VITA

**MURUGAPPA KRISHNAN (Murgie)**

Dept of Accounting, Finance and Business Law
College of Business and Economics, Radford University
Radford, VA 24142
(540)831-5668

90 New England Ave, # 6
Summit, NJ 07901-1830
(908) 739-0917 (e-fax)

**E-mail**: **murgie@rutgers.edu**
**SSRN Page: http://ssrn.com/author_id=16801**

## Education:

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| Ph.D. | The Wharton School, University of Pennsylvania, 1987 |
| M.B.A. | Finance/Quantitative Methods<br>IIM-A, India, 1981 |
| B.Com. | Loyola College, University of Madras, India, 1979 |

## Employment:

Assistant Professor, Purdue University, Fall 1987 - 1994
Visiting Assistant Professor, Carnegie-Mellon University, 1992-1993
Associate Professor, University of Minnesota, Summer 1994 - 1998
Associate Professor, Rutgers University, Fall 1998 – 2003.
Visiting Associate Professor, Baruch College, 2003-2006.
Associate Professor, Yeshiva University, 2006-2013
Visiting Associate Professor, Hofstra University, Spring 2014
Professor, William Paterson University, Fall 2014-
Visiting Professor, Rutgers University, 2016-2017
Visiting Professor, Radford University, Fall 2017-

## Teaching Interests and Experience:

Undergraduate - Intermediate financial accounting, introductory financial accounting, cost and managerial accounting, advanced financial accounting.
Introductory finance, international finance (senior elective).
MS, Accounting – Contemporary topics in accounting, financial and managerial accounting (regular, professional master's, online)
MBA - Financial accounting (core course), financial and managerial accounting (core course), intermediate financial accounting. Financial statement analysis. (Regular, professional master's, online).
Executive MBA (international) - Financial accounting (core course), comparative international reporting; energy sector reporting issues.
Ph.D. - Seminar in asset pricing under perfect and imperfect competition, disclosure policy, and intermediation (taken by students in Accounting, Finance and Economics).

## Research Interests:

Disclosure in financial markets; asset pricing with private information and imperfect competition; Indian financial markets; industrial organization; shop-floor productivity.

# **Summary of Teaching Statement**

(This is a summary of a longer teaching statement, plus other testimonials and student ratings, included separately.)

- Experience includes all accounting classes at introductory, intermediate and advanced levels barring auditing and tax. Introductory and international finance. Doctoral level courses in asset pricing and disclosure. I have taught different age groups from college freshmen to mid-career executives; and in different formats – traditional in-class, online, hybrid, executive and professional. Have taught outside the US in Poland and India, besides teaching at a wide variety of schools, and classes varying in size even at the undergrad or master's levels from under ten to over 250.
- In introductory classes my objectives have been to introduce business language, provide adequate practice, show connections to other courses, and to provide multiple ways for a student to demonstrate learning, besides just exams, such as group research into one company.
- In graduate classes I have emphasized more a user than a preparer perspective, both in financial and managerial accounting, to show that numbers can be manipulated often even within the rules, and therefore to understand incentives and opportunities that arise, and to be skeptical.
- In my doctoral classes I have tried to develop the mathematical tools to make students comfortable with important classes of models in the theory of asset pricing with private information, and disclosure to a financial market. And to show that empirical work can be predicated on underlying models of equilibrium.
- Besides numerical student evaluations and student comments, I think it is important to also look at the reports of in-class or other observations (by Susan Ambrose, Carnegie-Mellon; Prof. Glen Berryman, U of Minnesota; and prof. Glenn Hueckel, Purdue University). I consider these important pieces of evidence.
- For MBA classes like in managerial accounting where I've used discussions based on contemporary questions (health care, defense contracts, the Wells Fargo scam) to understand the role of incentives, even a sampling of a copy of my online discussion boards will be useful. Those who have taught online and face to face will recognize that these online discussion boards are like a qualitative lower bound on the kinds of discussions that take place in face-to-face classes. Therefore I think this evidence is important.

## Summary of Research Statement

(This is a summary of a longer research statement included separately.)

- My research relates to asset pricing with private information, under both perfect and imperfect competition; accounting and disclosure policy; and industrial organization.
- Most of my efforts have been in theoretical modeling, and includes work published in Econometrica, RAND Journal of Economics, Journal of Financial Markets, and Contemporary Accounting Research.
- I have also done empirical work, mostly predicated on a formal underlying equilibrium model. Some of this deals with analyst forecasts.
- This work is at the intersection of accounting, finance and economics.
- In recent years I have also become interested in questions arising in Indian financial markets. Some of these are also relevant to audiences elsewhere, as in the current working paper looking at how price-setters in financial markets are influenced during an earnings announcement window, not only by what the firm releases but also by what one class of institutional investors learns on its own.
- In analyst forecast papers, forecast errors in general are partly a function of how posterior beliefs are distorted by psychological factors, and partly by how given posterior beliefs, strategic factors lead to herding or bias. To date, papers have assumed either one or the other. In ongoing work we study analyst forecast errors that allow us to look both at a factor distorting posterior beliefs (over-confidence or under-confidence) and a strategic feature given posterior beliefs (herding) in the same model, and provide estimates of both of these parameters together.

## Awards:

NSE-NYU Stern Research Award (October 2014) – (joint with Srini Rangan, IIM-Bangalore) – Research grant of $7500 under an initiative to increase academic research into Indian financial markets, funded by India's National Stock Exchange, administered by NYU Finance Dept. Our proposal was among the 6 competitively funded from 40+ proposals.

NSE-IGIDR Corporate Governance Initiative Research Award (November 2015) – (joint with Srini Rangan, IIM-Bangalore) – Research grant of $2000, besides travel support for a major research conference in August 2015, funded by India's national Stock Exchange, administered by IGIDR. Competitively funded.

Best Paper Award, 2016 International Conference on Financial Markets and Corporate Finance (for "Foreign Institutional Investment and Future Returns: Evidence from an Emerging Economy," with Srini Rangan).

Outstanding Paper Award, Indian Institute of Capital Markets Conference, Bombay, India, December 2006 (for "Information Efficiency on Futures Markets on India's National Stock Exchange," with Yu Cong).

Best Paper Award, National Conference on Indian Capital Markets, Gurgaon, India, April 2007 (for "Liquidity in an Emerging Market: Evidence from India's National Stock Exchange,").

Distinguished Paper Award, American Accounting Association Mid-Atlantic Meeting, Parsippany, NJ, (for "Analysts' Herding Propensity: Theory and Evidence from Earnings Forecasts").

Honorable Mention, Rutgers Faculty of Management Teaching Award for 1999-2000.

## Papers Published Or Accepted For Publication[1]:

**"Stock Price Impact of Diversity in Investor Beliefs," Applied Economics Letters, March 2019,** Pages 1466-4291, https://doi.org/10.1080/13504851.2019.1584361

I re-examine the association between diverse investor beliefs and stock prices within the context of an imperfect competition model. The relationship is ambiguous because of several different effects of a change in diversity in investor beliefs. This has implications for empirical design and explains why 40 years of evidence on this association is inconclusive.

**"Who Herds? Who Doesn't? Estimates of Herding in Analysts' Earnings Forecasts" with Rong Huang, John Shon and Ping Zhou), Contemporary Accounting Research, Volume 34, Issue 1, Spring 2017, Pages 374–399, available online at** http://onlinelibrary.wiley.com/doi/10.1111/1911-3846.12236/full**)**

This paper invokes rational expectations to develop a new proxy for analysts' posterior beliefs and uses this to motivate a measure of imitation driven herding propensity in the context of an explicit analyst optimization problem. We find that most analysts herd toward the prevailing consensus and document factors associated with herding propensity even after controlling for forecast sequence patterns that reflect analysts' slow learning. We also validate our herding propensity measure by confirming its predictive power in explaining the cross-sectional variations in analysts' out-of-sample herding behavior and forecast accuracy. Our parametric herding measure performs better than a non-parametric measure recently proposed by Bernhardt, Campello and Kutsoati (2006). Finally, we find that forecasts adjusted for analysts' herding or anti-herding propensity are less biased than the raw forecasts. This adjustment formula can help researchers and investors obtain better proxies for analysts' unbiased earnings forecasts.

[1] Citation counts in a separate document. Google Scholar also provides a quick summary.

**“Measuring Firm-Specific Informational Efficiency Without Conditioning On A Public Announcement” (with Yu Cong) (Applied Financial Economics, May 2012, 22:21, 1799-1809)**

Estimates overall information efficiency in Indian single-stock and index futures markets without examining price reaction to an announcement. The strategy is to estimate primitive parameters of a Hellwig (1980) model. Our primary findings show that there is considerable variation across firms in these parameters despite only large active firms being available for futures trading. Overall informational efficiency varies with variables related to corporate governance – it increases in promoters’ and foreign institutional investors’ stakeholding, and if the board of directors has a majority that is independent, and decreases if the chairman of the board is also the CEO, and if overall trading activity is fragmented across domestic and international markets. The NIFTY index shows a higher signal to signal plus noise ratio than for any of the firms. This is consistent with the idea that less manipulability is associated with greater informational efficiency.

**“Event Study With Imperfect Competition and Private Information.” (with Yu Cong and Ran Hoitash) <u>Review of Quantitative Finance and Accounting</u>, 34, 3, April 2010, pp.383-411.**.

We compute MLEs of primitive parameters of a Kyle-type model, within earnings announcement windows, and before and after such windows. We find that all of the variance parameters are higher within an earnings announcement window, despite unexpected earnings itself being positively associated with price surprise. Our results are consistent with the model in Fischer-Stocken (2004). Our evidence also suggests that the acquisition of private information is not significantly related to abnormal trading volume. We observe that a greater diffuseness of beliefs given public information alone, and even more so, liquidity noise, are the primary drivers of abnormal trading volume in an event window.

**"Herding, Momentum, and Investor Over-reaction," (with Ran Hoitash). <u>Review of Quantitative Finance and Accounting</u>, <u>30, 1, January 2008</u>, pp.25-47**.

We study the impact of noise or quality of prices on returns, construct a firm-quarter-specific measure of speculative intensity (SPEC) based on autocorrelation in daily trading volume adjusted for the amount of information available, and find that speculative intensity has a significant positive impact on returns. Both cross-sectional and time series variation in SPEC are consistent with conventional wisdom, and with implications of theories of herding as in DeLong et al. (1990). We find that high-SPEC firms drive the returns to momentum trading strategies and that investor over-reaction is significant only in the case of high-SPEC firms.

**"How Do Shop-Floor Supervisors Allocate Their Time?" (with Ashok Srinivasan). <u>International Journal of Production Economics</u>, 105, 1, January 2007, pp. 97-115.**

We consider a setting where a shop-floor supervisor can allocate his time towards increasing productivity either directly by contributing on the line, or indirectly by helping coworkers solve problems. Within the context of a simple non-cooperative sequential game designed to capture salient incentives of worker and supervisor, we show that for indirect activity to emerge in equilibrium, targets should be sufficiently stiff. Also an increase in discretionary time is accompanied by increases in both direct and indirect activity. We validate the model using data obtained from a Japanese manufacturing plant in the Midwest.

**“Review of Gu. Z. and J.S. Wu, ‘Earnings Skewness and Analyst Forecast Bias,’ <u>International Journal of Forecasting</u>, 20, 4, Fall 2004, pp.734-736.**

**"Prices As Aggregators Of Private Information: Evidence From S&P 500 Futures Data" (with Jin-Wan Cho). Journal of Financial and Quantitative Analysis. Vol 35, No. 1, March 2000, pp. 111-126. LEAD paper.**

We show that a version of the Hellwig (1980) model has the property that the parameters of the (price, terminal value) joint distribution can be inverted to obtain its primitive parameters. Using currency futures data, in which case terminal values can be treated as observable, we provide estimates of primitive parameters such as the precision of private information and supply noise. We also provide estimates of ancillary quantities such as the weights on different types of information in the agents' expectation function, and estimates of the signal-to-noise ratio.

**"To Believe or Not to Believe" ( with Utpal Bhattacharya), Journal of Financial Markets (1999). pp. 69-98.**

We develop a theory of corporate disclosure under moral hazard, and show why managers may have an incentive to make their reports informative, even when these reports are cheap talk and can be manipulated with impunity. In a non-cooperative setting we show that they may do so to minimize suspicion and suspicion-induced reliance on alternative sources of information by financial market participants. We also develop a distinction between the hard data hypothesis and the soft data hypothesis regarding the nature of corporate disclosure. Our work provides foundations for treating positive and negative earnings surprises as good and bad news even if it is assumed that GAAP and the external auditor cannot adequately constrain an opportunistic manager. It also provides testable restrictions on bid-ask spreads.

**"Do Supervisory Inputs Matter In A Capital Intensive Industry? -- Some Evidence From A Japanese Car Transplant" (with Ashok Srinivasan), Managerial and Decision Economics, Vol.18, (1997), pp. 235-245.**

We estimate a translog production function based on data from a Japanese automobile plant in the Midwest where output is determined by capital and different supervisory time inputs. The model allows for heteroskedastic errors, where this heteroskedasticity is a function of various variables affecting perceived target severity. We find that while as expected capital inputs are important, each supervisory time input is also significant in this capital intensive industry. Linear homogeneity in these inputs is rejected. We find evidence of asymmetry in substitution among different components of supervisory time. This asymmetry has implications for the allocation of time to different supervisory tasks.

**"Insider Trading and Asset Pricing in an Imperfectly Competitive Multi-Security Market" (with Jordi Caballé), Econometrica, Vol. 62, No. 3 (May 1994), pp. 695-704. . (Available online if your school subscribes to JSTOR, or similar service.)**

We study a multi-security market in a correlated environment with asymmetric information and imperfect competition, in which market makers learn about each payoff from every order flow, even as informed traders manipulate what they can learn. Where classical portfolio theory focuses on diversification in order to reduce portfolio variance, our model focuses on incentives to diversify generated solely by the existence of private information, and the desire therefore to minimize learning by other agents. We find that the equilibrium matrix governing the relationship between the price vector and the vector of order flows is symmetric positive definite.

**"On An Equivalence Between the Kyle (1985) and Glosten-Milgrom (1985) Models," Economic Letters, Vol. 40, No. 2 (October 1992), pp. 333-338.**

This paper introduces a binary version of the Kyle (1985) model, and shows that there is an essential equivalence between the Kyle (1985) and the Glosten-Milgrom (1985) extensive forms, despite the difference that only in the latter traders know the exact price at which a trade will take place. Given identical distributions of terminal value and strategy spaces, exactly the same results obtain in terms of informativeness and expected trader profits. In particular, this allows the pricing rule in a binary version of the Kyle (1985) model to be interpreted as the bid-ask quotes in a Glosten-Milgrom (1985) model. The model makes the analysis of discrete strategies more convenient.

**"Preemptive Investment and Resalable Capacity" (with Lars-Hendrik Röller), <u>RAND Journal of Economics</u>, Winter 1993, pp. 479-502. (Available online if your school subscribes to JSTOR, or similar service.) LEAD paper.**

In the context of an entry game a la Spence (1979) and Dixit (1980) we replace the classical assumption of irreversible investment with the empirically more plausible assumption that investment is resalable. We show that an inability to commit can help rather than hurt. Resalability increases the complexity of the incumbent's choice problem but also furnishes her with an additional strategic variable. This shows that in an analysis of limited commitment the nature of the source of such limits can be important, and that the first-mover advantage may be magnified despite a loss of the ability to commit.

**"Regulating Price-Liability Choices to Improve Welfare" (with Lars-Hendrik Röller), <u>Economics Letters</u>, Vol. 33, No. 4 (August 1990), pp. 375-383.**

We study regulation in markets where firms choose price-liability combinations. Our work implies that a recently suggested regulatory rule, restricting the maximum liability that can be assumed, does not increase consumer welfare. We also study a rule inspired by the German audit market, in which maximum liability is restricted but only as a multiple of the price, and show that this rule can also reduce consumer welfare, and even be Pareto inferior.

**<u>Working papers (under review, or being revised for resubmission)</u>:**

**"How Informed Are Foreign Institutional Investors: Evidence from India's NSE," (With Srini Rangan)**

We build and estimate the primitive parameters of a model of imperfect-competition asset pricing, with two possibly correlated signals, a corporate disclosure and a trading signal.

**"Foreign Institutional Investment and Future Returns: Evidence from an Emerging Economy," (with Srini Rangan)**

We document the returns of FIIs, and examine whether they make money, and if they do, if this is because they are informed, or in spite of not being informed.

**"Insider Trading Around Earnings Announcements: Evidence from India," (with Srini Rangan)**

We examine the behavior and performance of insiders around earnings announcements. We also consider the impact of a peculiar feature on Indian data – self-reported trades that seem illegal.

**"A Simple Measure Of Liquidity, With Estimates From India's National Stock Exchange" (with Charlie Lee)**

Market liquidity is viewed as the ease of finding a counter-party. We motivate and define a simple empirical measure of liquidity that focuses on this attribute, by using information from both executed and unexecuted orders. We explore its implications for empirical work by estimating this measure using data from India's National Stock Exchange, and a benchmark SEC dataset from the US.

**"A Theory of Analyst Forecast Bias"**

We show that a strategic analyst concerned with the combined accuracy of his sequence of forecasts, can benefit from an initial biased forecast in order to gain access to management's private information, and improve his subsequent forecast, even if both the manager and the financial market are rational, provided there is also a fraction of non-strategic analysts whose presence provides camouflage for the strategic analyst. Besides explaining documented declining positive bias, our theory suggests a new testable prediction.

**Work in progress:**

**"Errors in Analysts' Forecasts from Overconfidence and Herding"**

The literature studying forecast errors has assumed either that errors arise in the formation of posterior beliefs (as in the behavioral literature) or given unbiased posteriors, that they are introduced strategically (as in the bias literature). We develop a model in which both kinds of errors arise, and estimate both an overconfidence parameter governing errors in posterior beliefs, and a herding propensity parameter governing strategic error.

**"Security Design with Multiple Projects and Insider Trading" (with Jordi Caballé)**

We consider the problem of an entrepreneur committed to undertaking possibly correlated projects, who must decide whether to issue one or two securities. There is a tradeoff between the costs due to leakage of additional information when there are two securities and benefits from being able to implement divergent trading strategies (e.g. go long in one, short in the other). The principle departure is the manner in which we hold noise constant: when making this comparison, we model the behavior of liquidity traders explicitly. We characterize the optimal tradeoff as a function of the correlation in posterior beliefs, and liquidity trading. We also study the impact of correlation in terminal values, in errors in private signals, and between private and public signals.

