Landscape – 1970s

- Much capital markets research was aimed at understanding the time-series properties of earnings.
    - Ball and Watts 1972, Brooks and Buckmaster 1976, Albrecht et al. 1977, Salamon and Smith 1977, and Watts and Leftwich 1977.

- General Conclusion: <u>Earnings approximate a random walk</u>. Sophisticated time-series models rarely provide an economically significant improvement, and even when they do it comes at high cost.

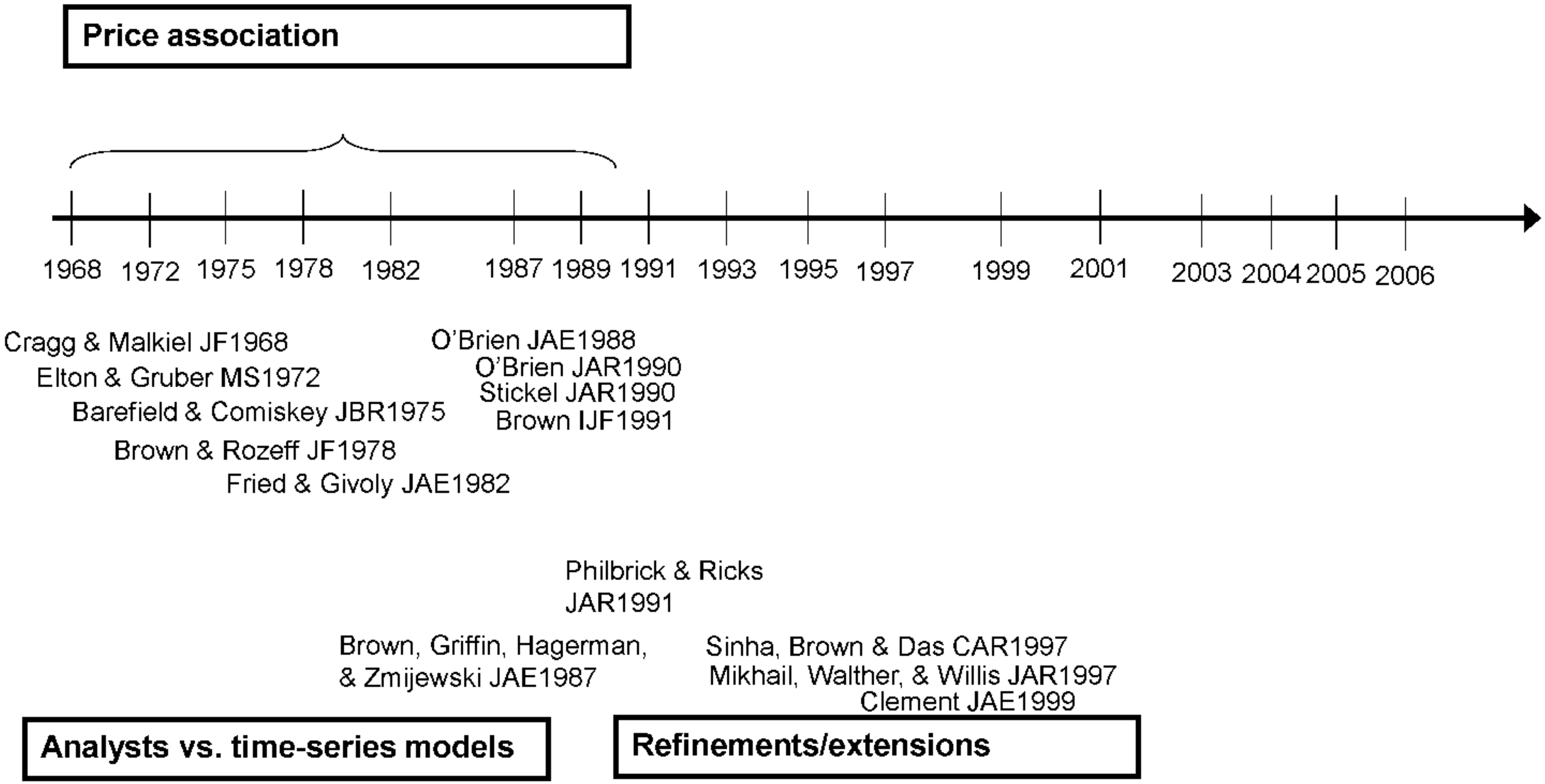
- *"The ability of random walk models to "outpredict" the identified Box-Jenkins models suggests that the random walk is still a good description of the process generating annual earnings in general, and for individual firms."* Watts and Leftwich (1977, 269)

- Brown (1993, 295) declares the issue of whether annual earnings follow a random walk as *"pretty much resolved by the late 1970s."*

Landscape – 1980s

- Newly available analyst data becomes available (i.e., Value-Line, I/B/E/S).
- “Horse-race studies” comparing time-series and analyst forecasts.
- Brown and Rozeff 1978, Fried and Givoly 1982, and Brown et al. 1987a,b
- General Conclusion: Analyst forecasts generally dominate time-series forecasts of earnings. Analyst superiority is attributed to:
    - **Information Advantage**
        - They know all information in TS and more
    - **Timing Advantage**
        - They issue forecasts after the end of the lagged TS

Timeline of Analysts vs. Time-Series Research



Landscape – Today

- Researchers generally regard this literature as having conclusively shown that analysts' forecasts are a superior proxy for earnings expectations.

- Kothari (JAE2001) concludes that
  - The time-series properties of earnings literature is fast becoming extinct because of "the easy availability of a better substitute" which is "available at a low cost in machine-readable form for a large fraction of publicly traded firms." (p. 145)
  - "[C]onflicting evidence notwithstanding, in recent years it is common practice to (implicitly) assume that analysts' forecasts are a better surrogate for market's expectations than time-series forecasts." (p. 153)

Landscape – Today (cont.)

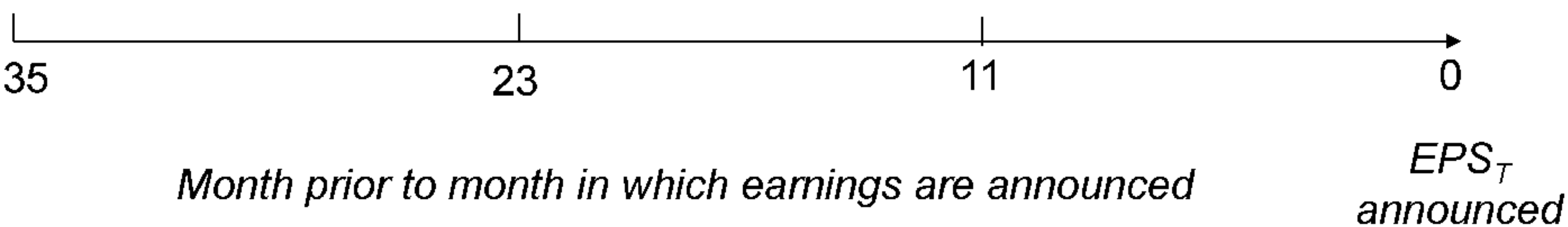
- Random Walk
  - Still descriptive (Lorek, Willinger & Bathke RQFA2008)

- Valuation and cost of capital literature:
  - Researchers use analyst forecasts over some short horizon and then extrapolate to value a perpetuity.
  - Example: Dhaliwal et al. (JAE 2007), Frankel & Lee (JAE1998), etc.
    - One-year-ahead: FY1 (I/B/E/S Consensus forecast)
    - Two-years-ahead: FY2
    - Three-years-ahead: FY3 = FY2 x (1+LTG)
    - Four-years-ahead: FY4 = FY3 x (1+LTG)
    - Five-years-ahead: FY5 = FY4 x (1+LTG)
  - Exceptions: Allee (2009); Hou, Van Dijk and Zhang (2010)

Data

- 1983-2007 (25 years)
- Minimal constraints on data
  - Biggest constraint is presence on *I/B/E/S*
    - EPS forecast, actual EPS, stock price
  - Sales on *Compustat* in year t-1
  - Earnings in year t-1 > 0
    - Hayn (1995): losses less persistent than profits
      $\Rightarrow$ bias results in favor of random walk (but not really)
  - *CRSP* returns for last analysis

- Consensus forecasts in months 0 to -35



Month prior to month in which earnings are announced

Forecast errors

- Random Walk
  - Minimizes data demands
  - Performs as well or better than higher order models (consistent w/ Lorek, WIllinger & Bathke RQFA2008)
  - *We aim to do nothing to "help" RW forecasts

- Forecast of EPS for year T as of t months prior to the month EPS_T announced
  - Analysts: $|(FEPS_{T,t} – EPS_T)| / Price_t$
  - Time-series: $|(EPS_{T-1} – EPS_T)| / Price_t$

	#Forecasts	#Firm-years	#Firms
FY1:	740,070	69,483	10,140
FY2:	611,132	60,170	9,037
FY3:	468,777	46,226	7,070

- Analyst superiority = RWFE – AFE
  - $>0 \Rightarrow$ analysts more accurate than random walk
  - $<0 \Rightarrow$ random walk more accurate than analysts

Table 2 Descriptive Statistics

	Mean	Q1	Median	Q3
Sales	>374	110	374	1,384
BTM	0.58	0.31	0.50	0.75
Age	8.2	4	7	12
# Analysts	7.6	2	5	10

* A hypothetical data requirement of 10 years (as in Fried and Givoly 1982) would eliminate 70% of the observations in our sample).

Scaling and winsorizing

$$Error = \left| \frac{(\text{Actual} - \text{Predicted})}{|\,\text{Actual}\,|} \right|$$

% > 1.00

Months Prior to RDQE	Analysts Forecasts Errors	Random Walk Errors
1 Month (Mature Firms)	2.90%	10.50%
1 Month	5.20%	14.20%
11 Months	16.50%	14.60%
23 Months	22.60%	19.70%
35 Months	29.50%	26.20%

**The 1.00 cut-off was reasonable in earlier studies. Fried and Givoly (1982) report that only 0.5% of their observations have scaled forecast errors that are greater than 1.00.

Table 2 Descriptive Statistics (i.e., Forecast– Actual)

Panel C: Signed Forecast Errors

	Mean	**Median**	**Q1**	**Q3**
Signed Random Walk Errors				
11 Months	0.0086	-0.0055	-0.0153	0.0108
23 Months	0.0033	-0.0091	-0.0260	0.0150
35 Months	-0.0038	-0.0124	-0.0363	0.0166
Signed Analysts' Forecasts Errors				
11 Months	0.0194	0.0028	-0.0041	0.0209
23 Months	0.0272	0.0090	-0.0049	0.0391
35 Months	0.0332	0.0162	-0.0047	0.0541

Table 3 – Main Results
Analysts' forecast superiority, Full sample

FY1			FY2			FY3		
Months Prior	**Firm-years**	**Analyst Superiority**	**Months Prior**	**Firm-years**	**Analyst Superiority**	**Months Prior**	**Firm-years**	**Analyst Superiority**
0	32,723	0.0245	12	29,072	0.0120	24	21,944	0.0072
1	66,224	0.0236	13	55,447	0.0106	25	41,766	0.0055
2	66,104	0.0227	14	56,659	0.0095	26	42,827	0.0044
3	65,794	0.0212	15	56,575	0.0081	27	42,941	0.0033
4	65,458	0.0182	16	56,023	0.0063	28	42,588	0.0019
5	65,158	0.0155	17	55,360	0.0049	29	42,272	0.0007
6	64,787	0.0131	18	54,458	0.0037	30	41,753	(0.0000) NS
7	64,361	0.0102	19	53,195	0.0022	31	40,952	(0.0012)
8	63,869	0.0081	20	51,832	0.0012	32	40,137	(0.0020)
9	63,200	0.0064	21	49,745	0.0004	33	38,925	(0.0027)
10	62,103	0.0041	22	46,501	(0.0006)	34	36,836	(0.0035)
11	60,289	0.0025	23	42,124	(0.0011)	35	33,789	(0.0040)

Analyst are more accurate than RW by 25 basis-pts

RW is more accurate than Analysts by 40 basis-pts

Table 4 – Analysts' forecast superiority and firm age

Panel A: FY1 – 11 months prior to RDQE

Firm Age	Firm-years	Analysts'Superiority	RW Forecast Error	Analysts' Forecast Error
1	2,534	0.0007	0.0534	0.0527
2	6,321	0.0015	0.0405	0.0391
3	5,867	0.0005	0.0382	0.0378
4	5,109	0.0005	0.0379	0.0374
5+	40,335	0.0033	0.0301	0.0268

Panel B: FY2 – 23 months prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	1,413	(0.0102)	0.0628	0.0730
2	3,969	(0.0072)	0.0528	0.0599
3	3,810	(0.0048)	0.0511	0.0559
4	3,404	(0.0028)	0.0472	0.0500
5+	29,447	0.0008	0.0396	0.0388

Panel C: FY3 – 35 months prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	1,119	(0.0186)	0.0735	0.0871
2	2,954	(0.0147)	0.0647	0.0785
3	3,011	(0.0084)	0.0604	0.0670
4	2,794	(0.0060)	0.0584	0.0618
5+	23,868	(0.0012)	0.0498	0.0488

Table 5: Partitions for size and analyst following

Panel A: Small Firms

FY1			FY2				FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority		Months Prior	Firm-years	Analysts' Superiority
0	6,897	0.0256	12	5,786	0.0085		24	3,067	0.0007
1	13,845	0.0252	13	10,871	0.0074		25	6,006	(0.0023)
2	13,737	0.0242	14	11,087	0.0060		26	6,192	(0.0040)
3	13,535	0.0225	15	10,885	0.0045		27	6,114	(0.0054)
4	13,396	0.0191	16	10,574	0.0020		28	5,968	(0.0074)
5	13,175	0.0162	17	10,204	0.0004	NS	29	5,836	(0.0086)
6	13,009	0.0132	18	9,799	(0.0012)		30	5,626	(0.0096)
7	12,815	0.0098	19	9,299	(0.0026)		31	5,366	(0.0106)
8	12,607	0.0071	20	8,759	(0.0040)		32	5,055	(0.0119)
9	12,341	0.0052	21	8,023	(0.0055)		33	4,707	(0.0131)
10	11,906	0.0023	22	6,987	(0.0066)		34	4,152	(0.0151)
11	11,314	(0.0003)	23	5,804	(0.0078)		35	3,521	(0.0167)

Table 5: Partitions for size and analyst following

Panel B: Low Analyst Following

FY1			FY2			FY3		
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**
0	9,089	0.0314	12	8,001	0.0110	24	8,634	0.0063
1	18,744	0.0311	13	14,945	0.0102	25	16,197	0.0036
2	18,704	0.0289	14	15,648	0.0085	26	16,784	0.0022
3	18,557	0.0267	15	15,890	0.0066	27	16,848	0.0005 NS
4	18,422	0.0224	16	16,055	0.0043	28	16,672	(0.0014)
5	18,265	0.0185	17	16,138	0.0027	29	16,489	(0.0030)
6	18,104	0.0151	18	16,319	0.0008 NS	30	16,180	(0.0035)
7	18,062	0.0109	19	16,646	(0.0009)	31	15,556	(0.0051)
8	17,880	0.0080	20	16,901	(0.0022)	32	14,941	(0.0063)
9	17,636	0.0058	21	17,310	(0.0032)	33	13,992	(0.0074)
10	17,113	0.0026	22	17,924	(0.0041)	34	12,501	(0.0087)
11	16,264	0.0000 NS	23	18,185	(0.0045)	35	10,544	(0.0099)

Table 6: Partitions by magnitude of change in EPS

Panel A: The 33% of Forecasts with the Least Extreme Forecasted Change in EPS

FY1			FY2			FY3		
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**
0	10,915	0.0025	12	9,679	0.0174	24	7,305	0.0140
1	22,093	0.0026	13	18,472	0.0156	25	13,910	0.0124
2	22,053	0.0025	14	18,881	0.0143	26	14,268	0.0115
3	21,954	0.0023	15	18,845	0.0125	27	14,300	0.0106
4	21,842	0.0020	16	18,654	0.0106	28	14,185	0.0097
5	21,743	0.0018	17	18,439	0.0087	29	14,075	0.0085
6	21,620	0.0016	18	18,139	0.0074	30	13,907	0.0078
7	21,481	0.0014	19	17,721	0.0058	31	13,645	0.0071
8	21,324	0.0013	20	17,260	0.0051	32	13,382	0.0065
9	21,110	0.0012	21	16,561	0.0041	33	12,968	0.0061
10	20,731	0.0012	22	15,488	0.0034	34	12,277	0.0057
11	20,117	0.0012	23	14,023	0.0029	35	11,263	0.0053

Table 6: Partitions by magnitude of change in EPS

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1			FY2				FY3			
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**		**Months Prior**	**Firm-years**	**Analysts' Superiority**	
0	20,131	0.0025	12	9,695	0.0090		24	7,319	0.0018	
1	10,881	0.0616	13	18,483	0.0077		25	13,924	0.0005	NS
2	22,029	0.0591	14	18,885	0.0067		26	14,272	(0.0007)	NS
3	21,988	0.0566	15	18,865	0.0057		27	14,316	(0.0021)	
4	21,881	0.0530	16	18,684	0.0042		28	14,196	(0.0037)	
5	21,761	0.0453	17	18,463	0.0028		29	14,088	(0.0049)	
6	21,657	0.0381	18	18,157	0.0014		30	13,908	(0.0058)	
7	21,530	0.0320	19	17,728	0.0000	NS	31	13,639	(0.0076)	
8	21,385	0.0244	20	17,276	(0.0012)		32	13,360	(0.0087)	
9	21,217	0.0190	21	16,584	(0.0025)		33	12,964	(0.0095)	
10	20,993	0.0143	22	15,498	(0.0035)		34	12,267	(0.0109)	
11	20,635	0.0083	23	14,042	(0.0040)		35	11,256	(0.0115)	

Market expectation tests

- We estimate:

$$\text{Return} = \alpha + \beta\ \text{RWFE} + \epsilon_{\text{it}}$$
$$\text{Return} = \text{a} + \text{b}\ \text{AFE} + \text{e}_{\text{it}}$$

where the return accumulation period is equaled to forecast horizon.

