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## **Forecast Bias and Analyst Independence\***

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Phillip J. McKnight<sup>1</sup>, Steven K. Todd<sup>2</sup>

**Abstract:**

*This paper examines the accuracy of equity analysts who provide earnings forecasts for European companies. We find strong evidence of institutional bias in analysts' forecasts, specifically, when analysts move between sell-side employers and independent employers, they issue more accurate forecasts while they are employed by independent firms. Moreover, these differences persist when we hold constant the set of firms these mobile analysts research. We find statistically significant differences in the forecast accuracy of sell-side and independent analysts. The optimistic bias of sell-side analysts appears to be related to underwriting activity. Analysts employed by lead underwriters produce less accurate forecasts for newly public companies than do either buy-side or independent analysts. The optimistic bias persists for a five-year period following an IPO.*

**Key Words:** *Analysts, Forecasts, Bias, Sell-side, Buy-side, Independent*

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**JEL Classification:** *G12, G14*

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<sup>1</sup> *University of Wisconsin, Sheldon B. Lubar School of Business, Milwaukee, WI 53201; Tel: 920-791-0339; Email: [mcknighp@uwm.edu](mailto:mcknighp@uwm.edu).*

<sup>2</sup> *Loyola University Chicago, Quinlan School of Business, 820 N. Michigan Avenue, Chicago, IL 60611; Tel: 312-915-7218; E-mail: [stodd@luc.edu](mailto:stodd@luc.edu)*

## **1. Introduction**

In his testimony to the U.S. Senate, in June, 2002, New York State Attorney General, Eliot Spitzer, argued that the investment advice Merrill Lynch offered its clients was tainted and plagued by conflicts of interest. Equity analysts at times functioned as sales representatives for the firm's investment bankers. Analysts frequently stated private opinions that were at odds with their public assessments of stocks. Moreover, compensation for analysts was tied to the success of investment banking activities, rather than the accuracy of analysts' earnings forecasts.

Six months after Spitzer's testimony to Congress, ten of Wall Street's largest firms agreed to pay \$1.4 billion to settle allegations by federal and state regulators that they provided misleading investment advice to customers. As part of the settlement, Merrill Lynch, J.P. Morgan Chase, Citigroup, and Credit Suisse First Boston all agreed to separate their equity research from investment banking activities. They also agreed to spend \$450 million to develop "independent" research. Conventional wisdom argues that independent research is better than sell-side (investment banking) research. We wish to test this hypothesis.

We develop a novel methodology for testing whether analyst bias results from institutional factors (such as conflicts of interest attributable to analyst-employer activities) or individual analyst factors (such as firm selection, analyst productivity and forecast age). We study a subset of mobile analysts who work at multiple analyst-employers during their careers. We examine whether the forecast accuracy of these mobile analysts changes as they move from one analyst-employer to another.

We also develop a new way of classifying equity analysts based on the activities of their employers. We consider three employer classes (sell-side, buy-side and independent firms) and seven employer activity groups: active underwriters, underwriters, syndicate members, asset managers, non-underwriting brokers, non-underwriting banks and pure research firms. We test for differences in forecast quality across analyst-employer classes and activity groups.

We find that when analysts move between sell-side employers and independent employers, they issue more accurate forecasts while they are employed by independent firms. Moreover, these differences persist when we hold constant the

set of firms these mobile analysts research. These results are consistent with institutional factors contributing to bias.

We provide evidence that an analyst's accuracy is related to the employer class at which she begins her career. Analysts who start their careers at buy-side employers do not suffer from institutional biases. On the other hand, analysts who start their careers at either sell-side or independent employers appear to be susceptible to institutional biases as they move from one employer class to another.

The optimistic bias of sell-side analysts appears to be related to underwriting activity. We find that analysts employed by lead underwriters produce more optimistic forecasts for newly public companies than do either buy-side or independent analysts. The optimistic bias of analysts employed by lead underwriters persists for a five-year period following an IPO.

We examine the determinants of analyst forecast errors. Consistent with institutional biases impacting analyst accuracy, we find that forecast errors increase when the analyst is employed by a sell-side firm and decrease when the analyst is employed by an independent firm. The analyst-employer class at which an analyst begins her career is also important in explaining forecast errors. Forecast errors increase when the analyst begins her career at a sell-side firm and decrease when the analyst begins her career at either a buy-side or independent firm.

We find that analysts who research European companies exhibit the same optimistic bias in their earnings forecasts as their peers who examine U.S. companies. Over the period 1988 – 2005, the mean forecast error is 13.6%. Independent analysts produce the most accurate forecasts and sell-side analysts produce the least accurate forecasts. We find that forecast accuracy varies substantially within the sell-side and independent analyst-employer classes. Analysts affiliated with active underwriters are more accurate and less optimistic than analysts affiliated with syndicate members. On the other hand, analysts who are employed by non-underwriting banks or brokers are more accurate and less optimistic than analysts employed by pure research firms.

The remainder of the paper is organized as follows. Section II reviews the literature. Section III describes our methodology and data set. Our empirical results appear in Section IV. Section V concludes the paper.

## **2. Literature Review**

Do equity analysts issue biased forecasts? Many researchers conclude so. Analyst forecasting errors are large and display an optimistic bias (Dreman and Berry, 1995; Brown, 1997). Analysts have a tendency to herd, where herding is defined as “excessive agreement” among forecasts and recommendations (Welch, 2000). Stock recommendation changes are sticky in one direction, with analysts reluctant to downgrade securities (Conrad, Cornell, Landsman and Rountree, 2006). Moreover, there is evidence that analysts collude with firms to play an “earnings-guidance game,” where optimistic forecasts are issued at the start of the year and then ‘walked down’ to a level that firms can beat by the end of the year (Richardson, Teoh and Wysocki, 2004, Brown, 2000, Matsumoto, 2002 and Thalassinos *et al.*, 2012).

Several competing explanations have been offered for analyst forecast bias. Some researchers conclude that bias is related to investment banking or brokerage activities. Analysts are biased because of conflicts of interest introduced by underwriting relationships (Michaely and Womack, 1999, Bradshaw, Richardson and Sloan, 2003). Compared to independent analysts, analysts affiliated with investment banks offer inferior stock recommendations (Cliff, 2007). Moreover, investor trading strategies based on independent research are more profitable than those based on affiliated research, with the exception of sell recommendations (Barber, Lehavy and Trueman, 2005). Alternatively, sales and trading activities induce bias. Analysts at pure brokerage firms are more optimistic than those employed by underwriters (Cowen, Groysberg and Healy, 2005).