**Invited Papers Presented at Refereed Regional, National, and International Society Meetings and/or Educational Institutions:**

"To Believe or Not to Believe"
Sixth World Congress of the Econometric Society, Barcelona; University of California, Berkeley; Economics Dept., University of Delaware; Econometric Society, Atlanta; Annual International Meetings of Association Francaise de Finance at Universite Paris-Dauphine; Midwest Math Econ Meeting, NSF-Institute for Decision Sciences Meetings, SUNY-Stony Brook, July 1995; International Conference on Game Theory and Economics, Indian Institute of Science, Bangalore; Western Finance Association, Oregon.

"Test of a Restriction From a Multi-Asset Model With Private Information and Strategic Behavior"
Columbia University; Universities Research Conference on Asset Pricing and Financial Markets, National Bureau of Economic Research, Boston; Finance Dept.,Stanford University, Universite de Toulouse, HEC-ISA, Econometric Society (Cambridge).

"Setting Accounting Standards: Does the FASB Promote Independence?"
Columbia University, Southeastern Economic Theory Meetings, Econometric Society (Cambridge).

"Insider Trading and Asset Pricing in an Imperfectly Competitive Multi-Security Market"
Universities Research Conference on Asset Pricing and Financial Markets, National Bureau of Economic Research, Boston; Stanford University; Econometric Society, Munich; Annual International Meetings of Association Francaise de Finance at Universite Paris-Dauphine; Econometric Society, Ann Arbor; University of Illinois at Urbana-Champaign; INSEAD, France; Hong Kong University of Science and Technology.

"Corporate Earnings Reports: Cheap Talk or Verifiable Information," (now called "To Believe Or Not To Believe");
University of California, Berkeley; American Accounting Association, 1992, Carnegie-Mellon University, University of Minnesota, Tulane University.

"Unverifiable Corporate Reports: Cheap Talk or Verifiable Information," (now called "Cheap Talk and the Suspicion Effect: A Test");
Conference on Microeconomic Functioning and Organization of Financial Markets, Aix-en-Provence, France, European Meeting of the Econometric Society, Istanbul, August, 1996.

"Regulating Price Liability Competition to Improve Welfare,"

European Meeting of the Econometric Society, Munich; American Accounting Association Mid-Atlantic Meeting.

"Entry Game With Resalable Capacity (now called "Preemptive Investment with Resalable Capacity")
European Economic Association Meeting, Bologna; University of Delaware OR Workshop, Econometric Society (Philadelphia); International Conference on Game Theory, Florence; Midwest Math Econ (Champaign), International Economic Association World Congress (Moscow), August 1992.

"A Theory of Analyst Forecast Bias"
American Accounting Association Meetings, Florida, August 1995; Sixth Annual Conference on Financial Economics and Accounting, University of Maryland, November 1995; International Conference on Game Theory and its Applications, Indira Gandhi Institute of Development Research, Bombay, January, 1996.

"Sources of Volatility in a Dynamic Financial Market with Insider Trading"
Econometric Society Seventh World Congress, Tokyo; Carnegie-Mellon University; Finance Department, University of Minnesota, November 1995; Econometric Society Asian Meetings, Delhi, India, December 1996.

"Skewness of Earnings and the Believability Hypothesis"
Indiana University at Bloomington, September 1996; Finance Department, University of Minnesota, Fall/Winter, 1996-97; Oxford University, October, 1996; Paris Inter-University Meetings ("Malinvaud Conference"), December, 1996; Indira Gandhi Institute of Development Research, Bombay, January, 1997; Koc University, Turkey; December 1998; WZB, Berlin, Germany, January 1999; University of Freiburg (Economics Dept), January 1999; University of Vienna, Austria; Nanyang Technological University, January 1999, London Business School, October 1999; Singapore Management University, June 2000.

"How Do Production Targets Affect Team Leaders' Strategies To Raise Productivity: Theory and Evidence"
Summer Symposium on Accounting Research, Hong Kong University of Science and Technology, June

1997.

"Incentives in Outsourcing Internal Auditing?"
Midwest Economic Theory Meetings, Bloomington, Indiana, October 1997; American Accounting Association Meetings, New Orleans, August 1998.

"Liquidity in an Emerging Market: Evidence from India's National Stock Exchange"
IIT, Madras; IFCAI, Hyderabad; IGIDR, Bombay; IIM-Ahmedabad, January 2005; IIT Bombay, August 2006; National Conference on Indian Capital Markets (Best Paper Award), Gurgaon, India, April 2007; IIM Kozhikode, January 2008; International Conference on India and Emerging Financial Markets, IGIDR, Bombay, January 2008..

"Event Study With Imperfect Competition and Private Information."
IFCAI, Hyderabad; John E. Peterson, Jr. Distinguished Seminar, Virginia Tech, April 2005; American Accounting Association Annual Meetings, August 2005;
Institute for Financial Management Research, Madras, August 2006; City University of Hong Kong, October 2006.

"Information Efficiency on Futures Markets on India's National Stock Exchange."
IIT Madras, August 2006; Korea University, October 2006; Econometric Society, Indian Institute of Capital Markets Conference (Outstanding Paper Award), December 2006; IIM Bangalore, January 2008; Econometric Society Singapore Meeting, July 2008; International Conference on Finance, Accounting and Global Investments, IMI, New Delhi, India, August, 2008; American Accounting Association Annual Meetings, August 2008.

"Who Herds? Who Doesn't?" (revised title "Analysts' Herding Propensity: Theory and Evidence from Earnings Forecasts")
Carnegie-Mellon University (Fall 2005);.Nanyang Technological University, October 2006; AAA Financial Accounting and Reporting Conference, January 2007; AAA Mid-Atlantic Meetings (Distinguished Paper Award), Parsippany, NJ.

"A Study of Ratings Changes at the Margin of Investment and Speculative Grades"
IIT-Madras, August 2010; Rutgers University, April 2011

"Financial Markets – International Differences" (part of 2-day conference on Cross-Cultural Differences and Economic Development)
DG Vaishnav College, University of Madras, August 2011.

**Miscellaneous Publications:**
Letter to the Indian Express, April 12, 2008 (won "Letter of the Week" Award), responding to "Wealth of Nations," by Saubhik Chakrabarti.

**Research Grants:**

NSE-NYU Stern Research Award (October 2014) – (joint with Srini Rangan, IIM-Bangalore)

NSE-IGIDR Research Award (November 2014) ) – (joint with Srini Rangan, IIM-Bangalore)

Econometric Society, 1990; National Bureau of Economic Research, 1990; XL International Travel Grant, 1989-1990, Purdue Research Foundation (1988, 1989, 1990, 1991), Econometric Society, 1995.

University of Minnesota:

Graduate School Grant-in-Aid, Jan-Dec, 1995 (joint with Bal Radhakrishna).
Institute for International Studies and Programs International Travel Grant, 1995.
Carlson School of Management International Travel Grant, 1995, 1996.
Graduate School Grant-in-Aid, Jan-Dec, 1996 (joint with Judy Rayburn).

Professional Affiliations:

American Accounting Association, American Economic Association, American Finance Association, Econometric Society.

**Referee Service:**

The Accounting Review Contemporary Accounting Research
Management Science Review of Economic Studies
American Economic Review Review of Financial
Studies European Economic Review Mathematical
FinanceManagerial Decision and Economics Journal of
Operations Management
Journal of Financial Markets International Journal of Production
Economics American Accounting Association, Mid-Atlantic Meeting
International Accounting Research Conference 1992
National Stock Exchange Research Review Board
Journal of Economic Theory

**Other Service to the Profession, to improve emerging market databases:**

Since emerging markets like India have become more important even in the eyes of US investors, research into emerging markets has also become more important. But the lack of convenient databases has limited empirical research. Partly this has been due to severely limited transparency and ineffective regulation. Since 2004 I have been engaged in diverse efforts to improve this situation, including using India's Right To Information Act (2005), working with Members of Parliament to raise related questions, and filing a writ petition in the Bombay High Court. Many related documents can be seen on the RTI volunteer website, www.rtiindia.org. To date the most significant effect on financial market data infrastructure in India as a result of these efforts has been SEBI's release of Foreign Institutional Investor transaction data, now in public domain (see http://www.sebi.gov.in/sebiweb/investment/statistics.jsp?s=fii), and updated to maintain a lag of no more than six months. **So today even an application under the Right To Information Act is not necessary to obtain this data.**

While this effort was motivated by my own academic research interest in Indian financial markets, the effort to advance transparency among Indian regulators has been beneficial to everyone doing research in Indian financial markets. Hence I list this as significant service to the profession.

**University Service:**

Undergraduate Internship Program Committee (1995-96), Minnesota Supercomputer Institute, University of Minnesota (the committee's charge includes direction of the Undergraduate Internship Program in Graphics and Supercomputing).
Parking Services Committee (2000-3), Faculty of Management, Rutgers University.
Recruiting Committee (Accounting), SSSB, Yeshiva University
Curriculum Review Committee, SSSB, Yeshiva University.

MBA Graduate Studies Task Force, William Paterson University

**Miscellaneous**:

Visitor, INSEAD, France (Summer 1989).
Visitor, WZB, Berlin, Germany (December 1994).
Visitor, Universidad Autonoma de Barcelona (January-February 1996; September 1996; January-February 1997).

Invited participant, Conference on Microeconomic Functioning and Organization of Financial Markets at Aix-en-Provence, France, Fall 1989.

Invited participant, European Summer Symposium in Financial Markets, Gerzenzee, Switzerland (organized by the Centre for Economic Policy Research, European version of the NSF-NBER Meetings), July 11-21, 1994.

Invited Discussant - American Accounting Association , 1991,
- Econometric Society Winter Meetings (January 1993),
- Chemical Bank/Imperial College Conference on Forecasting with High Frequency Data.

Participating faculty member - USAID-sponsored collaborative Executive MBA at the Warsaw School of Economics, Poland, November 1995; January 1997, January 1998, January 1999.
- Executive training at Silesian Technical University, Katowice, Poland, in collaboration with Center for Nations in Transit, Hubert Humphrey Institute, University of Minnesota, January 1998.

Guest MBA Lecturer – Goa Institute of Management, August 2007.

Guest PhD Faculty
– IIT Madras (Asset Pricing with Private Information), August 2006; April 2007. Also presented research there every summer since.)
- Nanyang Tech, Singapore (Asset Pricing), October 2006.
- IIM Bangalore – Visitor, Jan 2015 (for 4 PhD lectures).
- IIT-Kharagpur – June-July, 2017 – models of asset pricing, corporate disclosure.

## APPENDIX – Brief Summary of Recent Activities

Teaching

- Taught several sections of financial accounting, managerial accounting, intermediate accounting -- undergrad, MBA (regular, professional and online), Professional MS in Accounting; introductory finance, international finance.
- Taught introductory finance and a senior elective on international finance.
- Was invited by IIM Bangalore in January 2015 to give 4 PhD lectures on asset pricing with private information. Taught PhD classes in June-July 2017 at IIT-Kharagpur.

Service

Spent significant time in 2014-2015 on the Graduate Studies Task Force which is reviewing the MBA curriculum, trying to align with the school's goals for expansion, and coordinating between the committee and the department. Participated in activities relating to AACSB accreditation.

Research

- Obtained 2 very competitive research grants, NSE-NYU Stern Initiative (controlled by NYU) and the NSE-IGIDR Initiative (controlled by IGIDR). These are worldwide research grant competitions, in which applications are received even from the very best research schools. They also involve a condition to meet various deadlines – for an initial draft to be sent to referees appointed by NYU or IGIDR, responses to referees' comments, submission of a revised draft before an international conference deadline, and for a subsequent draft after the conference.
- Papers accepted at Contemporary Accounting Research, the top Canadian accounting research journal, and at Applied Economics Letters..
- Have also been working on revisions of four papers listed on my vita. Three of these are related to grants received, and have been presented at competitive research conferences, and are under review, or being revised for submission or resubmission.

REFERENCES

1. Prof. Jonathan Glover Columbia Business School 3022 Broadway 605B Uris Hall New York, NY 10027; e-mail: jg3463@columbia.edu ( +1-212-854-1911)

2. Prof. William Baber, Georgetown University. 37th and O Streets, N.W., Washington D.C. 20057; email: wrb7@georgetown.edu (+1-202-687-0100)

3. Prof. Utpal Bhattacharya, The Hong Kong University of Science and Technology, Clear Water Bay, Kowloon Hong Kong; email: ubhattac@ust.hk (+852-2358-7533)

Murugappa (Murgie) Krishnan
murgie@gmail.com
+1-908-376-9795 (Google Voice)

90 new England Ave Apt 6
Summit, NJ 07901-1830
Sept 5, 2013

Dear Sir/Madam:

I am writing to apply to your school for a faculty position in finance. I enclose supporting materials, including a CV, teaching and research credentials, published and unpublished papers.

For references you may contact:

1. Prof. Bill Baber (wrb7@georgetown.edu)

2. Prof. Jonathan Glover (jglover@andrew.cmu.edu)

3. Prof. Utpal Bhattacharya (ubhattac@indiana.edu)

4. Prof. Dan Palmon (dpalmon@business.rutgers.edu)

5. Prof. Prem Jain (pcj3@georgetown.edu)

Please let me know if you have any further questions. Thank you.

Sincerely,

Murugappa Krishnan

Murugappa Krishnan

# Who Herds? Who Doesn't? Estimates of Analysts' Herding Propensity in Forecasting Earnings*

RONG HUANG, *Baruch College–CUNY*

MURUGAPPA (MURGIE) KRISHNAN, *William Paterson University and Rutgers University*

JOHN SHON, *Fordham University*

PING ZHOU, *Neuberger Berman Investment Advisor*

## ABSTRACT

We develop parametric estimates of the imitation-driven herding propensity of analysts and their earnings forecasts. By invoking rational expectations, we solve an explicit analyst optimization problem and estimate herding propensity using two measures: First, we estimate analysts' posterior beliefs using actual earnings plus a realization drawn from a mean-zero normal distribution. Second, we estimate herding propensity without seeding a random error, and allow for nonorthogonal information signals. In doing so, we avoid using the analyst's prior forecast as the proxy for his posterior beliefs, which is a traditional criticism in the literature. We find that more than 60 percent of analysts herd toward the prevailing consensus, and herding propensity is associated with various economic factors. We also validate our herding propensity measure by confirming its predictive power in explaining the cross-sectional variation in analysts' out-of-sample herding behavior and forecast accuracy. Finally, we find that forecasts adjusted for analysts' herding propensity are less biased than the raw forecasts. This adjustment formula can help researchers and investors obtain better proxies for analysts' unbiased earnings forecasts.

# Grégarisme ou dissidence? Estimations relatives à la propension des analystes au ralliement dans la prévision des résultats

## RÉSUMÉ

Les auteurs élaborent des estimations paramétriques de la propension au ralliement (grégarisme) induite par l'imitation que manifestent les analystes et leurs prévisions de résultats. En recourant aux attentes rationnelles, ils résolvent un problème explicite d'optimisation avec lequel doit composer l'analyste et estiment la propension au ralliement à l'aide de deux mesures : en premier lieu, ils estiment les opinions *a posteriori* des analystes en utilisant les résultats réels ainsi qu'une réalisation tirée d'une distribution normale à moyenne zéro; en second lieu, ils estiment la propension au ralliement sans introduire d'erreur aléatoire, en

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permettant les signaux d'information non orthogonaux. Ce faisant, ils évitent le recours généralement critiqué à la prévision précédente de l'analyste à titre de variable de substitution à ses opinions *a posteriori*. Les auteurs constatent que plus de 60 pour cent des analystes se rallient au consensus existant, et que la propension au ralliement est associée à divers facteurs économiques. Ils valident également leur mesure de la propension au ralliement en confirmant son pouvoir prédictif dans l'explication de la variation transversale du comportement de ralliement hors échantillon des analystes et de l'exactitude de leurs prévisions. Enfin, les auteurs constatent que les prévisions ajustées pour tenir compte de la propension des analystes au ralliement sont moins biaisées que les prévisions brutes. Cette forme d'ajustement est susceptible d'aider les chercheurs et les investisseurs à obtenir de meilleures variables de substitution aux prévisions de résultats non biaisées des analystes.

## 1. Introduction

Market participants use security analysts' outputs—most salient of which are earnings forecasts—to guide their investment decisions (e.g., Stickel 1990; Womack 1996; Barber, Lehavy, McNichols, and Trueman 2001, 2003). The aggregation of multiple earnings signals from multiple analysts forms a consensus, which is more informative than the sum of its individual parts. In this context, several prior studies have examined the notion of analysts' propensity to herd in their forecasts. Herding refers to the notion that analysts take actions to drift toward the prevailing consensus, regardless of the information contained in the consensus. Because such herding behavior reduces the idiosyncratic information that unique (nonherded) forecasts can provide, such herding behavior is argued to reduce the informativeness of consensus estimates (e.g., Trueman 1994). However, extant studies that examine analysts' herding behavior do not agree as to whether—or to what degree—analysts are herding toward a prevailing consensus; or whether the observed pattern is the result of efficient information aggregation (e.g., Clement and Tse 2005; Bernhardt, Campello, and Kutsoati 2006; Clement, Hales, and Xue 2011; Keskek, Tse, and Tucker 2014).

In this paper, we develop a novel approach to measure the existence—and magnitude—of analysts' propensity to herd. This propensity to herd is meant to capture the cost of imitating a prevailing consensus forecast (as opposed to making an unbiased forecast based upon all available information). We develop a parametric model assuming that each analyst minimizes a quadratic cost, where there are terms for (i) being inaccurate, and (ii) deviating from the prevailing consensus. This latter cost term is an innovation that enables us to parameterize the propensity to herd. The first-order condition in this optimization problem serves as the estimating equation for the herding propensity parameter $h$.[1]

Empirically, we exploit the rational expectations idea that analysts' posterior beliefs are correct on average. We estimate herding propensity using two measures. First, we estimate analysts' posterior beliefs using actual earnings plus a realization drawn from a mean-zero normal distribution. Second, we estimate herding propensity without seeding a random error, and allow for nonorthogonal information signals. We extract an estimate of herding propensity, $h$, by examining how earnings forecasts, the prevailing consensus, and the estimated posterior belief are related to each other. Importantly, this parameterization also enables us to specifically adjust *each individual analyst's* raw (herding-affected) forecast, thus reducing the bias that such forecasts exhibit.

1. Specifically, the first-order condition of this cost function enables us to derive a proportional relationship between forecast bias and the deviation of the prevailing consensus from an analyst's posterior belief, where the constant of proportionality between the two is a simple monotone function of herding propensity. This herding propensity parameter $h$ is the weight placed on deviating from the prevailing consensus.

Our sample is comprised of 1,438,336 individual analysts' earnings forecasts, spanning the 21-year period between 1990 and 2010. Our empirical tests suggest that there exists a significant tendency for analysts to issue forecasts that exhibit herding towards a prevailing consensus. Specifically, we find that approximately 63 percent of analysts exhibit herding, whereas approximately 16 percent of analysts exhibit anti-herding. The estimated herding propensity varies across time, with higher levels of herding during the recent financial crisis, as well as in recessionary years. It also varies cross-sectionally in predictable ways across several dimensions, including forecast horizon, analyst following, broker/employer size, and forecast order. Our estimated herding propensity is distinct and incrementally significant from what we refer to as the effect of analysts' *slow learning*, where analysts observe other signals and rationally extract information from such signals to issue unbiased forecasts.