- Market Expectation Proxy Ratio = β / b

Table 7: Associations with market returns

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = \alpha + b\left(Forecasted\ EPS_{T,M} - EPS_T\right) + e_T$$

FY1			FY2				FY3			
Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	30,411	0.345	12	28,003	0.602		24	21,097	0.784	
1	62,355	0.395	13	53,654	0.678		25	40,377	0.831	
2	63,455	0.342	14	54,664	0.707		26	41,336	0.843	
3	63,419	0.396	15	54,473	0.742		27	41,369	0.874	
4	63,101	0.540	16	53,882	0.798		28	40,992	0.908	
5	62,790	0.632	17	53,196	0.833		29	40,674	0.928	
6	62,441	0.685	18	52,319	0.888		30	40,151	0.962	
7	62,016	0.735	19	51,113	0.912		31	39,409	1.001	NS
8	61,540	0.795	20	49,789	0.953		32	38,624	1.017	NS
9	60,915	0.838	21	47,783	1.007	NS	33	37,455	1.057	
10	59,936	0.905	22	44,672	1.008	NS	34	35,435	1.081	
11	58,261	0.939	23	40,500	1.032		35	32,530	1.099	

The association between returns and RW is 94% of the association between returns and analyst forecast errors.

Table 8: Market returns, by size & analyst following

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = \alpha + b\left(Forecasted\ EPS_{T,M} - EPS_T\right) + e_T$$

Panel A: Small Firms

FY1				FY2				FY3			
Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	6,558	0.1813		12	7,275	0.6957		24	3,396	0.9083	
1	13,382	0.3422		13	13,711	0.7238		25	6,575	0.8822	
2	13,474	0.4286		14	14,068	0.7550		26	6,814	0.9084	
3	13,364	0.4433		15	13,887	0.7793		27	6,757	0.9330	
4	13,227	0.5309		16	13,468	0.8111		28	6,552	0.9392	NS
5	13,001	0.6186		17	12,974	0.8496		29	6,422	0.9495	NS
6	12,838	0.6610		18	12,424	0.9076		30	6,173	0.9550	NS
7	12,643	0.7170		19	11,713	0.8973		31	5,844	0.9762	NS
8	12,431	0.8323		20	10,906	0.9676	NS	32	5,491	1.0016	NS
9	12,176	0.8551		21	9,808	1.0151	NS	33	5,028	1.0965	
10	11,750	0.9273	NS	22	8,168	1.0043	NS	34	4,258	1.1229	
11	11,167	0.9431	NS	23	6,392	1.0277	NS	35	3,431	1.1230	

Table 8: Market returns, by size & analyst following

Panel B: Low analyst following

FY1			FY2			FY3		
Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b
0	8,522	0.4728	12	5,691	0.6681	24	3,010	0.9507 NS
1	17,567	0.5084	13	10,710	0.6871	25	5,901	0.9674 NS
2	17,746	0.4986	14	10,912	0.7337	26	6,077	0.9682 NS
3	17,688	0.5739	15	10,706	0.7421	27	5,993	0.9786 NS
4	17,582	0.6328	16	10,395	0.8069	28	5,842	1.0100 NS
5	17,437	0.7040	17	10,026	0.8506	29	5,706	1.0230 NS
6	17,289	0.7165	18	9,631	0.9414 NS	30	5,502	1.0464 NS
7	17,220	0.7617	19	9,140	0.9273 NS	31	5,247	1.0736 NS
8	17,039	0.8377	20	8,606	0.9721 NS	32	4,941	1.0892 NS
9	16,825	0.9025	21	7,878	1.0209 NS	33	4,596	1.1288
10	16,383	0.9530 NS	22	6,849	1.0100 NS	34	4,045	1.2025
11	15,615	0.9823 NS	23	5,687	1.0570 NS	35	3,426	1.1849

Table 9: Market returns, by magnitude of change in EPS

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = \alpha + b\left(Forecasted\ EPS_{T,M} - EPS_T\right) + e_T$$

Panel A: The 33% of Forecasts with the Least Extreme Forecasted Change in EPS

FY1				FY2				FY3			
Months Prior	Firm-Years	β/b		Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	9,023	0.9388	NS	12	7,763	0.6330		24	5,840	0.7597	
1	18,254	0.9280	NS	13	14,935	0.7053		25	11,227	0.7974	
2	18,188	0.9300	NS	14	15,145	0.7316		26	11,462	0.8336	
3	18,083	0.9620	NS	15	15,057	0.7808		27	11,466	0.8514	
4	18,018	0.9882	NS	16	14,865	0.8222		28	11,356	0.8433	
5	17,921	0.9764	NS	17	14,697	0.8603		29	11,264	0.8631	
6	17,807	0.9807	NS	18	14,479	0.8661		30	11,101	0.9067	
7	17,710	0.9866	NS	19	14,147	0.9241		31	10,891	0.9716	NS
8	17,566	0.9767	NS	20	13,783	0.9412		32	10,696	0.9870	NS
9	17,398	0.9794	NS	21	13,218	0.9643	NS	33	10,337	$\boxed{1.0163}$	NS
10	17,143	0.9772	NS	22	12,365	0.9747	NS	34	9,777	$\boxed{1.0334}$	NS
11	16,646	0.9791	NS	23	11,269	0.9930	NS	35	9,034	$\boxed{1.0473}$	NS

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1			FY2			FY3			
Months Prior	Firm-Years	β/b	Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b	
0	8,795	0.2981	12	7,575	0.5937	24	5,566	0.8875	
1	17,647	0.3710	13	14,701	0.6814	25	10,831	0.8781	
2	17,619	0.3270	14	14,892	0.7739	26	10,975	0.8875	
3	17,498	0.3560	15	14,823	0.7831	27	10,950	0.9032	
4	17,319	0.5213	16	14,617	0.7384	28	10,811	0.9513	NS
5	17,210	0.6093	17	14,426	0.8124	29	10,741	0.9741	NS
6	17,103	0.6808	18	14,171	0.9003	30	10,587	0.9953	NS
7	16,903	0.7110	19	13,800	0.9175	31	10,376	$\boxed{1.0477}$	
8	16,709	0.7550	20	13,433	$\boxed{1.0186}$	32	10,130	$\boxed{1.0967}$	
9	16,438	0.7822	21	12,856	$\boxed{1.0476}$	33	9,823	$\boxed{1.0626}$	
10	16,084	0.8471	22	11,983	$\boxed{1.0304}$	34	9,269	$\boxed{1.1096}$	
11	15,650	0.8717	23	10,852	$\boxed{1.0735}$	35	8,493	$\boxed{1.1257}$	

Table 10: Panel multivariate regression

$$Analysts'Superiority_{T,M} = \gamma_0 + \gamma_1\ \#Analysts_T + \gamma_2\ STD_{T,M} + \gamma_3\ BTM_{T-1}$$
$$+\gamma_4\ Sales\ _{T-1} + \gamma_5\ Forecast\Delta_{T,M} + \varepsilon_T$$

Months Prior RDQE	Intercept	#Analysts	STD	BTM	Sales	Forecasted Δ
0	-0.0083	-0.0021	0.0055	0.0035	0.0015^{NS}	0.0279
1	-0.0072	-0.0022	0.0052	0.0028	0.0017	0.0262
2	-0.0079	-0.0013	0.0043	0.0030	0.0017	0.0253
3	-0.0079	-0.0013	0.0047	0.0029	0.0012	0.0238
4	-0.0071	-0.0005	0.0039	0.0024	0.0005^{NS}	0.0206
5	-0.0055	0.0003^{NS}	0.0027	0.0025	-0.0002^{NS}	0.0175
6	-0.0054	0.0006	0.0025	0.0022	0.0001^{NS}	0.0148
7	-0.0050	0.0011	0.0015	0.0019	0.0004^{NS}	0.0115
8	-0.0047	0.0015	0.0009	0.0017	0.0007^{NS}	0.0092
9	-0.0041	0.0016	0.0004	0.0015	0.0010	0.0069
10	-0.0026	0.0015	-0.0003	0.0010	0.0012	0.0043
11	-0.0017	0.0018	-0.0011	0.0008	0.0012	0.0025
12	0.0076	-0.0002^{NS}	0.0050	0.0045	0.0058	-0.0064
13	0.0070	0.0003^{NS}	0.0031	0.0041	0.0055	-0.0057
14	0.0056	0.0008	0.0031	0.0042	0.0053	-0.0057
15	0.0046	0.0011	0.0020	0.0042	0.0049	-0.0050
16	0.0028	0.0017	0.0010	0.0037	0.0052	-0.0048
17	0.0012	0.0022	0.0000^{NS}	0.0036	0.0054	-0.0043
18	0.0005^{NS}	0.0028	-0.0007	0.0036	0.0048	-0.0043
19	-0.0015	0.0031	-0.0014	0.0033	0.0049	-0.0037
20	-0.0023	0.0037	-0.0019	0.0030	0.0048	-0.0035
21	-0.0029	0.0038	-0.0023	0.0026	0.0054	-0.0036
22	-0.0036	0.0038	-0.0028	0.0024	0.0057	-0.0035
23	-0.0079	0.0057	-0.0027	0.0019	0.0062	-0.0035
24	0.0048	0.0009	-0.0005^{NS}	0.0051	0.0094	-0.0074
25	0.0026	0.0023	-0.0016	0.0059	0.0090	-0.0074
26	0.0026	0.0025	-0.0023	0.0056	0.0093	-0.0078
27	0.0019	0.0029	-0.0026	0.0053	0.0094	-0.0083
28	0.0007^{NS}	0.0035	-0.0028	0.0052	0.0096	-0.0089
29	-0.0007^{NS}	0.0039	-0.0028	0.0047	0.0096	-0.0090
30	-0.0020	0.0042	-0.0033	0.0046	0.0106	-0.0093
31	-0.0027	0.0046	-0.0035	0.0042	0.0104	-0.0097
32	-0.0036	0.0049	-0.0038	0.0038	0.0108	-0.0099
33	-0.0040	0.0051	-0.0040	0.0035	0.0111	-0.0103
34	-0.0060	0.0054	-0.0044	0.0030	0.0133	-0.0108
35	-0.0062	0.0058	-0.0048	0.0019	0.0127	-0.0108

Conclusion

- DISCLAIMER: Prior research was appropriately deliberate in its sample selection and other research design choices, and the conclusions drawn are warranted.
    - However, as is common in our field, it is the subsequent researcher who over-generalizes findings from prior studies.

- **Analysts** only appear persistently superior to a simple earnings extrapolation for **short horizons for large firms**.
- Equivalently, **time-series** forecasts perform as well or better than analysts over **moderate-to-long forecast horizons, and especially for smaller, younger firms**.

TYPICAL STUDY:
1. Data from 1960 and 1970.
2. Sample size ranges from fifty to a few hundred.
3. Models require a minimum of 10 years of data, and some require as many as 20 years of data.
4. Forecast horizons range from 1 quarter-ahead to 18 months-ahead.
5. Reported differences are typically statistically significant in favor of analysts, only modest magnitudes .

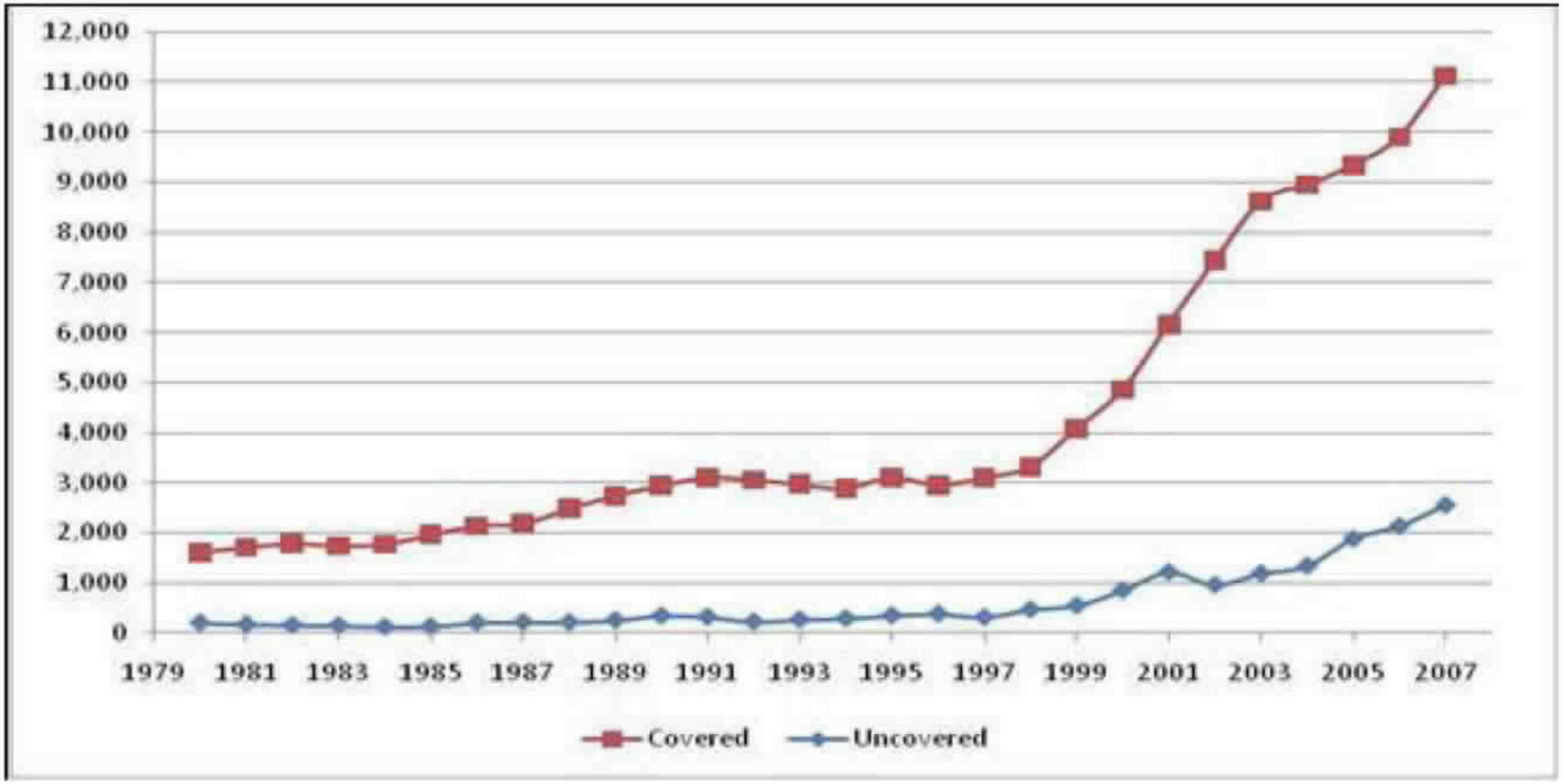
Table 1

Paper	Sample and Time Period	Time-Series (TS) Models and Data Requirements	Outliers	Forecast Horizon	Difference in Forecast Accuracy	Analysts' Superiority Determinants
Brown and Rozeff (1978)	50 firms from 1972 through 1975.	Three TS models using quarterly data, requiring complete data for 20 years.	Winsorized forecast errors at 1.0	One to five quarters ahead.	Median difference in forecast errors between all univariate forecasts and the analysts' forecast is significantly greater than zero.	
Collins and Hopwood (1980)	50 firms from 1951 through 1974.	Four TS models, requiring a minimum of 76 quarters of data.	Winsorized forecast errors at 3.0	One to four quarters ahead.	Four quarters out, analysts' forecast errors are 31.7% compared to the best TS error of 32.9%. One quarter out, mean analysts' forecast error are 9.7% compared to the best TS error of 10.9%.	
Fried and Givoly (1982)	424 firms from 1969 through 1979.	Modified submartingale models, requiring a minimum of 10 years of past data.	Winsorized forecast errors at 1.0	8 months prior to the fiscal end.	Analysts' forecast errors are 16.4% of realized EPS compared to 19.3% for the best TS model.	
Hopwood and McKeown (1982)	258 firms from 1974 through 1978.	Random walk and 7 other TS models, requiring at least 12 years (48 quarters) of data.		One to four quarters ahead.	Four quarters out (annual), absolute analysts' forecasts errors are 22.5% compared to absolute forecast errors of 26.1% for random walk.	Number of days separating TS and analysts' forecast – positive
Brown, Hagerman, Griffin, and Zmijewski (1987)	233 firms from the 1975 through 1980.	3 TS models, requiring a minimum of 60 quarters of data.	Winsorized forecast errors at 1.0	One, two, and three quarters ahead.	Three-quarters-ahead, analysts' forecast errors are 28.7% and TS forecast errors are 33%.	Forecast horizon – negative
Brown, Richardson, and Schwager (1987)	Sample 1: 168 firms from Q1-1977 through Q4-1979.	Quarterly random-walk model.		One, two, and three quarters ahead.	For the one month horizon, the log of the squared ratio of TS to analysts' forecast errors is 0.56.	Firm size – positive; Prior analysts' forecast dispersion – negative

Table 1 (cont.)