Other researchers conclude that forecast bias is not related to conflicts associated with analyst-employer activities. After controlling for forecast age, firm resources and analyst workloads, there is no relation between forecast bias and investment banking/brokerage activities (Agrawal and Chen, 2008). There is no evidence that the lucrative fees investment banks earn on mergers and acquisition advisory work influence analyst objectivity (Kolasinski and Kothari, 2008). Moreover, there is no evidence that analysts show bias towards firms that file for bankruptcy (Clarke, Ferris, Jayaraman and Lee, 2005). In fact, analysts employed by investment banks produce less optimistic and more accurate earnings forecasts than analysts employed by independent research firms (Jacob, Rock and Weber, 2003) or brokerages (Clarke, Khorana, Patel and Rau, 2004).

If bias isn't related to analyst-employer conflicts, what is its cause? Bias may be rational. Under certain analyst-utility assumptions, forecasts which minimize expected error are characterized by an optimistic bias (Lim, 2001). Bias might result from the use of judgmental heuristics (Affleck-Graves, Davis and Mendenhall, 1990), or from analysts catering to investor beliefs (Lai, 2004). Alternatively, estimates of bias might be imprecise because of data censorship (Hayes and Levine, 2003), or asymmetries in the distribution of forecast errors (Abarbanell and Lehavy, 2003). Bias might result from earnings skewness (Gu and Wu, 2003) or variations in disclosure requirements (Higgins, 1998). It is also possible that bias occurs naturally in certain incentive contracts that account for the interaction between analysts and firm managers (Mittendorf and Zhang, 2005).

Are analysts rewarded for forecast accuracy? Accuracy is rewarded, but so is optimism. Controlling for accuracy, analysts who are optimistic are more likely to experience favorable job changes (Hong and Kubik, 2003). In fact, analysts face a trade-off between being optimistic and generating short-term trades for their employers or being accurate and cultivating a reputation for accuracy that generates long-term trades (Jackson, 2005). Although buy recommendations generate increased trading activity, analysts cannot generate trades for their employers by simply adding error to their forecasts (Irvine, 2004).

Up until its repeal by Congress in 1999, Glass-Steagall legislation had a significant impact on U.S. financial firms and their activities. No such legislation restricted banking activities in Europe. Differences in the regulatory environments for U.S. and European banks, and differences in the banking environments across European countries make the question of analyst bias a particularly interesting international issue. In this paper, we seek to shed light on this issue.

### **3. Methodology**

We measure analyst independence by focusing on the activities of analyst-employers. We consider three analyst-employer classes: sell-side firms, buy-side firms and independent firms. Sell-side firms are investment banks that engage in trading and underwriting activities for corporate clients. Buy-side firms are asset management firms engaged primarily in investment activities for retail and institutional customers. Buy-side firms include pension funds and mutual funds.

Independent firms are pure research firms, brokers or banks that do not underwrite securities or manage money.

We attempt to isolate the institutional factors that might induce forecast bias by tracking analysts through their careers and by focusing on the forecast accuracy of mobile analysts who move from one class of analyst-employer to another. For example, Jane Smith might start her career as an analyst at Deutsche Bank, an investment bank. Mid-way through her career, Jane Smith might change employers, leaving Deutsche Bank for Cordius Asset Management. At a later date, Jane Smith might change employers again, leaving Cordius Asset Management for Limmat, an independent research firm. Throughout her career, Jane Smith might specialize in the analysis of food companies, such as Nestlé. One question we can ask is whether Jane Smith's forecasts of Nestlé's earnings change as she changes employers. If so, it might be because institutional biases at Deutsche Bank or Cordius Asset Management impact Ms. Smith's objectivity. For example, if Deutsche Bank is underwriting a debt issue for Nestlé, or if Deutsche Bank holds shares of Nestlé stock, then Ms. Smith's analysis of Nestlé might be tainted by her employer's relationship with Nestlé. She might be more inclined to issue a favorable earnings forecast for Nestlé when Deutsche Bank is her employer, just to keep her employer's customer satisfied.

We conduct our analysis with the help of two large databases: I/B/E/S and SDC. The Institutional Brokers Estimate System (I/B/E/S) reports the earnings forecasts and stock recommendations of an incomplete set of equity analysts employed by sell-side firms, buy-side firms and independent research firms. We collect information for all analysts who research European companies over the period 1988 through 2005. The Securities Data Corporation (SDC) reports the stock and bond offerings of a comprehensive set of publicly traded corporations. All underwriting relationships for all security issues are documented in this database

We begin our analysis with 352 distinct analyst-employer names from the I/B/E/S database. A single analyst-employer might use multiple names to distinguish among company subsidiaries. We group the 352 distinct analyst-employer names into 245 distinct families. For example, Rabo Securities belongs to the same family as Rabo Effectenbank NV and Darier, Hentsch & Cie belongs to the same family as Lombard, Odier, Darier, Hentsch & Cie.

We use SDC data for all publicly issued European debt and equity securities over the period 1988 – 2005 to determine whether an analyst-employer is an underwriter. Active underwriters are those who rank in the top-ten based on the number of transactions in which they serve as lead (or co-lead) underwriter. Over the sample period we examine, the following ten firms comprise the active underwriting class: Credit Suisse First Boston, Deutsche Bank, DG Bank, Swiss Bank Corp., Commerzbank, Dresdner Bank, Suedwestdeutsche Landesbank, BNP Paribas, UBS and WestLB. Underwriters are those who serve as lead (or co-lead) underwriter on at least one transaction over the sample period. We identify 107 analyst-employer families as underwriters. Some of these firms (e.g., Goldman Sachs, Morgan Stanley, Merrill Lynch) are active underwriters in the U.S., but they do not make the top-ten list in Europe.

Next, we identify 35 analyst-employer families that do not lead (or co-lead) underwrite but that do serve as underwriting syndicate members on at least one transaction over the sample period. This group includes firms such as Bear Stearns and Daiwa Securities.

The remaining 94 analyst-employer families are categorized individually as brokers (40), asset managers (19), non-underwriting banks (20), and pure research firms (10) based on their principal business activity as revealed in financial statements (where available), SEC registration lists, corporate websites and Nelson's Directory of Investment Research. We are unable to classify 5 analyst-employer names.

We combine the seven activity groups into three analyst-employer classes as follows. Active underwriters, underwriters and syndicate members are combined to form a sell-side class. Asset managers belong to the buy-side class. Brokers, non-underwriting banks and pure research firms are combined to form an independent employer class.

In distinguishing among sell-side, buy-side and independent firms, we err on the side of our null hypothesis that there are no differences in forecast accuracy across analyst-employer classes. Our sell-side class includes analyst-employers that participate as underwriters on only one or two transactions. These firms might classify themselves, at least at some point in time, as independent firms, mostly in the business of providing research. By labeling these firms underwriters, we bias

our tests against finding differences in forecast quality across analyst-employer classes.