Moreover, if our estimates of herding propensity are valid and reasonably stable over time, we expect to find that our ex ante estimates of herding propensity can predict aspects of analysts' forecast behavior out-of-sample. We show that our in-sample herding propensity estimates can predict the cross-sectional variation in analysts' out-of-sample herding behavior and forecast accuracy (e.g., Brown and Mohammad 2003).

Lastly, because our estimates of herding propensity are parametric, we are able to adjust individual analyst's raw forecasts to calculate "unherded" forecasts—our candidate measure of unbiased forecasts. For the majority of analysts, we find that our adjusted forecasts exhibit less bias relative to the raw, unadjusted forecasts.

We make several contributions to the extant literature. Our first contribution is methodological. Prior studies have only been able to observe analysts' *reported* forecasts —not their posterior beliefs—and thus use a prior forecast as a proxy for posterior beliefs (e.g., Clement and Tse 2003, 2005; Gleason and Lee 2003). This approach produces questionable inferences, as it altogether ignores the constant flow of new information that analysts are actually exposed to in the real world. In this study, we meet this challenge by introducing a novel and intuitive proxy for posterior beliefs that enables us to examine herding propensity and by including the prevailing consensus forecast as a signal in forming posterior beliefs. Moreover, unlike prior studies that model a world of nonsequential, simultaneous-move forecasts (e.g., Ottaviani and Sørensen 2006; Marinovic, Ottaviani, and Sørensen 2011a,b), our simple model of forecasting is consistent with the sequential nature of earnings forecasting that occurs in the real world/market (i.e., consensus forecasts that are continuously updated with the addition of each new forecast that arrives in the time series) and is therefore more consistent with the empirical data.

Second, our study is the first to adjust raw earnings forecasts for estimated herding bias. Prior studies, such as Trueman (1994), recommend adjusting forecasts for errors and biases. Such adjustments are not possible in prior studies that examine herding at the forecast level (e.g., Hong, Kubik, and Soloman 2000; Clement and Tse 2005). Our approach therefore introduces a method of unveiling some value-relevant private information embedded in earnings forecasts that is lost because of analysts' herding behavior.

Third, while prior studies examine herding at the forecast level (e.g., Hong et al. 2000; Clement and Tse 2005), our estimates of herding are also measured at the analyst level. Examining herding at the analyst level enables us to discern, for instance, whether herding arises from a few herders making several forecasts, or instead arises because the majority of analysts exhibit herding to some degree. Our evidence at the analyst level suggests that herding is a pervasive feature of the population of individual analysts.

Lastly, we perform out-of-sample tests of our herding measures to increase the validity of our findings and find that our in-sample estimates are able to predict cross-sectional variation in out-of-sample herding behavior and forecast accuracy (e.g., Brown and Mohammad 2003).

We note that it is unlikely that our herding estimates are driven by the incentive to meet-or-beat or by analyst forecast bias as documented in prior studies (Richardson, Teoh, and Wysocki 2004). The correlation between our herding estimate and analyst-level forecast bias is very low. Furthermore, while forecast bias is negatively associated with book-to-market and positively associated with firm size and monthly forecast horizons, our herding estimate does not vary systematically with size or book-to-market, and is significantly positive in all horizons. The evidence suggests that forecast biases and herding estimates seem to capture different aspects of analyst forecasts.

The remainder of this study is organized as follows. In section 2, we discuss prior literature. In section 3, we describe our model. In section 4, we present our data and sample. In section 5, we discuss empirical results, and in section 6 we present additional analyses. Finally, in section 7 we conclude.

## 2. Related literature

Earnings forecasts represent one of the primary outputs arising from sell-side analysts' efforts (e.g., Schipper 1991; Asquith, Mikhail, and Au 2005). Such forecasts are the subject of intense examination by researchers, the financial media, and other market participants because the aggregation of these forecasts forms a consensus forecast—which represents the premier proxy for market expectations. It is in this context that researchers examine the potential errors and biases in analysts' forecasts, which will ultimately have an adverse impact on the measurement of the consensus forecast, or market expectations.

Errors in an analyst's forecasts can arise from errors in processing or interpreting available information (i.e., errors in forming posterior beliefs).[2] Such errors adversely affect the accuracy of an analyst's forecasts, and such forecast accuracy certainly has an effect on the analyst's reputation and career (e.g., Hong et al. 2000; Ke and Yu 2006). However, analysts care about more than just forecast accuracy (e.g., Clement and Tse 2003). Besides errors in forming posterior beliefs, biases in forecasts can also arise. In this line of work, analysts are assumed to form their posterior beliefs efficiently, but deliberately alter their forecasts for strategic reasons unrelated to their posterior beliefs (e.g., currying favor with management).[3]

Another stream of literature suggests that analysts have a desire to *herd* in their forecasts beyond what is justified by their beliefs. *Herding* is a specific type of bias, defined as the tendency for a forecast to drift toward the prevailing consensus in an attempt to better mimic or imitate the consensus, regardless of the information contained in the consensus. The accounting, finance, and economics literatures offer a variety of explanations for such herding behavior (e.g., Welch 2000; Zitzewitz 2001). When an analyst's ability relates to skills in interpreting public information, Prendergast (1993) argues that low-ability analysts have an incentive to herd with prior forecasters to show that they "get it."[4] Zitzewitz (2001) argues that an incentive convexity—while being right and away from consensus is not rewarded much, being wrong and away may be penalized severely—can also create an

2. Extant studies that examine this type of effort assume away the possibility of strategic error (e.g., Elliott, Philbrick, and Wiedman 1995; Zhang 2006).
3. For example, analysts may use their biased earnings forecasts (i) to curry favor with firm management to obtain better access to management's private information (e.g., Lim 2001; Ke and Yu 2006), (ii) to improve forecast accuracy anticipating managements' reporting strategy (e.g., Beyer 2008), or (iii) because such pandering can affect other sources of income such as brokerage commission or investment banking business (e.g., Haynes 1998; Beyer and Guttman 2011; Dugar and Nathan 1995; Lin and McNichols 1998).
4. Alternatively, Prendergast and Stole (1996) show that if an analyst's ability relates to access to private information, high-ability analysts will have posterior beliefs that are farther away from consensus than the average analyst; so low-ability analysts will have an incentive to *anti-herd* to mimic those with greater ability. As track records develop over time, it is possible that analysts' abilities are less hidden and signaling arguments would have more force only in the case of less experienced analysts.

incentive to herd. Consistent with these predictions, Stickel (1990) finds that analysts' forecast revisions are correlated with changes in the prevailing consensus and this correlation is weaker for members of the Institutional Investor All-American Research Team, suggesting that these members are less likely to herd. Similarly, Hong et al. (2000) find that inexperienced analysts deviate less from the prevailing consensus than experienced analysts; and inexperienced analysts are more likely to lose their jobs after providing inaccurate or bold forecasts than experienced analysts.

Analysts' herding propensity can also vary with prior forecasting performance, as well as individual analysts' experience or self-confidence. Clarke and Subramanian (2006) find an inverted U-shaped relation between analysts' forecast herding and their prior performance and a negative relation between forecast herding and experience. Kim and Pantzalis (2003) document that analysts' forecast dispersion is lower for global multisegment firms than for domestic single-segment firms, suggesting that analysts' task difficulty is one of the determinants of herding behavior.

Examining the particular characteristics of herded forecasts, Clement and Tse (2005) find that such forecasts are less accurate and reflect less of analysts' relevant private information relative to anti-herding forecasts.[5] Gleason and Lee (2003) study forecast revisions and find that revisions that are high in innovation (i.e., those that diverge from the prevailing consensus) exhibit a more protracted market reaction relative to those revisions that are low in innovation (i.e., those that drift toward the prevailing forecast). The authors conclude that the market does not make a sufficient distinction between revisions that provide new information and revisions that merely move toward the prevailing consensus.

Several theoretical papers characterize the informational properties of the consensus forecast when analysts are faced with the trade-off between incentives to predict accurately versus their desire to be close to a mean prediction. These studies integrate the reputational theory with the competitive theory of strategic forecasting (e.g., Ottaviani and Sørensen 2006; Marinovic et al. 2011a,b; Morris and Shin 2002). Specifically, when reputational concerns dominate competition concerns, the information content of forecasts deteriorates and only categorical information may be supplied. In contrast, when strong competition dominates reputational concerns, individual forecasts become highly differentiated. Lastly, reputational concerns and competition may offset one another, inducing forecasters to truthfully report their conditional expectations. However, these "beauty contest" models see forecasting as a simultaneous-move game, where a prevailing consensus is not observable until the entire game is over—thus making the concept of herding undefinable.

## 3. The model

### *Analyst's optimization problem*

The primary objective of our study is to empirically estimate herding propensity parameters (at both the analyst and aggregate levels) and identify characteristics associated with the parameter estimates. Relative to extant models that consider only forecast accuracy, the main innovation of our model is the introduction of a meaningful role for herding in the analyst's objective function.

Our simple setting has important consequences for our empirical methods. Specifically, the characterization of an analyst's objective function requiring an explicit trade-off between forecast accuracy and herding with the prevailing consensus leads to a model with

5. Consistent with this, Keskek et al. (2014) find that better analysts participate earlier in information discovery and analysis and, therefore, early forecasts in an analyst information-production period are more informative than later forecasts in that period.

a single parameter to be estimated—the herding propensity parameter $h$. We can exactly identify this parameter with one moment restriction.

Define the following variables:

$a \equiv$ actual earnings,
$f \equiv$ analyst earnings forecast, the choice variable,
$p \equiv \mathrm{E}(\tilde{a}|\text{analyst information set}) \equiv$ analyst's posterior belief (i.e., belief based on all private and public information available to the analyst),
$c \equiv$ prevailing consensus (function of preceding analyst forecasts).

We assume that the analyst chooses $f$ to minimize, given $h > -1$

$$\pi = \mathrm{E}(\tilde{a} - f)^2 + h(c - f)^2. \tag{1}$$

Equation (1) tells us that the analyst's objective function ($\pi$) has two terms. The expectation in the first term is computed after conditioning on all available private and public information, including the prevailing consensus $c$. It is the familiar mean-squared error, representing a concern for accuracy. If this was the only factor influencing the analyst, then he would always issue an unbiased forecast. The second term captures the influence of prevailing consensus on analysts' earnings forecasts. The parameter $h$ scales this effect, which we refer to as the herding propensity parameter. This *herding propensity parameter*, $h$, is simply the cost of deviating from the prevailing consensus. A positive $h$ indicates herding; a negative $h$, anti-herding. For positive $h$, $h$ greater (less) than one means that the analyst is more (less) concerned about forecast deviation from the prevailing consensus than about forecast accuracy. The higher the $h$, the higher the herding propensity. When $h$ is zero, only forecast accuracy matters: this value of $h$ arises when there is no herding and the analyst's forecasts are unbiased. Note that we allow $h$ to be negative, indicating anti-herding. We impose the restriction that $h > -1$ to ensure that the objective function is always strictly convex in the analyst's choice variable $f$.[6]

Given (1) and the strict convexity of the objective function, the first-order condition is adequate to define the optimal choice of $f$.

LEMMA 1. *The first-order condition for the analyst's optimization problem is*

$$(1 + h)f = p + hc, \tag{2}$$

*and the forecast deviation from the analyst's posterior belief (i.e., bias)* $f - p$ *is*

$$f - p = (h/(1 + h))(c - p). \tag{3}$$

Bias and $h$ have a nonlinear but monotone relationship. The choice coefficient $h/(1 + h)$ scales the difference between the prevailing consensus and an analyst's posterior belief $(c - p)$ to get the forecast bias $(f - p)$. As $h$ increases, so does the bias. For positive $h$, the bias moves the analyst's forecast $f$ from the posterior belief $p$ closer to the prevailing consensus $c$, which accords with customary definitions of herding (e.g., Bernhardt et al. 2006). In the limit as $h \to \infty$, the coefficient on $(c - p)$ in (3) approaches 1 and the analyst's earnings forecast becomes the same as the prevailing consensus. As $h \to -1$, the objective function (1) approaches linearity and the choice variable $f$ depends on the sign

6. Morris and Shin's (2002) objective function has a family resemblance to our objective function. However, in their study, the players make a simultaneous—not sequential—choice in their forecasts, thus making the concept of herding difficult to conceptualize (since a prevailing consensus will not be observable until the entire game is over). Such herding behavior is markedly different from the herding behavior observed in real-world settings.

of ($c - p$) and it is unbounded. When $h$ is zero, the optimal choice of the analyst is to make an unbiased forecast and it is meaningful, in the context of this model, to regard that as no-herding.

### *Herding propensity estimator, $h^1$*

The function $g\ (f;\ p,\ c \mid h)$ in the first-order condition helps define the analyst's optimal choice of $f$. Notice that the first-order condition provides a population moment condition which defines the expected error, and can serve as an estimating equation for a herding propensity estimator, which we call $h^1$:

$$g(f; p, c|h) = 0 \Rightarrow E(g(f; p, c|h)) = 0. \tag{4}$$

Replacing this condition with the corresponding sample moment, we can solve for the estimator for $h^1$. The variables $f$, $p$ and $c$ are assumed to have distributions that satisfy regularity conditions (e.g., ergodicity) that guarantee that the sample means will converge to the population means. This is sufficient to guarantee consistency of our $h$-estimator.[7] This estimator is the solution to a formal generalized method of moments (GMM) or least squares minimization problem. The main theoretical result, which is the basis for all of our empirical work, is given below in Theorem 1.

THEOREM 1.

(a) *Given a sample of size N the optimal estimator for $h^1$ is given by*

$$\hat{h} = Max\left\{\left(\frac{\bar{f} - \bar{p}}{\bar{c} - \bar{f}}\right), -1 + \tau\right\}, \tag{5}$$

*where the overbars denote sample means, for arbitrarily small $\tau > 0$.*

(b) *The asymptotic standard error of $\hat{h}$ (for strictly interior $\hat{h}$, i.e. $\hat{h} > -1 + \tau$) is given by the square-root of $\frac{Var(g(f;p,c|h))}{\left[\frac{dg}{dh}\right]^T\left[\frac{dg}{dh}\right]} = \frac{Var(g(f;p,c|h))}{\sum_{i=1}^{N}(y_i - f_i)^2}$ where $Var(g(f;\ p,c \mid h))$ is the sample variance of the restriction computed at each observation, and $[dg\ /\ dh]$ is the N-by-1 gradient vector where each element represents the gradient of the restriction $g(f;\ h)$ evaluated at each observation.*

The above solution for $\hat{h}$ follows from the first-order condition. Since we need to maintain the restriction that $h > -1$, to ensure that the range for $\hat{h}$ is closed, we assume that $\hat{h} \geq -1 + \tau$ , where $\tau$ is equal to $10^{-6}$ (the default value in statistical packages such as SAS). Because we have an explicit formula (5), we do not need to specify any particular $\tau$ but set any unrestricted estimate $<-1$ to the boundary value. To obtain the asymptotic standard error, we use the standard formula from asymptotic theory (e.g., Greenberg and Webster 1983, 55, equation 2.3.6). The regularity conditions assumed in the formula require that the parameter value be strictly interior, hence the formula for the standard error does not apply to the boundary estimate of $\hat{h} > -1 + \tau$.[8]

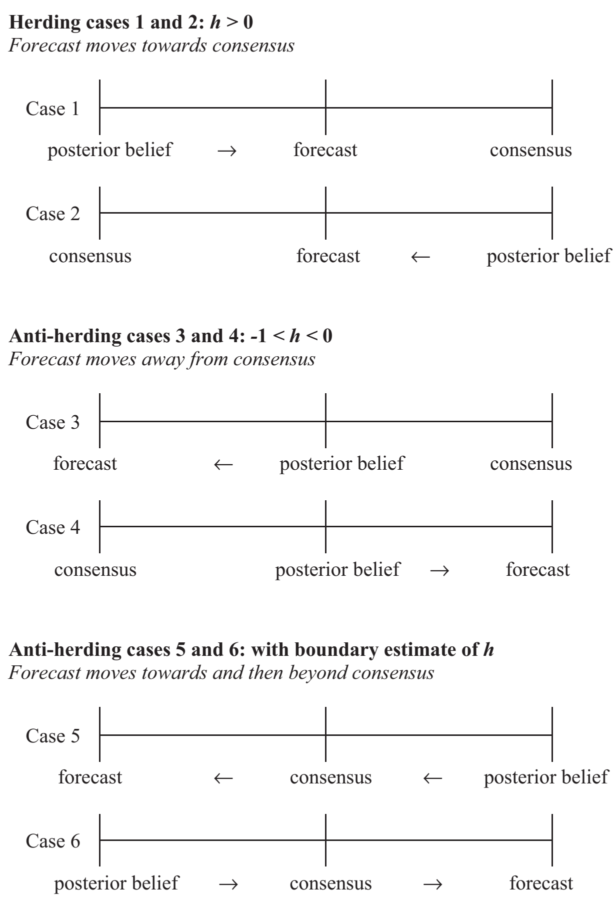
7. This broad regularity condition of ergodicity has been used extensively in the GMM literature (e.g., Hansen and Singleton 1982) to allow for departures from i.i.d. and to rule out pathological cases. It essentially assumes that the variance of each variable is sufficiently bounded and can be estimated from a historical time series. In the Appendix, we discuss in detail why our estimator of herding propensity in (5) is consistent.

8. For estimates that represent boundary estimates, we use a no-replacement bootstrapping technique as prescribed by Horowitz (2001) to obtain standard errors. Specifically, for each analyst with a boundary estimate, we estimate $\hat{h}$ by randomly removing one forecast made by the analyst from the sample and we run this procedure 1,000 times. We then use the standard error of the simulated distribution of $\hat{h}$ to determine the significance of our original boundary $\hat{h}$ estimate.

The formula for the interior estimate of $\hat{h}$ given in (5) is very informative. Note that it is positive only when the numerator and denominator of the first term in the maximand have the same sign. This case arises only when the sample means obey one of two inequalities: either $\bar{p}<\bar{f}<\bar{c}$, or $\bar{p}>\bar{f}>\bar{c}$. So the herding forecast must on average represent a movement from the posterior belief of the analyst toward the prevailing consensus at the time of the forecast. The estimator $\hat{h}$ can be negative only when the numerator and denominator in the maximand are of opposite sign. This case arises only if either $\bar{f}<\bar{p}<\bar{c}$, or $\bar{f}<\bar{p}<\bar{c}$. So the forecast must on average be a movement away from the prevailing consensus. We shall refer to this case as anti-herding. Our model also enables us to identify anti-herding cases that arise from boundary estimates of $\hat{h}$. The boundary value of $\hat{h}$ arises only when either $\bar{p}<\bar{c}<\bar{f}$, or $\bar{p}<\bar{c}<\bar{f}$. This case corresponds to a movement on average of the forecast not only in the direction of the prevailing consensus but even beyond.