Brown, Richardson, and Schwager (1987)	Sample 2: 168 firms from 1977 through 1979.	Annual random-walk model.		Horizons of 1, 6, and 18 months prior to the fiscal year-end date.	For the one month horizon, the log of the squared ratio of TS to analysts' forecast errors is 1.08.	Firm size – positive; Prior analysts' forecast dispersion – negative
Brown, Richardson, and Schwager (1987)	Sample 3: 702 firms from 1977 through 1982.	Annual random-walk model.		Horizons of 1, 6, and 18 months prior to the fiscal year-end date.	Log of the squared ratio of TS to analysts' forecast errors is 1.01 for the one month horizon.	Firm size – positive; Prior analysts' forecast dispersion – negative
O'Brien (1988)	184 firms from 1975 through 1982.	Two TS models, requiring 30 consecutive quarters of data.	Deleted absolute forecast errors larger than $10	Horizons of 5, 60, 120, 180, and 240 trading days prior to the earnings announcement date.	At 240 trading days (one year), analysts' forecast errors are $0.74 compared to TS forecast errors of $0.96.	Forecast horizon – positive
Kross, Ro, and Schroeder (1990)	279 firms from 1980 through 1981.	Box-Jenkins model, requiring 28 quarters of data.		Last available one-quarter-ahead forecast.	Natural log of 1 + absolute TS error - absolute analysts' error is positive across all industries (ranging from (0.043 to 0.385)).	Earnings variability – positive; *Wall Street Journal* coverage – positive; # of days separating TS and analysts' forecasts – positive
Lys and Soo (1995)	62 firms from 1980 through 1986.	Box-Jenkins model, requiring 20 years of data.	Removed one firm	Up to 8 quarters ahead.	Across all horizons, the mean (median) absolute analysts' forecast error is 4.4% (2.8%) and the mean (median) absolute TS error is 26.8% (1.4%).	Forecast horizon – negative
Branson, Lorek, and Pagach (1995)	223 firms from 1988 through 1989.	ARIMA model, requiring 11 years of complete data.		One quarter ahead.	The median absolute percentage forecast error (Actual - predicted)/actual)) from TS minus analysts' forecasts is 7.22%.	Conditional on the firm being small: earnings variability – positive; firm size – negative

Figure 3: Mean assets for firms <u>with</u> (in maroon) and <u>without</u> (in blue) earnings forecasts on I/B/E/S



I have no idea what you're talking about...

...so here's a bunny with a pancake on its head.

A re-examination of analysts' superiority over time-series forecasts of annual earnings

Mark T. Bradshaw
Boston College

Michael S. Drake
The Ohio State University

James N. Myers
University of Arkansas

Linda A. Myers
University of Arkansas

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A re-examination of analysts' superiority over time-series forecasts of annual earnings

Abstract: In this paper, we re-examine the widely-held belief that analysts' earnings per share (EPS) forecasts are superior to forecasts from a time-series model. Using a naive random walk time-series model for annual earnings, we investigate whether and when analysts' annual EPS forecasts are superior. We also examine whether analysts' forecasts approximate market expectations better than expectations from a simple random walk model. Our results indicate that simple random walk EPS forecasts are more accurate than analysts' forecasts over longer forecast horizons and for firms that are smaller, younger, or have limited analyst following. Moreover, analysts' superiority is less prevalent when analysts forecast large changes in EPS. These findings recharacterize generalizations about the superiority of analysts' forecasts over even simple time-series-based earnings forecasts and suggest that they are incomplete and/or misleading. Our findings suggest that in certain settings, researchers can reliably use time-series-based forecasts in studies requiring earnings expectations.

A re-examination of analysts' superiority over time-series forecasts of annual earnings

1 Introduction

Research on analysts' forecasts originated from a need within capital markets research to find a reliable proxy for investor expectations of earnings per share (EPS). The need for a proxy was necessitated by a growing interest in the relation between accounting earnings and stock returns that began with Ball and Brown (1968). Prior to the widespread availability of analysts' forecasts, much capital markets research was aimed at better understanding the time-series properties of earnings in an effort to gauge the association between earnings expectations and stock prices (e.g., Ball and Watts 1972; Brooks and Buckmaster 1976; Albrecht et al. 1977; Salomon and Smith 1977; Watts and Leftwich 1977). Numerous time-series specifications are examined in these studies, but the overall evidence points towards *sophisticated* time-series models of annual earnings rarely providing an economically significant improvement over a *simple* random walk model in terms of reduced forecast errors.[1] This led Brown (1993, 295) to observe that the general consensus among researchers is that earnings follow a random walk, which he states was "pretty much resolved by the late 1970s."

In a parallel stream of studies between 1968 and 1987, many researchers examined whether *analysts'* forecasts are superior to *time-series* forecasts. The culmination of that research is Brown et al. (1987a), who conclude that analysts' forecasts are superior to time-series forecasts because of both an information advantage and a timing advantage. This conclusion was followed by a sharp decline in research on the properties of time-series forecasts. Indeed, in a review of the capital markets literature, Kothari (2001, 145) observes that the time-series

[1] We note that prior research finds consistent evidence that sophisticated time-series models of *quarterly* earnings outperform a simple random walk model (see, for example, Lorek (1979) and Hopwood et al. (1982)). However, we focus our examination on forecasts of annual earnings as we explain later in the introduction.

properties of earnings literature is fast becoming extinct because of "the easy availability of a better substitute" which is "available at a low cost in machine-readable form for a large fraction of publicly traded firms."[2] Thus, it appears that academics have generally concluded that analysts' forecasts of annual earnings are superior to those from time-series models.

In this paper, we re-examine the widely-held belief that analysts' annual EPS forecasts are superior to those from time-series models. We do this by comparing the performance of simple random walk annual earnings forecasts to that of analysts' annual earnings forecasts, and by correlating the associated forecast errors with long-window market returns. Given information and timing advantages (Brown et al. 1987a), it seems improbable that analysts would *not* provide more accurate forecasts than a simple random walk model. However, the prior research upon which the conclusion that analysts are superior is based is subject to numerous caveats (e.g., small samples, bias towards large firms, questionable economic significance, etc.), as we further discuss below. Moreover, analysts are subject to a number of conflicting incentives that can result in biased or inaccurate forecasts (Francis and Philbrick 1993; Dugar and Nathan 1995; McNichols and O'Brien 1997; Lin and McNichols 1998).

As noted in Bradshaw (2009), the accounting literature is unique in its conclusion that expert forecasts are superior to forecasts from time-series models. For example, findings from research in economics, genetics, and physics are largely consistent with time-series models outperforming experts.[3] Obviously, forecasts of macroeconomic variables like interest rates, unemployment, and GDP are different from forecasts of accounting earnings because firm

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[2] Kothari (2001, 153) further states that "conflicting evidence notwithstanding, in recent years it is common practice to (implicitly) assume that analysts' forecasts are a better surrogate for market's expectations than time-series forecasts."

[3] For example, in the economics literature, Belongia (1987) examines expert and time-series forecasts of interest rates and finds that time-series forecasts are more accurate. Similarly, Fintzen and Stekler (1999) and Loungani (2000) find that time-series forecasts of recessions and of gross domestic product (GDP) are more accurate than expert forecasts. In addition, in the genetics literature, Orr (1998) finds that random walk describes the time-series properties of genetic drift, and in physics, Mazo (2002) finds that random walk describes Brownian motions.

managers can affect both analysts' forecasts (through guidance) and accounting earnings (through financial reporting discretion) (Watts and Zimmerman 1990; Matsumoto 2002). This interaction clearly gives financial analysts' forecasts of EPS an advantage vis-à-vis expert forecasts of 'less controllable' economic outcomes like interest rates or GDP.

Furthermore, relative to the extensive amount of analyst forecast data currently available, the empirical results of the early studies examining analysts versus time-series models are based on very small samples. For example, Brown and Rozeff (1978) use forecasts for only 50 firms from 1972 through 1975, and Fried and Givoly (1982) – arguably the most extensive sample in this early literature – use forecasts for only 424 firms from 1969 through 1979. In addition to the limited availability of machine readable data when these studies were performed, another explanation for the small sample sizes is the data demands of ARIMA models, which require a long time series of earnings (e.g., 10 to 20 years) to estimate time-series parameters. Other common research design choices, such as the selection of only December fiscal year-end firms or only firms trading on the New York Stock Exchange (which bias samples towards large, mature, and stable firms), may also affect early results. Finally, as is well-known, the firms followed by analysts are biased towards larger firms with institutional following (Bhushan 1989) and with more extensive disclosures (Lang and Lundholm 1996), which censors the availability of analysts' forecasts for other firms. The generalizability of the early evidence on analysts' forecast superiority is accordingly limited, as is made clear by descriptions in these studies about their sample characteristics and by other important caveats.

Researchers now utilize analysts' earnings forecasts as a proxy for expected earnings for samples of firms that are not well-represented in these early studies. For example, Lee (1992), Clement et al. (2003), and Jegadeesh and Livnat (2006) use analysts' forecasts to proxy for earnings expectations for small firms (which are underrepresented in the early studies on the accuracy of analysts' versus time-series forecasts). Similarly, researchers sometimes use analysts' forecasts of earnings over horizons that are not represented in these early studies (which rarely examine forecast horizons beyond one year). For example, in the valuation and cost of capital literature (e.g., Frankel and Lee 1998; Claus and Thomas 2001; Gebhardt et al. 2001; Easton et al. 2002; and Hribar and Jenkins 2004), analysts' earnings forecasts are often used as a proxy for longer-horizon earnings expectations, such as two- to five-year-ahead earnings. One notable exception is Allee (2010) who utilizes exponential smoothing time-series forecasts for two-year horizons to estimate the firm-specific cost of equity capital. He finds that cost of equity capital estimates using time-series forecasts are reliably associated with risk proxies (e.g., market volatility, beta, leverage, size, book-to-price, etc.) and concludes that researchers and investors may use time-series forecasts of earnings to estimate the implied cost of equity capital for firms not covered by analysts.

Our empirical tests are based on annual earnings with forecast horizons ranging from 1 month through 36 months. We focus solely on annual earnings because we are interested in evaluating analysts' superiority over both short and long forecast horizons and the availability of quarterly analysts' earnings forecasts is generally limited to several quarters ahead. Furthermore, it is unlikely that random walk forecasts are superior to analysts' forecasts in the quarterly setting, where both the information and timing advantage of analysts are greatest.[4] Our focus on annual earnings forecasts is also consistent with the extensive use of these forecasts in research on the cost of equity capital and valuation, where longer horizon forecasts are the most cogent in terms of their influence on valuation-related estimates.

[4] We do not directly examine this conjecture, but our near-term forecasts of annual earnings are analogous to quarterly forecasts for the fourth quarter and for these very short forecast horizons, the results are consistent with analysts dominating time-series models.

We document several surprising findings. First, for longer forecast horizons, analysts' forecasts do *not* consistently provide more accurate estimates of future earnings than time-series models, even when analysts have timing and information advantages. Second, for forecast horizons where analysts *are* more accurate than random walk forecasts (i.e., shorter forecast horizons of several months), the differences in forecast accuracy are economically small. Third, random walk forecasts are more accurate than analysts' forecasts for estimating two-year-ahead earnings in approximately half of the forecast horizons analyzed, and random walk forecasts strongly dominate analysts' forecasts of three-year-ahead earnings. Fourth, over longer forecast horizons, analysts' forecast superiority is prevalent only in limited settings, such as when analysts forecast negative changes or small absolute changes in EPS. Finally, the associations between random walk versus analysts' forecast errors and stock returns track the results of our forecast accuracy tests. Over the shortest forecast horizon, when analysts' forecasts and earnings announcements occur almost simultaneously, the association between analysts' forecast errors and returns is three times larger than that between random walk forecast errors and returns. However, over longer forecast horizons, returns are more strongly associated with random walk forecast errors than with analysts' forecast errors, suggesting that random walk forecasts are a better proxy for market expectations of earnings than consensus analysts' forecasts over all but very limited forecast horizons.

These results conflict with common (often implicit) assertions that analysts' forecasts are uniformly a better proxy for investor expectations than are forecasts from time-series models. For example, Frankel and Lee (1998, 289) state that *I/B/E/S* earnings forecasts "should result in a more precise proxy for market expectations of earnings." They use these forecasts as a proxy for expected earnings for horizons of up to three years. Similarly, Easton et al. (2002) proxy for expected earnings using analysts' forecasts for horizons of up to four years, and Claus and Thomas (2001) use analysts' forecasts for horizons of up to five years. The evidence that time-series forecasts perform as well or better than analysts' forecasts suggests that the generalizability of research typically confined to firms for which analysts forecast long-term earnings (i.e., large, mature firms) might be reliably enhanced by substituting time-series forecasts for those of analysts and by expanding the samples of firms examined.

Although the tenor of our conclusions appears to contradict conclusions in early analysts' forecast research and questions the use of analysts' forecasts in more recent studies, we emphasize that early research was deliberate in its sample selection and other research design choices, and the conclusions were drawn appropriately. As in many literatures, it is the subsequent researcher who over-generalizes findings in the prior literature (Bamber et al. 2000). The early research examines the relative accuracy of time-series versus analysts' forecasts using samples of firms that are large, mature, and stable, and studies fairly limited forecast horizons. For these types of firms, over relatively short horizons, we also find that analysts' forecasts consistently outperform forecasts from a random walk model (and from all of the other time-series models that we evaluate).[5] However, we do emphasize that for all but the very shortest of forecast horizons, analysts' forecast superiority is economically small for the average firm. Moreover, for smaller firms and for firms with low analyst following, we find that analysts' superiority is quite small, and over longer horizons, analysts' forecasts are not superior to random walk forecasts.

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[5] In untabulated analyses, we also find that random walk forecasts are superior to forecasts from more complicated time-series models such as random walk with a drift. This superiority exists for two reasons. First, analysts are better at estimating earnings for firms with sufficient data to calculate the time-series parameters in some complicated time-series models because longer time-series availability is associated with more mature firms. Second, adding time-series parameters to a random walk forecast does not help much because the negative serial correlation in EPS changes is very small.

Our study is also subject to an unavoidable sample bias because to assess analysts' forecasts relative to time-series forecasts, we are necessarily constrained to use data for firms with available analyst forecasts. Thus, we cannot avoid biasing our sample towards covered firms. However, as we document, the percentage of firms without analyst coverage has fallen from more than 50% in the 1990s to approximately 25% and firms without analyst coverage have median total assets of less than $100 million. A second design choice is that, because analysts forecast earnings purged of transitory or special items, we use actual earnings per *I/B/E/S* (rather than earnings from Compustat) to calculate forecast errors based on analysts' forecasts and random walk. This is necessary in order to make the analyst and random walk forecast errors comparable.

The remainder of this paper proceeds as follows. In section 2, we review the prior literature. We describe our data and develop hypotheses in section 3. We present the results of our tests in section 4, and section 5 concludes.

2 Prior research and motivation

2.1 Prior Research

Numerous studies examine the time-series properties of annual earnings, motivated by a need for a well-specified expectations model to be used in asset pricing tests. The early studies (e.g., Little 1962; Ball and Watts 1972) provide evidence that annual earnings approximate a simple random walk process. Subsequent studies (e.g., Albrecht et al. 1977; Watts and Leftwich 1977) find that this simple time-series characterization performs at least as well as more complex models of annual earnings, such as random walk with drift or Box Jenkins.[6] Based on this

[6] Albrecht et al. (1977) also show that the choice of scalar is important to the relative accuracy of predictions from random walk versus random walk with drift models. Specifically, a random walk model outperforms a random walk

evidence, Brown (1993, 295) concludes that earnings follow a random walk and that this was "pretty much resolved by the late 1970s." In addition to the empirical evidence, the random walk model is advantageous because it does not require a long time series of data, which restricts the sample size and induces survivor bias.

A stream of literature based on these prior studies compares the accuracy of earnings forecasts from time-series models to that of analysts' forecasts. These studies can be broadly classified into one of two lines of research. The first line asks whether analysts' forecasts *are superior to* forecasts derived from time-series models. These studies are motivated by the intuition that analysts' forecasts should be more accurate than time-series forecasts for a number of reasons (e.g., analysts have access to more information and have a timing advantage), and these studies provide evidence that analysts' forecasts are more accurate than time-series forecasts. For example, Fried and Givoly (1982) argue that analysts' superiority is related to an *information advantage* because analysts have access to a broader information set, which includes non-accounting information as well as information released after the prior fiscal year. They compare prediction errors (defined as (forecasted EPS – realized EPS) / |realized EPS|) based on analysts' forecasts made approximately eight months prior to the fiscal-end date to those based on forecasts from two time-series models. The eight-month forecast horizon roughly corresponds to the annual forecast horizon of time-series models based on earnings releases, which typically occur by four months after fiscal year-end. Fried and Givoly (1982) report prediction errors of 16.4 percent using analysts' forecasts versus 19.3 percent using a modified sub-martingale random walk model and 20.3 percent using a random walk model.[7] The

with drift model when earnings are deflated by stockholders' equity but underperforms when earnings are not deflated.

[7] Fried and Givoly (1982) analyze a modified submartingale model that uses the firm's past earnings growth as the drift term as well as an index model that uses past earnings growth of the Standard & Poor's 500 as the drift term.

differences among these prediction errors seem small but are statistically significant. Fried and Givoly (1982) also find that analysts' forecast errors are more closely associated with security price movements than are forecast errors from time-series models. Collins and Hopwood (1980) document similar evidence using a slightly longer forecast horizon. Using forecasts made four quarters prior to year-end, they find mean analysts' forecast errors of 31.7 percent compared to 32.9 percent for their most accurate time-series forecast, again, an economically small but statistically significant difference.