We examine the accuracy of analyst forecasts across analyst-employer classes and activity groups. The most commonly used measure of forecast accuracy is forecast error, which measures the difference between forecasted earnings and actual firm earnings. Following Hong and Kubik (2003), we scale our measure of forecast error by the price of the stock at the time of an earnings announcement. Other variables which we use in our analysis include firm size (the natural log of a firm's market capitalization), analyst productivity (the number of distinct firms that an analyst researches in the year a forecast is made), forecast immediacy (the number of days from the first earnings estimate to the forecast revision), and a measure of analyst coverage known as residual analyst coverage. This is computed by regressing the natural logarithm of (1 + # of analysts covering a firm) on the natural logarithm of market capitalization, and using the residuals from this regression as a proxy for the incremental effect of analyst coverage (See Bhushan, 1989; Brennan and Hughes, 1991; and Hong *et al.*, 2000).

We focus on analyst forecasts rather than stock recommendations because the latter measure of analyst sentiment is sticky. When analysts initiate coverage for a firm, they often produce a report that lists a one-year (or longer-term) share price target. Recommendations often accompany and summarize these price targets. Analysts may be reluctant to revise their recommendations frequently and appear flippant. In fact, Barber *et al.* (2006) show that nearly half of all recommendations are left unchanged when they are revisited, approximately 300 days after they were first made. Earnings forecasts, in contrast, are generally more responsive to short-term news events. Richardson, Teoh and Wysocki (2004) show that analysts often revise their earnings forecasts on a quarterly (or monthly) basis. Moreover, McKnight and Todd (2006) show that a trading strategy based on forecast revisions dominates one based on recommendations or changes in recommendations.

#### **4. Empirical Results**

Summary statistics for our European data appear in Table 1. This table reports descriptive statistics on analysts and earnings forecasts for three broad classes of analyst-employers (sell-side, buy-side and independent firms) for the period January 1988 through May 2005 for all I/B/E/S reported firms within 16 European countries



(Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and United Kingdom). Panel A reports forecast activity by year and by analyst-employer class; Panel B examines analyst-employer productivity; Panel C considers analyst productivity; Panel D examines firm-country characteristics. In this table and all subsequent tables, we trim the data at the 1% and 99% percentiles to reduce the impact of outliers and data errors.

**Table 1: Descriptive Statistics**

<b>Panel A: Analyst-Employers, Analysts and Estimates</b>									
	<b>Sell-side</b>			<b>Buy-side</b>			<b>Independent</b>		
<b>Year</b>	<b>Analyst-Employers</b>	<b>Distinct Analysts</b>	<b>Estimates</b>	<b>Analyst-Employers</b>	<b>Distinct Analysts</b>	<b>Estimates</b>	<b>Analyst-Employers</b>	<b>Distinct Analysts</b>	<b>Estimates</b>
1988	57	387	17,219	4	29	267	16	102	1,831
1989	88	551	36,994	4	50	514	20	130	3,623
1990	107	799	49,940	4	67	951	23	184	5,264
1991	126	1,172	66,964	5	69	1,672	27	213	7,022
1992	149	1,396	83,279	8	87	2,363	37	247	8,473
1993	165	1,829	116,109	8	78	2,733	42	285	10,191
1994	172	2,018	57,716	9	72	1,075	41	276	4,934
1995	177	2,717	40,320	12	58	622	39	324	4,456
1996	177	3,652	82,461	13	80	1,354	40	380	10,167
1997	181	4,647	126,190	14	113	2,305	46	453	16,140
1998	185	5,054	139,631	14	114	2,995	51	456	17,385
1999	186	5,410	148,059	14	127	3,444	47	398	15,150
2000	174	5,692	149,507	13	135	2,905	49	425	13,031
2001	164	6,018	144,811	11	124	2,539	42	408	12,052
2002	151	6,070	153,961	10	103	2,150	36	373	13,158
2003	123	5,947	168,096	8	82	2,077	33	374	12,679
2004	112	5,695	181,250	6	66	1,454	27	351	12,238
2005	115	4,938	155,605	5	40	995	25	321	9,489
<b>TOTAL</b>			<b>1,918,112</b>			<b>32,415</b>			<b>162,298</b>
<b>Families</b>	<b>152</b>			<b>19</b>			<b>70</b>		

We see in Panel A that equity analysts generated more than 2 million earnings forecasts for European firms over the period 1988 – 2005. Most of the forecasts were made by analysts employed by sell-side firms. Less than 10% of the forecasts were made by buy-side or independent analysts. Because I/B/E/S does not purport to collect data from all research analysts, we cannot say whether the reported

frequencies across analyst-employer classes are representative of all research activity.

Reported forecast activity generally increases from 1988 through 1993, then it declines dramatically. The number of reported estimates generally increases through the mid- and late 1990s, then drops off again in 2000 or 2001. Reporting activity generally follows the world economy, with a lag. During recessions, research activity is typically reduced.

Over the sample period, there are 152 distinct sell-side analyst-employers, 19 distinct buy-side analyst-employers and 70 distinct independent analyst-employers, once we aggregate at the family level. The number of un-aggregated analyst-employers providing estimates generally peaks in the late 1990s. A similar pattern obtains for the number of distinct analysts, although the number of distinct sell-side analysts peaks in 2002.

**Table. 1: Descriptive Statistics (cont'd)**

<b>Panel B: Analyst-Employer Productivity</b>									
Year	Sell-side			Buy-side			Independent		
	Mean Analysts per Employer	Mean Estimates per Analyst	Mean Estimates per Analyst per Firm per Year	Mean Analysts per Employer	Mean Estimates per Analyst	Mean Estimates per Analyst per Firm per Year	Mean Analysts per Employer	Mean Estimates per Analyst	Mean Estimates per Analyst per Firm per Year
1988	15.5	44.5	3.3	7.5	9.2	2.0	7.9	17.3	2.4
1989	14.6	67.1	4.7	13.3	10.3	1.8	8.7	27.9	2.8
1990	16.7	62.5	5.1	19.0	14.2	2.4	11.0	28.6	2.8
1991	19.5	57.1	5.1	16.6	24.2	3.0	10.9	33.0	3.0
1992	19.6	59.7	5.4	13.6	27.2	3.5	9.1	34.3	2.9
1993	21.0	63.5	6.7	12.4	35.0	4.3	9.1	35.8	3.3
1994	19.7	28.6	4.1	9.8	14.9	2.5	8.6	17.9	2.5
1995	21.7	14.8	2.4	5.3	10.7	2.2	9.2	13.8	2.0
1996	25.6	22.8	3.0	6.9	16.9	2.7	10.4	26.8	2.8
1997	31.2	27.2	3.4	8.5	20.4	2.8	10.6	35.6	3.6
1998	31.3	27.6	3.6	8.4	26.3	3.0	9.4	38.1	3.7
1999	31.3	27.4	3.8	9.2	27.1	3.2	8.6	38.1	3.4
2000	34.6	26.3	4.0	10.5	21.5	3.0	8.8	30.7	3.3
2001	38.6	24.1	4.0	11.3	20.5	2.8	9.8	29.5	3.6
2002	42.4	25.4	4.2	10.3	20.9	2.6	10.4	35.3	4.6
2003	51.0	28.3	4.6	10.3	25.3	2.7	11.4	33.9	4.4
2004	54.2	31.8	5.2	11.0	22.0	3.0	13.1	34.9	4.8
2005	45.9	31.5	5.9	8.0	24.9	4.7	13.0	29.6	4.6

In Panel B, we see that sell-side firms employ many more analysts on average than either buy-side or independent firms. Time-series mean values for the number of analysts per employer are 29.7, 10.7 and 10.0 respectively for sell-side, buy-side and independent firms. We also see that sell-side analysts generate more estimates on average than either buy-side or independent analysts. Time-series mean values for the number of estimates per analyst are 37.2, 20.6, and 30.1 respectively for sell-side, buy-side and independent analysts. At the firm level, consistent with the pattern observed in Panel A, mean estimates per analyst generally increase from 1988 – 1993, then decline dramatically. Productivity recovers in the mid- and late 1990s, then declines again in 2000 or 2001.

