are made concerning (i) the size of the peer group, (ii) the peer selection rule and, (iii) the method of aggregation employed. First, since a lower comparability of target firm and peers, a higher variance of the multiples and, a lower degree of marketability of the peers demand larger peer groups, I employ 10 peers according to sample characteristics. Research shows that the optimal size of the peer group is between 5 and 10 peers for most industry sectors, with a negative relationship between the size of the peer group and the number of available peers [58]. Some studies employ small peer groups consisting of four to five peers, respectively [59, 60], while in the oil and gas sector larger peer groups are found to generally yield superior synthetic multiples [61]. Second, I select peers estimating a Hausman-Taylor regression [62], allowing some of the regressors to be correlated with the individual effects [63]. The instrumental variables are selected according to both, variables employed in prior research [5, 6, 9, 14, 64-68] and, simply, data availability on transactions, pricing and, company information. The resulting set of 19 instrumental variables is assigned to four categories: (i) deal characteristics, (ii) transaction characteristics, (iii) market (for corporate takeovers) characteristics and, (iv) firm characteristics, with the latter being further categorized according to the three primary drivers of firm value (profitability, growth and, risk). For the definitions of the variables and related research see table 8 in the appendix. Third, I employ the harmonic mean and the median (corresponding to the aggregation method employed for the valuation errors) to aggregate the synthetic peer group multiples [6, 57].

Finally, I evaluate the performance of the multiples according to bias and accuracy. To evaluate bias, I employ the relative absolute valuation error, since it is both, exposed to a systematic upwards bias and avoids positive and negative deviations to net out (and hence, allows for a one-dimensional results figure) [7, 65, 69, 70]. It is denoted by

$$RAVE_i^{\delta_{i,j}} = \left| \frac{\widehat{\lambda_i^{\delta_{i,j}}} - \lambda_i^{\delta_{i,j}}}{\lambda_i^{\delta_{i,j}}} \right| \quad (4)$$

where i is the index on firm transactions, $\delta_{i,j}$ is the value driver (with j indicating operating sales, EBITDA, EBIT, EBT and, total assets), $RAVE_i^{\delta_{i,j}}$ is the relative absolute valuation error on the corresponding value driver, $\widehat{\lambda_i^{\delta_{i,j}}}$ is the estimated enterprise value multiple on the corresponding value driver and, $\lambda_i^{\delta_{i,j}}$ is the observed enterprise value multiple on the corresponding value driver.

To evaluate accuracy, I employ the relative log-scaled absolute valuation error, since it avoids both, an upwards bias as well as the netting effect of positive and negative deviations, and, hence, considers solely the strength of the deviation [1, 6, 52, 53, 56, 57, 71, 72]. It is denoted by

$$RLAVE_i^{\delta_{i,j}} = \left| ln\left(\frac{\widehat{\lambda_i^{\delta_{i,j}}}}{\lambda_i^{\delta_{i,j}}} \right) \right| \quad (5)$$

where i is the index on firm transactions, $\delta_{i,j}$ is the value driver (with j indicating operating sales, EBITDA, EBIT, EBT, and, total assets), $RLAVE_i^{\delta_{i,j}}$ is the relative log-scaled absolute valuation error on the corresponding value driver, $\widehat{\lambda_i^{\delta_{i,j}}}$ is the estimated enterprise value multiple on the corresponding value driver and, $\lambda_i^{\delta_{i,j}}$ is the observed enterprise value multiple on the corresponding value driver.

I aggregate the relative absolute valuation errors employing the harmonic mean, since this maximizes the explanatory power on bias of the error measure itself [12, 13, 15, 66, 73]. In order to ensure unbiased estimates on accuracy, I aggregate the relative log-scaled absolute valuation errors employing the median [57, 73].

5. Results

5.1. Performance by Multiples and Peer Pool Settings

In this section I examine the cross-sectoral performance of the multiples across various peer pool settings. Table 3 reports the results on the tests on bias and accuracy reported for the five multiples as well as aggregated, with the superior multiple in each peer pool being indicated in bold numbers. For the countries forming the various peer pools see table 9 in the appendix.

Table 3. *Performance (test on bias and accuracy) by multiples and peer pool settings.*

Panel A: Test on Bias

Multiples	Geographical/Political Regions			
	European Union	**Europe**	**OECD**	**World**
Aggregated	0.1240	0.1197	0.0935	0.0844
EPV/Sales	0.1651	0.1236	0.1466	0.1278
EPV/EBITDA	0.1149	0.1331	0.0830	0.0865
EPV/EBIT	0.1502	0.0908	0.0967	0.0807
EPV/Total Assets	0.0881	0.1100	0.0713	0.0582
EQV/EBT	0.1326	0.1664	0.0976	0.0776

Multiples	Cultural Regions				
	English	**French**	**German**	**Scandinavian**	**(Post) Communist**
Aggregated	0.0809	0.0684	0.0784	0.0420	0.1270
EPV/Sales	0.0910	0.2025	0.1473	0.1775	**0.0800**
EPV/EBITDA	0.0866	0.1457	0.0830	**0.0109**	0.2046
EPV/EBIT	0.0811	0.1357	0.0834	0.1628	0.0897
EPV/Total Assets	0.0782	0.0228	0.0531	0.0941	0.1743
EQV/EBT	0.0707	0.1037	0.0711	0.1959	0.1967

Panel B: Test on Accuracy

Multiples	Geographical/Political Regions			
	European Union	**Europe**	**OECD**	**World**
Aggregated	0.6461	0.6364	0.6193	0.6010
EPV/Sales	0.8843	0.8838	0.7831	0.7584
EPV/EBITDA	0.6599	0.6502	0.5594	0.5257
EPV/EBIT	0.7826	0.7500	0.5738	0.5316
EPV/Total Assets	0.4651	0.4633	0.4029	0.3789
EQV/EBT	0.5662	0.5622	0.5186	0.5004

Multiples	Cultural Regions				
	English	**French**	**German**	**Scandinavian**	**(Post) Communist**
Aggregated	0.4039	0.6076	0.4555	0.6512	0.7257
EPV/Sales	0.5705	0.8766	0.5578	0.8362	0.8466
EPV/EBITDA	0.3633	0.6115	0.4858	0.6110	0.6604
EPV/EBIT	0.3857	0.7496	0.5250	0.6441	0.7250
EPV/Total Assets	0.3579	0.4273	0.3232	0.4225	0.6453
EQV/EBT	0.4382	0.5447	0.4376	0.8073	0.7617

EPV indicates enterprise value, EQV indicates equity value. Panel A reports the results on bias employing the relative absolute valuation error aggregated by the harmonic mean. Panel B reports the results on accuracy employing the relative log-scaled absolute valuation error aggregated by the median.