A related line of research investigates the source of this apparent superiority. For example, Brown et al. (1987b) find that analysts' forecast superiority is positively (negatively) related to firm size (forecast dispersion). Similarly, Brown et al. (1987a) provide evidence consistent with analysts possessing an information advantage in that they better utilize information available on the date on which the time-series forecast is made, which Brown et al. (1987a) label a "contemporaneous advantage," and with analysts better utilizing information acquired between the date on which the time-series forecast is made and the date on which the analysts' forecast is made, which they label a "timing advantage." Subsequent research supports their conclusion that analysts' superiority is negatively associated with the forecast horizon (Kross et al. 1990; Lys and Soo 1995). Finally, O'Brien (1988) argues that analysts' superiority stems from their use of time-series models along with a broader information set that includes information about industry and firm sales and production, general macroeconomic information, and other analysts' forecasts. Consistent with this, Kross et al. (1990) find that the analysts' advantage is positively associated with firm coverage in the *Wall Street Journal*.

Our focus is limited to the random walk model out of simplicity; refinement to incorporate past earnings growth would likely improve the performance of time-series forecasts relative to analysts' forecasts, but would require longer time series, thus biasing the sample.

Collectively, these studies use samples comprised mainly of large firms. One exception is Branson et al. (1995) who re-examine the question of whether analysts' forecasts are superior to forecasts from time-series models using a sample of small market capitalization firms (where the median market value of equity is $215 million). Using one-quarter-ahead forecasts, they find that analysts' forecasts are also more accurate than time-series forecasts for their sample, but conclude that time-series models might be useful for small firms without analyst following. More recently, Allee (2010) examines cost of equity capital estimates based on time-series forecasts, so is able to extend his analyses to firms without analyst following. He uses two-year-ahead annual forecasts combined with the Easton (2004) implementation of the Ohlson and Jeuttner-Nauroth (2005) earnings growth valuation model to back-out the implied cost of equity capital. His results are also encouraging with respect to the usefulness of time-series forecasts in a valuation setting.

To succinctly summarize and place some structure on the prior research on analysts' versus time-series forecasts, table 1 summarizes twelve important studies on the relative performance of time-series and analysts' forecasts. We compile summary data on the sample size and time-period, the time-series models investigated, data requirements, treatment of outliers, forecast horizon, and summary results. Several observations are noteworthy. First, these studies typically use time-series data from the 1960s and 1970s. Second, the sample sizes are small by current capital markets research standards, ranging anywhere from only 50 to only a few hundred firms. Third, the time-series models used require a minimum of 10 years of data, and some require as many as 20 years of data. Fourth, the forecast horizons studied range from one quarter ahead in the quarterly setting to 18 months ahead in the annual setting, with the majority focused on the quarterly forecast horizon. Fifth, forecast accuracy is generally evaluated using the absolute value of forecast errors scaled by either actual EPS or stock prices. Sixth, the reported differences in forecast accuracy between analysts and time-series models are typically statistically significant and analysts typically 'win,' but the economic magnitudes of the differences appear modest at best. Finally, the analysts' forecast advantage is positively associated with firm size and is negatively associated with prior dispersion in analysts' forecasts and forecast horizon.

2.2 Why re-examine the relative forecast accuracy of analysts versus time-series models?

Two factors, combined with the availability of analysts' forecasts for a large number of public firms, motivate our re-examination of the superiority of analysts' forecasts over time-series forecasts. First, our review of the accounting and finance literature above suggests that it took approximately two decades (i.e., the 1970s and 1980s) for the literature to conclude that analysts are better at predicting future earnings than are time-series models. As Kothari (2001) notes, due to this conclusion and the increased availability of analysts' forecast data in machine-readable form, the literature on time-series models quickly died.[8] However, as noted above and as evident in table 1, this generalized conclusion is primarily based on studies investigating small samples of firms that are large, mature, and stable, and the margin of analysts' superiority over time-series forecasts is not overwhelming. However, analysts' forecasts are used pervasively in the literature as proxies for market expectations for all firms, both large and small. This general reliance on analysts' forecasts contrasts with Walther (1997), who concludes that the market does not consistently use analysts' forecasts or forecasts from time-series models to form expectations of future earnings; her evidence indicates that market participants place more

[8] Since the 1980s, the forecasting literature has focused on refinements to better understand various features of analysts' forecasts, such as the determinants of analysts' forecast accuracy (Clement 1999), bias in analysts' forecasts (Lim 2001), and the efficiency of analysts' forecasts with respect to public information (Abarbanell 1991).

weight on time-series forecasts relative to analysts' forecasts as analyst following decreases. Additionally, it is not obvious that analysts are equally skilled at predicting earnings for large and small firms (or for firms that differ on other dimensions).

The second motivation for our re-examination is that a significant number of firms were not covered by analysts during the sample periods studied in early research and, therefore, are excluded from research that requires longer-term earnings forecasts. If analysts' forecasts over long horizons are not superior to time-series forecasts, then requiring firms to have available analysts' forecasts unnecessarily limits the data upon which this research is based and hence, is a costly restriction. To get a sense of the cost (in terms of sample exclusion) of requiring analysts' forecasts, we identify the number of firms with available financial and market data not included in *I/B/E/S*. Figure 1 plots of the percentage of public firms with available data in *Compustat* and in the Center for Research in Securities Prices (*CRSP*) that *do not* have analysts' one- and two-year-ahead earnings forecasts and long-term growth forecasts available in *I/B/E/S*.[9] As illustrated in figure 1, the percentage of firms with available *Compustat* and *CRSP* data that do not have one-year-ahead analyst forecast data in *I/B/E/S* was approximately 50% through the early 1990s but in recent years, the percentage of firms without one-year-ahead analyst forecasts has declined to approximately 25%. Figure 2 plots the median assets of firms with available *Compustat* and *CRSP* data, sorted by whether they are covered by analysts on *I/B/E/S*. As noted in prior research, the uncovered firms are considerably smaller (Bhushan 1989). Whereas the difference in median total assets between covered and not covered firms was relatively small through the early 1990s, it is now quite large; the median total assets of firms without analysts' forecasts is generally below $100 million. Thus, broadly speaking, the evidence in figures 1 and

[9] We identify this sample by starting with all firms in *Compustat* with positive total assets. We retain all firms with monthly stock price data as of the fiscal-end month available from *CRSP*. Finally, we use *I/B/E/S* data to identify whether consensus forecast data as of the fiscal-end month are available for the remaining firms.

2 highlights the sample effects of requiring analysts' forecasts in terms of excluding otherwise useable data. As noted in the introduction, we cannot avoid this sample selection issue, but because analyst coverage is much greater in recent years, we are able to include the majority of public firms in our analyses.

2.3 Empirical Methodology

In the first set of tests, we compare the accuracy of analysts' forecasts of annual earnings to that of time-series forecasts over various horizons ranging from 1 through 36 months prior to the earnings announcement date. The time-series forecasts that we examine are based on both annual realizations and annual realizations updated with subsequent quarterly realizations. We employ a random walk time-series forecast for three reasons. First, as noted above, there is very little evidence suggesting that more sophisticated time-series models are more accurate than simple time-series models of annual earnings (Albrecht et al. 1977; Watts and Leftwich 1977; Brown et al. 1987a). Second, random walk requires no parameter estimates and so, does not have the data demands of more complicated ARIMA models. That is, using the random walk forecast rather than more complex time-series models frees us from further data requirements that would skew our analyses to large, mature firms, as in prior research.[10] Third, Klein and Marquardt (2006) find that losses occur with increasing frequency over time, suggesting that the earnings process is becoming more volatile. Thus, random walk may be more descriptive than more complicated ARIMA models.

Consistent with prior studies, we expect analysts' superiority to decrease as the forecast horizon increases (Brown et al. 1987a). Next, we investigate settings where we would expect analysts to have less of an information advantage. That is, we compare the forecast accuracy of

[10] In addition, the use of random walk is consistent with Occam's razor, which advocates simplicity.

analysts' forecasts to that of a time-series model for young firms, small firms, and firms with low analyst following. We also examine how much information analysts add when they forecast positive versus negative changes in EPS and when they forecast large versus small changes in EPS.[11]

In the second set of tests, we examine the association between random walk forecast errors and stock returns, and the association between analysts' forecast errors and stock returns.[12] Here, we also expect the relative strength of the correlation between analysts' forecast errors and returns over the correlation between random walk forecast errors and returns to decrease as the forecast horizon increases and expect the relative strength of the correlation between analysts' forecast errors and returns to be lower in settings where analysts should have less of an advantage or when analysts forecast greater changes in future earnings.

As a final test, we investigate analysts' superiority in a multivariate setting. For each forecast horizon, we estimate regressions with our measure of analysts' superiority as the dependent variable and proxies for the quality of the information environment, firm risk, and the analysts' forecasted changes in earnings as covariates. The objective of this test is to investigate the incremental impact of these factors on analysts' superiority and to assess whether the impact changes across the various forecast horizons.

3 Data

We first collect data from the *I/B/E/S* consensus file and from the *Compustat* annual file. Our sample spans a 25 year period, from 1983 through 2008. We attempt to impose minimal

[11] When analysts forecast no change in EPS, the random walk forecast and the analysts' forecasts are equal; thus, analysts' forecasts differ most from random walk forecasts when analysts forecast large changes in EPS.
[12] Thus, we our tests following Foster (1977) who first put forth the dual evaluative criteria of predictive ability and capital market association.

constraints on data availability. For a firm-year observation to be included in our sample, the prior year's EPS, at least one earnings forecast, the associated stock price, and the EPS realization for the target year must be available from *I/B/E/S*. For supplementary tests using quarterly data to form annual earnings forecasts, we further require that quarterly EPS realizations be available from *I/B/E/S*. We require that sales (our proxy for size) be available from *Compustat* for the year immediately preceding the forecast.[13] Because losses are less persistent than positive earnings (Hayn 1995), we further limit our analyses to firm-years with positive earnings in the base year.[14] In sensitivity analyses, we find that including loss firms does not change our overall conclusions.[15] Finally, for the market-based tests, we require sufficient monthly data from *CRSP* to calculate returns over the specified holding periods, which slightly reduces the sample for these tests.

For each target firm-years' earnings (EPS_T), we collect the *I/B/E/S* consensus analysts' forecast made in each of the previous 36 months. For the first 12 previous months (i.e., 0 through 11 months prior), we use FY1 (the one-year-ahead earnings forecast) as the measure of the analysts' forecast of earnings, and the EPS one year prior (EPS_{T-1}) as the random walk forecast of earnings. Thus, for the first year prior to the target year's earnings announcement, we

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[13] For the analyses that can be done without *Compustat* data (i.e., the main results, analyses related to firm age, and analyses related to the number of analysts following), the *Compustat* restriction makes no substantive difference in the results. However, we impose this restriction across all analyses to facilitate sample consistency between the tables.

[14] The base year is defined as the year immediately preceding the forecast. For example, letting the target year be year T, when forecasting one-year-ahead earnings, the base year is year T-1; when forecasting two-year-ahead earnings, the base year is T-2; etcetera.

[15] In unreported analyses, we find that random walk forecasts perform poorly for fiscal periods following a loss; however, analysts' forecasts also perform poorly for these firms. While including loss firms does not change the results over horizons of one year or less, the random walk results improve somewhat relative to analysts' forecasts for forecast horizons of two and three years when loss firms are included. Although the lack of persistence of losses makes random walk a poor predictor of future earnings when the base year's earnings are negative, analysts are aware of the base year's earnings before they make their forecasts, so this data restriction does not provide time-series models with a natural advantage.

have 12 pairs of forecast errors.[16] For each pair, the analysts' forecast error is the difference between the analysts' forecast and realized earnings (EPS_T) and the random walk forecast error is the difference between EPS_{T-1} and EPS_T. We then take the absolute value of the forecast errors and scale by price as of the analysts' forecast date. We obtain 844,643 consensus forecasts, representing 77,013 firm-years and 10, 919 firms, with sufficient data to be included in the one-year-ahead (FY1) analyses.

For the 12 through 23 months prior to the target year's earnings announcement date, we use the *I/B/E/S* forecasts of FY2 (the two-year-ahead earnings forecast). As with the forecasts of FY1, there are 12 monthly forecasts of FY2. For these months, the random walk forecast of earnings is equal to EPS_{T-2}. We obtain 715,730 consensus forecasts, representing 68,870 firm-years and 9, 870 firms, with sufficient data to be included in the two-year-ahead (FY2) analyses.

Finally, for the 24 through 35 months prior to the target year's earnings announcement date, we construct estimates of FY3 (the three-year-ahead earnings forecast) because few analysts forecast three-year-ahead earnings directly. We construct these estimates using the method outlined in studies like Frankel and Lee (1998), Lee et al. (1999), Gebhardt et al. (2001), and Ali et al. (2003). This method generates the FY3 forecast from the FY2 forecast adjusted by the mean analysts' long-term growth forecast as follows:

$$\mathrm{FY3} = \mathrm{FY2} \times (1 + \mathrm{LTG\%}) \tag{1}$$

where FY2 is defined above and LTG is the long-term growth forecast from *I/B/E/S*. Thus, to be included in the FY3 sample, a firm must report positive base year earnings (EPS_{T-3}) and have a

[16] Note that when the earnings announcement is made early in the calendar month, there will not be an earnings forecast in that calendar month. For these observations, there are only 11 forecasts of FY1. Thus, there are approximately half as many month 0 observations as there are month 1 observations.

FY2 forecast and a long-term growth forecast available in *I/B/E/S*.[17] We next calculate the pairs of forecast errors, analogous to the FY1 and FY2 analyses. We obtain 545,354 *I/B/E/S* consensus forecasts, representing 53,561 firm-years and 7, 636 firms, with sufficient data to be included in the three-year-ahead (FY3) analyses.

Our primary random walk-based forecasts of future earnings are simply the lagged annual realized earnings:

$$E_{T-\tau}(EPS_T) = EPS_{T-\tau} \quad \in \tau = \{1, 2, 3\} \tag{2}$$

For FY1 forecasts, the random walk forecast is the realized EPS from the previous fiscal year, and for FY2 (FY3), the random walk forecast is the realized EPS two (three) years prior to the forecast year. We also examine the sensitivity of the results to the alternative random walk forecast formed using the sum of the prior four quarters of EPS ($QEPS_{T-1}$). Note that 11 months prior to the earnings announcement, the random walk forecast based on annual realizations (EPS_{T-1}) and the random walk forecast based on quarterly realizations ($QEPS_{T-1}$) will be equal because they are based on the same four quarters. However, 9 months prior to the earnings announcement, EPS_{T-1} will not change but $QEPS_{T-1}$ will be equal to the sum of quarterly EPS from the prior four quarters (in this case, Q2 through Q4 of the prior year (T-1) and Q1 of the current year (T)).

4 Results

4.1 Descriptive Statistics

Panel A of table 2 presents descriptive statistics for the 68,870 firm-years with sufficient data to estimate random walk forecast errors and analysts' forecast errors 11 months prior to the

[17] We also test the robustness of our results to using explicit FY3 forecasts when available in *I/B/E/S*. We find that our general conclusions are unchanged.

target earnings announcement. Untabulated statistics reveal that a hypothetical data requirement of 10 years of prior earnings data (e.g., Fried and Givoly 1982) would eliminate more than 60 percent of the observations, so estimating more complex time-series forecasts would result in a considerable loss of sample observations. We also find that the mean (median) observation has only 7.6 (5) analysts following, consistent with a large number of the firms in our sample having relatively sparse analyst coverage (i.e., only 1 or 2 analysts following).

As noted in table 1, prior literature frequently scales forecast errors by reported earnings and many important studies in this literature (e.g., Brown and Rozeff 1978; Fried and Givoly 1982; Brown et al. 1987a) winsorize forecast errors at 100 percent. For a sample comprised of large, mature firms and for forecasts with short horizons, this winsorization rule is reasonable because it results in very few of the analysts' forecast errors being winsorized. For example, Fried and Givoly (1982) find that approximately 0.5 percent of their sample observations have scaled forecast errors that are greater than 100 percent. Moreover, for the subsample of firms in our study that are at least 10 years old, we find that one month prior to the earnings announcement date, only 4.3 percent of scaled absolute analysts' forecast errors are greater than 100 percent. However, we find that for younger firms and over longer forecast horizons, many more extreme forecast errors exist. When we include younger firms in the analyses, the proportion of analysts' forecast errors (at the same one month forecast horizon) that are greater than 100 percent of reported earnings increases to 6.0 percent. Moreover, this proportion rises dramatically as the forecast horizon lengthens.

In panel B of table 2, we present the proportion of the absolute forecast errors (scaled by reported earnings) that are greater than 100 percent to illustrate the consequences of scaling forecast errors by reported earnings. Thirty-five months prior to the earnings announcement, almost 32 percent of analysts' forecast errors and 26 percent of random walk forecast errors are greater than 100 percent. Because winsorizing 32 percent of the sample could severely affect the reported results, in the analyses that follow, we scale forecast errors by price, as reported in *I/B/E/S*.[18] Scaling by price limits the number of extreme observations so that less than one percent of observations for both random walk forecast errors and analysts' forecast errors are greater than 100 percent at every forecast horizon. Thus, scaling by price provides a more accurate picture of the relative forecast accuracy of analysts versus random walk.

In panel C of table 2, we examine the bias in both types of forecasts. We report descriptive statistics for signed analysts' forecast errors and signed random walk forecast errors scaled by price at 11, 23, and 35 months prior to the earnings announcement date. We find that both forecast errors are biased, and that the absolute magnitudes of the bias for the median forecast errors are similar, but the biases are in the opposite direction. Specifically, the median random walk forecasts are negatively biased, while the median analysts' forecast errors are positively biased. The negative bias in random walk forecast errors occurs because EPS tends to grow by approximately 50 basis points per year and the random walk model does not allow for this growth. Analysts' forecast errors are biased such that the median analysts' forecast error is consistently positive and is much larger at longer horizons. This pattern of bias in analysts' forecast errors is consistent with findings in Richardson et al. (2004).