**Table 1: Descriptive Statistics (cont'd)**

<b>Panel C: Analyst Productivity</b>									
	<b>Sell-side</b>			<b>Buy-side</b>			<b>Independent</b>		
<b>Year</b>	<b>Mean Firms Per Analyst</b>	<b>Mean Estimates Per Firm</b>	<b>Mean Days to Forecast Revision</b>	<b>Mean Firms Per Analyst</b>	<b>Mean Estimates Per Firm</b>	<b>Mean Days to Forecast Revision</b>	<b>Mean Firms Per Analyst</b>	<b>Mean Estimates Per Firm</b>	<b>Mean Days to Forecast Revision</b>
1988	13.3	8.8	103	4.7	2.8	139	7.3	2.7	112
1989	14.4	16.1	96	5.6	2.2	147	9.9	3.8	101
1990	12.4	21.4	90	5.9	3.0	119	10.2	4.3	110
1991	11.3	25.1	86	8.1	3.8	98	11.0	5.1	100
1992	11.0	30.4	84	7.7	4.8	84	11.8	4.8	93
1993	9.5	44.9	86	8.2	5.6	83	10.8	6.0	90
1994	7.0	26.1	86	5.9	3.1	99	7.2	4.4	98
1995	6.2	14.1	109	5.0	2.5	130	7.0	3.0	132
1996	7.7	27.5	112	6.3	3.2	122	9.7	5.1	121
1997	7.9	38.1	109	7.4	3.6	113	9.8	7.2	115
1998	7.6	42.1	108	8.8	4.2	115	10.5	7.6	111
1999	7.2	43.2	101	8.4	4.7	120	11.2	7.1	110
2000	6.6	44.8	94	7.2	4.1	110	9.3	7.0	104
2001	6.0	47.5	87	7.3	4.3	100	8.2	8.2	92
2002	6.1	54.7	84	8.2	4.2	96	7.7	10.0	82
2003	6.1	62.5	78	9.5	4.4	89	7.8	9.8	79
2004	6.1	77.7	73	7.3	4.3	78	7.3	10.7	76
2005	5.4	96.0	69	5.3	5.9	66	6.4	11.4	71

In Panel C, we see that buy-side analysts typically provide earnings forecasts for 5 - 8 firms, while sell-side and independent analysts typically cover more firms. Time-series mean values for the number of firms per analyst are 8.4, 7.0 and 9.1 for sell-side, buy-side and independent analysts. The statistics on analyst productivity mirror similar statistics for analyst-employer productivity, with productivity generally rising between 1988 and 1993, and then declining. Productivity recovers in the mid- and late 1990s, and then declines again in 2000 or 2001.

In Panel C we see that sell-side analysts typically revise their earnings forecasts before either buy-side or independent analysts. Time-series mean values for the number of days to the first forecast revision are 91.9, 106.0 and 99.8 for sell-side, buy-side and independent analysts.

**Table 1: Descriptive Statistics (cont'd)**

<b>Panel D: Firm-Country Characteristics</b>								
Country Name	# of Firms	Distinct Analyst-Employers	Distinct Analysts	Estimates	Mean Analysts per Firm	Mean Estimates per Analyst per Firm per Year	Mean Forecast Error	Mean Days to Forecast Revision
Austria	141	71	580	20,627	13.6	3.1	0.126	110
Belgium	164	107	1156	50,352	22.6	4.0	0.363	93
Germany	903	126	3514	255,754	22.5	3.7	0.090	101
Spain	255	103	1728	112,437	35.6	3.8	0.809	100
France	957	122	3925	393,894	29.6	4.2	0.103	87
Greece	99	23	143	3,847	5.0	2.8	0.335	107
Italy	370	110	1848	81,483	23.5	3.3	0.065	102
Netherlands	283	126	2442	180,385	44.7	4.1	0.070	95
Portugal	98	50	469	12,650	14.2	3.1	1.501	100
Switzerland	292	124	1974	142,906	30.0	4.5	0.076	96
Turkey	106	22	128	4,519	6.5	2.3	0.058	108
United Kingdom	2482	132	4483	557,152	15.6	4.6	0.067	89
Denmark	278	79	895	62,596	13.3	4.9	0.063	89
Finland	202	95	1026	61,447	21.3	4.4	0.111	80
Norway	254	66	990	68,835	15.4	5.4	0.127	67
Sweden	463	120	1809	118,926	16.3	4.9	0.065	74

Panel D reports the distribution of the earnings forecasts by firm-country. Most of the forecasts cover British, French and German firms. The data for Greece and Turkey are sparse, reflecting a lack of depth in the equity markets in these countries.

There is considerable cross-sectional variation in analyst coverage and forecast errors. Dutch firms enjoy the highest analyst coverage, while firms in Greece and Turkey are sparsely covered. Estimates for Norwegian firms are revised most frequently (and most quickly) and estimates for Turkish firms are revised least frequently. Mean forecast errors are highest in Portugal and Spain and lowest in Turkey and Denmark.

We continue our analysis in Table 2, where we report mean forecast errors for each of the seven analyst-employer activity groups. This table reports statistics on analyst-employer families, estimates and forecast errors for seven analyst-employer activity groups for the period January 1988 through May 2005 for all I/B/E/S reported firms within 16 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and United Kingdom).

For the full sample (2,127,810 observations) the mean forecast error is 13.60%. There is quite a bit of variation across analyst-employer activity groups. For each group, we report the t-statistic associated with the null hypothesis that the activity group mean forecast error does not differ from the sample mean forecast error.