The results for the test on bias indicate that the least biased multiple varies across peer pool settings. Furthermore, the results indicate enterprise value multiples to outperform the equity value multiple (except for the peer pool capturing countries of English origin) and the multiples to perform differently across peer pools. The results for the test on accuracy indicate the enterprise value to total assets multiple to dominate across all peer pool settings generating most accurate multiple estimates, being followed by the equity value multiple (as indicated for the geographical/political peer pools). Furthermore, the results indicate the multiples estimates to improve with an increase in peer pool size (as indicated by the geographical/political peer pools). Therefore, the results allow for the general conclusion that (i) contradictory results on multiple's bias concluded in prior research may be attributed to the varying peer pools employed, (ii) contradictory results on multiple's accuracy may not be attributed to the varying peer pools employed (but to other sample characteristics), (iii) valuation analysts are advised to employ larger peer pools and, (iv) valuation analysts may emphasize the enterprise value to total assets multiple valuing high-tech firms (although intangible assets not captured by the multiple play an important role for high-tech firms).

5.2. Performance by High-Tech Sector Segmentation and Peer Pool Settings

In this section I examine the aggregated performance of sectoral multiples across various peer pool settings. Table 4 reports the results on the tests on bias and accuracy for all five multiples aggregated as well as for the eight predefined high-tech industries separated, with the sectoral multiples outperforming the cross-sectoral multiple being indicated in bold numbers. For the countries forming the various peer pools see table 9 in the appendix.

Table 4. *Performance (test on bias and accuracy) by sector segmentation and peer pool settings.*

Panel A: Test on Bias

High-Tech Industries	Geographical/Political Regions			
	European Union	Europe	OECD	World
Cross-Sectoral	0.1240	0.1197	0.0935	0.0844
Computer Hardware and Electronics Manufacturing	0.1039	0.0998	0.0415	0.0742
Communications	0.1003	0.0862	0.1134	0.0836
Software Development	0.1270	0.1297	0.1034	0.0879
Medical Technology	0.0802	0.1037	0.0519	0.0706
Electrical Manufacturing	0.1710	0.1021	0.1324	0.0701
Internet & IT-Services	0.1225	0.1701	0.0671	0.0043
Automotive	0.0653	0.0243	0.0079	0.0900
Other High-Tech Industries	0.1189	0.0763	0.0897	0.0390

High-Tech Industries	Cultural Regions				
	English	French	German	Scandinavian	(Post) Communist
Cross-Sectoral	0.0809	0.0684	0.0784	0.0420	0.1270
Computer Hardware and Electronics Manufacturing	0.0778	0.0639	0.0953	0.2839	0.2108
Communications	0.0773	0.1175	0.1026	0.0759	0.0533
Software Development	0.0739	0.1179	0.0965	0.2628	0.1373
Medical Technology	0.1361	0.0440	0.0894	0.1115	0.1421
Electrical Manufacturing	0.0430	0.0932	0.0714	0.1802	0.2134
Internet & IT-Services	0.0951	0.1735	0.1020	0.1997	0.0043
Automotive	0.1077	0.0224	0.0208	0.4019	0.0168
Other High-Tech Industries	0.1034	0.1131	0.0655	0.1235	0.1734

Panel B: Test on Accuracy

High-Tech Industries	Geographical/Political Regions			
	European Union	Europe	OECD	World
Cross-Sectoral	0.6461	0.6364	0.6193	0.6010
Computer Hardware and Electronics Manufacturing	0.4783	0.4647	0.4344	0.4319
Communications	0.5695	0.5212	0.5075	0.4961
Software Development	0.6250	0.6310	0.5382	0.5418
Medical Technology	0.5459	0.5393	0.4885	0.5058
Electrical Manufacturing	0.6731	0.6638	0.6037	0.5902
Internet & IT-Services	0.6662	0.6295	0.5989	0.5785
Automotive	0.4181	0.4327	0.4252	0.4507
Other High-Tech Industries	0.6242	0.6642	0.5119	0.5235

High-Tech Industries	Cultural Regions				
	English	French	German	Scandinavian	(Post) Communist
Cross-Sectoral	0.4039	0.6076	0.4555	0.6512	0.7257
Computer Hardware and Electronics Manufacturing	0.3462	0.3341	0.4329	0.5999	0.5678
Communications	0.3955	0.4588	0.4853	0.5893	0.4604
Software Development	0.3745	0.4914	0.4744	0.7790	0.6542
Medical Technology	0.4074	0.5517	0.4382	0.5281	0.5197
Electrical Manufacturing	0.4337	0.5509	0.5018	0.8564	0.6755
Internet & IT-Services	0.3497	0.6897	0.5266	0.7562	0.1457
Automotive	0.4457	0.1966	0.2750	0.1203	0.2842
Other High-Tech Industries	0.4190	0.5780	0.3893	0.4761	0.7701

Panel A reports the results on bias employing the relative absolute valuation error aggregated by the harmonic mean. Panel B reports the results on accuracy employing the relative log-scaled absolute valuation aggregated by the median.

The results for the test on bias indicate sectoral multiples to outperform the cross-sectoral multiple, but at varying levels across peer pools. For peer pools formed by geographical/political characteristics, the sectoral multiples in the sectors Computer Hardware and Electronics, Medical Technology and, Other High-Tech Industries are less biased across all peer pools, while the Software Development multiple does not improve in any peer pool. Instead, for peer pools formed by cultural characteristics, none of the sectoral multiples outperforms the cross-sectoral multiple across all peer pools, with no sectoral multiple outperforming the cross-sectoral multiple in any sector for Scandinavian countries. This may be attributed to the small sample size for this cultural region. The results for the test on accuracy indicate sectoral multiples to outperform the cross-sectoral multiple in the geographical/political peer pools in most sectors. A somewhat similar, but weaker, conclusion can be drawn for the cultural peer pools. Therefore, the results allow for the general conclusion that (i) contradictory results concluded in prior research on multiple`s bias may strongly be attributed to the peer pool employed, (ii) the accuracy of sectoral multiples shows only a weak relationship with the peer pool employed, and, thus, the somewhat contradictory results found in previous research may be attributed to the value driver employed, (iii) since the sectoral multiples do not show a clear improvement with an increase in the size of the peer pool, valuation analysts may not be forced to employ large-sized peer pools and, (iv) valuation analysts are advised to further break down the high-tech sector.