4.2 Tests of Analysts' Superiority Using Absolute Forecast Errors

We present the main results of our tests in table 3. In panel A of table 3, we compare the forecast accuracy of random walk forecasts based on annual EPS to that of the analysts'

[18] The price reported in *I/B/E/S* is usually the price at the end of the day prior to the day on which the forecast is released. However, our results are insensitive to the measurement date for price. Specifically, our results are essentially unchanged when we scale by the first price for the fiscal year.

consensus forecasts for the full sample. We calculate the analysts' superiority over the random walk model as follows (firm subscripts omitted):

$$Analysts' \, Superiority = \frac{|EPS_{T-1} - EPS_T| - |Forecasted \, EPS_{T,M} - EPS_T|}{Price_{T,M}} \qquad (3)$$

where *Forecasted EPS* is the consensus analysts' forecast (i.e., FY1, FY2, or FY3) issued M months prior to the earnings announcement for year T earnings. At each forecast horizon, we calculate mean *Analysts' Superiority*. A positive mean indicates that analysts are superior to a random walk model at that particular forecast horizon, on average, and a negative mean indicates that a random walk model is superior to analysts at that particular forecast horizon, on average.[19]

The first set of columns in panel A, labeled FY1, presents the mean analysts' superiority during months 0 through 11 prior to the earnings announcement. For the full sample, our results confirm those in the prior literature – analysts' forecasts *are* more accurate than forecasts from time-series models (specifically, forecasts from a random walk model) and their superiority is more evident as the earnings announcement approaches. For forecasts made in the same month as the earnings announcement (i.e., 0 months prior), analysts' forecasts are more accurate than random walk forecasts by 282 basis points. This result is not surprising given that this is the forecast horizon where analysts have the greatest timing and information advantages. In other words, for most firms, the random walk forecast is approximately one year old at this time and analysts have the advantage of having access to all of the news that has occurred over the year and to the earnings announcements made in the first three quarters of the year (i.e., to three of the four quarterly earnings numbers used to calculate EPS_T). In contrast, 11 months prior to the

[19] Note that the measurement of analysts' forecast superiority requires matched pairs of random walk forecasts and analysts' forecasts. That is, for a given firm-year observation, we require both a random walk forecast (so a prior earnings realization) and a consensus analysts' forecast, as well as the reported earnings.

earnings announcement date, analysts' superiority is only 35 basis points, which is approximately 88 percent smaller than analysts' superiority in month 0.

The second set of columns, labeled FY2, presents the mean analysts' superiority from 12 through 23 months prior to the earnings announcement. Here, we use the consensus analysts' forecasts of two-year-ahead earnings and the random walk forecast is earnings reported two years prior to the target date. Again, analysts' forecasts are significantly more accurate than random walk forecasts from 12 through 21 months prior to the earnings announcement, but as with FY1, their relative superiority falls monotonically as the forecast horizon lengthens. Moreover, at month 21, analysts' superiority is only 3 basis points, and by months 22 and 23, the random walk forecast is significantly more accurate than analysts' forecasts on average, so time-series forecasts are superior. However, the difference in accuracy is economically trivial, at 7 and 14 basis points respectively.

The third set of columns, labeled FY3, presents the mean analysts' superiority from 24 through 35 months prior to the earnings announcement. Again, analysts' superiority falls monotonically, from 66 basis points at 24 months prior to -41 basis points at 35 months prior, as their timing and information advantages increase.

In panel B of table 3, we compare the forecast accuracy of random walk forecasts based on quarterly EPS (i.e., the sum of EPS for the prior four quarters) to that of the analysts' consensus forecasts for the full sample. We find that the magnitude of analysts' superiority is smaller with quarterly updating than with the annual random walk forecast (reported in panel A) at every horizon. To illustrate, in panel B, analysts' superiority ranges from 62 basis points to -26 basis points, compared to a range of 282 basis points to -41 basis points in panel A. This decrease in magnitude is to be expected since quarterly updating reduces analysts' information and timing advantages. We also find that the sign and significance of analysts' superiority for the FY1 and FY2 horizons are very similar to those in panel A. Specifically, in FY1, we find that analysts are more accurate at every horizon. In FY2, we find that analysts and random walk forecasts are no different at 21 and 22 months prior, and that random walk forecasts are more accurate at 23 months prior. However, in FY3, we find a marked difference from the pattern in panel A. Here, random walk forecasts are more accurate than analysts' forecasts (or, at least, as accurate as analysts' forecasts) for almost all horizons.

Finally, in panel C of table 3, we compare the forecast accuracy of random walk forecasts using explicit FY3 forecasts to that of the analysts' consensus forecasts for the full sample. By construction, the results for FY1 and FY2 are identical to those in panel A. For FY3, we find that analysts' superiority falls monotonically from 54 basis points at 24 months prior to 20 basis points at 35 months prior. This pattern is similar to that in panel A, but the magnitudes are smaller at every horizon in FY3.

Overall, the results presented in table 3 reveal that, consistent with prior literature, analysts are better than time-series models at predicting earnings over relatively short windows. However, as the forecast horizon grows, analysts' superiority decreases and becomes negative, so that random walk forecasts are superior to analysts' forecasts when the forecast horizon is sufficiently long. Moreover, the results across the various panels reveal that quarterly updating to the random walk forecasts reduces the magnitude of analyst superiority and that random walk forecasts for FY3 based on long-term growth forecasts and explicit FY3 forecasts are very similar. For the remainder of our analyses, we focus on random walk forecasts based on annual EPS because these forecasts give the analysts the greatest information and timing advantages, thus biasing our results against random walk.

4.2.1 Partitioning on firm age

Table 4 partitions observations based on firm age, measured as the number of years that the firm's earnings have been reported in *I/B/E/S*. Because samples in prior literature are comprised of mature firms, we separate observations into young firms versus mature firms to compare the relative forecast accuracy between the two groups. Panel A reveals that even one-year-ahead earnings are much more difficult to forecast for young firms than for mature firms. Specifically, for firms in their first year on *I/B/E/S*, the mean analysts' forecast error 11 months prior is 409 basis points while the matching random walk forecast error is 426 basis points. For firms that have been on *I/B/E/S* for at least five years, the mean analysts' forecast error is approximately 25 percent smaller, at 305 basis points, while the random walk forecast error is 347 basis points. Thus, it appears that mature firms are inherently more predictable, and although the random walk forecast error is smaller for mature firms than for young firms, the superiority of analysts' forecasts is greater for mature firms. For firms in their first year on *I/B/E/S*, analysts' superiority is only 18 basis points, but for the firms that are at least five years old, analysts' superiority is 41 basis points.

The difference in second year forecast accuracy is even more striking. At month 23, analyst superiority is negative for firms that are four years old or less, indicating random walk forecast superiority. Moreover, for firms in their first year on *I/B/E/S*, the differences are quite large, with random walk forecast superiority of 56 basis points. Thus, for firms in their first year on *I/B/E/S*, analysts' forecasts are less accurate than random walk forecasts by more than one-half percent of price at the 23 month forecast horizon. In contrast, for firms that have been on *I/B/E/S* for at least five years, analysts' forecasts are only slightly more accurate than random walk forecasts (by 3 basis points).

The results for FY3 presented in panel C are even more striking. At month 35, time-series forecast superiority is evident regardless of firm age. For firms in their first year on *I/B/E/S*, random walk forecasts are superior to analysts' forecasts by 116 basis points. However, for firms that have been on *I/B/E/S* for at least five years, the superiority of random walk forecasts is only 12 basis points at month -35.

4.2.2 Partitioning on firm size

Table 5 partitions observations based on firm size or on analyst following. To partition on firm size, each year, we partition all firms on *Compustat* with positive sales into two groups, large firms and small firms, using the median sales in the year as the threshold. Because *I/B/E/S* firms are generally larger than *Compustat* firms, fewer than half of the firms are classified as small using this threshold. As reported in panel A, analysts' superiority for small firms is much smaller than for large firms. In fact, for small firms, random walk is superior in 5 and 10 of the 12 monthly forecast horizons during FY2 and FY3, respectively. Moreover, some of these differences are economically significant. For example, at the 23 month forecast horizon, the difference is almost one and a half percent of price, and at the 35 month forecast horizon, the difference is more than one percent of price.

4.2.3 Partitioning on analyst following

In panel B, we report similar results for lightly followed firms (i.e., those followed by one or two analysts). While analysts' forecasts are superior in most months, for early fiscal-year forecasts, the difference in the accuracy of random walk forecasts and analysts' forecasts is economically trivial (e.g., it is only 12 basis points 11 months prior). Consistent with the results in table 4, results for FY2 and FY3 are similar, with random walk forecasts dominating analysts' forecasts at numerous forecast horizons.

4.3 The Relation between Analysts' Superiority and the Sign of the Forecasted Change in EPS

Table 6 partitions observations based on the sign of the analysts' forecasted change in EPS. Comparing the results in panels A (positive forecasted changes) with those in panel B (negative forecasted changes) across all horizons, we find that analysts forecast negative earnings changes less often than positive earnings changes, but when they do forecast negative changes, analysts' superiority is much stronger. Most strikingly, at 11 months prior to the earnings announcements, analysts' superiority is less than 1 basis point for the 59,086 positive forecasted changes in EPS, and is 209 basis points for the 11,789 negative forecasted changes in EPS.

We find similar evidence over FY2 forecast horizons. At 23 months prior to the earnings announcement, random walk forecasts are superior to analysts' forecasts by 29 basis points (see panel A) when analysts forecast positive changes in EPS. However, over this same horizon, analysts' superiority is 168 basis points when analysts forecast negative changes in EPS (see panel B). Here, we also find that analysts rarely forecast negative changes in two-year-ahead EPS. For example, at month -23, there are 47,260 positive forecasted changes and only 3,903 negative forecasted changes.

Finally, for FY3, when analysts forecast positive changes in EPS, random walk forecasts are superior to analysts' forecasts starting 30 months prior to the earnings announcement. The difference between analysts' forecast error and random walk forecast error is almost one half percent of price in month -35. However, when analysts forecast negative changes in earnings, analysts' superiority is very large, ranging from 8.52 percent of price at month -24 to 10.6 percent of price at month -35. That said, the small number of negative forecasted changes in

FY3 across these horizons indicates that analysts very rarely forecast negative changes in three-year-ahead earnings (i.e., approximately 1 in 1,000 forecasted changes are negative over this horizon).

4.4 The Relation between Analysts' Superiority and Absolute Forecasted Change in EPS

Table 7 partitions observations based on the absolute magnitude of the analysts' forecasted change in EPS. As discussed above, when analysts forecast no change in EPS, the random walk forecasts and the analysts' forecasts are equal. Thus, to further examine whether analysts' superiority varies with the forecasted change in EPS, we partition the observations into small, moderate, and large forecasted changes in EPS. For this analysis, we calculate the absolute value of the analysts' forecasted change in EPS and let the lowest and highest 33 percent represent small and large forecasted changes respectively. The difference in analysts' superiority between the extreme forecasts and the moderate forecasts is always large, but the direction of the effect differs for short and long forecast horizons.

Comparing the results in panel A (for the partition with the least extreme forecasted changes) with those in panel B (for the partition with the most extreme forecasted changes), we find that for short horizons (i.e., FY1 forecasts), analysts' superiority is strongest when the absolute forecasted change in EPS is extreme. At the one month forecast horizon, for the group of firms with the smallest forecasted change, analysts' superiority is only 44 basis points, but for the group of firms with the largest forecasted change, analysts' superiority is 570 basis points. However, this relative superiority deteriorates as the horizon lengthens. For example, for the group of firms with small forecasted changes, analysts' superiority is only 17 basis points 10 months prior to the earnings announcement, while at the same horizon, analysts' superiority is

117 basis points for the group of firms with large forecasted changes. Although analysts' superiority diminishes as the horizon lengthens, in the first year, analysts' superiority is always significantly greater for the group of firms with large forecasted changes in EPS than for the group of firms with small forecasted changes in EPS.

The results differ, however, over longer horizons. For the group of firms with small forecasted changes, analysts' forecasts are more accurate than random walk forecasts over each of the 36 monthly horizons in FY2. However, for the group of firms with large forecasted changes, random walk dominates in a large number of forecast horizons. At 23 months prior to the earnings announcement, when analysts have no timing advantage and a slight information advantage, random walk forecasts are 61 basis points more accurate than analysts' forecasts for the group of firms with large forecasted changes and are 27 basis points more accurate for the group of firms with small forecasted changes. In addition, analysts are not superior to random walk for the group of firms with large forecasted changes in FY2 until month 18, when analysts have a 4 month timing advantage. This compares to month 21 for the full sample.

The difference in accuracy between the groups with large versus small forecasted changes is even greater for forecasts made for FY3. As with two-year-ahead forecasts, analysts' forecasts of three-year-ahead earnings are always superior to random walk forecasts for the group of firms with the least extreme forecasted changes in EPS. However, for the groups of firms with the most extreme forecasted changes, analysts' superiority is significantly positive in only 3 of the 12 forecast horizons; this occurs 26 months prior to the earnings announcement, when analysts have an 9 month timing advantage. From 28 through 35 months prior to the earnings announcement, random walk forecasts are superior to analysts' forecasts, and the difference is 69 basis points at the 35 month horizon. In other words, when analysts forecast large changes in three-year-ahead earnings, a simple random walk estimate of those earnings is more accurate by approximately 70 percent of price on average. Over the same horizon, when analysts forecast a small change in earnings, their forecasts are more accurate than a simple random walk estimate by approximately 20 percent of price.

4.5 Tests of Analysts' Superiority Using Market Expectations

Next, we examine the associations between time-series forecast errors and stock returns and between analysts' forecast errors and stock returns over various forecast horizons. To the extent that stock prices react to earnings surprises, higher associations between forecast errors and stock returns indicate a greater correspondence between the forecasts and ex ante market expectations. We regress stock returns measured from the month of the forecast through the month of the earnings announcement on forecast errors from random walk and analysts' forecasts using a seemingly unrelated regression system:

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T \tag{4}$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T \tag{5}$$

The coefficient β measures the relation between returns and random walk forecast errors, and the coefficient b measures the relation between returns and analysts' forecast errors. We report tests on the ratio of the regression coefficients β to b. We estimate this system for each of the 36 forecast horizons from 0 months prior (i.e., when analysts' forecasts and earnings are announced in the same month) to 35 months prior to the earnings announcement. Thus, we measure stock returns and forecast errors contemporaneously such that the returns accumulation period and the forecast horizon are equal. For example, when the forecast horizon is 12 months in length, the returns accumulation period is also 12 months in length and the forecast horizon and returns accumulation period represent the same 12 months.

In panel A of table 8, we present the estimation results for models (4) and (5) across all forecast horizons using annual EPS. As the forecast horizon lengthens, the association between stock returns and forecast errors increases for both random walk and analysts' forecasts. The random walk coefficient ranges from 0.069 in the 1 month forecast horizon regression to 3.454 in the 24 month forecast horizon regression. Similarly, the analysts' forecast coefficient ranges from 0.148 in the 1 month forecast horizon regression to 3.354 in the 24 month forecast horizon regression. While the coefficients on both errors increase with the length of the forecast horizon, they grow at different rates.

We find that the relative weights that the market seems to assign to random walk forecast errors and analysts' forecast errors tend to track fairly closely to the accuracy tests in table 3. Over the shortest forecast horizon, when analysts' forecasts and earnings announcements coincide in the same calendar month, the association between stock returns and random walk forecast errors is 47 percent of the association between stock returns and analysts' forecast errors. However, the relative magnitudes of the stock return associations grow nearly monotonically, so that at the 11 month forecast horizon, the random walk coefficient is 72 percent of the analysts' forecast error coefficient. To summarize, at the one year horizon, analysts' forecasts dominate random walk-based forecasts as a proxy for market expectations, which mirrors the accuracy results from table 3. However, the relative ability of analysts' forecasts to proxy for market expectations is much stronger at the one month forecast horizon than over longer forecast horizons.

The pattern for FY2 forecasts is similar, but analysts' forecasts are a significantly better proxy for market expectations than random walk forecasts only for horizons shorter than 21 months. For the 23 month forecast horizon, the random walk forecast is a significantly better proxy for market expectations, on average. Finally, for forecasts of FY3, analysts' forecasts are a better proxy in only 6 of the 12 months. For forecast horizons of 32 through 35 months, random walk is again a significantly better proxy for market expectations. Overall, it appears that market expectations track fairly closely to the forecast accuracy results. Over horizons where analysts' forecasts are more accurate than random walk forecasts, analysts' forecasts seem to provide a better proxy for market expectations. However, over horizons where random walk forecasts are more accurate than analysts' forecasts, random walk forecasts seem to provide a better proxy for market expectations.

In panel B of table 8 we present the results using random walk forecasts based on quarterly EPS (i.e., the sum of EPS for the prior four quarters). For FY1, we find that random walk forecasts are as good a proxy for market expectations as analysts' forecasts in the month of the earnings announcement. Thereafter (i.e., in months 1 through 11), we find that analysts' forecasts are a better proxy for market expectations. In addition, in FY2, we find that analysts' forecasts are the better proxy for market expectations in only 5 of the 12 months, and in FY3, random walk forecasts are a better proxy in all of the months.

4.5.1 Partitioning on firm size and on analyst following

Panels A and B of table 9 present the estimation results for models (4) and (5) for small firms and for lightly followed firms, respectively. In panel A, for FY1, we find that β/b ranges from 44 percent for the shortest forecast horizon to 84 percent for the 11 month forecast horizon. Moreover, analysts' forecasts are no better than random walk forecasts as a proxy for market expectations 10 and 11 months prior to the earnings announcement. For FY2 and FY3, we find that analysts' forecasts are no better than random walk forecasts over horizons of 19 through 23 months and 26 through 31 months prior to the earnings announcement, respectively, and that random walk forecasts dominate analysts' forecasts over horizons of 32 through 35 months prior.