**Table 2: Forecast Errors by Analyst-Employer Activity Groups**

<b>Analyst-Employer</b>	<b># of Distinct Families</b>	<b># of Estimates</b>	<b>Mean Forecast Error</b>	<b>Standard Deviation</b>	<b>t-stat</b>
Active Underwriters	10	519,569	.1316	.8114	-3.50*
Underwriters	107	1,268,896	.1411	.8398	5.47*
Syndicate Members	35	129,647	.1367	.7632	0.31
Asset Managers	19	32,415	.1311	.7285	1.20
Brokers	40	134,629	.0933	.5439	-26.95*
Banks	20	27,412	.1025	.5313	-10.28*
Pure Research	10	15,242	.2965	1.5818	12.46*
<b>All</b>	<b>241</b>	<b>2,127,810</b>	<b>.1360</b>	<b>.8158</b>	

**Note:** Forecast error is the difference between predicted earnings per share and actual earnings per share, scaled by the stock price at the time of the earnings announcement. A t-statistic is reported that tests the null hypothesis that the mean forecast error within an activity group differs from the sample mean forecast error. \* (\*\*) [\*\*\*] denotes significance at 1% (5%) and [10%] levels.

Most of the earnings forecasts come from underwriters (1,268,896 observations) or active underwriters (519,569 observations). Compared to the sample mean, active underwriters (the top ten) generate more accurate and less optimistic earnings forecasts, while underwriters generate less accurate and more optimistic earnings forecasts. The forecasts of syndicate members resemble the sample mean.

The mean forecast error for buy-side firms (asset managers) is 13.11%, which resembles the global mean. Within the independent analyst-employer class, we examine brokers, banks and pure research firms. Compared to the sample mean forecast error, brokers, on average, generate more accurate and less optimistic forecasts with a mean forecast error of 9.33%. This result is at odds with U.S. evidence that analysts at pure brokerage firms are more optimistic than those employed by underwriters (Cowen, Groysberg and Healy, 2005). Banks resemble brokers in that their forecasts are more accurate and less optimistic than the sample mean. Pure research firms generate forecasts that are significantly more optimistic than the sample mean. In fact, pure research firms produce the least accurate forecasts.

When we aggregate the seven analyst-employer activity groups into the three major classes (sell-side firms, buy-side firms and independent firms), we find that the independent analysts produce statistically smaller forecast errors. Our European results provide a stark contrast to U.S. evidence that sell-side analysts produce less optimistic and more accurate earnings forecasts than independent analysts (Jacob, Rock and Weber, 2003). Our results are consistent with U.S. evidence that sell-side analysts offer inferior stock recommendations (Cliff, 2007).

In Table 3, we examine the movement of analysts from one employer class to another. This table reports analyst-employer transition frequencies for analysts providing earnings forecasts for the period January 1988 through May 2005 for all I/B/E/S reported firms within 16 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and United Kingdom). The matrix counts the number

of distinct analysts moving between sell-side, buy-side and independent analyst-employers. The diagonal reports the number of stationary analysts.

**Table 3: Analyst-Employer Transition Frequencies**

<b>From:</b>	<b>To:</b>		
	<b>Sell-Side</b>	<b>Buy-Side</b>	<b>Independent</b>
<b>Sell-side</b>	8,970	26	110
<b>Buy-side</b>	18	155	2
<b>Independent</b>	87	1	637

Most analysts are stationary within an employer class, as documented by the large values along the diagonal of the matrix. There are 8,970 stationary sell-side analysts, 155 stationary buy-side analysts and 637 stationary independent analysts. Although analysts may routinely move from one investment bank to another, as documented by Hong and Kubik (2003), movements between sell-side and buy-side firms are much less frequent. The most common move among employer classes appears to be sell-side to independent, with 110 distinct analysts making this transition.

We continue our analysis of forecast accuracy in Table 4 where we examine mobile analysts over their careers, as they move from one class of analyst-employer to another. This table reports forecast error statistics for three broad classes of analyst-employers (sell-side, buy-side and independent firms). The sample period is January 1988 through May 2005. The sample includes all stocks representing 16 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and United Kingdom). The sample includes all stocks that mobile analysts research as they move from one employer class to another.

**Table 4: Forecast Errors by Mobile Analysts: All Stocks**

<b>Panel A: Analysts Employed by Exactly Two Employer Classes</b>					
<b>Analyst-Employer Classes</b>	<b>Sell-side Mean FE (N)</b>	<b>Buy-side Mean FE (N)</b>	<b>Indep. Mean FE (N)</b>	<b>Mean Difference (t-stat)</b>	<b>Distinct Analysts</b>
Sell-side – Buy-side	0.091 (18,313)	0.078 (7,165)		0.013*** (1.71)	45
Sell-side – Independent	0.086 (162,793)		0.065 (48,208)	0.021* (9.55)	194
Buy-side – Independent		0.108 (623)	0.270 (769)	-0.162* (3.42)	3
<b>Panel B: Analysts Employed by Three Employer Classes</b>					
<b>Analyst-Employer Classes</b>	<b>Sell-side Mean FE (N)</b>	<b>Buy-side Mean FE (N)</b>	<b>Indep. Mean FE (N)</b>	<b>Mean Difference (t-stat)</b>	<b>Distinct Analysts</b>
Sell-side – Buy-side	0.105 (132,422)	0.197 (5,885)		-0.092* (6.18)	36
Sell-side – Independent	0.105 (132,422)		0.055 (13,169)	0.050* (14.77)	36
Buy-side – Independent		0.197 (5,885)	0.055 (13,169)	0.142* (9.45)	36

**Note:** Forecast error is the difference between predicted earnings per share and actual earnings per share, scaled by the stock price at the time of the earnings announcement. The t-statistics that are reported test for differences in the mean forecast errors of analyst-employer class pairs. N denotes the number of observations. \* (\*\*) [\*\*\*] denotes significance at 1% (5%) and [10%] levels.

Panel A focuses on those analysts who work at exactly two employer classes, either sell-side and buy-side, sell-side and independent, or buy-side and independent firms. Here we see that for those 194 distinct analysts who work at both sell-side and independent employers, there is a statistically significant difference in the mean forecast errors associated with these two employer classes. The mean forecast error for the 162,793 sell-side estimates is 8.6%; the mean forecast error for the 48,208 buy-side estimates is 6.5%; the mean difference is 2.1% and it is statistically significant (with a t-stat of 9.55). The results are similar for those analysts who work at both sell-side and buy-side employers. For this group of 45 distinct analysts, the mean forecast error for the 18,313 sell-side estimates is 9.1%; the mean forecast error for the 7,165 buy-side estimates is 7.8%; the mean difference is 1.3%, which is marginally significant (with a t-stat of 1.71).



In Panel B of Table 4 we examine mobile analysts who work at three employer classes. Here we see that for those 36 distinct analysts who work at sell-side, buy-side and independent employers, there are statistically significant differences in the mean forecast errors associated with these three classes. The mean forecast error for the 13,169 independent estimates is 5.5%; the mean forecast error for the 132,422 sell-side estimates is 10.5%; and the mean forecast error for the 5,885 buy-side estimates is 19.7%. Sell-side estimates are less accurate than independent estimates (with a mean difference of 5.0% and a t-stat of 14.77), but more accurate than buy-side estimates (with a mean difference of -9.2% and a t-stat of 6.18). Independent estimates are more accurate than buy-side estimates (with a mean difference of 14.2% and a t-stat of 9.45).