5.3. Performance by Country High-Tech Indicator Segmentation and Peer Pool Settings

In this section I examine whether a segmentation according to country-specific high-tech indicators improves the performance of cross-sectoral multiples across the various peer pool settings and, thus, is a viable alternative to the high-tech industry segmentation. Table 5 reports the results on the tests on bias and accuracy for all five multiples aggregated for various segmentations according to country-specific high-tech indicators: (i) Research & development expenditure in percent of the gross domestic product (R&D% GDP), technology exports in percent of the gross domestic product (TE%GDP) and, technology exports in percent of total manufactured exports (TE%TME), with the countries sorted in descending order and grouped into quarters (according to the number of observations on multiples) from the countries with the highest percentage (quarter 1) to the lowest percentage (quarter 4). (ii) Labor force needed per patent application (LFPA), with the countries sorted in ascending order and grouped into quarters (according to the number of observations on multiples) from the countries with the lowest labor force (quarter 1) to the highest labor force (quarter 4) needed. (iii) High-tech index being computed as the weighted mean of the previous four indicators, grouped into quarters (according to the number of observations on multiples) from countries with the highest index (quarter 1) to the lowest index (quarter 4) as well as grouped into four minimum range clusters, again from countries with the highest index (cluster 1) to the lowest index (cluster 4). For the countries forming the various peer pools (being limited to the geographical/political peer pools due to sampling) as well as the classification of countries according to the country high-tech indicators and the quarters/clusters, respectively, see table 9 in the appendix. The quarters/clusters outperforming the aggregate performance are indicated in bold numbers.

Table 5. *Performance (test on bias and accuracy) by country high-tech indicator segmentation and peer pool settings.*

Panel A: Test on Bias

Country High-Tech Indicator	European Union	Europe	OECD	World
Aggregated/Cross-Sectoral	0.1240	0.1197	0.0935	0.0844
R&D%GDP				
Quarter 1	0.1149	0.1629	0.1188	0.0698
Quarter 2	0.0897	0.0918	0.0408	0.0899
Quarter 3	0.0966	0.0864	0.0847	0.0992
Quarter 4	0.1541	0.1701	0.0698	0.1272
LFPA				
Quarter 1	0.1048	0.0563	0.0698	0.0712
Quarter 2	0.1610	0.1002	0.0676	0.0752
Quarter 3	0.1235	0.0998	0.1263	0.0773
Quarter 4	0.1804	0.1497	0.1197	0.1197
TE%GDP				
Quarter 1	0.0737	0.0206	0.0980	0.0970
Quarter 2	0.0814	0.1055	0.0709	0.1207
Quarter 3	0.1343	0.1343	0.0882	0.1273
Quarter 4	0.1339	0.1674	0.0939	0.0490
TE%TME				
Quarter 1	0.1028	0.0973	0.0301	0.0001
Quarter 2	0.0965	0.0968	0.0472	0.0691
Quarter 3	0.1055	0.1161	0.1149	0.1330
Quarter 4	0.1894	0.1437	0.1288	0.0699
High-Tech Index (quarters)				
Quarter 1	0.1592	0.1315	0.0698	0.0162
Quarter 2	0.0979	0.0979	0.1050	0.1178
Quarter 3	0.0132	0.1527	0.1172	0.0889
Quarter 4	0.1673	0.1486	0.1447	0.1284
High-Tech Index (clustered)				
Cluster 1	0.1584	0.0995	0.0712	0.0690
Cluster 2	0.0856	0.1508	0.1137	0.0825
Cluster 3	0.2215	0.1055	0.1245	0.0200
Cluster 4	0.1030	0.0352	0.1525	0.0777

Panel B: Test on Accuracy

Country High-Tech Indicator	European Union	Europe	OECD	World
Aggregated/Cross-Sectoral	0.6461	0.6364	0.6193	0.6010
R&D%GDP				
Quarter 1	0.6763	0.7021	0.6183	0.4577
Quarter 2	0.5177	0.4710	0.4428	0.5275
Quarter 3	0.4511	0.5227	0.5266	0.4522
Quarter 4	0.6704	0.6488	0.4577	0.6204
LFPA				
Quarter 1	0.5998	0.5931	0.3765	0.3842
Quarter 2	0.6456	0.6471	0.3766	0.4778
Quarter 3	0.4774	0.4725	0.6274	0.6244
Quarter 4	0.7194	0.7402	0.6114	0.5999
TE%GDP				
Quarter 1	0.5854	0.4830	0.4449	0.4403
Quarter 2	0.6428	0.6109	0.5784	0.5952
Quarter 3	0.5444	0.5444	0.5559	0.5868
Quarter 4	0.6813	0.6761	0.5229	0.5082
TE%TME				
Quarter 1	0.4805	0.4781	0.3838	0.4020
Quarter 2	0.5888	0.5927	0.4397	0.4478
Quarter 3	0.5979	0.6057	0.6328	0.6370
Quarter 4	0.6839	0.6744	0.5925	0.5764
High-Tech Index (quarters)				
Quarter 1	0.6769	0.6534	0.3764	0.3842
Quarter 2	0.4971	0.4971	0.4929	0.5549
Quarter 3	0.5268	0.5569	0.6132	0.4724
Quarter 4	0.6822	0.7035	0.5771	0.6230
High-Tech Index (clustered)				
Cluster 1	0.6408	0.5906	0.3842	0.3744
Cluster 2	0.5723	0.5990	0.5522	0.4217
Cluster 3	0.6729	0.5878	0.4853	0.5642
Cluster 4	0.6853	0.6885	0.6848	0.6629

Panel A reports the results on bias employing the relative absolute valuation error aggregated by the harmonic mean. Panel B reports the results on accuracy employing the log-scaled absolute valuation error aggregated by the median.

The results for the test on bias (as reported in panel A) indicate that the multiples segmented into quarters outperform the aggregated multiple unsystematically for the various country high-tech indicators. Furthermore, the results indicate no systematic relationship between the magnitude of bias and peer pools. Finally, the country high-tech indicator segmented multiples show no material improvement over the sectoral multiples irrespective of the peer pool setting employed. The results for the test on accuracy (as reported in panel B) similarly indicate the country high-tech indicator segmented multiples to unsystematically outperform the aggregated multiple, but with a weak tendency to improve for the larger peer pools. Furthermore, the multiples show no material improvement over sectoral multiples across all peer pools. Therefore, the results allow for the general conclusion that (i) valuation analysts may not gain improvement when sub-segmenting the peer pools by country high-tech indicators on both, bias and accuracy, (ii) the size of the peer pool has no material impact on the performance of the country high-tech indicator segmented multiples and, (iii) valuation analysts may employ sectoral multiples or country high-tech indicator segmented multiples alternately.