See Figure 1 for a graphical illustration of these inequalities. The inequalities satisfied by our sample moments of forecasts (*f*), posterior beliefs (*p*) and consensus (*c*) for the herding and anti-herding cases match the definitions (at the level of a forecast) in Bernhardt et al. (2006). Clement and Tse (2005) count Cases 3, 4, 5, and 6 as bold forecasts (defined not in terms of sample means but individual observations, and measuring deviations from prior forecasts which serve as their proxy for analyst posterior beliefs).

**Figure 1** Inequalities among posterior belief, forecast and consensus, and herding propensity



Observe that the first-order condition in Lemma 1 can be solved for the posterior belief to yield

$$p = f + h(f - c). \tag{6}$$

This has a significant practical implication. It tells us that if we have an estimate of herding propensity $h$ from past data, then given a measure of the current prevailing consensus $c$, the current raw forecast $f$ can be adjusted for herding to yield a candidate value of the analyst's posterior belief $p$, which we describe as the adjusted forecast. We test the significance of these forecast adjustments empirically in section 5.

***Measurement of analysts' posterior beliefs (p)***

The primary difficulty in gauging the relevance of imitation-driven herding versus information-based clustering arises from the fact that empirical researchers observe only the forecasts reported by financial analysts, and not their posterior beliefs. This impact of analysts' posterior beliefs being unobservable is a central issue in the forecasting literature. Prior studies use an analyst's prior forecast as the proxy for his posterior belief. Using the prior forecast as the reference point or proxy ignores the effect of new information. Yet because of its simplicity to implement—and the lack of a better alternative—the literature continues to use this proxy. Though in a different setting this assumption may be an innocuous one, in this particular setting of analysts operating in an environment where there is a constant flow of new information into the market, it can create significant doubts about the inferences that arise from this literature. This is why we believe that developing an alternative proxy for an analyst's posterior belief is an important methodological contribution.

A key departure of our paper from prior work, then, is the way we estimate each analyst's posterior belief $p$. We use the rational expectations assumption in two different ways. For our first approach, we define $p = a + u$ where $a$ is the actual earnings announced,[9] and $u$ is a random number drawn from a mean-zero normal distribution that has the variance $s$ (e.g., McFadden and Ruud 1994).[10] We assume here that analysts correctly anticipate the actual earnings. However, analysts are correct only in the mean and they can still make unsystematic errors. This assumption enables us reconcile this measure with the voluminous evidence that forecasts are not perfect and that there is variation among analyst-firms and analyst-firm-years with respect to forecast accuracy.

To complete the definition of the random term $u$, we must specify the variance $s$. Since $u$ is positively correlated with the overall forecast error, we estimate $s$ using the variance of past forecast errors. For each analyst-firm-year, we use the entire history of forecast errors of the same analyst-firm up to and including the current year to estimate the forecast error variance $s$. This specification allows for variations in $s$ across analysts, firms, and years. By limiting ourselves to the history up to the current period, we avoid any look-ahead bias.[11] Incorporating these idiosyncratic factors allows us to capture the fact that analysts differ in their experience, skills, and quantity and quality of private information. We require at least three observations of forecast errors for each analyst-firm to estimate the variance $s$.

9. This is roughly analogous to the assumption in McNichols and Wilson (1988), where an agent's time $t$ belief about bad debts is measured empirically by the time $t + 1$ realized bad debts.
10. This practice of adding a zero-mean random number also has a precedent in the literature on the simulated method of moments estimation. For example, McFadden and Ruud (1994) state that when an estimator depends only on the sample means, adding a zero-mean random error does not affect the asymptotic properties of the estimator.
11. We also explore several alternatives, such as using only the history up to the prior period, or limiting the history to a fixed number of prior periods. Untabulated results and inferences are qualitatively unchanged.

The way we measure posterior beliefs implies that for any two analysts $i$ and $j$, with information sets $I_i$ and $I_j$, the seeded errors $u$ are orthagonal. So it will be the case that

$$\mathrm{Cov}((\tilde{\mathrm{E}}(\tilde{\mathrm{a}}|\mathrm{I_i}) - \tilde{\mathrm{a}}), (\tilde{\mathrm{E}}(\tilde{\mathrm{a}}|\mathrm{I_j}) - \tilde{\mathrm{a}})|\tilde{\mathrm{a}} = \mathrm{a}) = 0. \tag{7}$$

This is consistent with an underlying primitive information structure in which the total information contained in earnings is viewed as the sum of orthogonal information innovation components.[12] This orthogonal structure has been used extensively in the macroeconomics and finance literature to capture short-lived information advantage. See Admati and Pfleiderer (1988) for an example that uses this information structure in the context of an asset-pricing model.

### *Alternative herding propensity estimator, $h^2$*

In this subsection, we derive an alternative rational expectations estimator for $h$, denoted as $h^2$, which does not require orthogonal factor structure as the $h^1$ estimator above. Let $p$ the posterior belief of an analyst be given by

$$p = E(\tilde{a}|c, \theta_i), \tag{8}$$

where the conditioning arguments are the prevailing consensus $c$ and everything else the analyst uses (public or private; and observable or unobservable to a researcher), which we summarize as $\theta_i$. We only require unbiasedness and impose no additional structure on the expectation in (8) above.

Substituting the above for the value of the posterior $p$ in the first-order condition, namely, (2), we get

$$(1 + h)f = E(\tilde{a}|c, \theta_i) + hc. \tag{9}$$

The expectation of (10) yields the population moment that serves as our estimating equation (i.e., this population moment defines our *expected error*). This yields

$$(1 + h)\bar{f} = \bar{a} + h\bar{c}. \tag{10}$$

since the ex ante expectation of that posterior; that is, $E(E(\tilde{a} \mid \cdot))$ is always just the prior mean $\bar{a}$. As in the case of the first estimator, we can easily solve for the interior solution satisfying $h > -1$.

$$h^2 = (\bar{f} - \bar{a})/(\bar{c} - \bar{f}). \tag{11}$$

Compare this estimator with the first estimator for $h$:

$$h^1 = (\bar{f} - \bar{p})/(\bar{c} - \bar{f}). \tag{12}$$

So we have a very similar formula. The role of the posterior sample mean $\bar{p}$ in the previous estimator in (12) is now played in (11) by the prior mean of actual earnings $\bar{a}$. Note that even though we assume only unbiased and not perfect posteriors, the form of $h^2$ is the same as what we would get if we assumed that analysts have perfect foresight. It is important to note, though, that there are subtle trade-offs involved in choosing between the two alternative estimators. The approach we have outlined here for $h^2$ does not require seeding errors to construct an explicit posterior belief since (11) above relies instead only on the sample mean of actual earnings. Conversely, the approach we outline in section 3 for $h^1$ enables us to explicitly adjust for two pervasive empirical features of forecasts documented in extant literature: (i) analysts' forecasts are not perfect, and (ii) there is

12. A formal derivation is available upon request.

heterogeneity in analyst forecast quality. Because the orthogonal errors we seeded have zero means, and because the variance of forecast errors is an order of magnitude smaller than actual earnings, we should expect the two alternative estimators for $h$ to yield very similar values, at least in cases where an estimate is based on a large enough number of observations. And we show later in this paper that this is indeed the case.

## 4. Data and sample

### *Sample selection*

Our final sample consists of 1,438,336 individual analysts' annual EPS forecasts spanning 21 years (1990–2010).[13] We obtain analysts' one-year-ahead earnings forecasts ($f$) and actual earnings data from I/B/E/S. For each forecast, we require nonmissing information for (i) the value of the forecast, (ii) the corresponding actual earnings, (iii) date of the forecast, and (iv) date of earnings announcement. We measure forecast errors by subtracting actual EPS from forecasted EPS, scaled by the lagged stock price. The top and bottom 0.5 percent of forecast errors are deleted. We also remove forecasts issued by unidentified analysts (i.e., those with analyst code of "000000" in I/B/E/S). To remove stale forecasts, we only retain forecasts released within 480 days before earnings announcement dates.

We require each forecast in our sample to have a prevailing consensus forecast ($c$). Our primary measure of the consensus forecast is the average of the last forecast made by each analyst prior to the current forecast (e.g., Bernhardt et al. 2006). Untabulated tests reveal that our results and inferences are qualitatively unchanged when the consensus is measured in alternative ways.[14] Lastly, we require sufficient data to compute analysts' posterior beliefs, which we discuss in detail below.

### *Descriptive statistics*

Table 1 presents descriptive statistics for the key variables in our sample. Overall, our sample is qualitatively similar to those of other recent studies (e.g., Clement and Tse 2005; Bernhardt et al. 2006). For instance, the mean (median) earnings-forecast *Accuracy* is 0.014 (0.005). The mean (median) forecast *Deviation*, which is the difference between the forecast and the prevailing consensus, is 0.007 (0.002), which suggests a positive skew. We also include several analyst-specific characteristics, including *Firm Experience*, *General Experience, Firms Followed*, and *Industries Followed*. These analyst characteristics are also in line with prior studies.

## 5. Empirical results: Herding propensity ($\hat{h}$)

### *Estimates of herding propensity ($\hat{h}$) at aggregate levels*

#### *Pooled and subperiod estimates*

In Table 2, we present results from our estimation of $h$, as motivated and discussed in equations (5) and (11) from section 3. The estimated $h$ represents the herding propensity for the full sample of analyst forecasts. We first discuss the estimates based on $h^1$ from (5). Our estimate of herding for the aggregate sample, from 1990 to 2010, is 3.317. Recall that an estimate of $h$ greater than 0 is an indication of herding, suggesting that analysts'

13. We start our sample from 1990 because I/B/E/S has disseminated forecasts within 24 hours since 1989, which minimizes measurement error because of the difference between published forecast dates and actual forecast dates. We do not include the year 1989 because forecast dates in 1989 may not be completely accurate. However, in unreported robustness tests we include data from 1989 and our results are unchanged. In an earlier version, we used data from 1983 with little difference in test results.
14. We consider two alternative measures for consensus: (i) the forecast-horizon-weighted average of the last forecast made by each analyst prior to the current forecast, where the forecast horizon is the distance between the forecast date and the annual earnings announcement date, and (ii) the average of the last forecast made by each analyst within 30 days prior to the current forecast; this further removes stale forecasts.

TABLE 1
Descriptive statistics

| Variable | Mean | SD | 25th | Median | 75th |
|---|---|---|---|---|---|
| *Forecast Accuracy* | 0.014 | 0.033 | 0.001 | 0.005 | 0.013 |
| *Deviation* | 0.007 | 0.016 | 0.001 | 0.002 | 0.007 |
| *Days Elapsed* | 11.23 | 16.95 | 1 | 5 | 13 |
| *Forecast Horizon* | 151.37 | 96.73 | 68 | 154 | 241 |
| *Dispersion* | 0.008 | 0.015 | 0.002 | 0.004 | 0.009 |
| *Following* | 13.91 | 8.95 | 7 | 12 | 19 |
| *Broker Size* | 51.44 | 41.72 | 18 | 40 | 74 |
| *Forecast Frequency* | 5.76 | 3.60 | 4 | 5 | 7 |
| *Firm Experience* | 3.90 | 2.67 | 2 | 3 | 5 |
| *General Experience* | 6.68 | 4.18 | 3 | 6 | 9 |
| *Firms Followed* | 13.94 | 8.41 | 9 | 13 | 17 |
| *Industries Followed* | 3.44 | 2.56 | 2 | 3 | 4 |

**Notes:**

This table presents summary statistics of various analyst and firm characteristics. The sample includes 1,438,336 one-year-ahead annual earnings forecasts from 1990 to 2010 with data necessary to construct all characteristics reported in this table. *Forecast Accuracy* is defined as the absolute value of the difference between an analyst's annual EPS forecast and the actual annual EPS, deflated by the lagged stock price. *Deviation* is the absolute difference between an analyst's annual EPS forecast and the prevailing consensus forecast, deflated by the lagged stock price. We require at least three forecasts to construct the consensus forecast. *Days Elapsed* is the number of calendar days passed since the last annual EPS forecast issuance. *Forecast Horizon* is the number of days between the forecast date and the annual earnings announcement date. *Dispersion* is the standard deviation of annual EPS forecasts, deflated by the lagged stock price. *Following* is the number of analysts following the firm in question. *Broker Size* is the number of analysts employed by the analyst's brokerage firm. *Forecast Frequency* is the total number of forecasts issued by the analyst in a particular year for the firm in question. *Firm Experience* is the number of years an analyst has been issuing at least one earnings forecast per year for the firm in question. *General Experience* is the number of years an analyst has been issuing at least one earnings forecast per year for any firm in the I/B/E/S sample. *Firms Followed* is the number of firms covered by the analyst in question. *Industries Followed* is the number of two-digit SIC industries followed by the analyst in question.

forecasts ($f$) move from their posterior beliefs ($p$), closer to the prevailing consensus ($c$). Thus, consistent with prior studies like Clement and Tse (2005), we find evidence of herding. Unlike prior studies, we are able to parameterize the precise magnitude of herding in our sample. Examining subperiods, we find that herding began the early 1990s at about the sample mean, then dipped in the mid-1990s and early 2000s, but rose in the latter half of the 2000s, to a value of 4.435.[15]

The empirical results based on $h^2$ are qualitatively the same as those based on $h^1$. As before, we continue to find pervasive evidence of herding. Specifically, the estimate of

15. During the 2005–2010 subperiod, herding propensity increases from 2.130 in 2005 to 5.451 in 2008. It peaks at 6.654 in 2009 and then declines to 4.794 in 2010. The herding estimates thus seem to be relatively higher during the years of the financial crisis, suggesting that analysts may run to the safety of herding when faced with high uncertainty as a result of career concerns. Consistent with this finding, we also find that herding increases in other recessionary years such as 1990 ($h$ = 3.827), 1991 ($h$ = 3.845), and 2001 ($h$ = 3.915).

TABLE 2
Estimates of herding propensity: Aggregate level

| | Number of forecasts | Herding $h^1$ (orthogonal) | Herding $h^2$ (general) |
|---|---|---|---|
| **Panel A:** Full sample | | | |
| | 1,438,336 | 3.317*** | 3.545*** |
| **Panel B:** Subperiods | | | |
| 1990–1994 | 201,500 | 3.252*** | 3.680*** |
| 1995–1999 | 257,685 | 2.406*** | 2.683*** |
| 2000–2004 | 330,076 | 2.525*** | 2.745*** |
| 2005–2010 | 649,075 | 4.435*** | 4.508*** |
| **Panel C:** *Forecast Horizon* | | | |
| Horizon ≤ 69 | 362,657 | 0.987*** | 0.974*** |
| 69 < horizon ≤ 156 | 360,826 | 2.275*** | 2.316*** |
| 156 < horizon ≤ 247 | 362,754 | 5.082*** | 5.330*** |
| 247 < horizon | 352,099 | 10.799*** | 11.639*** |
| **Panel D:** *Analyst following* | | | |
| Following ≤ 5 | 365,697 | 4.597*** | 4.890*** |
| 5 < following ≤ 11 | 402,467 | 3.183*** | 3.507*** |
| 11 < following ≤ 18 | 324,031 | 2.441*** | 2.560*** |
| 18 < following | 346,141 | 1.698*** | 1.938*** |
| **Panel E:** *Broker Size* | | | |
| Broker size ≤ 18 | 382,415 | 4.385*** | 4.961*** |
| 18 < broker size ≤ 39 | 340,607 | 3.338*** | 3.608*** |
| 39 < broker size ≤ 73 | 357,373 | 3.033*** | 3.231*** |
| 73 < broker size | 357,941 | 2.503*** | 2.630*** |
| **Panel F:** *Forecast Order* | | | |
| Second forecast | 48,595 | 7.821*** | 7.729*** |
| Third forecast | 46,640 | 6.647*** | 6.765*** |
| Second to last forecast | 48,595 | 1.096*** | 1.221*** |
| Last forecast | 50,463 | 0.675*** | 0.815*** |
| **Panel G:** *Firm Experience* | | | |
| Experience ≤ 2 year | 714,152 | 3.580*** | 3.606*** |
| 2 year < Experience ≤ 3 year | 227,888 | 3.610*** | 3.268*** |
| 3 year < Experience ≤ 5 year | 257,542 | 3.536*** | 3.248*** |
| 5 year < Experience | 238,755 | 3.307*** | 3.216*** |
| **Panel H:** *General Experience* | | | |
| Experience ≤ 3 year | 362,298 | 3.856*** | 3.677*** |
| 3 year < Experience ≤ 6 year | 450,309 | 3.239*** | 3.281*** |
| 6 year < Experience ≤ 9 year | 300,207 | 2.802*** | 2.275*** |
| 9 year < Experience | 325,521 | 3.087*** | 3.236*** |

(The table is continued on the next page.)

TABLE 2 (continued)

| | Number of forecasts | Herding $h^1$ (orthogonal) | Herding $h^2$ (general) |
|---|---|---|---|
| **Panel I:** *Size ($M)* | | | |
| Size ≤ 607 | 335,157 | 3.564*** | 3.438*** |
| 607 < Size ≤ 2,031 | 355,043 | 3.227*** | 3.347*** |
| 2,031 < Size ≤ 7,533 | 369,465 | 2.689*** | 2.258*** |
| 7,533 < Size | 378,671 | 4.410*** | 4.084*** |
| **Panel J:** *BM* | | | |
| BM ≤ 1.41 | 340,995 | 3.812*** | 3.411*** |
| 1.41 < BM ≤ 2.21 | 366,664 | 2.419*** | 2.324*** |
| 2.21 < BM ≤ 3.66 | 374,407 | 0.626*** | 0.816*** |
| 3.66 < BM | 356,271 | 3.479*** | 3.722*** |

**Notes:**

This table reports estimates of herding propensity ($h^1$ and $h^2$) for the full sample and different subsamples. Estimator $h^1$ assumes orthogonal information signals, whereas estimator $h^2$ assumes no such restriction. For panels A through J, we obtain sample means of each parameter for each subsample and then compute $h^1$ using (5) and $h^2$ using (11). *Forecast Order* is the sequence of the forecast related to the annual earnings announcement date. *Size* is market value of equity measured in million dollars at year-end. *BM* is book-to-market defined as book value of equity divided by market value of equity measured at year-end. Other variables are defined as in Table 1. *** Significant at the 1 percent level.

herding for the aggregate sample is 3.545 based on $h^2$. We also find that herding began in the early 1990s at about the sample mean, then dipped in the mid-1990s and early 2000s, but rose in the latter half of the 2000s.