It is possible that mobile analysts generate more accurate forecasts when they are employed by independent firms than when they work at sell-side firms because the firms they research change as they move from one employer-class to another. We attempt to address this concern in Table 5, where we restrict the sample to a sub-set of fixed stocks that mobile analysts research as they move from one employer class to another. The table reports forecast error statistics for mobile analysts who move between sell-side, buy-side and independent employers. The sample period is January 1988 through May 2005. The sample includes all stocks representing 16 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and United Kingdom). Panel A focuses on those mobile analysts who work at exactly two employer-classes; Panel B examines very mobile analysts who work at all three employer-classes.

**Table 5: Forecast Errors by Mobile Analysts: Fixed Stocks**

<b>Panel A: Analysts Employed by Exactly Two Employer Classes</b>					
<b>Analyst-Employer Classes</b>	<b>Sell-side Mean FE (N)</b>	<b>Buy-side Mean FE (N)</b>	<b>Indep. Mean FE (N)</b>	<b>Mean Difference (t-stat)</b>	<b>Distinct Analysts</b>
Sell-side – Buy-side	0.085 (3,822)	0.076 (3,073)		0.009 (0.76)	32
Sell-side – Independent	0.066 (82,687)		0.056 (22,764)	0.010* (3.83)	150
Buy-side – Independent		0.171 (289)	0.152 (293)	0.019 (0.40)	3
<b>Panel B: Analysts Employed by Three Employer Classes</b>					

<b>Analyst-Employer Classes</b>	<b>Sell-side Mean FE (N)</b>	<b>Buy-side Mean FE (N)</b>	<b>Indep. Mean FE (N)</b>	<b>Mean Difference (t-stat)</b>	<b>Distinct Analysts</b>
Sell-side – Buy-side	0.268 (18,127)	0.287 (2,820)		-0.019 (0.64)	22
Sell-side – Independent	0.268 (18,127)		0.045 (3,292)	0.223* (20.31)	22
Buy-side – Independent		0.287 (2,820)	0.045 (3,292)	0.242* (8.89)	22

**Note:** Forecast error is the difference between predicted earnings per share and actual earnings per share, scaled by the stock price at the time of the earnings announcement. The t-statistics that are reported test for differences in the mean forecast errors of analyst-employer class pairs. N denotes the number of observations. \* (\*\*) [\*\*\*] denotes significance at 1% (5%) and [10%] levels.

In Panel A, we find that the mean forecast error associated with 22,764 independent estimates is significantly smaller than the mean forecast error associated with 82,687 sell-side estimates generated by 150 distinct, mobile analysts for a fixed set of firms. The difference between the mean forecast errors of mobile analysts who work at both sell-side and independent firms is 1.0%. This is statistically significant (with a t-stat of 3.83). On the other hand, there is no statistically significant difference between the mean forecast errors associated with the 3,822 sell-side estimates and the 3,073 buy-side estimates generated by 32 distinct, mobile analysts who cover a fixed set of stocks. Nor is there a statistically significant difference between the buy-side and independent estimates generated by 3 mobile analysts.

In Panel B, we find statistically significant differences between the 18,127 sell-side estimates and the 3,292 independent estimates generated by 22 distinct, very mobile analysts who cover a fixed set of stocks. The difference between the mean forecast errors for sell-side and independent estimates is 22.3%, which is statistically significant (with a t-stat of 20.31). We also find statistically significant differences between the 2,820 buy-side estimates and the 3,292 independent estimates generated by these same 22 distinct, very mobile analysts. The difference between the mean forecast errors for buy-side and independent estimates is 24.2%, which is statistically significant (with a t-stat of 8.89).

Collectively, Tables 4 and 5 reveal that when analysts move between sell-side or buy-side firms and independent firms, they generate more accurate earnings forecasts while they are employed by independent firms, especially if they have

experience at all three employer classes. Moreover, differences in coverage do not drive this result. One conclusion we can draw is that differences in culture, or reward systems across analyst-employer-classes may impact analysts' behavior. The analysts most susceptible to these effects could be those that are mobile.

We continue our analysis of forecast accuracy in Table 6, where we seek to determine whether the differences between sell-side, buy-side, and independent mean forecast errors for very mobile analysts (i.e., those who work at all three employer-classes during their careers) are related to the employer class at which an analyst begins her career. Table 6 reports forecast error statistics for mobile analysts who have worked at sell-side, buy-side and independent employers. The sample period is January 1988 through May 2005. The sample includes all stocks representing 16 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and United Kingdom). We restrict the sample to a fixed set of stocks that mobile analysts research as they move from one employer class to another. In Panel A, we sort on the analyst's employer class at the start of her career; in Panel B, we sort on the analyst's employer class at the time an estimate is made.<sup>3</sup>

**Table 6: Forecast Errors by Mobile Analysts: Career Start**

<b>Panel A: Sort on Career Start</b>				
<b>Career Start</b>	<b>Sell-side Mean FE (N)</b>	<b>Buy-side Mean FE (N)</b>	<b>Indep. Mean FE (N)</b>	<b>Mean Difference (t-stat)</b>
<b>Sell-side Start</b>				
Sell-side – Buy-side	0.296 (15,081)	0.295 (2,274)		0.001 (0.18)
Sell-side – Independent	0.296 (15,081)		0.034 (2,519)	0.262* (21.00)
Buy-side – Independent		0.295 (2,274)	0.034 (2,519)	0.261* (8.47)
<b>Buy-side Start</b>				

<sup>3</sup> We assume an analyst begins her career at the employer-class associated with the first occurrence of her name in the I/B/E/S database. We cannot be certain where an analyst begins her career because I/B/E/S does not purport to comprehensively track all sell-side, buy-side and independent analysts.

Sell-side – Buy-side	0.057 (1,556)	0.049 (162)		0.008 (1.03)
Sell-side – Independent	0.057 (1,556)		0.059 (387)	-0.002 (0.28)
Buy-side – Independent		0.049 (162)	0.059 (387)	-0.010 (0.87)
<b>Independent Start</b>				
Sell-side – Buy-side	0.222 (1,387)	0.358 (360)		-0.136 (1.53)
Sell-side – Independent	0.222 (1,387)		0.110 (323)	0.112* (2.69)
Buy-side – Independent		0.358 (360)	0.110 (323)	0.248* (2.84)

**Note:** Forecast error is the difference between predicted earnings per share and actual earnings per share, scaled by the stock price at the time of the earnings announcement. The t-statistics that are reported test for differences in the mean forecast errors of analyst-employer class pairs. N denotes the number of observations. \* (\*\*) [\*\*\*] denotes significance at 1% (5%) and [10%] levels.