6. Robustness Tests

In this section, I test the results on accuracy on both, whether they are robust to the valuation error and the size of the peer group employed. First, I repeat the computations in order to evaluate whether the previous results are sensitive to the valuation error employed. Therefore, I replace the relative log-scaled absolute valuation error by the relative squared valuation error, since the latter does not only indicate the strength of the deviation between the estimated and the observed multiple, but is sensitive to extreme values yielding larger errors in case of severe over- or underestimation [11]. This incorporates valuable information on the distribution and homogeneity. The relative squared valuation error is denoted by

$$RSVE_i^{\delta_{i,j}} = \left(\frac{\widehat{\lambda_i^{\delta_{i,j}}} - \lambda_i^{\delta_{i,j}}}{\lambda_i^{\delta_{i,j}}}\right)^2 \tag{6}$$

where i is the index on firm transactions, $\delta_{i,j}$ is the value driver (with j indicating operating sales, EBITDA, EBIT, EBT and, total assets), $RSVE_i^{\delta_{i,j}}$ is the relative squared valuation error on the corresponding value driver, $\widehat{\lambda_i^{\delta_{i,j}}}$ is the estimated enterprise value multiple on the corresponding value driver and, $\lambda_i^{\delta_{i,j}}$ is the observed enterprise value multiple on the corresponding value driver.

As with the relative log-scaled absolute valuation error, in order to ensure unbiased estimates on accuracy, I aggregate the results of the relative squared valuation error employing the median.

Table 6 reports the results on the test on accuracy by multiples, high-tech sector segmentation and, country high-tech indicator segmentation, employing the relative squared valuation error. The superior multiple (panel A), the sectoral multiples outperforming the cross-sectoral multiple (panel B) and, the quarters/clusters for the country high-tech indicator segmented multiples outperforming the aggregated multiples (panel C) are indicated in bold numbers. For the countries forming the various peer pools see table 9 in the appendix.

Table 6. *Performance (test on accuracy) by multiples, sector segmentation, country high-tech indicator segmentation and, peer pool settings.*

Panel A: Performance (test on accuracy) by multiples and peer pool settings

Multiples	**Geographical/Political Regions**			
	European Union	**Europe**	**OECD**	**World**
Aggregated	0.3412	0.3337	0.2556	0.2399
EPV/Sales	0.5359	0.5335	0.4411	0.4287
EPV/EBITDA	0.3637	0.3492	0.2770	0.2434
EPV/EBIT	0.4674	0.4421	0.2889	0.2745
EPV/Total Assets	0.1857	0.1826	0.1450	0.1272
EQV/EBT	0.2710	0.2663	0.2355	0.2286

Multiples	**Cultural Regions**				
	English	**French**	**German**	**Scandinavian**	**(Post) Communist**
Aggregated	0.1470	0.5334	0.1863	0.3418	0.4017
EPV/Sales	0.2167	0.5568	0.2584	0.5038	0.4823
EPV/EBITDA	0.1205	0.3284	0.2143	0.3205	0.3662
EPV/EBIT	0.1379	0.4295	0.2450	0.3469	0.3930
EPV/Total Assets	0.1168	0.1612	0.1003	0.1683	0.3305
EQV/EBT	0.1678	0.2546	0.1726	0.4567	0.4439

Panel B: Performance (test on accuracy) by sector segmentation and peer pool settings

High-Tech Industries	**Geographical/Political Regions**			
	European Union	**Europe**	**OECD**	**World**
Cross-Sectoral	0.3412	0.3337	0.2556	0.2399
Computer Hardware and Electronics Manufacturing	0.2014	0.1915	0.1744	0.1723
Communications	0.2807	0.2462	0.2277	0.2173
Software Development	0.3264	0.3270	0.2522	0.2532
Medical Technology	0.2508	0.2548	0.2098	0.2243
Electrical Manufacturing	0.3625	0.3634	0.3036	0.2960
Internet & IT-Services	0.3439	0.3065	0.2917	0.2905
Automotive	0.1675	0.1655	0.1632	0.1805
Other High-Tech Industries	0.3267	0.3333	0.2287	0.2373

High-Tech Industries	**Cultural Regions**				
	English	**French**	**German**	**Scandinavian**	**(Post) Communist**
Cross-Sectoral	0.1470	0.5334	0.1863	0.3418	0.4017
Computer Hardware and Electronics Manufacturing	0.1119	0.1082	0.1661	0.2955	0.2712
Communications	0.1370	0.1853	0.2094	0.2741	0.1927
Software Development	0.1280	0.2090	0.1995	0.4751	0.3410
Medical Technology	0.1530	0.2598	0.1715	0.1973	0.2429
Electrical Manufacturing	0.1666	0.2706	0.2118	0.6084	0.3814
Internet & IT-Services	0.1123	0.3799	0.2419	0.3476	0.0233
Automotive	0.1756	0.0382	0.0751	0.8280	0.0720
Other High-Tech Industries	0.1582	0.3007	0.1378	0.1919	0.4528

Panel C: Performance (test on accuracy) by country high-tech indicator segmentation and peer pool settings

Country High-Tech Indicator	**European Union**	**Europe**	**OECD**	**World**
Aggregated/Cross-Sectoral	0.3412	0.3337	0.2556	0.2399
R&D%GDP				
Quarter 1	0.3476	0.3899	0.3154	0.1836
Quarter 2	0.2357	0.1913	0.1814	0.2394
Quarter 3	0.1746	0.2331	0.2373	0.1869
Quarter 4	0.3591	0.3408	0.1836	0.3222
LFPA				
Quarter 1	0.2896	0.2934	0.1300	0.1352
Quarter 2	0.3388	0.3408	0.1303	0.2052
Quarter 3	0.1941	0.1942	0.3203	0.3216
Quarter 4	0.4048	0.4236	0.3047	0.3021