*Cross-sectional variation in herding propensity estimates*

In the remaining panels of Table 2, we present herding propensity, as it systematically varies across several dimensions of the analyst or his forecast. We present results for both estimators, $h^1$ and $h^2$. Results across these two alternative estimators are qualitatively very similar, so we largely discuss the results of $h^1$. In panel C, we present the herding propensity across different portfolios of forecast horizon. We define forecast horizon as the distance between forecast date and year-end annual earnings announcement date. Specifically, analysts tend to herd less when earnings announcements are imminent, with a herding propensity $h^1$ of 0.987 when forecast horizons are less than 69 days.[16] Conversely, they tend to herd more in longer forecast horizons, with an estimated $h^1$ of 10.799 when forecast horizons are more than 247 days. Panel C of Table 2 shows that the propensity to herd increases monotonically as the forecast horizon increases. This phenomenon is consistent with the argument in Graham (1999) that information uncertainty induces herding behavior because there is less uncertainty about the earnings information as earnings announcement dates are approaching.

16. We remove the forecasts issued on the day of or the day after the earnings announcement to mitigate the concern that an anti-herding forecast issued within this window could be because of the arrival of public information instead of an analyst's tendency to anti-herd. We find a higher average herding estimate after excluding these forecasts.

In panel D, we report that herding systematically varies with analyst following (coverage). We do not have any ex ante prediction regarding the relation between herding and analyst following. On one hand, the crowd effect could be stronger when the crowd is larger. On the other hand, there may be greater value to deviating from the crowd when the crowd is larger. Our finding suggests that analysts tend to herd less when analyst following is high, with an estimated $h^1$ of 1.698 when coverage is greater than 18. Conversely, estimated $h^1$ is 4.597 when coverage is less than five. Panel D of Table 2 shows that the herding propensity decreases monotonically with the increase in analysts following. So the evidence supports the notion that analysts benefit more from deviating from the consensus when analyst following is larger. In panel E, we show that analysts employed by larger brokerage firms tend to herd less, perhaps because larger brokerage firms tend to be more prestigious and hire analysts with better skills and/or more self-confidence. Specifically, we find our estimated $h^1$ monotonically decreases from 4.385 for our smallest broker-size portfolio to 2.503 for our largest broker-size portfolio.

In panel F, we present results across varying order of the forecasts issued. We find the propensity to herd is highest for the second forecast of the quarter, with an estimated $h^1$ of 7.821. There is a monotonic decrease in $h^1$, with the last forecast of the quarter exhibiting an estimated 0.675.

In panels G and H, we examine the herding estimates based on analysts' characteristics, such as firm experience and general experience. *Firm Experience* is the number of years an analyst has been issuing at least one earnings forecast per year for the firm in question, and *General Experience* is the number of years an analyst has been issuing at least one earnings forecast per year for any firm in the I/B/E/S sample. We find that analysts herd in all the subsamples while there is no systematic pattern of variation between herding propensity and analyst firm and general experience.

Lastly, in panels I and J, we present herding estimates for different size and book-to-market ratio groups. *Size* is market value of equity in million dollars measured at year-end. *BM* is the book-to-market ratio defined as book value of equity divided by market value of equity measured at year-end. Once again we do find that analysts herd in all the subsamples. However, herding estimates do not vary systematically with size or book-to-market.

Results across all panels are qualitatively similar for $h^2$. We still find evidence that herding propensity increases with forecast horizons and decreases with analyst following, broker size, and forecast order.

### *Estimates of herding propensity ($\hat{h}$) at the analyst level*

Prior studies examine herding at the forecast level. In this subsection, we present estimates of herding propensity, $h$, obtained at the level of the individual analyst. Such analyst-level analysis enables us to infer whether forecast-level herding documented in prior studies arises from just a small minority of herding analysts that make frequent forecasts, or whether such herding arises from a majority of analysts that herd.

Because our formula for analysts' herding propensity is valid asymptotically, we require an analyst to issue at least 20 forecasts in estimating his herding propensity.

In panel A of Table 3, the top line indicates that 4,775 analysts—or 68.73 percent of all herding propensity estimates ($h^1$)—are positive ($h > 0$), suggesting that most analysts tend to herd.

Panel B of Table 3 reports the statistical significance of the herding propensity estimates $h^1$ at the 5 percent level. We find that of the total 6,947 analysts we examine, a total of 4,378 of them (63.02 percent of the sample) tend to herd, whereas 16.19 percent of the analysts tend to anti-herd. Lastly, we find 20.79 percent of the analysts are unbiased in their forecasts. Collectively, our evidence suggests that most analysts tend to herd, though

TABLE 3
Estimates of herding propensity ($h^1$ and $h^2$): Analyst level

**Panel A:** Distribution of analysts based on herding propensity (orthogonal $h^1$)

| Herding propensity | $h_i \rightarrow -1$ | $-1 < h_i \leq 0$ | $h_i > 0$ | Total |
|---|---|---|---|---|
| Herding $h^1$ | 1,563 | 609 | 4,775 | 6,947 |
| (orthogonal) | 22.50% | 8.77% | 68.73% | |
| Herding $h^2$ | 1,377 | 688 | 4,882 | 6,947 |
| (general) | 19.82% | 9.91% | 70.27% | |

**Panel B:** Distribution of analysts classified as anti-herding, no herding, and herding (based on orthogonal $h^1$)

| Herding propensity | Anti-herding | No herding | Herding | Total |
|---|---|---|---|---|
| Herding $h^1$ | 1,125 | 1,444 | 4,378 | 6,947 |
| (orthogonal) | 16.19% | 20.79% | 63.02% | |
| Herding $h^2$ | 1,089 | 1,242 | 4,616 | 6,947 |
| (general) | 15.68% | 17.88% | 66.44% | |

**Notes:**

This table reports the distribution of analysts based on their herding propensity. For each analyst, we employ the forecasts issued over the 1990–2010 sample period to obtain sample means of each parameter and compute the analyst's herding propensity based on orthogonal information signals, $h^1$ (see (5)) or herding propensity based on signals not restricted to be orthogonal, $h^2$ (see (11)). We require an analyst to issue at least 20 forecasts in estimating his herding propensity. In panel A, we report the total number of analysts for whom the herding estimates approach negative one, are between negative one and zero, and are greater than zero. In panel B, we report the total number of analysts for whom the herding estimates are significantly negative (anti-herding), statistically insignificant (no herding), and significantly positive (herding).

a significant proportion of analysts does anti-herd. Results are qualitatively similar for $h^2$. This evidence is consistent with the widely held presumption that herding among financial analysts is pervasive. It also suggests that the aggregate evidence is not caused by a few herding analysts forecasting extensively.

### *Out-of-sample estimates of herding propensity ($\hat{h}$) and forecast accuracy*

Prior studies typically examine the in-sample determinants of herding forecasts (e.g., Clement and Tse 2005). In this section, we use two out-of-sample tests to validate our in-sample estimates of herding propensity. Specifically, we examine how our in-sample analyst-specific herding propensity estimates can explain (i) out-of-sample herding behavior, as well as (ii) out-of-sample future forecast accuracy. Ours is the first study to examine such out-of-sample herding behavior.

We use a rolling window design for the out-of-sample tests. For every out-of-sample year, we use the previous five years as the estimation period. We estimate herding propensity $h$ for each analyst that issues at least 20 forecasts in the estimation period, and apply this in-sample estimate of $h$ to the year immediately after the estimation period.[17] Since our sample starts from 1990, the first out-of-sample year is 1995. So for the year 1995, $h$

17. Our results are robust to different requirements of minimum number of forecasts such as 30 or 40.

is estimated using data from 1990 to 1994. We thus have 16 out-of-sample years (1995–2010). Using the Fama and MacBeth (1973) approach, we estimate 16 annual cross-sectional regressions and report the average coefficients and corresponding statistics.

*Out-of-sample predictions of herding behavior*

We first examine whether our in-sample herding propensity estimates are useful in predicting out-of-sample herding behavior. We examine this issue by estimating a model motivated by Clement and Tse (2005, equation 3), with in-sample herding propensity estimates added as an additional explanatory variable. The model is as follows, where *i* and *t* are analyst and time subscripts:

$$\begin{aligned} Forecast\,Boldness_{it} = {} & \beta_0 + \beta_1 \hat{h}_{it} + \beta_2 Days\,Elapsed_{it} + \beta_3 Forecast\,Horizon_{it} \\ & + \beta_4 Past\,Accuracy_{it} + \beta_5 Broker\,Size_{it} + \beta_6 Forecast\,Frequency_{it} \\ & + \beta_7 Firm\,Experience_{it} + \beta_8 General\,Experience_{it} \\ & + \beta_9 Firms\,Followed_{it} + \beta_{10} Industries\,Followed_{it} + \varepsilon_{it}, \end{aligned} \tag{13}$$

where *Forecast Boldness* is the absolute deviation of future forecasts from their immediately preceding consensus forecasts, scaled by the lagged stock price,[18] $\hat{h}_{it}$ is the herding propensity estimated at the analyst level using data from the previous five years. *Days Elapsed* is the number of calendar days passed since the last annual EPS forecast issuance. *Forecast Horizon* is the number of days between the forecast date and the year-end annual earnings announcement date. *Past Accuracy* is the analyst's forecast accuracy in the previous year, measured as the absolute forecast error of the last forecast issued by the analyst at least 30 days prior to the last year's annual earnings announcement date, scaled by the lagged stock price; the variable is transformed so that a larger value indicates higher accuracy. *Broker Size* is the number of analysts employed by the analyst's brokerage firm. *Forecast Frequency* is the total number of forecasts issued by the analyst in a particular firm-year. *Firm Experience* is the number of years an analyst has been issuing at least one earnings forecast per year for the firm in question. *General Experience* is the number of years an analyst has been issuing at least one earnings forecast per year for any firm in the I/B/E/S sample. *Firms Followed* is the number of firms covered by the analyst. *Industries Followed* is the number of two-digit SIC industries followed by the analyst.

Following Clement and Tse (2005), we normalize all variables (except $\hat{h}$) to range between zero and one.[19] To standardize $\hat{h}_{it}$, we first rank it into percentiles and then scale it to range between zero and one.

We report the results of our Fama-MacBeth regressions in panel A of Table 4. The estimated coefficient on our key variable, $\hat{h}_{it}$ (in-sample herding propensity), is significantly negative based on $h^1$ (−0.009, *t* −2.76), suggesting that analysts that exhibit relatively higher in-sample herding propensity also exhibit lower out-of-sample forecast boldness

18. Clement and Tse (2005) classify earnings forecasts as bold if they are above or below both an analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast. All other forecasts are classified as herding. We do not use this measure of forecast boldness because it assumes that the analyst's posterior belief is his prior forecast while we use a different proxy for the analyst's posterior belief. This difference makes the direct comparison between our results and their results difficult. Hence, we focus on their second measure of forecast boldness, the absolute deviation from the previous consensus.

19. The scaling procedure standardizes the variables, essentially rescaling the raw variables to range between zero and one. Following Clement and Tse (2005), we compute the scaled values of those variables with the following formula: Scaled $X = (X - Min\ X) / (Max\ X - Min\ X)$, where *X* is a variable and *Min* (*Max*) represents the *minimum* (*maximum*) value of the variable for a particular firm-year. Scaled *Accuracy* has the same denominator as the formula above, but the numerator is (*Max Accuracy* − *Accuracy*).

TABLE 4
Out-of-sample association between herding propensity and forecast boldness or forecast accuracy

**Panel A:** Forecast boldness

| Variable | Herding $h^1$ (orthogonal) | | Herding $h^2$ (general) | |
|---|---|---|---|---|
| | Coefficient | *t*-statistic | Coefficient | *t*-statistic |
| Intercept | 0.198 | 25.41 | 0.204 | 29.59 |
| *Herding Propensity* | −0.009 | −2.76 | −0.011 | −3.08 |
| *Days Elapsed* | 0.055 | 15.05 | 0.053 | 12.05 |
| *Forecast Horizon* | 0.029 | 2.33 | 0.023 | 1.86 |
| *Past Accuracy* | −0.028 | −5.94 | −0.022 | −6.94 |
| *Broker Size* | 0.036 | 7.50 | 0.046 | 8.00 |
| *Forecast Frequency* | 0.022 | 10.45 | 0.020 | 8.34 |
| *Firm Experience* | 0.017 | 6.90 | 0.016 | 5.29 |
| *General Experience* | 0.032 | 7.46 | 0.027 | 5.91 |
| *Firms Followed* | 0.027 | 7.46 | 0.028 | 8.05 |
| *Industries Followed* | 0.011 | 3.87 | 0.010 | 3.48 |
| Adjusted $R^2$ (%) | 11.64 | | 17.90 | |

**Panel B:** Forecast accuracy

| Variable | Herding $h^1$ (orthogonal) | | Herding $h^2$ (general) | |
|---|---|---|---|---|
| | Coefficient | *t*-statistic | Coefficient | *t*-statistic |
| Intercept | 0.916 | 141.13 | 0.917 | 127.08 |
| *Herding Propensity* | −0.013 | −5.79 | −0.010 | −3.61 |
| *Days Elapsed* | −0.050 | −21.03 | −0.053 | −21.44 |
| *Forecast Horizon* | −0.379 | −28.28 | −0.391 | −25.14 |
| *Past Accuracy* | 0.050 | 14.20 | 0.046 | 13.51 |
| *Broker Size* | 0.004 | 1.71 | 0.004 | 1.50 |
| *Forecast Frequency* | −0.038 | −18.08 | −0.036 | −21.63 |
| *Firm Experience* | −0.003 | −1.62 | −0.002 | −0.65 |
| *General Experience* | −0.005 | −2.16 | −0.003 | −1.56 |
| *Firms Followed* | −0.014 | −3.66 | −0.012 | −2.48 |
| *Industries Followed* | −0.024 | −6.84 | −0.028 | −7.53 |
| Deviation from year-end consensus | −6.112 | −11.78 | −6.744 | −13.20 |
| Deviation from preceding consensus | 4.205 | 10.68 | 4.898 | 16.70 |
| Adjusted $R^2$ (%) | 31.91 | | 35.95 | |

**Notes:**

This table reports out-of-sample associations between forecast boldness, forecast accuracy and estimates of herding propensity. Estimator $h^1$ assumes orthogonal information signals, whereas estimator $h^2$ assumes nonorthogonal information signals. *Forecast Boldness* is the absolute value of the difference between the consensus forecast and the analyst EPS forecast, deflated by the lagged stock price, scaled to range between 0 and 1 for each firm-year. *Forecast Accuracy* is the absolute value of the difference between the actual EPS and the analyst EPS forecast, deflated by the lagged stock price, scaled to range between 0 and 1 for each firm-year. This variable is transformed so that a larger value indicates higher accuracy. We perform a rolling regression analysis; that is, each year, we estimate analysts' herding propensity using data over the previous five years. We obtain sample means of each parameter for the previous five years and then compute $h^1$ using (5) and $h^2$ using (11). All independent variables are scaled to range between 0 and 1 and are as described in Table 1. We estimate 16 annual cross-sectional regressions from 1995 to 2010 and report average yearly coefficients and Fama and MacBeth (1973) *t*-statistics.

(i.e., higher levels of out-of-sample herding). Results are qualitatively similar for $h^2$. This result lends support to the stability of our herding propensity estimates.

The signs of other independent variables are largely consistent with those in Clement and Tse (2005). Interestingly, we find analysts' *Firm Experience* is strongly and positively associated with *Forecast Boldness* (0.017, $t$ 6.90), but Clement and Tse do not find this variable to be significant. However, our results are consistent with those in Clarke and Subramanian (2006), who find that analysts' experience has a positive effect on future boldness. Similarly, Mikhail, Walther, and Willis (2003) document that analysts' underreaction to prior earnings information is reduced as their experience following a firm increases.

*Out-of-sample predictions of forecast accuracy*

We examine the out-of-sample explanatory power of herding propensity with respect to forecast accuracy using a model motivated by Clement and Tse's (2005) equation (5), again adding in-sample herding propensity estimates as an additional explanatory variable, and using all forecasts instead of the latest forecasts. All variables are again transformed/standardized. We estimate the following model, where $i$ and $t$ are analyst and time subscripts:

$$\begin{aligned} \mathit{Forecast\,Accuracy}_{it} = \beta_0 &+ \beta_1 \hat{h}_{it} + \beta_2 \mathit{Days\,Elapsed}_{it} + \beta_3 \mathit{Forecast\,Horizon}_{it} \\ &+ \beta_4 \mathit{Past\,Accuracy}_{it} + \beta_5 \mathit{Broker\,Size}_{it} + \beta_6 \mathit{Forecast\,Frequency}_{it} \\ &+ \beta_7 \mathit{Firm\,Experience}_{it} + \beta_8 \mathit{General\,Experience}_{it} \\ &+ \beta_9 \mathit{Firms\,Followed}_{it} + \beta_{10} \mathit{Industries\,Followed}_{it} \\ &+ \beta_{11} \mathit{Deviation\,from\,year\text{-}end\,consensus}_{it} \\ &+ \beta_{12} \mathit{Deviation\,from\,preceding\,consensus}_{it} + \varepsilon_{it}, \end{aligned} \tag{14}$$

where *Forecast Accuracy* is the absolute difference between earnings forecast and actual earnings deflated by the lagged stock price. *Deviation from year-end consensus* is the absolute difference between the earnings forecast and the year-end consensus, where year-end consensus is the average of all forecasts issued within 90 days from the annual earnings announcement date, scaled by the lagged stock price. *Deviation from preceding forecast* is the absolute difference between the earnings forecast and the preceding consensus forecast, scaled by the lagged stock price.

All other variables are defined as in (13) above.

The regression results are reported in panel B of Table 4. We find that, consistent with our prediction, the coefficient on in-sample herding propensity $h^1$ is significantly negative (−0.013, $t$ −5.79), suggesting that analysts who tend to herd in-sample have lower forecast accuracy out-of-sample. Results are qualitatively similar for $h^2$. This result is consistent with Clement and Tse's (2005) results that bold forecasts tend to be more accurate. The signs and significance of all other independent variables are highly consistent with those reported in Clement and Tse (2005). Collectively, our test on out-of-sample forecast accuracy suggests that our ex ante estimates of herding propensity are predictive of future forecast accuracy.

Overall, we find the results across our two alternative measures, $h^1$ and $h^2$, to be qualitatively very similar. Indeed, for analyst-level estimates, the correlation between the two estimates is significantly positive, with a Pearson (Spearman) correlation of 0.86 (0.89). For sake of brevity, in the rest of the paper, we present results based only on $h^1$.

***Ex post adjustments to earnings forecasts for herding behavior***

The parametric structure we introduce in this study—in particular the first-order condition in the analyst optimization problem—enables us to implement Trueman's (1994) recommendation that raw forecasts should be adjusted for herding propensity. From (6), we know the posterior belief $p = f + h(f - c)$. Once we have an estimate for $h$ from past data, we can use the above formula for $p$ to measure the posterior belief—even before actual earnings is observed—given the forecasts and prevailing consensus. We refer to such a $p$ as an adjusted forecast.