The results for lightly followed firms are reported in panel B, and are very similar to those reported in panel A (for small firms) for FY1 and FY2. That is, analysts' forecasts dominate random walk forecasts as a proxy for market expectations only over shorter forecast horizons. For three-year-ahead forecasts, analysts' forecasts are not a better proxy than random walk forecasts starting in month 30. Overall, the results reported in table 9 for small and lightly followed firms are consistent with the analysts' forecast accuracy results reported in table 5.

4.5.2 Partitioning on the sign of the forecasted change in EPS

Panels A and B of Table 10 present the estimation results for models (4) and (5) for firms with positive and negative forecasted changes in EPS, respectively. In panel A, when analysts forecast increasing EPS, we find that analysts' forecasts are no better than random walk forecasts as a proxy for market expectations across all horizons. Moreover, beginning 7 months prior to the earnings announcement, random walk forecasts dominate analyst forecasts. In stark contrast, in panel B, when analysts forecast decreasing EPS, we find that analysts' forecasts dominate random walk forecasts as a proxy for market expectations across all horizons. This evidence is consistent with that presented in table 6 and suggests that analysts do much better than random walk forecasts when they forecast negative changes in earnings.

4.5.3 Partitioning on the absolute forecasted change in EPS

Panels A and B of table 11 present the estimation results for models (4) and (5) for firms with small and large analysts' forecasts of the change in EPS, respectively. In panel A, for FY1, FY2, and FY3, we find no statistical differences between the coefficients on the random walk forecast errors and on the analysts' forecast errors when analysts forecast the least extreme changes in EPS. Thus, analysts' forecasts are no better than random walk forecasts as a proxy for market expectations when analysts forecast small changes in EPS.

In panel B, we present the results when analysts forecast the most extreme changes in EPS. For FY1, we find that analysts' forecasts dominate random walk forecasts as a proxy for market expectations in all months. However, in FY2, we find that random walk forecasts are as good a proxy for market expectations as analysts' forecasts over horizons greater than 22 months, and in FY3, we find that random walk forecasts dominate for horizons of 34 and 35 months. Overall, the market expectation results in Table 11 track fairly closely to the forecast accuracy results presented previously.

4.6 Multivariate Tests

As a final test, we investigate analysts' superiority in a multivariate setting which controls for the information environment of the firm as well as for risk factors. Specifically, we estimate the following regression separately for each of the 36 forecast horizons:

$$\begin{aligned} Analysts'\,Superiority_{T,M} = {} & \gamma_0 + \gamma_1\,\#Analysts_T + \gamma_2\,STD_{T,M} + \gamma_3\,BTM_{T-1} \\ & + \gamma_4\,Sales_{\,T-1} + \gamma_5\,Forecast\ Increase_{T,M} + \gamma_6\,|Forecast\ \Delta|_{T,M} + \\ & + \gamma_7 Post\ FD_{T,M} + \varepsilon_T \end{aligned} \tag{6}$$

where: *#Analysts* is the number of analysts in the consensus forecast of EPS in year T made in month M; *STD* is the standard deviation of analysts' forecasts for year T earnings as measured in month M; *BTM* is the book-to-market ratio (from *Compustat*) measured at the end of year T-1; *Sales* (from *Compustat*) is measured at the end of year T-1; *Forecast Increase* is an indicator variable set equal to one if analysts forecast a positive change in EPS and to zero otherwise; $|Forecast\Delta|$ is the absolute value of the forecasted change in EPS (i.e., $|Forecasted\ EPS_T - EPS_{T-1}|$) implied by the analysts' forecast of year T earnings as measured in month M; and *Post FD* is an indicator variable set equal to one if the forecast is issued after passage of Regulation Fair Disclosure in October 2000, and zero otherwise. We include this control for the pre- versus post-Regulation Fair Disclosure (Reg FD) environment based on evidence in prior research that after passage of Reg FD, analysts invest more time gathering information about the firms they cover and that their forecasts are less biased (see, e.g., Mohanram and Sunder (2006) and Drake and Myers (2009)).

In table 12, we present the estimation results for equation (6) for each of the 36 forecast horizons. We find that the book-to-market ratio, sales revenue (size), the forecasted increase in EPS indicator variable, the absolute value of the analysts' forecasted change in EPS, and the *Post FD* indicator variable are all significantly related to the level of analysts' superiority over almost every forecast horizon. In addition, the number of analysts' estimates and the standard deviation of the estimates are significantly related to the level of analysts' superiority in the majority of the forecast horizons. Although several factors (such as the number of analysts and sales) are correlated with one another, each is significantly related to analysts' superiority over the vast majority of horizons. In addition, the most consistent and strongest relation is that the forecasted increase in EPS indicator variable is highly significant at every horizon. For forecasts that are in the same fiscal year as the earnings being forecasted (i.e., FY1 forecasts), the coefficient on the forecasted increase indicator variable is consistently negative, revealing that analysts' forecasts of decreasing EPS are more accurate than random walk forecasts across all forecast horizons. This is true even after controlling for the number of forecasts, variance in those forecasts, size, book-to-market, the absolute forecasted change in EPS, and whether the forecast is made post Reg FD. We also find that the coefficient on the post Reg FD indicator variable is positive and significant in all but 4 of the 36 horizons, suggesting that the regulation has lead to an increase in the accuracy of analysts' forecasts.

5 Conclusion

In this paper, we show that the widely held belief that analysts' forecasts of annual earnings are superior to time-series forecasts is not fully descriptive. Although analysts' earnings forecasts consistently beat random walk earnings forecasts over short windows, for longer forecast horizons, analysts' superiority declines, and at certain horizons, analysts' forecasts are dominated by random walk forecasts. This is especially true for small firms, young firms, thinly followed firms, and when analysts forecast positive or more extreme changes in earnings. We link this finding to stock returns, and show that the market seems to rely on random walk forecasts (or similar simple models of earnings) at longer horizons, but tends towards analysts' forecasts as the forecast horizon becomes shorter.

While our results are not inconsistent with prior literature that concludes that analysts' forecasts are superior to forecasts from time-series models in a general sense, we find that over longer horizons, analysts' forecasts lose their relative superiority to time-series forecasts. In fact, we show that even a simple random walk forecast performs as well, in both an economic and statistical sense, relative to analysts' forecasts. This is important because analysts' forecasts are not available for a large number of firms. Our findings suggest that investors can reasonably rely on random walk forecasts when implementing long-term buy-and-hold valuation strategies, and similarly, researchers interested in phenomena that require longer-term earnings expectations can work with larger samples than those comprised of firms with long-term analysts' forecasts. In addition, because our results suggest that the use of a simple random walk model to form forecasts in securities analysis is feasible, we suggest that declining analyst coverage alleged to have resulted from increased regulation in the securities industry (Mohanram and Sunder 2006) may be less detrimental than some assume.

It is important to note that our results do not refute the results of studies that use analysts' forecasts to proxy for market expectations. Moreover, our finding that random walk forecasts are more accurate than analysts' forecasts over long horizons does not imply that random walk forecasts would improve prediction models of firm value, the cost of capital, or stock returns. We leave these issues for future research.

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Table 1 Prior Literature

Paper	Sample and Time Period	Time-Series (TS) Models and Data Requirements	Outliers	Forecast Horizon	Difference in Forecast Accuracy	Analysts' Superiority Determinants
Brown and Rozeff (1978)	50 firms from 1972 through 1975.	Three TS models using quarterly data, requiring complete data for 20 years.	Winsorized forecast errors at 1.0	One to five quarters ahead.	Median difference in forecast errors between all univariate forecasts and the analysts' forecast is significantly greater than zero.	
Collins and Hopwood (1980)	50 firms from 1951 through 1974.	Four TS models, requiring a minimum of 76 quarters of data.	Winsorized forecast errors at 3.0	One to four quarters ahead.	Four quarters out, analysts' forecast errors are 31.7% compared to the best TS error of 32.9%. One quarter out, mean analysts' forecast error are 9.7% compared to the best TS error of 10.9%.	
Fried and Givoly (1982)	424 firms from 1969 through 1979.	Modified submartingale models, requiring a minimum of 10 years of past data.	Winsorized forecast errors at 1.0	8 months prior to the fiscal end.	Analysts' forecast errors are 16.4% of realized EPS compared to 19.3% for the best TS model.	
Hopwood and McKeown (1982)	258 firms from 1974 through 1978.	Random walk and 7 other TS models, requiring at least 12 years (48 quarters) of data.		One to four quarters ahead.	Four quarters out (annual), absolute analysts' forecasts errors are 22.5% compared to absolute forecast errors of 26.1% for random walk.	Number of days separating TS and analysts' forecast – positive
Brown, Hagerman, Griffin, and Zmijewski (1987)	233 firms from the 1975 through 1980.	3 TS models, requiring a minimum of 60 quarters of data.	Winsorized forecast errors at 1.0	One, two, and three quarters ahead.	Three-quarters-ahead, analysts' forecast errors are 28.7% and TS forecast errors are 33%.	Forecast horizon – negative
Brown, Richardson, and Schwager (1987)	Sample 1: 168 firms from Q1-1977 through Q4-1979.	Quarterly random-walk model.		One, two, and three quarters ahead.	For the one month horizon, the log of the squared ratio of TS to analysts' forecast errors is 0.56.	Firm size – positive; Prior analysts' forecast dispersion – negative

Brown, Richardson, and Schwager (1987)	Sample 2: 168 firms from 1977 through 1979.	Annual random-walk model.		Horizons of 1, 6, and 18 months prior to the fiscal year-end date.	For the one month horizon, the log of the squared ratio of TS to analysts' forecast errors is 1.08.	Firm size – positive; Prior analysts' forecast dispersion – negative
Brown, Richardson, and Schwager (1987)	Sample 3: 702 firms from 1977 through 1982.	Annual random-walk model.		Horizons of 1, 6, and 18 months prior to the fiscal year-end date.	Log of the squared ratio of TS to analysts' forecast errors is 1.01 for the one month horizon.	Firm size – positive; Prior analysts' forecast dispersion – negative
O'Brien (1988)	184 firms from 1975 through 1982.	Two TS models, requiring 30 consecutive quarters of data.	Deleted absolute forecast errors larger than $10	Horizons of 5, 60, 120, 180, and 240 trading days prior to the earnings announcement date.	At 240 trading days (one year), analysts' forecast errors are $0.74 compared to TS forecast errors of $0.96.	Forecast horizon – positive
Kross, Ro, and Schroeder (1990)	279 firms from 1980 through 1981.	Box-Jenkins model, requiring 28 quarters of data.		Last available one-quarter-ahead forecast.	Natural log of 1 + absolute TS error - absolute analysts' error is positive across all industries (ranging from (0.043 to 0.385)).	Earnings variability – positive; *Wall Street Journal* coverage – positive; # of days separating TS and analysts' forecasts – positive
Lys and Soo (1995)	62 firms from 1980 through 1986.	Box-Jenkins model, requiring 20 years of data.	Removed one firm	Up to 8 quarters ahead.	Across all horizons, the mean (median) absolute analysts' forecast error is 4.4% (2.8%) and the mean (median) absolute TS error is 26.8% (1.4%).	Forecast horizon – negative
Branson, Lorek, and Pagach (1995)	223 firms from 1988 through 1989.	ARIMA model, requiring 11 years of complete data.		One quarter ahead.	The median absolute percentage forecast error (Actual - predicted)/actual)) from TS minus analysts' forecasts is 7.22%.	Conditional on the firm being small: earnings variability – positive; firm size – negative

Table 2 Descriptive Statistics

Panel A: Firm Characteristics

	Mean	Median	Q1	Q3
Sales	2,921	410	125	1,504
BTM	0.5823	0.4985	0.3124	0.7391
Age	8.9340	7	3	13
# Analysts	7.5832	5	2	10

The sample consists of all firms with data available 11 months prior to the earnings announcement date. Sales are in $ millions. Book-to-Market (BTM) and Sales are measured as of the end of the base year. Age is measured as the number of prior years for which *I/B/E/S* has recorded annual EPS for the firm. # Analysts is the number of analysts following measured as NUMEST for the statistical period 11 months prior to the report date of annual earnings.

Panel B: Percent of Forecast Errors Greater than the Absolute Value of Reported Earnings

Months Prior to the Earnings Announcement Date	Analysts' Forecasts Errors	Random Walk Errors
Mature firms:		
1 Month	4.9%	16.4%
All firms:		
1 Month	6.4%	16.4%
11 Months	16.5%	19.5%
23 Months	28.8%	23.9%
35 Months	31.9%	25.6%

Panel percentages represent the proportion of forecast errors that exceed 100 percent of realized earnings. In the first row, the sample is restricted to mature firms with at least 10 prior years of annual EPS reported on *I/B/E/S*.

Panel C: Signed Forecast Errors

	Mean	Median	Q1	Q3
Signed Random Walk Errors				
11 Months	0.0020	-0.0052	-0.0156	0.0131
23 Months	-0.0050	-0.0082	-0.0260	0.0180
35 Months	-0.0013	-0.0108	-0.0357	0.0204
Signed Analysts' Forecasts Errors				
11 Months	0.0214	0.0030	-0.0043	0.0224
23 Months	0.0308	0.0104	-0.0044	0.0422
35 Months	0.0359	0.0173	-0.0041	0.0553

Forecast errors are measured as the difference between forecasted and actual earnings scaled by price 11, 23 or 35 months prior to the earnings announcement.

Table 3 Main Results Analysts' Forecast Superiority, Full Sample

Panel A: Based on Annual Updates of Random Walk

FY1			FY2			FY3		
Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority
0	36,688	0.0282	12	33,822	0.0134	24	25,418	0.0066
1	73,618	0.0267	13	63,869	0.0118	25	48,196	0.0050
2	73,791	0.0255	14	65,413	0.0105	26	49,347	0.0040
3	73,853	0.0237	15	65,660	0.0089	27	49,452	0.0031
4	73,953	0.0201	16	65,415	0.0066	28	49,293	0.0018
5	74,006	0.0172	17	65,059	0.0050	29	49,167	0.0007
6	74,030	0.0147	18	64,362	0.0038	30	48,769	(0.0000) [NS]
7	73,935	0.0117	19	63,185	0.0023	31	48,083	(0.0012)
8	73,759	0.0095	20	61,837	0.0013	32	47,301	(0.0019)
9	73,505	0.0076	21	59,738	0.0003	33	46,096	(0.0026)
10	72,630	0.0051	22	56,207	(0.0007)	34	43,869	(0.0035)
11	70,875	0.0035	23	51,163	(0.0014)	35	40,363	(0.0041)

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Panel B: Based on Quarterly Updates of Random Walk

FY1			FY2			FY3		
Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority
0	28,332	0.0062	12	25,715	0.0060	24	19,763	0.0012
1	58,314	0.0061	13	51,185	0.0048	25	39,156	(0.0001)
2	58,425	0.0054	14	52,235	0.0035	26	40,141	(0.0013)
3	55,886	0.0058	15	49,960	0.0028	27	38,484	(0.0021)
4	56,006	0.0073	16	49,820	0.0022	28	38,666	(0.0018) NS
5	57,093	0.0066	17	50,588	0.0014	29	39,459	(0.0019) NS
6	54,560	0.0062	18	47,991	0.0009	30	37,520	(0.0022) NS
7	54,628	0.0068	19	47,387	0.0008	31	37,237	(0.0018)
8	55,815	0.0059	20	47,732	0.0003	32	37,852	(0.0016)
9	53,366	0.0053	21	44,733	(0.0001) NS	33	35,630	(0.0004)
10	52,741	0.0054	22	42,586	0.0001 NS	34	34,384	(0.0008)
11	52,754	0.0046	23	40,529	(0.0003)	35	33,059	(0.0026)

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. NS Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Panel C: Based on Explicit FY3 Forecasts

FY1			FY2			FY3		
Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority
0	36,688	0.0282	12	33,822	0.0134	24	17,038	0.0054
1	73,618	0.0267	13	63,869	0.0118	25	28,659	0.0038
2	73,791	0.0255	14	65,413	0.0105	26	25,958	0.0026
3	73,853	0.0237	15	65,660	0.0089	27	22,901	0.0016
4	73,953	0.0201	16	65,415	0.0066	28	19,800	0.0005[NS]
5	74,006	0.0172	17	65,059	0.0050	29	17,938	(0.0000)[NS]
6	74,030	0.0147	18	64,362	0.0038	30	16,441	(0.0003)[NS]
7	73,935	0.0117	19	63,185	0.0023	31	14,842	(0.0008)
8	73,759	0.0095	20	61,837	0.0013	32	13,831	(0.0008)
9	73,505	0.0076	21	59,738	0.0003	33	12,917	(0.0011)
10	72,630	0.0051	22	56,207	(0.0007)	34	11,496	(0.0016)
11	70,875	0.0035	23	51,163	(0.0014)	35	10,295	(0.0020)

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 4 Analysts' Forecast Superiority and Firm Age

Panel A: FY1 – 11 Months Prior to RDQE

Firm Age	Firm-years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	6,175	0.0018	0.0426	0.0409
2	5,862	0.0015	0.0453	0.0438
3	4,983	0.0014	0.0491	0.0477
4	4,263	0.0031	0.0488	0.0458
5+	49,592	0.0041	0.0347	0.0305

Panel B: FY2 – 23 Months Prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	3,914	(0.0056)	0.0539	0.0596
2	3,756	(0.0065)	0.0590	0.0656
3	3,214	(0.0068)	0.0577	0.0645
4	2,802	(0.0049)	0.0541	0.0590
5+	37,477	0.0003	0.0427	0.0424

Panel C: FY3 – 35 Months Prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	2,338	(0.0116)	0.0671	0.0756
2	2,387	(0.0126)	0.0652	0.0746
3	2,081	(0.0094)	0.0619	0.0694
4	1,891	(0.0084)	0.0642	0.0697
5+	28,330	(0.0012)	0.0498	0.0491