Country High-Tech Indicator	European Union	Europe	OECD	World
TE%GDP				
Quarter 1	0.2925	0.2026	0.1785	0.1719
Quarter 2	0.3263	0.2988	0.2884	0.2929
Quarter 3	0.2465	0.2465	0.2623	0.2811
Quarter 4	0.3679	0.3625	0.2390	0.2263
TE%TME				
Quarter 1	0.2056	0.2093	0.1314	0.1469
Quarter 2	0.2953	0.2844	0.1751	0.1772
Quarter 3	0.2897	0.2867	0.3312	0.3323
Quarter 4	0.3695	0.3635	0.2945	0.2877
High-Tech Index (quarters)				
Quarter 1	0.3668	0.3352	0.1299	0.1347
Quarter 2	0.2206	0.2206	0.2116	0.2650
Quarter 3	0.2455	0.2615	0.3031	0.2030
Quarter 4	0.3738	0.3930	0.2887	0.3236
High-Tech Index (clustered)				
Cluster 1	0.3218	0.2983	0.1352	0.1268
Cluster 2	0.2815	0.3001	0.2587	0.1581
Cluster 3	0.3561	0.2807	0.2079	0.2718
Cluster 4	0.3765	0.3588	0.3688	0.3494

EPV indicates enterprise value, EQV indicates equity value. Panel A reports the results on the performance (accuracy) by multiples. Panel B reports the results on the performance (accuracy) by high-tech sector segmentation. Panel C reports the results on the performance (accuracy) by country high-tech indicator segmentation. For all panels, both, the synthetic peer group multiple and the relative squared valuation error, are aggregated employing the median.

Second, in order to evaluate whether the previous results are sensitive to the size of the peer groups employed, I repeat the computations (based on the relative log-scaled absolute valuation error) employing smaller peer groups capturing only five peers. Table 7 reports the results on the test on accuracy by multiples, high-tech sector segmentation and, country high-tech indicator segmentation. The superior multiple (panel A), the sectoral multiples outperforming the cross-sectoral multiple (panel B) and, the quarters/clusters for the country-specific high-tech indicators outperforming the aggregated multiples (panel C) are indicated in bold numbers. For the countries forming the various peer pools see table 9 in the appendix.

Table 7. *Performance (test on accuracy) by multiples, sector segmentation, country high-tech indicator segmentation and, peer pool settings.*

Panel A: Performance (test on accuracy) by multiples and peer pool settings

Multiples	Geographical/Political Regions			
	European Union	Europe	OECD	World
Aggregated	0.6901	0.6752	0.6590	0.6451
EPV/Sales	0.9366	0.9412	0.8276	0.7912
EPV/EBITDA	0.7093	0.6907	0.5723	0.5938
EPV/EBIT	0.8264	0.7867	0.6119	0.5644
EPV/Total Assets	0.4951	0.4967	0.4392	0.3806
EQV/EBT	0.6185	0.6022	0.5578	0.5435

Multiples	Cultural Regions				
	English	French	German	Scandinavian	(Post) Communist
Aggregated	0.4330	0.6514	0.4870	0.7038	0.7704
EPV/Sales	0.5396	0.9482	0.5921	0.9102	0.9375
EPV/EBITDA	0.3853	0.6536	0.5252	0.6578	0.7265
EPV/EBIT	0.4140	0.7969	0.5596	0.7160	0.7120
EPV/Total Assets	0.3769	0.4419	0.3565	0.4515	0.6593
EQV/EBT	0.4714	0.5948	0.4599	0.9119	0.8430

Panel B: Performance (test on accuracy) by sector segmentation and peer pool settings

High-Tech Industries	Geographical/Political Regions			
	European Union	Europe	OECD	World
Cross-Sectoral	0.6901	0.6752	0.6590	0.6451
Computer Hardware and Electronics Manufacturing	0.5056	0.4974	0.4605	0.4638
Communications	0.6031	0.5812	0.5508	0.5406
Software Development	0.6719	0.6825	0.5804	0.5886
Medical Technology	0.5972	0.5849	0.5174	0.5332
Electrical Manufacturing	0.7225	0.7118	0.6493	0.6363
Internet & IT-Services	0.7244	0.6669	0.6434	0.6040

High-Tech Industries	Geographical/Political Regions			
	European Union	Europe	OECD	World
Automotive	0.4293	0.4260	0.4389	0.4676
Other High-Tech Industries	0.6660	0.6875	0.5508	0.5582

High-Tech Industries	Cultural Regions				
	English	French	German	Scandinavian	(Post) Communist
Cross-Sectoral	0.4330	0.6514	0.4870	0.7038	0.7704
Computer Hardware and Electronics Manufacturing	0.3713	0.3607	0.4628	0.6366	0.6293
Communications	0.4255	0.4918	0.5112	0.6564	0.5266
Software Development	0.4083	0.5308	0.4967	0.8394	0.6639
Medical Technology	0.4499	0.5486	0.4633	0.5445	0.5579
Electrical Manufacturing	0.4781	0.5728	0.5234	0.9408	0.7179
Internet & IT-Services	0.3786	0.7232	0.5573	0.7676	0.1108
Automotive	0.4529	0.1951	0.2853	0.7698	0.2692
Other High-Tech Industries	0.4518	0.6218	0.4100	0.4971	0.8275

Panel C: Performance (test on accuracy) by country high-tech indicator segmentation and peer pool settings

Country High-Tech Indicator	European Union	Europe	OECD	World
Aggregated/Cross-Sectoral	0.6901	0.6752	0.6590	0.6451
R&D%GDP				
Quarter 1	0.7114	0.7443	0.6787	0.4938
Quarter 2	0.5557	0.5120	0.4795	0.5623
Quarter 3	0.4837	0.5535	0.5617	0.4895
Quarter 4	0.7281	0.6972	0.4938	0.6620
LFPA				
Quarter 1	0.6367	0.6362	0.4002	0.4062
Quarter 2	0.6986	0.6998	0.4062	0.5082
Quarter 3	0.5070	0.5165	0.6672	0.6684
Quarter 4	0.7557	0.7843	0.6543	0.6466
TE%GDP				
Quarter 1	0.6243	0.5212	0.4815	0.4764
Quarter 2	0.6891	0.6488	0.6137	0.6354
Quarter 3	0.5781	0.5830	0.5950	0.6306
Quarter 4	0.7227	0.7193	0.5637	0.5448
TE%TME				
Quarter 1	0.5016	0.5133	0.4028	0.4368
Quarter 2	0.6557	0.6480	0.4473	0.4850
Quarter 3	0.6386	0.6513	0.6677	0.6653
Quarter 4	0.7369	0.7260	0.6140	0.5928
High-Tech Index (quarters)				
Quarter 1	0.7260	0.6931	0.4002	0.4073
Quarter 2	0.5286	0.5286	0.5268	0.5936
Quarter 3	0.5779	0.6145	0.6493	0.5063
Quarter 4	0.7292	0.7593	0.6189	0.6644
High-Tech Index (clustered)				
Cluster 1	0.6838	0.6395	0.4062	0.4003
Cluster 2	0.6170	0.6470	0.5897	0.4546
Cluster 3	0.6625	0.6324	0.5241	0.6017
Cluster 4	0.7312	0.7411	0.7223	0.7135

EPV indicates enterprise value, EQV indicates equity value. Panel A reports the results on the performance (accuracy) by multiples. Panel B reports the results on the performance (accuracy) by high-tech sector segmentation. Panel C reports the results on the performance (accuracy) by country high-tech indicator segmentation. For all panels, both, the synthetic peer group multiple and the relative log-scaled absolute valuation error, are aggregated employing the median.