The results in Panel A suggest that analysts who start their careers at buy-side employers do not suffer from institutional biases. The differences between the mean forecast errors associated with the 1,556 sell-side, 162 buy-side and 387 independent estimates made by these analysts are not statistically significant. On the other hand, analysts who start their careers at either sell-side or independent employers appear to be susceptible to institutional biases as they move from one employer class to another. For example, focusing on analysts who begin their careers at sell-side employers, we find a statistically significant (t-stat = 21.00) 26.2% difference in the mean forecast errors associated with the 15,081 sell-side and 2,519 independent estimates. Likewise, for those analysts who begin their careers at independent employers, we find a statistically significant (t-stat = 2.69) 11.2% difference in the mean forecast errors associated with their 1,387 sell-side and 323 independent estimates.

**Table 6: Forecast Errors by Mobile Analysts: Career Start (cont'd)**

Panel B: Sort on Analyst-Employer Class				
Analyst-Employer Class	Sell-side Origin Mean FE (N)	Buy-side Origin Mean FE (N)	Indep. Origin Mean FE (N)	Mean Difference (t-stat)
<b>Sell-side estimates</b>				
Sell-side – Buy-side Origin	0.296	0.057		0.239*

	(15,081)	(1,556)		(19.59)
Sell-side – Independent Origin	0.296 (15,081)		0.222 (1,387)	0.074** (2.21)
Buy-side – Independent Origin		0.057 (1,556)	0.222 (1,387)	0.165* (5.30)
<b>Buy-side estimates</b>				
Sell-side – Buy-side Origin	0.296 (2,274)	0.049 (162)		0.247* (7.73)
Sell-side – Independent Origin	0.296 (2,274)		0.358 (360)	-0.062 (0.74)
Buy-side – Independent Origin		0.049 (162)	0.358 (360)	-0.309* (5.30)
<b>Independent estimates</b>				
Sell-side – Buy-side Origin	0.034 (2,519)	0.059 (387)		-0.025* (3.41)
Sell-side – Independent Origin	0.034 (2,519)		0.110 (323)	-0.076* (2.67)
Buy-side – Independent Origin		0.059 (387)	0.110 (323)	0.051*** (1.75)

**Note:** Forecast error is the difference between predicted earnings per share and actual earnings per share, scaled by the stock price at the time of the earnings announcement. The t-statistics that are reported test for differences in the mean forecast errors of analyst-employer class pairs. N denotes the number of observations. \* (\*\*) [\*\*\*] denotes significance at 1% (5%) and [10%] levels.

In Panel B, we find that sell-side and buy-side analysts produce more accurate forecasts if they begin their careers at buy-side employers. For example, the 5.7% mean forecast error associated with the 1,556 sell-side estimates made by analysts who started their careers at buy-side employers is statistically smaller than the 29.6% mean forecast error associated with the 15,081 sell-side estimates made by analysts who started their careers at sell-side employers. Analysts who begin their careers at buy-side employers produce 162 buy-side and 2,274 sell-side estimates with mean forecast errors of 4.9% and 29.6% respectively. The difference between the two mean forecast errors is 24.7% and it is statistically significant (t-stat = 7.73).

In contrast, independent analysts produce more accurate forecasts if they begin their careers at sell-side employers. These analysts generate 2,519 estimates with a mean forecast error of 3.4%. This is statistically smaller than the 5.9% mean forecast error associated with the 387 estimates made by independent analysts who started their careers at buy-side employers and the 11.0% mean forecast error associated

with the 323 estimates made by independent analysts who started their careers at independent employers.

The results in Table 6 support the idea that an analyst's accuracy is related to the employer class at which she begins her career.

We continue our analysis with an examination of forecast errors for newly public firms in Table 7. Here, we examine all IPOs originated in 16 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and United Kingdom) during the sample period, January 1988 through May 2005. We compare the earnings forecast errors attributable to analysts employed by the sell-side firms that act as lead underwriters for the newly public firms to the forecast errors associated with the buy-side and independent analysts that research those firms. Panel A covers all estimates over the sample period; Panel B examines estimates made up to five years after a company goes public; Panel C covers the period following the 5 year anniversary of an IPO.

**Table 7: Forecast Errors for IPOs**

<b>Panel A: All Years</b>					
<b>Analyst-Employer Classes</b>	<b>Sell-side Lead Mean FE (N)</b>	<b>Buy-side Mean FE (N)</b>	<b>Indep. Mean FE (N)</b>	<b>Sell-side Other Mean FE (N)</b>	<b>Mean Difference (t-stat)</b>
Sell-side – Buy-side	0.218 (10,717)	0.146 (1,739)			0.072* (3.45)
Sell-side – Independent	0.218 (10,717)		0.128 (7,975)		0.090* (7.53)
Buy-side – Independent		0.146 (1,739)	0.128 (7,975)		0.018 (0.90)
Sell-side Lead – Sell-side Other	0.218 (10,717)			0.205 (112,678)	0.013 (1.35)

**Table 7: Forecast Errors for IPOs (cont'd)**

<b>Panel B: First Five Years Following an IPO</b>					
<b>Analyst-Employer</b>	<b>Sell-side Lead Mean FE</b>	<b>Buy-side Mean FE</b>	<b>Indep. Mean FE</b>	<b>Sell-side Other Mean FE</b>	<b>Mean Difference</b>

Classes	(N)	(N)	(N)	(N)	(t-stat)
Sell-side – Buy-side	0.209 (5,197)	0.077 (705)			0.132* (9.38)
Sell-side – Independent	0.209 (5,197)		0.085 (2,935)		0.124* (9.99)
Buy-side – Independent		0.077 (705)	0.085 (2,935)		-0.008 (0.68)
Sell-side Lead – Sell-side Other	0.209 (5,197)			0.173 (38,043)	0.036* (3.12)
Panel C: Post-Five Year Anniversary of an IPO					
Analyst-Employer Classes	Sell-side Lead Mean FE (N)	Buy-side Mean FE (N)	Indep. Mean FE (N)	Sell-side Other Mean FE (N)	Mean Difference (t-stat)
Sell-side – Buy-side	0.227 (5,520)	0.193 (1,034)			0.034 (0.98)
Sell-side – Independent	0.227 (5,520)		0.153 (5,040)		0.074* (3.94)
Buy-side – Independent		0.193 (1,034)	0.153 (5,040)		0.040 (1.22)
Sell-side Lead – Sell-side Other	0.227 (5,520)			0.221 (74,635)	0.006 (0.39)

**Note:** Forecast error is the difference between predicted earnings per share and actual earnings per share, scaled by the stock price at the time of the earnings announcement. The t-statistics that are reported test for differences in the mean forecast errors of analyst-employer class pairs. N denotes the number of observations. \* (\*\*) [\*\*\*] denotes significance at 1% (5%) and [10%] levels.