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 5 Analysts' Forecast Superiority for Small Firms

Panel A: Small Firms

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	7,352	0.0301	12	6,283	0.0104	24	3,527	0.0026
1	14,882	0.0290	13	12,176	0.0091	25	7,158	(0.0002) NS
2	14,909	0.0276	14	12,490	0.0079	26	7,378	(0.0015)
3	14,914	0.0251	15	12,444	0.0061	27	7,383	(0.0024) NS
4	14,974	0.0213	16	12,305	0.0037	28	7,321	(0.0038)
5	14,997	0.0182	17	12,127	0.0019	29	7,273	(0.0048)
6	15,003	0.0153	18	11,852	0.0005 NS	30	7,121	(0.0059)
7	15,010	0.0120	19	11,473	(0.0009)	31	6,928	(0.0071)
8	14,991	0.0094	20	11,022	(0.0019)	32	6,683	(0.0077)
9	14,971	0.0070	21	10,462	(0.0030)	33	6,383	(0.0085)
10	14,758	0.0043	22	9,398	(0.0039)	34	5,818	(0.0096)
11	14,376	0.0022	23	8,161	(0.0047)	35	5,150	(0.0105)

Panel B: Low Analyst Following

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	9,949	0.0377	12	8,908	0.0130	24	9,743	0.0059
1	19,810	0.0365	13	16,062	0.0118	25	18,072	0.0037
2	19,863	0.0343	14	16,883	0.0099	26	18,780	0.0025
3	19,896	0.0309	15	17,358	0.0083	27	18,915	0.0012
4	19,966	0.0257	16	17,749	0.0056	28	18,849	(0.0004) NS
5	20,016	0.0212	17	18,153	0.0038	29	18,795	(0.0019)
6	20,099	0.0172	18	18,546	0.0020	30	18,549	(0.0025)
7	20,215	0.0130	19	19,060	0.0000 NS	31	17,996	(0.0041)
8	20,168	0.0097	20	19,515	(0.0012)	32	17,413	(0.0051)
9	20,144	0.0071	21	20,173	(0.0025)	33	16,399	(0.0060)
10	19,755	0.0037	22	21,079	(0.0036)	34	14,886	(0.0073)
11	19,030	0.0012	23	21,483	(0.0042)	35	12,764	(0.0082)

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 6 Analysts' Forecast Superiority Observations Partitioned by Positive and Negative Forecasted Change in EPS

Panel A: Positive Forecasted Changes in EPS

FY1			FY2			FY3		
Months Prior	Firm-years	Analysta' Superiority	Months Prior	Firm-Years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	22,706	0.0115	12	26,015	0.0059	24	25,314	0.0062
1	46,516	0.0113	13	50,326	0.0049	25	48,012	0.0046
2	47,310	0.0107	14	52,229	0.0039	26	49,171	0.0036
3	48,343	0.0098	15	53,645	0.0029	27	49,310	0.0028
4	49,986	0.0083	16	54,891	0.0016	28	49,181	0.0016
5	51,569	0.0070	17	55,685	0.0008	29	49,066	0.0005 NS
6	53,028	0.0058	18	55,951	0.0002 NS	30	48,689	(0.0002)
7	54,927	0.0044	19	56,044	(0.0007)	31	48,007	(0.0013)
8	56,506	0.0035	20	55,513	(0.0012)	32	47,234	(0.0020)
9	57,816	0.0024	21	54,164	(0.0017)	33	46,042	(0.0026)
10	59,104	0.0010	22	51,572	(0.0025)	34	43,813	(0.0036)
11	59,086	(0.0000) NS	23	47,260	(0.0029)	35	40,322	(0.0042)

Panel B: Negative Forecasted Changes in EPS

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	13,982	0.0553	12	7,807	0.0382	24	104	0.0852
1	27,102	0.0531	13	13,543	0.0373	25	184	0.1048
2	26,481	0.0521	14	13,184	0.0364	26	176	0.1083
3	25,510	0.0500	15	12,015	0.0361	27	142	0.1002
4	23,967	0.0449	16	10,524	0.0328	28	112	0.0915
5	22,437	0.0405	17	9,374	0.0298	29	101	0.0849
6	21,002	0.0370	18	8,411	0.0278	30	80	0.0603
7	19,008	0.0330	19	7,141	0.0251	31	76	0.0600
8	17,253	0.0293	20	6,324	0.0227	32	67	0.0514
9	15,689	0.0267	21	5,574	0.0203	33	54	0.0492
10	13,526	0.0234	22	4,635	0.0196	34	56	0.0688
11	11,789	0.0209	23	3,903	0.0168	35	41	0.1060

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. NS Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 7 Analysts' Forecast Superiority Observations Partitioned by the Magnitude of the Forecasted Change in EPS

Panel A: The 33% of Forecasts with the Least Extreme Forecasted Change in EPS

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	11,355	0.0044	12	12,195	0.0039	24	9,674	0.0025
1	23,178	0.0044	13	22,983	0.0038	25	17,997	0.0023
2	23,433	0.0043	14	23,360	0.0036	26	18,096	0.0017
3	23,851	0.0040	15	23,220	0.0032	27	17,798	0.0013
4	24,359	0.0035	16	22,701	0.0030	28	17,103	0.0009
5	24,512	0.0031	17	22,080	0.0028	29	16,628	0.0011
6	24,915	0.0028	18	21,526	0.0028	30	16,114	0.0015
7	25,348	0.0024	19	20,586	0.0027	31	15,386	0.0018
8	25,358	0.0021	20	19,591	0.0027	32	14,704	0.0016
9	25,588	0.0019	21	18,521	0.0027	33	13,975	0.0023
10	25,396	0.0017	22	16,872	0.0027	34	12,854	0.0024
11	24,480	0.0015	23	14,874	0.0027	35	11,443	0.0021

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	14,178	0.0593	12	11,127	0.0275	24	7,794	0.0066
1	27,629	0.0570	13	20,632	0.0237	25	14,711	0.0041
2	27,293	0.0549	14	21,304	0.0207	26	15,300	0.0022
3	26,628	0.0519	15	21,289	0.0172	27	15,513	0.0006 NS
4	25,784	0.0450	16	21,303	0.0119	28	15,792	(0.0016)
5	25,356	0.0385	17	21,499	0.0082	29	16,128	(0.0022)
6	24,567	0.0334	18	21,328	0.0055	30	16,243	(0.0033)
7	23,438	0.0273	19	21,122	0.0020	31	16,430	(0.0043)
8	22,900	0.0221	20	20,974	(0.0002) NS	32	16,507	(0.0042)
9	22,104	0.0177	21	20,413	(0.0024)	33	16,390	(0.0048)
10	21,216	0.0117	22	19,453	(0.0046)	34	15,886	(0.0066)
11	20,745	0.0074	23	18,141	(0.0061)	35	15,094	(0.0069)

Observations are partitioned into thirds based on the analysts' forecasted change in EPS as a percentage of price. The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 8 Market Expectations Random Walk Forecast Error versus Analysts' Forecast Error and Market Returns

Panel A: Based on Annual Updates of Random Walk

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

FY1			FY2			FY3		
Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b
0	34,601	0.471	12	32,710	0.437	24	24,848	0.841
1	69,470	0.426	13	62,350	0.587	25	47,490	0.867
2	70,881	0.414	14	63,729	0.651	26	48,554	0.885
3	71,313	0.454	15	63,867	0.734	27	48,585	0.916
4	71,428	0.580	16	63,566	0.829	28	48,413	0.932
5	71,515	0.640	17	63,203	0.874	29	48,302	0.956
6	71,596	0.644	18	62,531	0.909	30	47,915	0.987 NS
7	71,574	0.651	19	61,460	0.935	31	47,262	$\boxed{1.031}$ NS
8	71,485	0.702	20	60,223	0.959	32	46,534	$\boxed{1.049}$
9	71,347	0.738	21	58,282	0.995 NS	33	45,401	$\boxed{1.068}$
10	70,721	0.730	22	54,919	$\boxed{1.014}$ NS	34	43,240	$\boxed{1.085}$
11	69,243	0.717	23	50,114	$\boxed{1.030}$	35	39,842	$\boxed{1.102}$

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. NS indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Panel B: Based on Quarterly Updates of Random Walk

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

FY1				FY2				FY3			
Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	27,344	0.948	NS	12	25,052	0.995	NS	24	19,667	0.961	NS
1	56,436	0.815		13	50,170	0.987	NS	25	39,011	0.984	NS
2	57,647	0.796		14	51,194	0.956	NS	26	39,983	0.987	NS
3	55,432	0.792		15	48,927	0.949		27	38,307	0.997	NS
4	55,544	0.735		16	48,817	0.911		28	38,446	0.998	NS
5	56,645	0.732		17	49,591	0.919		29	39,277	0.995	NS
6	54,086	0.680		18	47,022	0.932		30	37,318	1.004	NS
7	54,153	0.656		19	46,432	0.953		31	36,996	1.034	
8	55,321	0.710		20	46,839	0.976	NS	32	37,605	1.040	
9	52,924	0.727		21	43,910	0.993	NS	33	35,437	1.050	
10	52,370	0.626		22	41,911	1.002	NS	34	34,230	1.058	
11	52,361	0.589		23	39,915	1.007	NS	35	32,889	1.067	

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. ^{NS} indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 9 Market Expectations Subsamples Random Walk Forecast Error versus Analysts' Forecast Error and Market Returns

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

Panel A: Small Firms

FY1				FY2				FY3			
Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	7,099	0.440		12	6,263	0.629		24	3,522	0.894	
1	14,435	0.360		13	12,141	0.698		25	7,152	0.919	
2	14,695	0.508		14	12,452	0.745		26	7,372	0.953	NS
3	14,847	0.591		15	12,405	0.793		27	7,376	0.967	NS
4	14,906	0.587		16	12,266	0.841		28	7,314	0.979	NS
5	14,927	0.631		17	12,090	0.889		29	7,266	0.988	NS
6	14,934	0.628		18	11,815	0.941		30	7,114	1.009	NS
7	14,944	0.659		19	11,439	0.963	NS	31	6,921	1.071	NS
8	14,923	0.743		20	10,993	0.974	NS	32	6,675	1.086	
9	14,904	0.785		21	10,435	1.023	NS	33	6,376	1.096	
10	14,695	0.815	NS	22	9,373	1.015	NS	34	5,812	1.126	
11	14,323	0.826	NS	23	8,139	1.049	NS	35	5,144	1.137	

Panel B: Low Analyst Following

FY1				FY2				FY3			
Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	8,969	0.562		12	8,190	0.696		24	9,239	0.871	
1	17,936	0.557		13	15,134	0.721		25	17,456	0.888	
2	18,217	0.545		14	15,859	0.760		26	18,086	0.919	
3	18,369	0.631		15	16,277	0.796		27	18,156	0.946	
4	18,462	0.729		16	16,621	0.879		28	18,067	0.959	
5	18,532	0.767		17	16,991	0.897		29	18,034	0.978	
6	18,650	0.720		18	17,396	0.931	NS	30	17,791	1.001	NS
7	18,788	0.757		19	17,966	0.935	NS	31	17,268	1.042	NS
8	18,809	0.822		20	18,478	0.961	NS	32	16,738	1.062	NS
9	18,873	0.851		21	19,209	0.999	NS	33	15,794	1.076	
10	18,653	0.901	NS	22	20,214	1.013	NS	34	14,349	1.091	
11	18,123	0.908	NS	23	20,774	1.033	NS	35	12,323	1.113	

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. ^{NS} indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 10 Market Expectations Subsamples Observations Partitioned by Positive and Negative Forecasted Change in EPS

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

Panel A: Analysts' Forecasts of Increasing EPS

FY1				FY2			FY3		
Months Prior	Firm-Years	β/b		Months Prior	Firm-Years	β/b	Months Prior	Firm-years	β/b
0	21,676	0.959	NS	12	25,186	$\boxed{1.232}$	24	21,607	$\boxed{1.129}$
1	44,354	0.906	NS	13	49,177	$\boxed{1.178}$	25	41,861	$\boxed{1.117}$
2	45,611	$\boxed{1.034}$	NS	14	50,958	$\boxed{1.151}$	26	43,129	$\boxed{1.114}$
3	46,747	0.964	NS	15	52,275	$\boxed{1.158}$	27	43,671	$\boxed{1.114}$
4	48,353	0.961	NS	16	53,470	$\boxed{1.146}$	28	44,215	$\boxed{1.107}$
5	49,930	$\boxed{1.024}$	NS	17	54,238	$\boxed{1.133}$	29	44,576	$\boxed{1.106}$
6	51,402	$\boxed{1.064}$	NS	18	54,516	$\boxed{1.133}$	30	44,663	$\boxed{1.112}$
7	53,308	$\boxed{1.075}$		19	54,667	$\boxed{1.117}$	31	44,566	$\boxed{1.127}$
8	54,921	$\boxed{1.088}$		20	54,212	$\boxed{1.112}$	32	44,141	$\boxed{1.128}$
9	56,301	$\boxed{1.113}$		21	52,964	$\boxed{1.121}$	33	43,277	$\boxed{1.135}$
10	57,728	$\boxed{1.154}$		22	50,510	$\boxed{1.136}$	34	41,448	$\boxed{1.152}$
11	57,891	$\boxed{1.170}$		23	46,378	$\boxed{1.143}$	35	38,310	$\boxed{1.160}$

Panel B: Analysts' Forecasts of Decreasing EPS

FY1			FY2			FY3		
Months Prior	Firm-Years	β/b	Months Prior	Firm-Years	β/b	Months Prior	Firm-years	β/b
0	12,923	0.477	12	7,522	0.177	24	3,239	0.636
1	25,114	0.395	13	13,171	0.368	25	5,627	0.686
2	25,268	0.373	14	12,769	0.448	26	5,423	0.713
3	24,564	0.417	15	11,590	0.540	27	4,912	0.756
4	23,073	0.529	16	10,094	0.677	28	4,196	0.748
5	21,583	0.584	17	8,963	0.726	29	3,724	0.753
6	20,192	0.552	18	8,013	0.755	30	3,250	0.810
7	18,264	0.523	19	6,791	0.785	31	2,694	0.853
8	16,562	0.541	20	6,009	0.813	32	2,391	0.866
9	15,044	0.546	21	5,316	0.840	33	2,122	0.885
10	12,991	0.450	22	4,407	0.831	34	1,790	0.857
11	11,350	0.337	23	3,734	0.840	35	1,530	0.872

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. ^{NS} indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 11 Market Expectations Subsamples Observations Partitioned by the Magnitude of the Forecasted Change in EPS

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

Panel A: The 33% of Forecasts with the Least Extreme Forecasted Change in EPS

FY1				FY2				FY3			
Months Prior	Firm-Years	*β/b*		Months Prior	Firm-Years	*β/b*		Months Prior	Firm-years	*β/b*	
0	11,398	0.945	NS	12	12,553	0.967	NS	24	10,350	0.961	NS
1	22,489	0.952	NS	13	23,006	0.971	NS	25	18,658	0.969	NS
2	22,944	0.960	NS	14	22,810	0.971	NS	26	18,285	0.967	NS
3	23,211	0.967	NS	15	22,218	0.975	NS	27	17,500	0.970	NS
4	23,571	0.995	NS	16	21,522	0.977	NS	28	16,659	0.973	NS
5	23,804	0.989	NS	17	21,082	0.981	NS	29	16,189	0.975	NS
6	24,157	0.987	NS	18	20,548	0.986	NS	30	15,533	0.978	NS
7	24,524	0.989	NS	19	19,623	0.984	NS	31	14,672	0.978	NS
8	24,334	0.986	NS	20	18,719	0.984	NS	32	13,858	0.982	NS
9	24,264	0.985	NS	21	17,712	0.984	NS	33	13,023	0.984	NS
10	23,747	0.979	NS	22	16,178	0.985	NS	34	11,982	0.991	NS
11	22,880	0.981	NS	23	14,539	0.986	NS	35	10,689	0.990	NS

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1				FY2				FY3			
Months Prior	Firm-Years	*β/b*		Months Prior	Firm-years	*β/b*		Months Prior	Firm-years	*β/b*	
0	12,988	0.475		12	10,651	0.296		24	6,983	0.729	
1	26,091	0.428		13	20,446	0.470		25	13,955	0.764	
2	26,280	0.414		14	21,302	0.546		26	14,806	0.791	
3	26,011	0.454		15	21,406	0.642		27	15,283	0.837	
4	25,071	0.573		16	21,287	0.758		28	15,696	0.854	
5	24,272	0.628		17	21,009	0.804		29	15,950	0.884	
6	23,395	0.615		18	20,751	0.842		30	16,160	0.929	
7	22,294	0.595		19	20,323	0.871		31	16,364	0.989	NS
8	21,723	0.640		20	20,011	0.898		32	16,389	$\boxed{1.010}$	NS
9	21,079	0.668		21	19,399	0.943		33	16,316	$\boxed{1.029}$	NS
10	20,607	0.626		22	18,472	0.962	NS	34	16,066	$\boxed{1.044}$	
11	20,210	0.580		23	16,945	0.980	NS	35	15,035	$\boxed{1.063}$	

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. ^{NS} indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 12 Multivariate Regression of Analysts' Superiority by Months Prior to Earnings Announcement Date

$$Analysts'Superiority_{T,M} = \gamma_0 + \gamma_1\,\#Analysts_T + \gamma_2\,STD_{T,M} + \gamma_3\,BTM_{T-1} + \gamma_4\,Sales_{\,T-1} + \gamma_5\,Forecast\ Increase_{T,M} + \gamma_6\,|Forecast\ \Delta|_{T,M} + \gamma_7 Post\ FD_{T,M} + \varepsilon_T$$