To test whether this adjustment is useful, we assume market participants have access to the same forecast history that we have and estimate $h$ for each analyst, and then adjust the next forecast by that analyst using $h$ as indicated in the above formula. We compute forecast errors for both the raw unadjusted forecasts and the adjusted forecasts, and use these errors to compute potential biases in each analyst's forecasts. We select all analysts with at least 20 earnings forecasts and use all historical forecasts of a given analyst for computing $h$ with an ever-increasing rolling window starting from the past 19 forecasts.[20] In untabulated results, we find that there is a nontrivial reduction in the forecast bias for 64.1 percent of the analysts in our sample (3,942 out of 6,150 analysts). This improvement in earnings forecasts is significant in the aggregate analysts data with Student's $t$-value of 28.66, Sign M-value of 867, and Signed Rank S value of 3,868,311. All these values are significant at the 1 percent level of significance.

This analysis implements one simple, straightforward empirical design. Even with the same formula for $p$, we can experiment with a variety of estimation and prediction windows and additional sample filters, which could result in a further reduction of bias. We have also assumed the same definition of the prevailing consensus as before, which is consistent with investors being moved by forecasts as reported. If we further dynamically change the measured prevailing consensus for adjustments to prior forecasts, it is possible that an even further reduction in bias is possible. Such further exploration has potentially significant practical value for other researchers and investment managers.

## 6. Other tests

### *Robustness tests*

We perform several robustness tests to ensure that our findings are not sensitive to our specification choices.

#### *Sample*

Our original sample was 1990–2010. We did not include pre-1990 observations because of data error issues in I/B/E/S documented in prior studies. In robustness tests, we also include observations from the 1983–1989 years. Results and inferences are qualitatively unchanged.

#### *Quarterly forecasts*

In untabulated robustness tests, we replicate our analysis using quarterly earnings forecasts and find $h$ continues to show significant herding ($h$ = 1.96).[21] Other results and inferences using quarterly estimates are qualitatively similar.

20. For example, we compute $h$ 181 times in a rolling forward way if the analyst makes 200 earnings forecasts. We compute $h$ 1,271,717 times on 6,150 analysts in the data.

21. Using a nonparametric measure of herding, Bernhardt et al. (2006) report evidence of anti-herding in their sample of quarterly earnings forecasts. In untabulated tests, we replicate their results for the same sample period. Further analysis reveals that the authors' $S$ measure (or its monotone transformation) and our $h$ measure are either weakly (Pearson) or significantly negatively (Spearman) correlated. Related to this, we find our $h$ measure is inversely related to earnings volatility, as predicted by Trueman (1994); however, Berhardt et al.'s nonparametric $S$ measure does not exhibit this inverse relation. This difference in results suggests that it is critical to consider a *parametric* measure of herding, as we do. If we know the form of the objective function, then parametric estimation will yield more efficient estimates; so the validation of our model is relevant to a choice between parametric and nonparametric approaches. This highlights the importance of our out-of-sample analyses in section 5.

*Variable measurement*

In calculating a prevailing consensus forecast, we used the average of the last forecast made by each analyst prior to the current forecast. In robustness tests, we consider two alternative measures: (i) the forecast-horizon-weighted average of the last forecast made by each analyst prior to the current forecast, and (ii) the average of the last forecast made by each analyst within 30 days prior to the current forecast. Results and inferences are qualitatively unchanged.

In calculating analysts' posterior beliefs, we specified the variance $s$ as the directly estimable variance of each analyst's forecast error. That is, for each forecast corresponding to an analyst firm-year, we used the entire history of forecast errors of the same analyst firm up to and including the current year to compute the forecast error variance. We explore several alternatives, such as using only the history up to the prior period, or limiting the history to a fixed number of prior periods (e.g., four quarters). Untabulated results and inferences are qualitatively unchanged.

Because our formula for analysts' herding propensity is valid asymptotically, we required an analyst to issue at least 20 forecasts in estimating his herding propensity. To examine the robustness of our estimate, we also estimate herding propensity based on requirements of at least 30 or 40 forecasts. Similar robustness tests were performed for our out-of-sample tests. Results and inferences are qualitatively unchanged.

***Alternative explanation: Slow learning, or walking-up/walking-down estimates***

Recent studies have suggested that analysts learn slowly or adjust their forecasts slowly. For instance, Richardson et al. (2004) provide evidence in the context of equity issues, where they argue also that forecast bias declines as analysts learn more. Cotter, Tuna, and Wysocki (2006) show that this pattern is driven in part by management guidance, whereas Ciccone (2005) suggests the pattern may prevail even in other contexts. As with most prior empirical studies, the possibility of such slow learning suggests that the pattern we document may merely reflect a monotonic "walk," up or down, in the direction of the actual announcement. This slow learning may not have anything to do with the influence of the prevailing consensus on analysts' earnings forecasts. Yet it is clear that such a pattern will also give rise to positive estimates of $h$ that indicate herding. For example, using the actual earnings ($a$) as a proxy for analysts' posterior beliefs ($p$), we have argued that herding occurs if an analyst's new forecast falls in between the prevailing consensus and analysts' posterior beliefs (i.e., $p < f < c$ or $p > f > c$). Assume that analysts are fully rational and their initial forecasts happen to be above actual earnings. As objective new information arrives, the revised forecast ($f$) could lie in between the prevailing consensus ($c$) and the actual earnings ($a$), even without any strategic choice to be close to the prevailing consensus.

To assess if our significant $h$ estimates are driven primarily by the walk-up/walk-down pattern, we construct an empirical measure of the likelihood of the walk-up or walk-down pattern arising from slow learning in the following way. For each firm $i$ in year $t$ we order all the forecasts in time as $\{f_k\}$, $k = 1, 2, \ldots N + 1$, where there are $N + 1$ forecasts before the actual announcement $\bar{a}$. If the walk-up/walk-down effect is strong we expect to see the sequence of forecasts to be dominated by a monotonically increasing or decreasing pattern. To capture this we first define $\{t_k\}$, $k = 1, 2, \ldots N$, where

$$\begin{aligned} t_k = 1 \quad \text{if} \quad & (i) \;\; \text{sign}(f_k - f_{reference}) = \text{sign}(\bar{a} - f_{reference}) \text{ and} \\ & (ii) \;\; (f_k - f_{reference}) < (\bar{a} - f_{reference}), \text{if} \quad (\bar{a} - f_{reference}) > 0, \text{or} \\ & \qquad (f_k - f_{reference}) > (\bar{a} - f_{reference}), \text{if} (\bar{a} - f_{reference}) < 0, \\ t_k = 0 \quad & \textit{otherwise}. \end{aligned}$$

TABLE 5
Estimates of herding propensity in subsamples partitioned by the "speed of learning"

| | Number of forecasts | Herding propensity ($h^1$) |
|---|---|---|
| **Panel A:** Slow learning indicator | | |
| Less likely slow learning | 963,924 | 2.981*** |
| More likely slow learning | 474,412 | 3.606*** |

**Panel B:** More likely slow learning

Distribution of herding propensity ($h_i$)

| $h_i \to -1$ | $-1 < h_i < 0$ | $h_i > 0$ |
|---|---|---|
| 1,049 | 267 | 3,258 |
| 22.9% | 5.8% | 71.2% |

Distribution of anti-herding, no herding, and herding analysts

| Anti-herding | No herding | Herding |
|---|---|---|
| 1,093 | 470 | 3,011 |
| 23.9% | 10.3% | 65.8% |

**Panel C:** Less likely slow learning

Distribution of herding propensity ($h_i$)

| $h_i \to -1$ | $-1 < h_i < 0$ | $h_i > 0$ |
|---|---|---|
| 934 | 536 | 3,130 |
| 20.3% | 11.7% | 68.0% |

Distribution of anti-herding, no herding, and herding analysts

| Anti-herding | No herding | Herding |
|---|---|---|
| 1,168 | 669 | 2,763 |
| 25.4% | 14.5% | 60.1% |

**Notes:**

This table reports aggregate estimates of herding propensity ($h^1$) for slow learning subsamples, as well as estimates at the analyst level, after partitioning the sample based on values of slow learning. Refer to section 6 for details about measuring slow learning. *** Significant at the 1 percent level.

Thus for each forecast after the first forecast for a given firm/year, we examine if the next forecast relative to a reference forecast matches in sign the overall movement from the reference forecast to the actual earnings announced. We consider two alternative reference forecasts: the immediately previous forecast and the first forecast in a sequence.[22] The side-conditions in (ii) above ensure that we only count forecasts that move toward the actual earnings but do not switch from say, optimism to pessimism. Previous work (e.g., Richardson et al. 2004), suggests that such switching more likely reflects strategy rather

22. Following Richardson et al. (2004), we report results for the case where the reference forecast is the first forecast. The results from the other definition of a reference forecast are qualitatively similar.

than slow learning. Without slow learning, the probability that $t_k = 1$ would equal one-half; with slow learning, this probability would exceed one-half. So we interpret a sequence of forecasts as representing a set of binomial trials, and compute the cumulative binomial probability of getting the observed number of successes. We then define a slow learning (*SL*) indicator taking the value of one if the cumulative binomial probability exceeds 90 percent and taking the value of zero otherwise.

Our slow learning indicator, *SL*, factors in the whole sequence of prior forecasts because our goal is to identify the walk-up/walk-down pattern that could arise from slow learning. Note that our method of defining *SL* assigns the same value to each forecast in a sequence of forecasts leading up to actual earnings. We then separately estimate $h$ for the sample with forecasts having $SL = 1$ (i.e., forecasts more likely to be part of a slow learning pattern), and with forecasts with $SL = 0$ (less likely to be part of a slow learning pattern). In general, not all instances of a walk-up/walk-down pattern will arise from slow learning, and some will arise from herding. Since *SL* over-counts cases where slow learning is more likely and under-counts cases of herding, our inference on herding propensity below is conservative.

Panel A of Table 5 shows that our estimated $h$ increases from 2.981 to 3.606 as we move from $SL = 0$ to $SL = 1$. We find herding is significant even when $SL = 0$. In panels B and C of Table 5, we mimic the results presented in Table 3, this time including partitions based on the likelihood of slow learning.[23] In general, we find that a significant majority of positive herding propensity estimates exists even when slow learning is less likely. Specifically, panel B shows that our estimated herding propensity $h$ is positive for 71.2 percent and statistically significant for 65.8 percent of analysts when we examine the More likely slow learning subsample. In panel C, we find that 68.0 percent of analysts that are less likely to be slow learning have positive herding propensity, whereas 60.1 percent of them have statistically significant positive herding propensity. These findings increase the confidence that our $h$ parameter does indeed capture herding toward the prevailing consensus rather than merely slow learning by analysts.

## 7. Conclusion

By invoking rational expectations, we develop a measure of imitation-driven herding propensity in the context of an explicit analyst optimization problem. We then estimate herding propensity using two measures: First, we estimate analysts' posterior beliefs using actual earnings plus a realization drawn from a mean-zero normal distribution. Second, we estimate herding propensity using rational expectations alone, relaxing the orthogonal factor structure requirement of our first measure, and thus allowing for nonorthogonal information signals. In both measures, we avoid the traditional criticism in the literature regarding the use of the analyst's prior forecast as the proxy for his posterior beliefs. Both measures yield qualitatively similar results. We find more than 60 percent of analysts herd toward the prevailing consensus even after controlling for forecast sequence patterns that reflect analysts' potential slow learning. We also document factors associated with herding propensity, such as forecast horizon, analyst following, broker/employer size, and forecast order.

Next, we validate our herding propensity measure by confirming its predictive power in explaining the cross-sectional variations in analysts' out-of-sample herding behavior and forecast accuracy.

23. Besides the version of *SL* in which each forecast in a sequence is assigned the same value, we also used a definition in which (6) is applied to each subsequence up to the current forecast, so that forecasts in the same sequence can have different *SL* values. The results were almost identical. The results in panels B and C are based on a measure of *SL* that allows the indicator value to vary across forecasts even within the same sequence.

Finally, we implement Trueman's (1994) recommendation that analyst forecasts be adjusted for herding propensity. We find that forecasts adjusted for analysts' herding or anti-herding propensity are less biased than the raw forecasts. Given the simplicity of the required adjustment, and many alternative ways of implementing this same adjustment (by varying estimation and prediction windows and sample filters), it seems likely that the bias can be reduced even further. This adjustment formula can help researchers and investors obtain better proxies for analysts' unbiased earnings forecasts when analysts herd or anti-herd. This should help applications that rely on proxies of analysts' unbiased earnings forecasts, such as the construction of consensus earnings forecasts, or the identification of good and bad news to guide investment decisions.

## Appendix

### *Consistency of herding estimator*

In this Appendix, we discuss why our estimator of $h$ given in (5) of Theorem 1 is a consistent estimator. We first note that convergence of the $h$ estimator only requires that sample means converge to population means. To see this, first start from the first-order condition which defines the population moment and provides the model for expected errors.

$$(1+h)f = p + hc \qquad (\textit{first-order condition}) \qquad (2)$$

$$\Rightarrow (1+h)f - p - hc = 0 \qquad (\textit{rewritten first-order condition}) \qquad (A.1)$$

$$\Rightarrow \mathrm{E}[(1+\mathrm{h})\mathrm{f} - \mathrm{p} - \mathrm{hc}] = 0 \qquad (\textit{population moment}) \qquad (A.2)$$

$$\Rightarrow (1+h)\mathrm{E(f)} - \mathrm{E(p)} - \mathrm{hE(c)} = 0 \qquad (\textit{rewritten population moment}) \qquad (A.3)$$

$$\Rightarrow (1+h)\bar{f} - \bar{p} - h\bar{c} = 0 \qquad (\textit{sample moment}) \qquad (A.4)$$

Hence the population $h$ is defined by (A.3) above, whereas our empirical estimate of $h$ is defined by (A.4) above. Therefore the question of consistency reduces to asking if the sample means in (A.4) converge to the population means in (A.3).

For the sample means in (A.3) to converge to the population means in (A.4), some restrictions are required. The tradition in the GMM literature (e.g., Hansen and Singleton 1982) has been to invoke a very broad regularity condition like ergodicity, which allows for departures from i.i.d., rules out pathological cases, and essentially assumes that the variance of each variable in (A.4) and (A.5) is sufficiently bounded and can be estimated from a historical time series.

An alternate and equivalent way to obtain our estimates of $h$ would be to rewrite the first-order condition as

$$f = \left(\frac{1}{1+h}\right)p + \left(\frac{h}{1+h}\right)c, \qquad (A.5)$$

which suggests the following zero-intercept linear regression model

$$f = \beta_1 p + \beta_2 c + \varepsilon, \qquad (A.6)$$

and our estimate for $h$ will then be given by $(\beta_2/\beta_1)$. This does have the advantage of being consistent with a more common statistical procedure, but would require us to specify the error distribution more precisely; for example., that the error $\varepsilon$ is distributed as a Newey-West error with a particular kernel and lag. However, our estimates of $h$ are consistent for even a family of Newey-West error distributions without any requirement to specify a particular kernel and lag.

**References**

Admati, A., and P. Pfleiderer. 1988. A theory of intraday trading patterns: Volume and price variability. *The Review of Financial Studies* 1 (1): 3–40.

Asquith, P., M. B. Mikhail, and A. S. Au. 2005. Information content of equity analyst reports. *Journal of Financial Economics* 75 (2): 245–82.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman. 2001. Can investors profit from the prophets? Security analyst recommendations and stock returns. *Journal of Finance* 56 (2): 531–63.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman. 2003. Reassessing the returns to analysts' stock recommendations. *Financial Analysts Journal* 59 (2): 88–96.

Bernhardt, D., M. Campello, and E. Kutsoati. 2006. Who herds? *Journal of Financial Economics* 80 (3): 657–75.

Beyer, A. 2008. Financial analysts' forecast revisions and managers' reporting behavior. *Journal of Accounting and Economics* 46 (2–3): 334–48.

Beyer, A., and I. Guttman. 2011. The effect of trading volume on analysts' forecast bias. *The Accounting Review* 86 (2): 451–81.

Brown, L. D., and E. Mohammad. 2003. The predictive value of analyst characteristics. *Journal of Accounting, Auditing and Finance* 18 (4): 625–47.

Ciccone, S. J. 2005. Trends in analyst earnings forecast properties. *International Review of Financial Analysis* 14 (1): 1–22.

Clarke, J., and A. Subramanian. 2006. Dynamic forecasting behavior by analysts: Theory and evidence. *Journal of Financial Economics* 80 (1): 81–113.

Clement, M. B., and S. Y. Tse. 2003. Do investors respond to analysts' forecast revisions as if forecast accuracy is all that matters? *The Accounting Review* 78 (1): 227–49.

Clement, M. B., and S. Y. Tse. 2005. Financial analyst characteristics and herding behavior in forecasting. *Journal of Finance* 60 (1): 307–41.

Clement, M. B., J. Hales, and Y. Xue. 2011. Understanding analysts' use of stock returns and other analysts' revisions when forecasting earnings. *Journal of Accounting and Economics* 51 (3): 279–99.

Cotter, J., I. Tuna, and P. D. Wysocki. 2006. Expectations management and beatable targets: How do analysts react to explicit earnings guidance? *Contemporary Accounting Research* 23 (3): 593–628.

Dugar, A., and S. Nathan. 1995. The effect of investment banking relationships on financial analysts' earnings forecasts and investment recommendations. *Contemporary Accounting Research* 12 (1): 131–60.

Elliott, J. A., D. R. Philbrick, and C. I. Wiedman. 1995. Evidence from archival data on the relation between security analysts' forecast errors and prior forecast revisions. *Contemporary Accounting Research* 11 (2): 919–38.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return and equilibrium: Empirical tests. *Journal of Political Economy* 81 (3): 607–36.

Gleason, C. A., and C. M. C. Lee. 2003. Analyst forecast revisions and market price discovery. *The Accounting Review* 78 (1): 193–225.

Graham, J. R. 1999. Herding among investment newsletters: Theory and evidence. *Journal of Finance* 54 (1): 237–68.

Greenberg, E., and C. E. Webster. 1983. *Advanced Econometrics: A Bridge To The Literature*. New York: John Wiley & Sons.

Hansen, L. P., and K. J. Singleton. 1982. Generalized instrumental variables estimation of nonlinear rational expectations models. *Econometrica* 50 (5): 1269–86.

Haynes, R. 1998. The impact of trading commission incentives on analysts' stock coverage decision and earnings forecasts. *Journal of Accounting Research* 36 (2): 299–320.

Hong, H., J. D. Kubik, and A. Soloman. 2000. Security analysts' career concerns and herding of earnings forecasts. *Rand Journal of Economics* 31 (1): 121–44.