The results reported in tables 6 and 7 indicate previous findings to be strongly robust, i. e., they are insensitive to both, the valuation error employed and the size of the peer group. Concerning the accuracy of multiples (as reported in the respective panels A), the enterprise value to total assets multiple again dominates across all peer pool settings, followed by the equity value multiple (except for some cultural peer pools) and, the multiples show a general tendency to improve with peer pool size (as indicated for the geographical/political peer pools). Sectoral multiples (as reported in the respective panels B) again outperform the cross-sectoral multiple in the geographical/political peer pools in most sectors as well as across the cultural peer pools, although indicating a somewhat weaker superiority, and, the sectoral multiples similarly do not show a clear improvement with an increase in the size of the peer pool. Finally, country high-tech segmented multiples (as reported in the respective panels C) again (unsystematically) outperform the aggregated multiple, show no material improvement over sectoral multiples across all peer pools and, the size of the peer pool has no material impact on the performance of the country high-tech indicator segmented multiples (but with a weak tendency to improve for the larger peer pools).

7. Conclusion

Empirical evidence on the performance of multiples reveals contradictory results that may be attributed to varying peer pool settings. Inconsistencies have been documented on (i) the performance of enterprise value as opposed to equity value multiples, (ii) the relative superiority of multiples according to the value driver employed and, (iii) the relative superiority of cross-sectoral multiples. Furthermore, the results reveal different peer pools to generate minimum errors on multiple's estimates across countries.

In this study, I examine the systematic impact of peer pooling on (i) the relative superiority of cross-sectoral multiples, (ii) the absolute superiority of sectoral multiples and, (iii) the absolute superiority of cross-sectoral multiples being segmented by various country high-tech indicators. Data on private market transactions is collected from 2000 until 2018, categorized into peer pools formed according to geographical/political criteria as well as according to cultural regions. The final sample population is 22,967 observations on private market transactions. The results allow for some general conclusions and recommendations. First, contradictory results in prior research on multiple's bias may be strongly attributed to the varying peer pools employed. Second, the enterprise value to total assets multiple clearly dominates across all peer pools on a cross-sectoral basis, indicating that contradictory results on multiple's accuracy may not be attributed to the varying peer pools employed (but to other sample characteristics). Third, the performance of sectoral multiples depends on the value driver employed, since they show only a weak relationship with the peer pool setting. Therefore, valuation analysts are recommended (i) to employ larger peer pools when employing cross-sectoral multiples (sectoral as well as country-specific high-tech indicator segmented multiples do not allow for this recommendation), (ii) to employ the enterprise value to total assets multiple valuing private high-tech firms, (iii) to further break down the high-tech sector into sub-sectors and, (iv) to employ sectoral multiples or country high-tech indicator segmented multiples alternately. All results are proved to be strongly robust.

The results of this study are restricted to a variety of limitations. First, following the main body of related research, all transactions of firms with negative earnings fundamentals remained disregarded, thus reducing the initial sample by about 30 percent (unreported). Including these firms might change the results considerably. Second, the sample is systematically modified according to value driver characteristics. As with all sample modifications, the information lost might again modify the results. Finally, the data provided is limited because (i) not all transactions occurring are recorded in the database employed (since there is no official obligation to register) and (ii) the recorded data is often inchoate and sometimes unreliable. Therefore, an increased data availability and reliability would allow for a more comprehensive analysis.

Appendix

Table 8. *Controlling variables employed.*

Category/Variables	Definition of variable/ Explanation and related literature
Deal characteristics:	
Negotiation success	Dummy causal factor vector according to magnitude of multiple in corresponding year (positive = highest quartile, neutral = quartiles 2 and 3, negative = lowest quartile). Methodology lends support to the bargaining power hypothesis suggesting that closely controlled firms may have significant bargaining strength, allowing the owners to receive premia exceeding acquirer's potential gains [74].
Private market transaction (acquisition) characteristics:	
Synergy	Dummy causal factor on acquirer being a financial investor or not (based on NACE Rev.2 industry affiliation, 0 = non-strategic (financial) buyer = two-digit codes 64 to 66 (banking and financing), 1 = otherwise = strategic buyer). An acquirer other than a financial investor may experience advantages through synergy from the private market transaction, causing the transaction price to include the value of the acquirer's individual expected synergies. Methodology is employed e. g. by [75-81].
Control	Dummy causal factor on private market transaction being a majority (control) share acquisition or a minority share acquisition (1 = majority share transaction = transaction resulting in a stake above 50 percent for the acquiror (no matter whether the acquirer already held a minority share prior to the transaction or not), 0 = minority share transaction = transaction resulting in a stake below 50 percent for the acquiror (no matter whether the acquirer already held a minority share prior to the transaction or not)). Control shares provide control benefits and control flexibility [82-84].
Diversification	Dummy causal factor on target company being engaged in one or more industries according to predefined high-tech industry groupings as well as two-digit NACE Rev.2 industry breakdown (1 = diversified company = engaged in two or more industries, 0 = pure play = otherwise). Diversified companies are valued lower than undiversified companies according to excess value and Tobin's q studies [85-96] and event studies [97-101]. Methodology is employed e. g. by [64, 102-104].
Region of private market	Dummy causal factor on region of transaction, as indicated by the country codes of acquirer and target firm (1 =