In Panel A, we see that analysts employed by lead underwriters show an optimistic bias in their forecasts for newly public companies. The mean forecast error for the 10,717 estimates of analysts employed by lead underwriters is 21.8%. This is statistically larger than the mean forecast error associated with the 1,739 estimates of analysts employed by buy-side firms (14.6%) or the mean forecast error associated with the 7,975 estimates of analysts employed by independent firms (12.8%).

The optimistic bias of analysts employed by lead underwriters persists over the five-year period following an IPO. In Panel B, we see that these analysts are more optimistic than buy-side, independent and sell-side analysts whose employers do not

act as lead underwriters. However, following the five-year anniversary of an IPO, the forecast errors of all sell-side analysts converge. In Panel C, we find no difference between the mean forecast errors associated with the 5,520 estimates generated by sell-side analysts whose employers act as lead underwriters and the 74,635 estimates generated by sell-side analysts whose employers do not act as lead underwriters. The results in Table 7 are consistent with underwriting activity being a major cause of sell-side analysts' bias and optimism.

We complete our analysis by examining the determinants of analyst forecast errors in Table 8. The table reports regression coefficients and Newey-West adjusted t-statistics in parentheses. The sample period is January 1988 through May 2005. The sample includes all stocks representing 16 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and United Kingdom).

**Table 8: Regressions Explaining Forecast Errors**

Panel A: All Stocks							
Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Ln (ME)	- 0.0034* (3.51)				-0.0020*** (1.96)	-0.0020** (2.04)	-0.0019*** (1.85)
Residual Analyst Coverage		- 0.0261* (4.06)			-0.0387* (5.08)	-0.0315* (4.65)	-0.0343* (5.46)
Analyst Productivity			- 0.0008* (10.00)		-0.0009* (10.89)	-0.0008* (10.68)	-0.0008* (10.87)
Forecast Immediacy				0.0002* (3.40)	0.0002* (2.88)	0.0002* (2.84)	0.0002* (2.87)
Sell-side Dummy					0.0235** (2.16)		
Buy-side Dummy						0.0169 (0.84)	
Independent Dummy							-0.0532* (5.97)
Sell-side Career Start					0.0524* (4.53)		





Career Start							(0.61)
R <sup>2</sup>	0.001	0.001	0.015	0.007	0.035	0.029	0.026

**Note:** Forecast error is the difference between predicted earnings per share and actual earnings per share, scaled by the stock price at the time of the earnings announcement. We regress analyst forecast errors on the following set of explanatory variables: ln(ME), the natural logarithm of the market value of the equity; residual analyst coverage, where the residuals come from month-by-month cross-sectional regressions of log (1 + # of analysts) on log (firm size); analyst productivity (the number of distinct firms that an analyst researches in the year a forecast is made); forecast immediacy (the number of days from the first earnings estimate to the forecast revision); dummy variables for sell-side, buy-side and independent analyst-employers; dummy variables for the analyst-employer class at which an analyst begins her career. \* (\*\*) [\*\*\*] denotes significance at 1% (5%) and [10%] levels.

In Panel A, we include all stocks covered by mobile analysts employed by three employer classes. In Panel B, we restrict the sample to a sub-set of fixed stocks that mobile analysts research as they move from one employer class to another. The dependent variable is our measure of analyst forecast error. The independent regressors include a measure of firm size, residual analyst coverage (defined in Section III), analyst productivity (the number of distinct firms that an analyst researches in the year a forecast is made), forecast immediacy (the number of days from the first earnings estimate to the forecast revision), dummy variables for sell-side, buy-side and independent analyst-employers and dummy variables for the analyst-employer class at which an analyst begins her career. The uni-variate regressions (Models 1 – 4) in Panel A show that forecast errors are positively related to forecast immediacy, and negatively related to firm size, residual analyst coverage and analyst productivity. The multi-variate regressions (Models 5 – 7) in Panel A show similar results. Most importantly, forecast errors increase when the analyst is employed by a sell-side firm and decrease when the analyst is employed by an independent firm. The analyst-employer class at which an analyst begins her career is also important in explaining forecast errors. Forecast errors increase when the analyst begins her career at a sell-side firm, and decrease when the analyst begins her career at either a buy-side or independent firm. All of these dummy variables are statistically significant in explaining the magnitude of analyst forecast errors.

In Panel B, we repeat the analysis using the fixed set of stocks that mobile analysts research as they move among the sell-side, buy-side and independent employer

classes. Here we find similar results, except that firm size is no longer a significant factor in explaining forecast errors. Forecast errors increase when the analyst is employed by a sell-side firm and decrease when the analyst is employed by either a buy-side or independent firm. Additionally, forecast errors increase when the analyst begins her career at a sell-side firm, and decrease when the analyst begins her career at a buy-side firm. For this subset of observations, the independent career start dummy variable is not statistically significant in explaining forecast errors.

## **5. Conclusion**

This paper examines the accuracy of equity analysts who provide earnings forecasts for European companies. We attempt to disentangle the institutional factors that might bias analysts' forecasts (such as conflicts of interest attributable to analyst-employer activities) from individual factors that might impact accuracy (such as firm selection, analyst productivity and forecast age) by studying a subset of mobile analysts who move among analyst-employer classes over their careers. We consider three classes of analyst-employers: sell-side firms, buy-side firms and independent firms. We test for differences in the forecast accuracy of analyst-employer classes.

We find that analysts who research European companies exhibit the same optimistic bias in their earnings forecasts as their peers who examine U.S. companies. Over the period 1988 – 2005, the mean forecast error is 13.6%. Independent analysts produce the most accurate forecasts and sell-side analysts produce the least accurate forecasts. The difference in accuracy between these two classes is statistically significant. We also find that forecast accuracy varies substantially within the sell-side and independent analyst-employer classes. Analysts affiliated with active underwriters are more accurate and less optimistic than analysts affiliated with syndicate members. On the other hand, analysts who are employed by pure research firms are less accurate and more optimistic than analysts employed by non-underwriting banks or brokers.

We find that when analysts move between sell-side employers and independent employers, they issue more accurate forecasts while they are employed by independent firms. Moreover, these differences persist when we hold constant the set of firms these mobile analysts research. These results are consistent with institutional factors contributing to bias.

We find that an analyst's accuracy is related to the employer class at which she begins her career. Analysts who start their careers at buy-side employers do not suffer from institutional biases. On the other hand, analysts who start their careers at either sell-side or independent employers appear to be susceptible to institutional biases as they move from one employer class to another.

The optimistic bias of sell-side analysts appears to be related to underwriting activity. We show that analysts employed by lead underwriters produce less accurate forecasts for newly public companies than do either buy-side or independent analysts. The optimistic bias persists for a five-year period following an IPO.

We examine the determinants of analyst forecast errors. Consistent with institutional biases impacting analyst accuracy, we find that forecast errors increase when the analyst is employed by a sell-side firm and decrease when the analyst is employed by an independent firm.

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