Horowitz, J. L. 2001. The Bootstrap. In *Handbook of Econometrics*, eds. J.J. Heckman and E. Leamer, Volume 5, Chapter 52, 3159–228. Amsterdam: North-Holland.

Ke, B., and Y. Yu. 2006. The effect of issuing biased earnings forecasts on analysts' access to management and survival. *Journal of Accounting Research* 44 (5): 965–99.

Keskek, S., S. Y. Tse, and J. W. Tucker. 2014. Analyst information production and forecast timing. *Review of Accounting Studies* 19 (4): 1504–31.

Kim, C., and C. Pantzalis. 2003. Global/industrial diversification and analyst herding. *Financial Analysts Journal* 59 (2): 69–79.

Lim, T. 2001. Rationality and analysts' forecast bias. *Journal of Finance* 56 (1): 369–85.

Lin, H., and M. F. McNichols. 1998. Underwriting relationships and analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics* 25 (1): 101–27.

Marinovic, I., M. Ottaviani, and P. N. Sørensen. 2011a. Modeling idea markets: Between beauty contests and prediction markets. In *Prediction Markets: Theory and Applications*, ed. L. V. Williams, Chapter 2, 4–17. London: Routledge.

Marinovic, I., M. Ottaviani, and P. N. Sørensen. 2011b. Forecasters' objectives and strategies. In *Handbook of Economic Forecasting*, ed. G. Elliott and A. Timmermann, Volume 2B, 689–720. Amsterdam: North-Holland.

McFadden, D. L., and P. A. Ruud. 1994. Estimation by simulation. *The Review of Economics and Statistics* 76 (4): 591–608.

McNichols, M., and P. Wilson. 1988. Evidence of earnings management from the provision of bad debts. *Journal of Accounting Research* 26 (Supplement): 1–31.

Mikhail, M. B., B. R. Walther, and R. H. Willis. 2003. The effect of experience on security analyst underreaction. *Journal of Accounting and Economics* 35 (1): 101–16.

Morris, S., and H. S. Shin. 2002. Social value of public information. 2002. *The American Economic Review* 92 (5): 1521–34.

Ottaviani, M., and P. N. Sørensen. 2006. The strategy of professional forecasting. *Journal of Financial Economics* 81 (2): 441–66.

Prendergast, C. 1993. A theory of "yes men". *American Economic Review* 83 (4): 757–70.

Prendergast, C., and L. Stole. 1996. Impetuous youngsters and jaded old-timers: Acquiring a reputation for learning. *Journal of Political Economy* 104 (6): 1105–34.

Richardson, S., S. H. Teoh, and P. D. Wysocki. 2004. The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. *Contemporary Accounting Research* 21 (4): 885–924.

Schipper, K. 1991. Commentary on analysts' forecasts. *Accounting Horizons* 5 (December): 105–22.

Stickel, S. E. 1990. Predicting individual analyst earnings forecasts. *Journal of Accounting Research* 28 (Autumn): 409–17.

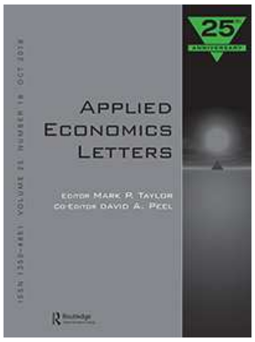
Trueman, B. 1994. Analyst forecasts and herding behavior. *Review of Financial Studies* 7 (1): 97–124.

Welch, I. 2000. Herding among security analysts. *Journal of Financial Economics* 58 (3): 369–96.

Womack, K. L. 1996. Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51 (1): 137–67.

Zhang, F. 2006. Information uncertainty and analyst forecast behavior. *Contemporary Accounting Research* 23 (2): 565–90.

Zitzewitz, E. 2001. Measuring herding and exaggeration by equity analyst and other opinion sellers. Working paper, Stanford University.



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# Stock price impact of diversity in investor beliefs

Murugappa (Murgie) Krishnan

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ARTICLE

# Stock price impact of diversity in investor beliefs

Murugappa (Murgie) Krishnan

Radford University, Radford, USA

**ABSTRACT**

I re-examine the association between diverse investor beliefs and stock prices within the context of an imperfect competition model. The relationship is ambiguous because of several different effects of a change in diversity in investor beliefs. This has implications for empirical design and explains why 40 years of evidence on this association is inconclusive.

**KEYWORDS**

Diverse beliefs; returns; correlated signals

**JEL CLASSIFICATION**

G12; G14

## I. Introduction

Does increasing diversity of investor beliefs cause stock prices to rise? Miller (1977) asserts that as belief diversity increases, short-sale restrictions would bite more, and supply restrictions would cause current prices to be higher. Williams (1977) assumes more diverse beliefs reflect more risk, and so risk-averse investors would require a higher return as compensation, causing prices to be lower. Forty years of evidence (see Han, Pan, and Zhang (2017) for a recent review) is inconclusive.

The Miller (1977) and Williams (1977) theories are not mutually exclusive, and it is possible both supply constraints from short-sale restrictions and requiring compensation for greater risk both matter, to different degrees in different cases. The empirical literature has often used diversity in analyst earnings forecasts to proxy for diversity in investor beliefs (e.g. Sadka and Scherbina (2007)). Other proxies for belief dispersion (see, e.g. Diether, Malloy, and Scherbina (2002), Epstein and Schneider (2008), and Han, Pan, and Zhang (2017)), such as turnover, unexplained trading volumes and breadth of mutual fund ownership, are potentially contaminated by other return predictors. Inconclusive evidence may reflect a problem with the underlying theories or with the empirical measures used to proxy for belief dispersion.

I re-examine the theoretical foundations of the above predictions within an imperfect competition model that is a priori more plausible on empirical grounds. The key comparative static relating belief diversity to stock price impact is in general ambiguous. To obtain a prediction necessarily involves imposing additional restrictions.

Even with risk-neutrality, in a single-asset Kyle model with correlated component payoff structure, we need assumptions about how payoff variability grows as belief diversity increases, and about the exact level of diversity, to predict if the stock price will rise. This raises sharper questions about how to interpret the prior literature, and about how the empirical designs used need to be modified.

In Section 2, we define a Kyle model with diverse beliefs and solve for equilibrium. In Section 3 I identify the comparative static relating belief diversity to asset returns and discuss different assumptions under which it can be computed, and the implications for interpreting prior empirical work.

## II. Model

The model describes a stock market under imperfect competition with private information, K traders and component payoffs with a single correlation parameter to model diverse beliefs parsimoniously.

### *Assumptions*

(A1) There is one risky asset, and one riskless asset (numeraire). The payoff to the risky asset is given by $\tilde{v},\ \tilde{v} = \sum_{i=1}^{K} \tilde{v}_i,\ \tilde{v}_i \sim N(0,1),\ Cov(v_i, v_j) = \rho,\ i \neq j.$ This structure, with two parameters $K$ (the number

**CONTACT** Murugappa (Murgie) Krishnan murgie@gmail.com

of strategic investors and payoff components, 'each investor knows a little') and $\rho$ (identical pairwise correlation in component payoffs, and beliefs), captures belief diversity simply.

For $Var(\tilde{v}) = K + K(K-1)\rho > 0$, we must have $\rho > -1/(K-1)$, so $\rho \in \left(-\frac{1}{K-1}, 1\right)$. Intuitively, for $K>2$, , while all can have beliefs that move tightly together, they cannot have beliefs with each diametrically opposed to every other.

(A2) A noise trader generates a random net demand of $\tilde{z}$, $\tilde{z} \sim N(0,1)$, this is intended to capture non-information-based trades.

(A3) Each strategic investor $i$, $i = 1, 2, \ldots K$, has perfect information about the $i^{th}$ component of the payoff (she observes $\tilde{v}_i = v_i$), and chooses a demand for the risky security, $x_i$. Because $Cov(v_i, v_j) = \rho$, $i \neq j$, each investor's $\tilde{v}_i$ is also informative about other agents' signals. The aggregate order flow from all strategic investors is $X = \sum_{i=1}^{K} x_i$.

(A4) We assume that there are competitive risk-neutral market makers whose competition makes them earn zero expected profits, given all publicly available information, viz., the aggregate order flow from both strategic investors and noise traders, $\omega = X + z$. Hence, the price $p = E(\tilde{v} \,|\, \omega)$. We also assume a linear pricing rule $p = \alpha + \lambda\omega$.

### *Definition of equilibrium*

An equilibrium is defined by a collection of trader strategies $x_i(v_i)$ and a pricing rule $p = \alpha + \lambda\omega$, such that

(1) Traders optimize: Given the above pricing rule, and any set of realized values $\{v_1, \ldots v_K, z\}$ each trader $i$ weakly prefers strategy $x_i(v_i)$ to any alternate strategy $x_i{}'(v_i)$.
(2) Market efficiency: for any aggregate order flow $\omega = X + z$, $p = E(v|\omega)$.

### *Properties of equilibrium*

Following Kyle (1985), it is straightforward to show

**Lemma 1**: The unique equilibrium of this model is defined by

a trader strategy[1] $x_i(v_i) = \left(\frac{1}{\lambda}\right)[(1+(K-1)\rho)v_i - \alpha - \lambda X]$, where

$$X = \left(\frac{1+(K-1)\rho}{(K+1)\lambda}\right)\sum_{i=1}^{K} v_i - \frac{K\alpha}{(K+1)\lambda} = \left(\frac{1+(K-1)\rho}{(K+1)\lambda}\right)v - \frac{K\alpha}{(K+1)\lambda}$$

I use the backward reaction mapping method in Caballe and Krishnan (1994),[2] under which the best response function of each strategic investor is a function of the conjectured aggregate demand of strategic investors, instead of the K-1 other strategic investors. This makes it easier to derive symmetry across strategic investors. I also show

**Proposition 1**: The equilibrium pricing rule is given by $p = \alpha + \lambda\omega$, where

$\alpha = 0$, $\lambda = \left(\frac{1+(K-1)\rho}{(K+1)}\right)\sqrt{K[K-(K-1)\rho]} > 0$, since $\rho > -1/(K-1)$. ■

## III. Key comparative static

The focus of this paper is on relating belief diversity to the current stock price. The natural parameter in our model governing belief diversity is $\rho$. The endogenous quantity defining price impact is $\lambda$, the coefficient of order flows in the pricing rule. So the question becomes: how is $\lambda$ affected by a change in $\rho$?

It is straightforward to compute $d\lambda/d\rho$. In general, it is ambiguous. But it is important to understand the reasons for this ambiguity. First consider some limits shown in Table 1.

The limits in Table 1 may tempt one to think that as $\rho$ increases, $\lambda$ increases. But computing the exact derivative shows this inference is wrong. Monotonicity holds only for $K = 2$. For any $K>2$, $\lambda$ is not monotone in $\rho$. For $K = 3$, when $\rho < 5/6$, $\frac{d\lambda}{d\rho} > 0$, while for $\rho > 5/6$, $\frac{d\lambda}{d\rho} < 0$. To predict the sign, we must condition on the level of $\rho$.

Ambiguity arises because an increase in $\rho$ has several effects, not all of the same sign. Firstly, from Table 1, given our parametrization, it causes

[1] Proposition 1 below will let us back-substitute for $\lambda$ in Lemma 1, but for this paper, that serves little purpose, and so to avoid a long expression in Lemma 1, I describe each investor's strategy in terms of $\lambda$.
[2] Details omitted here for brevity are available from the author upon request. The solution algorithm follows Kyle (1985) and Caballe and Krishnan (1994).

Table 1. Limits with respect to $\rho$. (Note, $\rho > -1/(K-1)$.).

| Limit | $\lambda = \left(\frac{1+(K-1)\rho}{(K+1)}\right)\sqrt{K[K-(K-1)\rho]}$ | $Var(\tilde{v}) = K + K(K-1)\rho$ |
|---|---|---|
| $\rho \to 1$ | $\left(\frac{(1+(K-1))\sqrt{K}}{(K+1)}\right)$ | $K + K(K-1)$ |
| $\rho \to -1/(K-1)$ | 0 | 0 |

an increase in the prior total payoff variance, $Var(\tilde{v})$. The greater this prior variance, the greater the information advantage of strategic investors, and so market makers will place more weight on order flows. But an increase in $\rho$ also causes the signals of different strategic investors to be more alike, so in that sense, the total information available to them is less. This means they have less of an information advantage and market makers place less weight on order flows. Further, when their information is alike, different investors are more like Cournot competitors with homogeneous goods, and they react more intensely to their information. This makes the order flow again more informative and so the weight on it rises. So there are multiple effects of an increase in $\rho$ on the aggregate information conveyed in order flows, and each dominates for different levels of $\rho$. This immediately tells us why we must control for the level of belief diversity when examining its change, to predict the price impact.

We can differentiate $\lambda$ with respect to $\rho$, keeping $Var(\tilde{v})$ constant. That would involve allowing $K$, the number of strategic investors to also change. When we do that (ignoring the technical point that $K$ is originally defined as the integer number of strategic investors, by just treating it as a continuous measure), for $K>2$ the ambiguity remains.

A reader may argue that this comparative static ambiguity is driven by the parametrization I adopt, with payoffs and signals defined with the same parameters. But the parametric structure in this paper only brings into stark relief a feature of this comparative static that would have to be encountered with *any* parametrization.

To see this, assume that we define payoff as just $\tilde{v}$, and signals of the form $\tilde{\theta}_i = \tilde{v} + \tilde{\varepsilon}_i$, with structure imposed on the joint distribution of the $\tilde{\varepsilon}_i, i = 1, 2, \ldots K$, to capture belief diversity. We still need to ask:

(a) Is the total amount of information with strategic investors constant as belief diversity or payoff volatility changes?
(b) Does each investor have the same amount of information, even as the number of investors changes?

To make a prediction about the association between the diversity in investor beliefs and price impact, we must decide which of the above factors are held constant or allowed to vary. Belief diversity is a subtle concept and is intimately related to the total amount of information available in the economy, and the prior total payoff variance or stock volatility. As our model shows, the effect of a change in belief diversity can only be predicted if the level of belief diversity is also known. The existing empirical literature has controlled for a variety of factors, such as earnings management and self-selection bias, but it has not addressed this core problem arising from the intrinsic relationship between belief diversity, prior payoff variance, and the total amount of information in the economy. This is one reason why four decades of empirical work examining this association is still inconclusive.

From monthly averages (for June and July 2013) of daily data for 47 firms from India's National Stock Exchange,[3] I construct changes in impact cost (like changes in $\lambda$) and trading volume. Trading volume is viewed as a measure of diversity of investor belief (the proxy for $\rho$ in the model), under the assumption that preferences and opportunities do not vary much over the two months. These changes are positively correlated. Conditioning upon June volume to create two subsamples, however, yields correlations of opposing sign. This shows that the key comparative static implication of our model is plausible.

[3]The data was drawn from https://www.nseindia.com/products/content/all_daily_reports.htm.

## IV. Concluding remarks

In contrast to Miller (1977) and Williams (1977), I adopt an imperfect competition model of a stock market, arguably more plausible than a perfect competition model. With such a model, I have shown that the general relationship between diversity of investor beliefs and price impact is ambiguous in sign. To get a prediction, it is necessary to make explicit assumptions about the level of belief diversity, total prior variance and the total information available to strategic traders, and how these changes as the diversity in beliefs changes. This also helps explain why the prior empirical literature examining the association between belief diversity and stock returns is inconclusive and suggests additional controls in empirical design matching the additional assumptions that are needed in the theory, to generate a sign prediction.

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## References

Caballe, J., and M. Krishnan. 1994. "Imperfect Competition in a Multi-Security Market with Risk Neutrality." *Econometrica: Journal of the Econometric Society* 62: 695–704. doi:10.2307/2951665.

Diether, K. B., C. J. Malloy, and A. Scherbina. 2002. "Differences of Opinion and the Cross Section of Stock Returns." *The Journal of Finance* 57 (5): 2113–2141. doi:10.1111/0022-1082.00490.

Epstein, L. G., and M. Schneider. 2008. "Ambiguity, Information Quality, and Asset Pricing." *The Journal of Finance* 63 (1): 197–228. doi:10.1111/j.1540-6261.2008.01314.x.

Han, J., Z. Pan, and G. Zhang. 2017. "Divergence of Opinion and Long-Run Performance of Private Placements: Evidence from the Auction Market." Working paper. Macquarie University.

Kyle, A. S. 1985. "Continuous Auctions and Insider Trading." *Econometrica: Journal of the Econometric Society* 53: 1315–1335. doi:10.2307/1913210.

Miller, E. M. 1977. "Risk, uncertainty, and divergence of opinion". The Journal of finance 32 (4) : 1151-1168.

Sadka, R., and A. Scherbina. 2007. "Analyst Disagreement, Mispricing, and Liquidity." *The Journal of Finance* 62 (5): 2367–2403. doi:10.1111/j.1540-6261.2007.01278.x.

Williams, J. T. 1977. "Capital Asset Prices with Heterogeneous Beliefs." *Journal of Financial Economics* 5 (2): 219–239. doi:10.1016/0304-405X(77)90019-8.

# GMM Estimates of a Structural Kyle-Type Model With Correlated Market and Non-Market Signals: Evidence from India

Murugappa (Murgie) Krishnan
Radford University
murgie@gmail.com

Srinivasan Rangan
Indian Institute of Management, Bangalore
srinivasan.rangan@iimb.ernet.in

Nikhil Vidhani
Indian Institute of Management, Bangalore
nikhil.vidhani16@iimb.ac.in

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# GMM Approach to Structural Estimation of a Kyle-Type Model Of an Event Study With Correlated Market and Non-Market Signals: Evidence from India

**Abstract:**

We model a correlated information structure in a financial market under imperfect competition in which the pricing rule depends on a corporate announcement and aggregate order flow. The equilibrium earnings response coefficient $\beta$ reflects not only the direct response to what firms reveal of their payoff, but also the effect of what the market learns from the firm's report about what traders know. This explains why estimated $\beta'$s are not restricted to the unit interval, and why they can be negative.

We then use Indian data to implement a GMM approach to structural estimation of the model. This relies critically on a property of the linear pricing rule that does not seem to have been exploited before, that it is a model for a realized price and not just an expected price. We adjust for endogeneity of FII trading and validate our model with out of sample model comparisons.

Our results indicate that what FIIs know exceeds what firms know, even at the time of an earnings announcement, by at least an order of magnitude. We also find that correlation between the two fundamental information components is generally significant, and negative for 72 out of 366 firms. Sub-sample analyses show that as firm size increases, the FIIs' information advantage declines ($\sigma_T$), market noise increases ($\sigma_Z$), and while the correlation parameter $\rho$ is not monotone in size, $\rho * \sigma_T$ is also declining in firm size. By comparing our estimates in the main model with benchmark models that have only an earnings signal, or only an FII trading signal, we document an absence of symmetry between the two signals: earnings is a substitute for the trading signal, but the trading signal is not a substitute but a complement to earnings.