Category/Variables	Definition of variable/ Explanation and related literature
transaction (acquisition)	cross-border transaction, 0 = domestic transaction). Methodology is employed e. g. by [105, 106].
Method of payment	Dummy causal factor (1 = payment made in cash or liabilities, 0 = otherwise). Methodology lends support to the information asymmetry hypothesis (shareholders of listed targets have no strong incentive to examine the potential acquirer closely, whereas the concentrated ownership of private firms provides their owners with powerful incentives especially when they are paid in stocks) and the corporate monitoring hypothesis (suggesting agency costs to be lower if some investors actively monitor managerial activities) [74]. Method of payment is concluded to be a powerful controlling variable in different settings: Transaction prices are significantly lower when buyers pay in cash providing immediate liquidity to the seller [107]; method of payment is significantly positively related to bidder returns [79]; wealth effects to targets and bidders are higher with cash versus stock deals [108-112]; share-bidders experience a significant negative abnormal return relative to cash-bidders [113, 114]; the signalling implications of the method of payment are likely to differ across bids for private and public targets [115-117]; bidders pay higher premia in more concentrated industries when payment is made with stocks [62]; investigating the relationship between the method of payment in acquisitions, earnings management and operating performance of the buyer [118]; investigating differences in acquisitions occurring during booming and depressed markets [119]; examining the relationship between the premium paid in acquisitions and deal size [104].
Market (for corporate takeovers) characteristics:	
Market condition, market activity	Vector of year dummies over sample period 2000 until 2019 (1 = transaction occurred in a given year, 0 = otherwise) Methodology lends support to the managerial herding hypothesis [119]. It is employed e. g. examining the relation between the premium paid in acquisitions and deal size [104, 120]; examining valuation differences in the boom and crash market periods relative to stable periods of IPOs [121, 122]; comparing the effectiveness of various industry classification codes [30, 62].
Firm characteristics – Profitability:	
Return on sales target firm	EBT divided by operating sales of fiscal year preceding the private market transaction. Variable is employed e. g. examining the performance of various industry groupings [33]; examining the performance of industry-related as compared to cross-sectoral multiples [70]; elaborating upon accuracy and drivers' evidence of multiples [5]; examining sell-side analyst's choice on peers [123]. Sometimes EBT is replaced by EBIT [124, 125].
Return on assets target firm	EBIT divided by total assets of fiscal year preceding the private market transaction. Variable is employed e. g. examining optimal peer selection formulae [66]; examining CEO compensation [126-128] as well as by [30, 33, 64].
Firm characteristics – Risk:	
Size of target firm	Natural logarithm of (indexed) annual operating sales of fiscal year preceding the private market transaction. Size of the target firm was concluded to be a relevant selection criterion [129, 130]. Variable is employed e. g. examining optimal peer group definition estimating betas of private firms [60]; examining shifts in the explanatory power of fundamentals in the valuation of IPOs in the new economy period [132]; examining CEO compensation [126, 127] as well as by [123, 131-133]. Sometimes alternative size measures such as ordinary sales or the natural logarithm of assets and market capitalization are employed [5, 30, 31, 59, 67, 70, 104, 125, 134-137].
Business risk	Dummy causal factor with business risk being proxied by the developmental stage of the private firm, represented by a date of incorporation within five years prior to the private market transaction (1 = date of incorporation within five years, 0 = otherwise). Methodology is employed e. g. by [30, 105, 130].
Legal form of acquirer	Dummy causal factor on whether the owners of the acquirer may be held responsible for firm debt or not (1 = public limited company (unlisted) or joint stock company (unlisted) = no responsibility for debt, 0 = otherwise = responsibility for debt).
Legal form of target firm	Dummy causal factor on whether the owners of the acquirer may be held responsible for debt of target firm purchased or not, or the prior owners of the target firm retain being held responsible for its debt (1 = public limited company (unlisted) or joint stock company (unlisted) = no responsibility for debt, 0 = otherwise = responsibility for debt). Variable is employed e. g. examining differences in returns for acquirers of public versus private firms [117].
Absolute size of private market transaction (acquisition)	Natural logarithm of deal value. Variable is employed e. g. by [104].
Relative size of private market transaction (acquisition)	Percentage of acquired share of equity. Variable is employed e. g. by [119].
Size ratio target to acquirer	Natural logarithm of operating sales of target to natural logarithm of operating sales of acquirer, both of fiscal year preceding the private market transaction. Variable is employed e. g. investigating the returns to shareholders of firms making multiple acquisitions [116]; examining the dependence of the acquirer gains on the relative size of the takeover partners [74]; investigating the short-term market response associated with the announcement of large domestic mergers and acquisitions [79] as well as by [104, 108, 131, 132, 138].
Size ratio of private market transaction (acquisition) to acquirer	Natural logarithm of deal value to natural logarithm of operating sales of acquirer of fiscal year preceding the private market transaction. Variable is employed e. g. by [104, 108, 138, 139].
Firm characteristics – Growth:	
Compound annual growth rate of target firm	Compound five-years annual growth rate of (indexed) operating sales preceding the private market transaction. Methodology is employed e. g. by [132] as well as with varying durations investigating the effect of R&D investments on the market value of firms [140], investigating the short-term market response associated with the announcement of large domestic mergers and acquisitions [79], elaborating upon accuracy and drivers' evidence of multiples [5] and,

Category/Variables	Definition of variable/ Explanation and related literature
	examining the impact of valuation model choice on target price accuracy [135]. Variable is employed e. g. by [27, 60, 66, 123, 137].
Firm characteristics – Other:	
Type of accounting	Dummy causal factor on type of accounting (1 = consolidated financial statement, 0 = otherwise). Variable is related to the finding that earnings quality of private firms depends on the type of accounting [141]. Variable is employed e. g. by [119].

Table 8 categorizes the 19 variables employed to select peers, defines them, gives methodological explanations and, reports related literature. Literature not already included in the reference list is additionally reported.