	γ_0	*#Analysts*	*STD*	*BTM*	*Sales*	*Forecast Increase*	*|Forecast Δ|*	*Post FD*
0	0.025	-0.004	0.004	0.009	-0.007	-0.031	0.023	0.003
1	0.024	-0.004	0.002	0.008	-0.006	-0.029	0.022	0.003
2	0.024	-0.003	0.001	0.008	-0.005	-0.029	0.021	0.003
3	0.023	-0.003	0.000 [NS]	0.007	-0.005	-0.029	0.021	0.004
4	0.023	-0.002	-0.001	0.006	-0.004	-0.028	0.019	0.003
5	0.022	-0.002	-0.001	0.005	-0.004	-0.026	0.017	0.002
6	0.021	-0.001	-0.002	0.005	-0.004	-0.025	0.015	0.002
7	0.019	0.000 [NS]	-0.003	0.004	-0.003	-0.024	0.013	0.003
8	0.018	0.000 [NS]	-0.003	0.004	-0.003	-0.022	0.011	0.003
9	0.017	0.001	-0.003	0.003	-0.002	-0.021	0.009	0.003
10	0.016	0.001	-0.003	0.002	-0.001	-0.02	0.007	0.003
11	0.015	0.001	-0.003	0.001	0.000 [NS]	-0.018	0.005	0.003
12	0.027	0.000 [NS]	-0.004	0.003	0.000 [NS]	-0.032	0.013	0.001 [NS]
13	0.026	0.000 [NS]	-0.004	0.003	0.001 [NS]	-0.032	0.012	0.001
14	0.026	0.000 [NS]	-0.005	0.004	0.001	-0.032	0.011	0.001
15	0.028	0.000 [NS]	-0.005	0.003	0.002	-0.033	0.01	0.002
16	0.026	0.001	-0.005	0.002	0.002	-0.031	0.007	0.001
17	0.022	0.001	-0.005	0.002	0.003	-0.028	0.005	0.001
18	0.02	0.002	-0.005	0.002	0.003	-0.025	0.004	0.002
19	0.017	0.002	-0.004	0.002	0.004	-0.023	0.002	0.002
20	0.016	0.002	-0.004	0.001	0.003	-0.021	0.001	0.002

21	0.014	0.002	-0.004	0.001	0.004	-0.018	0.000 [NS]	0.002
22	0.014	0.002	-0.004	0.000 [NS]	0.005	-0.018	-0.001	0.002
23	0.012	0.002	-0.004	-0.001 [NS]	0.005	-0.015	-0.001	0.001
24	0.029	0.000 [NS]	0.000 [NS]	0.001	0.002	-0.03	0.006	-0.001
25	0.028	0.000 [NS]	0.000 [NS]	0.002	0.002	-0.029	0.005	-0.001
26	0.029	0.000 [NS]	0.000 [NS]	0.002	0.002	-0.03	0.005	0.000 [NS]
27	0.028	0.001	0.000 [NS]	0.002	0.002	-0.03	0.004	0.001
28	0.029	0.002	0.000 [NS]	0.001	0.002	-0.031	0.002	0.001
29	0.026	0.002	0.000 [NS]	0.001	0.002	-0.029	0.001	0.002
30	0.024	0.002	0.000 [NS]	0.001 [NS]	0.003	-0.027	0.000 [NS]	0.002
31	0.022	0.002	-0.001	0.000 [NS]	0.002	-0.024	-0.001	0.002
32	0.019	0.003	-0.001	0.000 [NS]	0.002	-0.021	-0.002	0.002
33	0.018	0.003	-0.001	-0.001 [NS]	0.002	-0.019	-0.003	0.003
34	0.017	0.003	-0.001	-0.001	0.003	-0.019	-0.004	0.003
35	0.013	0.003	-0.001	-0.002	0.003	-0.014	-0.004	0.003

In this table, we regress analysts' superiority on a number of factors separately for each of the 36 forecast horizons. # Analysts is the number of analysts following measured as NUMEST for the statistical period 11 months prior to the report date of annual earnings. *STD* is the standard deviation of analysts' forecasts for year T earnings as measured in month M. Book-to-Market (BTM) and Sales are measured as of the end of the base year. |*ForecastΔ*| is the absolute value of forecasted change in EPS (i.e., |*Forecasted* $EPS_T - EPS_{T-1}$|) implied by the analysts' forecast of year T earnings as measured in month M. *Post FD* is an indicator variable set equal to one if the forecast is issued after passage of Regulation Fair Disclosure in October 2000, and zero otherwise. [NS] indicates that the coefficient is not significantly different from zero at the 5 percent level, two-sided.

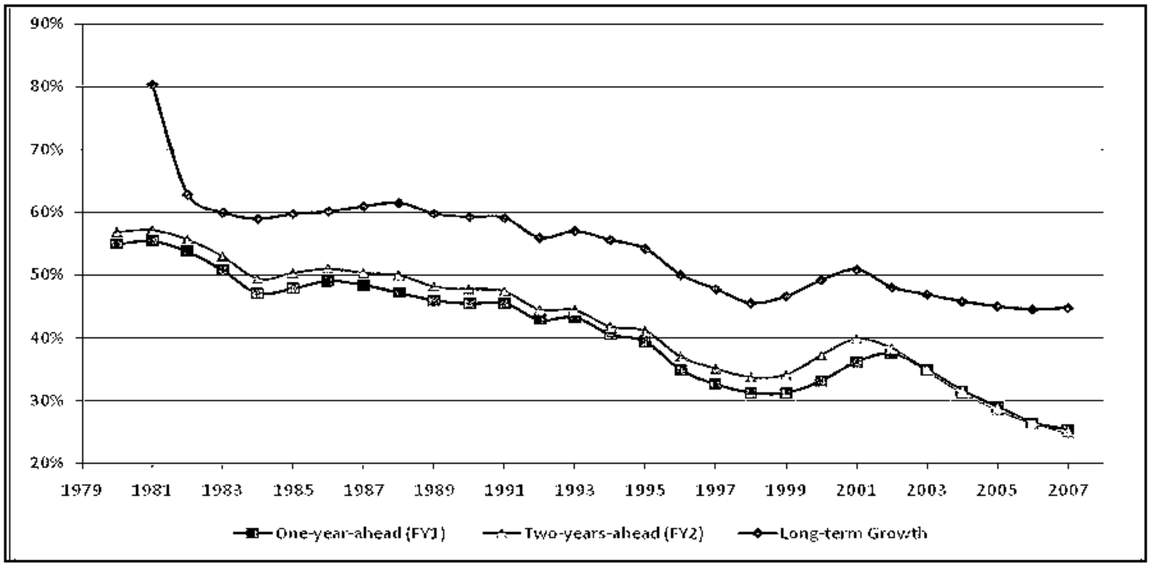

Fig. 1 Percentage of Firms with Available Data in *Compustat* and *CRSP* that are Uncovered in *I/B/E/S*

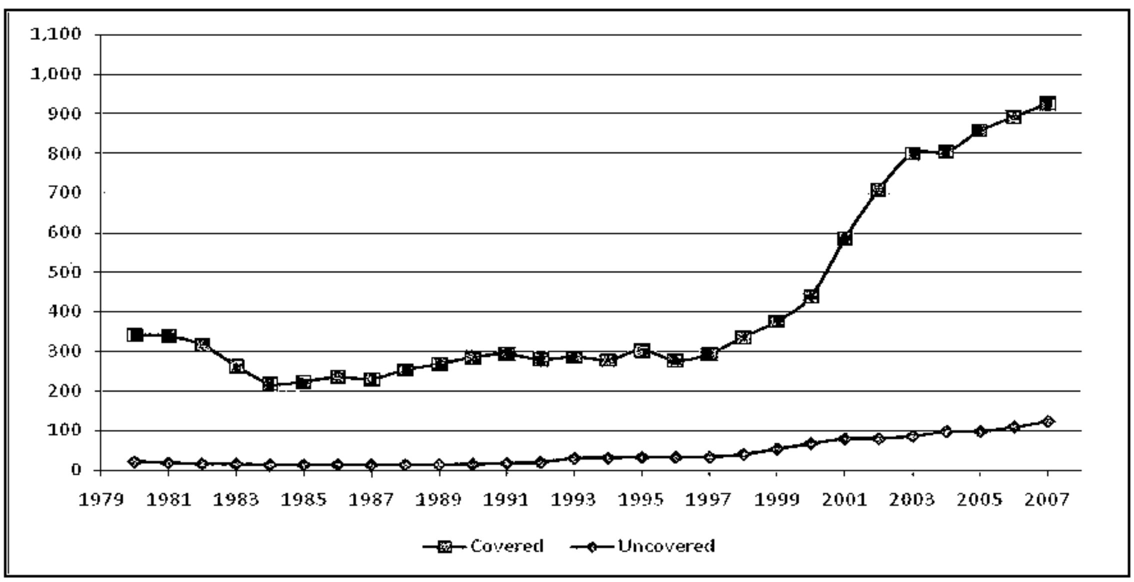

Fig. 2 Median Assets for Firms with and without One-year-ahead Earnings Forecasts in *I/B/E/S*

Analysts' Forecasts:
What Do We Know After Decades of Work?

Mark T. Bradshaw*
Boston College

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SYNOPSIS: Sell-side analysts have been the subject of hundreds of academic studies. In this paper, I offer perspectives on the state of our understanding of analysts based on prior academic research. Additionally, several observations are offered, which question how descriptive certain widely held beliefs are in light of the evidence. These observations on the literature serve as both criticisms and suggestions for future research.

Data Availability: Data used in this paper came from publicly available sources.

* This paper is based on a presentation ("How do analysts forecast earnings, and what do they do with these forecasts?") delivered at a conference sponsored by the Center for Accounting Research and Education at the University of Notre Dame, organized by Peter Easton. I wish to thank Peter for the invitation to address this topic, and also Jim Wahlen and Robert Lipe for encouraging me to transcribe the presentation in this document. Very helpful comments were received from David Weber. All omissions or inaccuracies are my own.

Analysts' Forecasts: What Do We Know After Decades of Work?

INTRODUCTION

Accountants are interested in the production and use of financial information. Consequently, a large number of academic accounting studies are concerned with whether sophisticated users of financial data understand such information and how they process it. Sophisticated users include sell-side analysts, short sellers, institutional investors, regulators, the financial press, and other market participants. However, a seemingly disproportionate amount of research has focused on sell-side analysts. For example, Brown (2000) highlights over 575 studies on expectations research, most of which are devoted to sell-side analysts' earnings forecasts and stock recommendations. Additionally, as of early 2006 there are over 500 papers listed on ssrn.com that have some emphasis placed on analysts, with most of these being posted after 1995.

Clearly, interest in sell-side analysts is great. As a result of this interest, our understanding of their role in the capital markets has grown over the past several decades during which academics have extensively studied sell-side analysts. Our understanding of sell-side analysts' behavior is not only beneficial to academics interested in a working framework that describes capital markets, but is also of interest to practitioners who operate in these markets. Managers of public companies must be able to communicate with analysts, and in particular, need to understand what information they want and how they process and communicate it. Investors with limited abilities or time to analyze individual securities often rely on the work of sell-side analysts, typically through the analysts' reports. Finally, regulators are keenly interested in the flow of information that facilitates functional and liquid markets, and analysts are one contributor to the critical flow of information.

The purpose of this commentary is to survey what we have learned about analysts' role in the capital markets and to comment on the state of our understanding of their analysts' activities. A primary conclusion is that our focus almost exclusively on earnings forecasts now obstructs the growth in our understanding of analysts' role in the capital markets. Whereas the initial reason researchers began examining analysts' earnings forecasts was to gauge their usefulness as a surrogate for time-series forecasts in studies of the efficiency of the capital markets, interest in analysts has grown such that analysts are perceived as an interesting economic agent in their own right, much like the literature that studies CEO's or CFO's. Thus, it is necessary for the literature to expand its focus on other activities performed by analysts and attempt to better model their incentives than has typically been done.

The literature on analysts is vast, and I make no representation to provide a comprehensive review of the literature. To the extent that I do mention specific studies, the citations are necessarily incomplete, so apologies are requested in advance. Second, to the extent that I mention work that I have done, it is done because it is convenient. Finally, many of the critical comments I have to make about the analyst literature are probably applicable to other streams of literature that purport to describe decision processes of capital market participants.

For those seeking comprehensive reviews of the literature, Givoly and Lakonishok (1984) provide a review of the very early literature, and Brown (1993) reviews literature up through the early 1990s. Discussions by P. Brown (1993), O'Hanlon (1993), Thomas (1993), and Zmijewski (1993) of L. Brown's (1993) literature review are each excellent and almost orthogonal to one another in the points they raise. Zmijewski's (1993) discussion is particularly recommended as relevant to the current state of the literature, which will be revisited later in the paper. Kothari (2001) provides a comprehensive review of the broader capital markets literature, which encompasses studies on analysts. Finally, Ramnath, Rock, and Shane (2008) review the literature since 1993 and provide taxonomy of that research.

Finally, Schipper's (1991) commentary that appeared in this journal did not have as its purpose a comprehensive review of the literature, but it is part of the 'required background reading' on sell-side analysts. The tenor of many of my views on the literature are present in her commentary, and many of the observations made by Schipper (1991) are perhaps even more applicable in assessing the current state of our knowledge of analysts' activities than they were in 1991. Indeed, the title of my paper is derived from an observation that surprisingly little research has been produced since her review that capitalizes on several observations made in that commentary.

The rest of the paper proceeds as follows. The next section discusses how research on analysts fits in with other capital markets research. I then briefly summarize the evolution of the current state of knowledge on analysts. Following this summary, ten observations on regularities and widely held beliefs from this literature are discussed. Many of these beliefs are critiqued and challenged, the result being suggestions for further work. The final section concludes.

WHAT IS IT WE SEEK TO UNDERSTAND?

As mentioned above, there are hundreds of studies performed by academics, aimed at understanding various aspects of analysts' activities. After decades of research, and the associated attention on this research by both academics and practitioners, it seems reasonable to articulate what it is we have been attempting to gain from this collective effort. To provide a context for the discussion that follows, it is worthwhile describing the analyst's role within the capital markets. Figure 1a provides a schematic that describes analysts' activities.

The first aspect of figure 1a that is important is that analysts reach some coverage decision. Analysts generally specialize by industry (Dunn and Nathan 2005), but within an industry analysts (or their employers) must decide what particular stocks to cover. For practical purposes, analysts tend to cover firms within an industry that is biased towards larger firms. Next, for any given stock that is covered, the analyst has access to a wide array of information, including security prices, firm-specific financial and operating information, industry data, and macroeconomic factors. Presumably, the value-added activity of the analyst is, not surprisingly, 'analysis.' Analysis encompasses the process through which the analyst considers a company's strategy, accounting policies, historical financial performance, future prospects for sales and earnings growth, and ultimately a valuation and purchase or sell recommendation. Based on the analysis, the analyst presumably draws a conclusion, most succinctly conveyed by a purchase or sell recommendation, but conclusions are likely more complex than a discrete stock recommendation and are conveyed through various communication channels.

The analysts' conclusions are conveyed to clients, investors, company management, and other market participants via *formal* or *informal* channels. Formal channels are the source of most of the data examined by academics, primarily drawn from analysts' formal reports and morning broker notes – archived by data providers such as Value Line and I/B/E/S. Analysts also give formal presentations to major clients and other investor groups. Similarly, they communicate results of their analyses informally through brokerage client communication, press interviews, industry meetings and conferences, and also by coordinating meetings between institutional investors and the firm managers. The end result is that part of the information communicated to the markets can be assessed *ex post* in terms of earnings forecast accuracy, recommendation profitability, and so on. Underlying this entire process are qualitative factors that affect the information gathering, analysis, and communication processes such as the analyst's ability, incentives, integrity, responsiveness to clients, and other such behavioral effects.

A potential problem for academics attempting to use the body of knowledge generated from research on analysts is demonstrated in figure 1b. For the most part, research methods do not really measure the most interesting part of the schematic, which is the analysts' analysis. This is literally a 'black box' in the figure. However, this is only a potential problem. What academics generally do instead of directly observing the analysts' decision process of analysis is to examine correlations between inputs, outputs, and conditioning variables to understand the analysis process.

A general characterization of the literature is as follows. Outputs extensively studied primarily include earnings forecasts and recommendations. A long line of research simply examines distributional properties of these outputs. As for inputs, researchers have primarily focused on prices and financial statement information. Additionally, recent research has begun to examine whether analyst ability and incentives affect the processing of inputs into forecasts and recommendations. The direction of a typical research study is typically two-way, meaning that the researcher measures a correlation between outputs (i.e., earnings forecasts, recommendations) and some other variable such as stock prices. For example, a typical approach is to examine whether forecasts or recommendations affect stock prices, as well as whether information in prices affects forecasts and recommendations. Other relations typically examined by researchers are unidirectional, examining whether inputs such as the information in financial statements is captured in earnings forecasts or recommendations. Similarly, researchers examine whether proxies for analysts' abilities and incentives affect the accuracy of forecasts and profitability of recommendations.

It should not matter that researchers do not directly observe the activities represented by the black box in figure 1b. In this literature, like many others that are archival in method, outputs from some economic setting are observed to infer how agents have behaved. For example, if forecasts made by analysts are observed and errors are measured, this can be informative about how well the analyst forecasted, which may give insight into the process by which the analyst derived the forecast. Indeed, most current studies designed to examine correlations between analysts' inputs and outputs draw conclusions in terms of what information analysts used, how they used this information, and whether the analysts 'fully used' such information. Unfortunately, the literature has evolved to the point where some penetration of the black box is now necessary to push the literature foreword. The latter part of the paper discusses areas where this might be