Table 9. *Country classification according to high-tech indicators.*

Country	Research & Development Expenditure in % of GDP				Labor Force per Patent Application				Technology Exports in % of GDP				Technology Exports in % of Total Manufactured Exports				High-Tech Index			
	EU	E	O	W	EU	E	O	W	EU	E	O	W	EU	E	O	W	EU	E	O	W
Argentina				4				4				4				4				4 (4)
Australia			3	3			2	2			4	4			4	4			4 (3)	3 (3)
Austria	2	2	3	2	2	2	3	3	2	2	2	2	3	3	4	4	3 (2)	3 (2)	3 (3)	3 (3)
Belgium	2	2	3	3	4	4	4	4	1	1	2	2	3	3	4	4	3 (2)	3 (2)	4 (3)	4 (4)
Bosnia and Herzegovina		4		4		4		4		4		4		4		4		4 (4)		4 (4)
Brazil				4				4				4				4				4 (4)
Bulgaria	4	4		4	4	4		4	3	3		3	4	4		4	4 (4)	4 (4)		4 (4)
Canada			3	3			2	2			3	3			4	4			4 (3)	3 (3)
Chile			4	4			4	4			4	4			4	4			4 (4)	4 (4)
China				4				4				1				1				2 (3)
Colombia				4				4				4				4				4 (4)
Croatia	4	4		4	4	4		4	4	4		3	4	3		4	4 (4)	4 (4)		4 (4)
Cyprus	4	4		4	4	4		4	4	4		4	2	2		3	4 (4)	4 (4)		4 (4)
Czech Republic	4	3	4	4	4	4	4	4	1	1	1	1	2	2	3	3	3 (2)	3 (2)	2 (2)	4 (4)
Denmark	1	1	2	2	2	2	3	3	3	3	3	3	3	3	4	3	3 (2)	3 (2)	3 (3)	3 (3)
Egypt				4				4				4				4				4 (4)
Estonia	4	3	4	4	4	4	4	4	1	1	1	1	2	2	3	3	3 (3)	3 (2)	3 (3)	4 (4)
Finland	1	1	1	1	2	2	3	3	3	3	3	3	3	3	4	4	2 (2)	2 (1)	3 (3)	2 (3)
France	2	2	3	3	2	2	3	3	2	2	3	2	1	1	2	2	2 (2)	2 (2)	3 (2)	3 (3)
Germany	1	1	2	2	1	1	3	2	1	2	2	2	3	3	3	3	1 (1)	1 (1)	3 (2)	2 (3)
Greece	4	4	4	4	4	4	4	4	4	4	4	4	3	3	4	4	4 (4)	4 (4)	4 (4)	4 (4)
Hong Kong				4				2				4				3				3 (3)
Hungary	4	4	4	4	4	4	4	4	1	1	1	1	2	2	3	3	1 (2)	1 (1)	2 (2)	4 (3)
Iceland		2	3	2		3	4	3		4	4	3		1	1	1		3 (2)	3 (2)	2 (3)
India				4				4				4				4				4 (4)
Indonesia				4				4				4				4				4 (4)
Ireland	4	3	4	4	4	4	4	4	1	1	1	1	1	1	1	1	3 (2)	3 (2)	2 (2)	3 (3)
Israel			1	1			3	2			2	2			3	3			2 (2)	2 (2)
Italy	4	4	4	4	3	3	4	3	4	4	4	3	4	4	4	4	4 (4)	4 (3)	4 (4)	4 (4)
Japan			2	2			2	1			3	3			3	3			2 (1)	1 (2)
Jordan				4				4				4				4				4 (4)
Kenya				4				4				4				4				4 (4)
Luxembourg	4	3	4	4	3	3	4	3	4	4	3	3	4	4	4	4	3 (3)	3 (3)	4 (4)	4 (4)
Malaysia				4				3				1				1				2 (3)
Malta	4	4		4	4	4		4	1	1		1	1	1		1	1 (1)	1 (1)		3 (3)
Montenegro		4		4		4		4		4		4		3		4		4 (4)		4 (4)
Netherlands	3	3	3	3	3	3	4	4	1	1	2	2	1	1	2	2	2 (2)	2 (1)	2 (2)	3 (3)
New Zealand			4	4			2	2			4	4			4	4			4 (3)	4 (3)
North Macedonia		4		4		4		4		4		4		4		4		4 (4)		4 (4)
Norway		3	4	3		1	3	2		4	4	4		2	3	3		3 (2)	4 (3)	3 (3)
Pakistan				4				4				4				4				4 (4)
Philippines				4				4				1				1				2 (3)
Poland	4	4	4	4	4	4	4	4	3	3	3	3	4	4	4	4	4 (4)	4 (4)	4 (4)	4 (4)
Portugal	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4 (4)	4 (4)	4 (4)	4 (4)
Romania	4	4		4	4	4		4	3	3		3	4	4		4	4 (4)	4 (4)		4 (4)
Russia		4		4		2		3		4		4		4		4		3 (3)		4 (4)
Serbia		4		4		4		4		4		4		4		4		4 (4)		4 (4)
Singapore				3				2				1				1				1 (1)
Slovak	4	4	4	4	4	4	4	4	1	1	2	2	4	4	4	4	3 (4)	3 (3)	4 (4)	4 (4)

Country	Research & Development Expenditure in % of GDP				Labor Force per Patent Application				Technology Exports in % of GDP				Technology Exports in % of Total Manufactured Exports				High-Tech Index			
	EU	E	O	W	EU	E	O	W	EU	E	O	W	EU	E	O	W	EU	E	O	W
Republic Slovenia	2	2	3	3	3	3	4	4	3	3	3	3	4	4	4	4	3 (3)	3 (3)	4 (3)	4 (4)
South Africa				4				4				4				4				4 (4)
South Korea			1	1			1	1			1	1			1	1			1 (1)	1 (1)
Spain	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4 (4)	4 (4)	4 (4)	4 (4)
Sri Lanka				4				4				4				4				4 (4)
Sweden	1	1	1	1	2	2	4	3	2	2	2	2	2	2	3	3	1 (1)	1 (1)	2 (2)	2 (3)
Switzerland		1	2	2		3	4	3		1	2	2		2	2	2		1 (1)	2 (2)	2 (3)
Taiwan				-				4				4				4				-
Thailand				4				4				1				2				4 (4)
Turkey		4	4	4		4	4	4		4	4	4		4	4	4		4 (4)	4 (4)	4 (4)
Ukraine		4		4		4		4		4		4		4		4		4 (4)		4 (4)
United Kingdom	3	3	4	4	1	1	3	3	3	3	3	3	2	2	3	3	3 (2)	3 (2)	3 (3)	4 (3)
United States			2	2			2	2			4	4			2	2			2 (2)	2 (3)

GDP indicates Gross Domestic Product, EU indicates European Union member countries, E indicates Europe, O indicates OECD counties and, W indicates World (total sample). A value in the respective column indicates a country's affiliation to the respective peer pool. For the first, third and, fourth indicator, a value of 1 indicates affiliation to quarter 1 (highest) and a value of 4 indicates affiliation to quarter 4 (lowest). For the second indicator, quarters are sorted in inverse order, thus a value of 1 (quarter 1) capturing the countries with the lowest and a value of 4 (quarter 4) capturing the countries with the highest indicators. For the high-tech index, values on quarters are reported without brackets, values on clusters in brackets (both sorted in descending order).

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