**Keywords:** Foreign Institutional Investors, Institutional Trading, Earnings Announcements,

# GMM Approach to Structural Estimation of a Kyle-Type Model Of an Event Study With Correlated Market and Non-Market Signals: Evidence from India

## 1. Introduction

Event studies relating to a corporate announcement have focused on the price reaction to the announcement itself. But other things can happen in the market at the time of an announcement. Here we also focus on trades by a class of significant institutional investors, foreign institutional investors (FIIs), another significant source of information to the market even at the time of an announcement. FIIs have become prominent in emerging markets. Their participation is determined in part by a careful optimizing strategy conditioned on information, and in part, like many other institutional traders, by retail pressures to meet insurance or pension claims or to respond to portfolio rebalancing decisions made by their customers with needs of their own. How important is the information gleaned from FII trades during an earnings announcement window relative to corporate earnings announcements? This is the key empirical question that we address in this paper.

We pose the question within the context of a model of asset pricing under imperfect competition that not only allows for variation in FII type, but one in which a key source of public information, earnings, is also available. Therefore, the competitive price-setters in our model observe both firm-provided earnings announcements and FII trading numbers from market statistics before setting prices. While FII trading signals are observable, whether or not they reflect information and strategy more, is not. That noise helps preserve FII incentives to gather potentially costly private information. A key theoretical result is that the equilibrium earnings response coefficient (ERC) reflects not only what firms reveal directly of their own component of total firm payoff but also about what traders know of the total payoff. This explains the full range of observed ERCs, from less than zero to greater than one.

We specify firm payoff information as a sum of component information innovations, a la Admati and Pfleiderer (1988), one component known to the firm, and another, to FIIs. But we allow these components to be correlated, which creates a rich enough environment to capture a variety of relationships between the two signals. We also take as primitive the posterior information advantages of firms and FII traders, rather than specifying a detailed information structure. This ensures the model is also parsimonious enough to allow estimation of even the deep parameters of the model, such as the variability of FIIs' private information, noise, and the correlation between corporate earnings public signal and FIIs' private information component. Estimates of the deep parameters, in turn, let us quantify various aspects of FII behavior that so far have only been discussed speculatively, and opens up additional questions. In contrast to most papers studying institutional trading, we test and adjust for endogeneity of these trades. we also validate the model with out of sample model comparisons. A novelty in our empirical approach is to exploit a property of a Kyle-type model that has not used before. The linear pricing rule is a natural source of moment conditions that makes GMM estimation easy.

Our study employs a database of daily stock-level trades of FIIs in India for the years 2003-2016. We integrate data on quarterly earnings announcements and stock returns from the PROWESS database with FII trades during the announcements to conduct tests of FII informedness. We find that what FIIs know exceeds what firms know, even at the time of an earnings announcement. We also find that correlation between the two fundamental information components is generally significant and can be negative for some firms. The combination of the negative correlation with the relatively higher information advantage of the FIIs, sometimes causes good news about firm earnings to be viewed as bad news by markets. As firm size increases, the FIIs' information advantage declines ($\sigma_T$), market noise increases ($\sigma_Z$), and while the correlation parameter $\rho$ is not monotone in size, $\rho * \sigma_T$ is also declining in firm size. When we compare firms making small profits with firms making small losses, we find that small-profit firms' earnings are weighted less than that of small-loss firms, suggesting that the market is skeptical. By comparing our estimates in the main model with benchmark models that have only an earnings signal, or only an FII trading signal, we document an absence of symmetry between the two signals: earnings is a substitute for the trading signal, but the trading signal is not a substitute but a complement to earnings. When we compare estimates from empirical models that reflect regimes with and without an earnings signal, we find evidence that is consistent with traders gathering information more at the time of an earnings announcement. This result is complementary to the result in papers that have noted that traders appear to allocate attention among announcing firms, and reflects directly the focal point argument of Schelling (1960).

The rest of the paper is organized as follows. In section 2, we provide a brief review of prior literature that relates to our research. Section 3 develops the model, and describes equilibrium properties. Section 4 describes certain design considerations for estimating our model that is nonlinear in parameters and provides variable definitions. Our data sources are presented in section 5 and our results are reported in section 6. In section 7 we provide additional remarks, and in section 8 we discuss our conclusions.

## 2. Prior Literature

### 2.1. Theory

Admati (1985) generalized the single-security noisy rational expectations model under perfect competition due to Hellwig (1980) to the case of multiple securities, allowing for general variance-covariance matrices governing payoffs, errors in private signals, and liquidity noise. She showed that a common intuition in a single-security setting, that a security price would be increasing in its own payoff need not hold with many securities and sufficient correlation. Caballé and Krishnan (1994) generalized the risk-neutral imperfect competition model due to Kyle (1985), to the case of N assets and K traders, with a similarly rich correlation structure, and showed that asset prices again need not be increasing in their own payoffs. They also showed that in a correlated environment portfolio diversification can arise for a reason unrelated to risk: to minimize the revelation of information.

Lundholm (1988), under perfect competition, and Manzano (1999), under imperfect competition, show that a similar ambiguity can arise even with one security, if there were multiple signals available; for example, a public signal like earnings together with private signals for each trader. A security's price may not increase in earnings. The key to this result is the information structure used in both these papers, where an asset has payoff $v$ and the signals, public and private, are of the form $s_i = v + e_i$, with Cov($e_i$, $e_j$) = C, $i \neq j$, C not necessarily zero. In this case, each signal has both a direct and an indirect effect. A large value of $s_i$ could indicate a high $v$, and this is the direct effect. On the other hand, it could indicate a large $e_i$, and, if the covariance between errors in signals is high enough, also a high $e_j, j \neq i,$ and consequently a lower $v$; this is the indirect effect. When the indirect effect dominates, good news can be bad news. We obtain a similar ambiguity in the sign of the coefficient on the public signal in our model, but it arises from a combination of a negative correlation between payoff components and a greater information advantage for traders, rather than firms, relative to the market.

One recent paper, Chung, Kim, Lim and Yang (2014) has some broadly similar goals to our paper and also models a setting with earnings and a trading signal under imperfect competition. But there are several key differences. Because the multiple signals in Chung et al (2014) are all about one common payoff component, the posterior means (including the price which is a payoff mean given signals) are always precision-weighted averages of signals and the prior, so the earnings response coefficient ($\beta$ in our model) is restricted to the unit interval. In our model, with a component payoff structure and a primitive unrestricted correlation parameter governing the components, $\beta$ is not restricted and can be negative or greater than one. It is therefore easier to reconcile with the empirical evidence. From an empirical perspective, their more explicit information structure poses a complex estimation challenge. In contrast, we take as primitive the posterior information advantages of agents. This yields a more parsimonious framework, which simplifies the estimation of primitive parameters.

Davila and Parlatore (2018) in a similar spirit consider estimation of measures of price informativeness within a linear-demand framework, and in one example where they impose more structure solve for some primitive parameters. The difference between their work and ours is that in our case, within a setting with more parametric structure we are able to estimate all primitive parameters, including parameters governing the precision of traders' private information, its correlation with the firm's information, and the level of background market noise. We exploit the linear pricing rule as a source for moment conditions to implement GMM.

### 2.2. Empirical Work

Our paper is related to several strands of empirical work. Previous evidence on the investment performance of FIIs (in several countries, including Finland, Indonesia, Japan, South Korea, and Taiwan) is mixed. While Grinblatt and Keloharju (2000), Huang and Shiu (2009), and Bae, Min, and Jung (2011) conclude that FIIs generate superior performance, Kang and Stulz (1997), Dvorak (2005), and Choe, Kho, and Stulz (2005) report the opposite. On India, while there are many news stories and anecdotes of FIIs' importance, formal evidence is scarce. Acharya, Anshuman, and Kumar (2014) find that stocks with high FII order flow innovations experience a coincident price increase that is permanent, whereas stocks with low innovations exhibit a coincident price decline that is in part transient, reversing itself within two weeks. The results are consistent with price pressure on stock returns induced by FII sales, as well as information being revealed, as in our model, through FII purchases and FII sales.

More generally there has been work, especially with US data, assessing if institutional trades are informative. The conclusion from most studies in this literature is that institutional investors are informed, and profit from their trades; their net buying is positively associated with subsequent stock returns (e.g., Nofsinger and Sias (1999); Gompers and Metrick (2001); Sias (2004); Pucket and Yan (2011), Ke and Petroni (2004); Yan and Zhang (2009); Campbell, Ramadorai, and Schwartz (2009), Hendershott, Livdan, and Schurhoff (2015)). But there are also papers with contrary evidence (e.g., Cai and Zheng (2004), Bushee and Goodman (2007), Griffin, Shu and Topaloglu (2012), Edelen, Ince, Kladlec (2016)).

Many papers have inferred institutional participation in the market from trade size (large trades). But Cready, Kumasm and Subasi (2014) show that institutions frequently use small trade sizes. They also show that institutions increase their order sizes substantially in announcement periods relative to non-announcement periods, presumably as an endogenous response to earnings news. Papers that use the Trades and Quotes (TAQ) database have also had to guess trade direction using rules relating whether trades take place closer to the bid or the ask, and making adjustments for the different speeds in recording trades and quotes, which can give rise to errors. Hu. Jo, Wang, and Xie (2018) survey 55 papers that used the Abel Noser (Ancerno) institutional trades database and so did not have to guess trade direction. However, a limitation of these studies is that Ancerno covers only a subset of institutional trades. The papers that use order flow data (e.g., Easley, Kiefer, and O'Hara (1997)) and the Ancerno institutional trades database do not test and correct for the endogeneity of order flows.

In contrast, the Foreign Institutional Investor database from India that we use lists every FII trade with masked trader IDs. We do not need to guess the trade direction. Our limitation is that FIIs are only one class of institutional traders, albeit a significant one for many stocks. This database is also public, free, and easily accessible by anyone.

Only a few empirical papers study earnings and institutional trades jointly. Daley, Hughes, Rayburn (1995) study the effect of block trades during earnings announcements, and ask if anticipated public announcements give rise to private information acquisition, and permanent price effects. Campbell, Ramadorai, and Schwartz (2009) show that institutional trades can lead to short-term losses but long-term gains because they anticipate earnings surprises and the post-earnings announcement drift. Hu, Ke and Yu (2018) show that transient institutions interpret small negative surprises correctly, and disagree with the suggestion that institutions overreact in these cases. These papers have been silent on the question of endogeneity of institutional trades. Because it was clear in our case that FII trading is not exogenous, we focused on identifying suitable instruments (lagged exchange rates, and lagged market returns) for FII trading.

## 3. Model

Our primary model is a model of asset pricing under imperfect competition with both public and private signals. The main objective is to ensure that the model is rich enough to address the empirical question about the degree to which FIIs are informed and strategic, while being simple enough to admit of easy estimation of even primitive parameters such as the correlation between public and private information, the informational advantage of FIIs, and the level of noise.

### 3.1. Assumptions

**(A1) Assets, asset payoffs, and information about asset payoffs:**

There is one risky asset, and one riskless asset (numeraire) with payoff and price equal to one. The payoff to the risky asset (and equivalently, information about this payoff) is given by $\tilde{v}$, $\tilde{v} = \tilde{v}_F + \tilde{v}_T$, where $\tilde{v}_F$ is the informational innovation component[1] for which the firm has an information advantage relative to others (captured in the data by unexpected earnings); and $\tilde{v}_T$ is the informational innovation component for which the institutional traders (FIIs) have an information advantage relative to others. The components $\tilde{v}_i \sim N(0, \sigma_i^2), i = F, T,$ with Cov $(\tilde{v}_F, \tilde{v}_T) = \rho.\sigma_F.\sigma_T$, $\rho \in (-1,1), \sigma_i > 0, i = F, T.$

This component structure for payoffs has been used before in, e.g., Admati and Pfleiderer (1988). But where they chose to make the total payoff a sum of orthogonal components, we allow the two components to be correlated. This is important in creating a setting where the two signals that price-setters observe – earnings announcements and trading signals – can be substitutes, complements or independent. This allows for more possibilities than with the more common structure where both public and private signals are about the same component, yet retains parsimony in terms of the number of parameters to be estimated.

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[1] The label information innovation component is used deliberately, to highlight the idea that our variables $\boldsymbol{\tilde{v}_F}$ and $\boldsymbol{\tilde{v}_T}$ need not represent cash flow payoffs, but are signals about such payoffs.

This structure provides additional advantages. We could interpret $\tilde{v}_i$ as perfect information on a component observable to $i, i = F,\ T$, and for ease of exposition and we will sometimes do that. But generally, it will be more convenient to interpret it as the informational advantage of $i$ relative to others, i.e., $\tilde{v}_i = E(\tilde{v} \mid \tilde{I}_i) - E(\tilde{v})$. By not having to specify the signals in the information sets $I_i$ we can save on some additional parameters while being slightly more general.[2] It does mean that the variance parameters $\sigma_F^2$ and $\sigma_T^2$ serve both as prior variances and as measures of informational advantage. The variance parameter $\sigma_F^2$ governing earnings can be estimated directly from the data, and so provides a convenient scale variable with which to interpret the magnitude of any estimates of $\sigma_T^2$.

It provides a simple way of describing whether firms know more or less than traders, without adding more notational burden. Firms have an advantage with respect to events within the firm, captured in the judgment reported in its summary earnings number. Traders have an advantage with respect to events outside the firm, which may include macroeconomic events, analysis of the competition, the links in the supply chain, government policy and even the state of the financial market. But this interpretation is only a suggestion. It is not essential.

**(A2) Agents:**

**Firm**: There is a firm, denoted by subscript $i = F$, which observes $\tilde{v}_F = v_F$ perfectly and reports it faithfully, as required to do so under accounting rules. Note, however, that because of the component structure of total firm payoff, seeing and reporting perfect information on one component is not the same as knowing and reporting "everything." Our assumption A1 above allows firms to know a lot or little. One interpretation is that auditing works and results in compliance (see, e.g., Shin (1994)). Alternatively, we could invoke models of cheap talk (for example, Bhattacharya and Krishnan (1999)) in which firms have an incentive to make truthful disclosures, despite being able to lie with impunity. In either case, this assumption is broadly consistent with the vast empirical literature that has documented a consistent

[2] For a convenient summary of the algebra of informational advantages, see the remarks following assumption (A3) in Caballé and Krishnan (1994).

positive association between unexpected earnings and abnormal returns, while also noting that only a small portion of price variation is explained by earnings variation, even within an earnings announcement window.

**Noise trader**: This trader generates a random net demand of $\tilde{z}$, $\tilde{z} \sim N(0, \sigma_z^2)$, $\tilde{z}$ uncorrelated with payoff components. This is intended to capture the non-strategic or non-information-based activity of FIIs.[3]

**Strategic trader**: This trader, denoted by subscript $i = T$, is intended to capture the behavior of strategic informed FIIs. She chooses a demand for the risky security, $x$, based on all information available to her: the public signal created by the firm's earnings announcement, $v_F$, and the perfect private signal about the second component, $\tilde{v}_T = v_T$, and the noise trade of some FIIs, $z$. Being able to observe $z$ is different from Kyle (1985), but similar to Rochet and Vila (1994). Therefore, the strategic trader is not just better informed than the market makers (who can only observe the aggregate FII demand, $\omega = x + z$), but their information is nested in hers.[4]

**Competitive market makers**: We assume that there are competitive risk-neutral market makers whose competition makes them earn zero expected profits, so the price they set for the risky asset is equal to the expected payoff from the security given all publicly available information. In the main model of this paper, that public information will consist of the earnings signal that the firm provides, $v_F$, and the aggregate FII order flow, $\omega = x + z$. Hence, the price $p = E(\tilde{v} \mid v_F, \omega)$. We also assume a linear pricing rule, $p = \alpha + \beta v_F + \lambda\omega$. Given the uniqueness of equilibrium result in Rochet and Vila (1994), this ex-ante assumption of a linear pricing rule is not really an additional restriction but makes the solution procedure more convenient.

[3] We have studied a variant of the model in the paper that allows for $z$ to be correlated with a payoff component. It is possible to compute equilibrium even in such a model, but the added analytical complexity yields no additional intuition about FII or market behavior, but complicates parameter estimation substantially.

[4] Rochet and Vila (1994) adopt this for an important theoretical reason. Given a nested information structure, and exogenous total profits in the game, they show uniqueness of equilibrium under otherwise very general assumptions. In the Kyle (1985) framework, uniqueness has only been shown given a linear pricing rule, and uniqueness of equilibrium in general is still an open question.

Notice that while the aggregate FII trading signal is observable (as assumed in our empirical work), because some FIIs may trade for non-informational reasons, while other FIIs are informed and strategic, the FII private information, $v_T$, cannot be unraveled. Unlike Rochet and Vila (1994) we make this assumption here primarily for empirical reasons. In the empirical sequel, later in this paper, we will associate the observable FII trading signal with the aggregate demand from all kinds of FIIs, i.e., with $\omega = x + z$. In a paper where the primary focus is on FII behavior we implicitly regard other kinds of strategic and noise traders as being of at best second-order importance, and so we ignore their behavior.

### 3.2. Definition of equilibrium

An equilibrium of this model is defined by a trader (FII) strategy $x(v_F, v_T, z)$ and a pricing rule $p = \alpha + \beta v_F + \lambda\omega$, such that we have

(i) Trader optimization: Given the above pricing rule, and any triple of realized values $\{v_F, v_T, z\}$ the trader $T$ has a demand strategy $x(v_F, v_T, z)$ that is at least as good as any alternate strategy $x'(v_F, v_T, z)$.

(ii) Market efficiency: for any realization of earnings $v_F$ and aggregate FII order flow $\omega = x + z$, the price $p = E(v|v_F, \omega)$.

### 3.3. Properties of equilibrium

Proposition 1: The unique equilibrium of this model is defined by

a trader (FII) strategy $x(v_F, v_T, z) = \tau_0 + \tau_1 v_F + \tau_2 v_T + \tau_3 z$, where

$$\tau_0 = 0,\ \tau_1 = \left(\frac{-\rho\sigma_z}{2\sigma_F(\sqrt{1-\rho^2})}\right),\ \tau_2 = \left(\frac{\sigma_z}{2\sigma_T(\sqrt{1-\rho^2})}\right),\ \tau_3 = -\left(\frac{1}{2}\right), \text{ and}$$

a pricing rule $p = \alpha + \beta v_F + \lambda\omega$, where

$$\alpha = 0,\ \beta = 1 + \rho\left(\frac{\sigma_T}{\sigma_F}\right),\ \lambda = \left(\frac{\sigma_T(\sqrt{1-\rho^2})}{\sigma_z}\right).$$

The proof is outlined in the appendix. In the key final step, we equate coefficients in the pricing rule, to get three equations of the form, $\alpha = f_1(\alpha, \beta, \lambda)$, $\beta = f_2(\alpha, \beta, \lambda)$, $\lambda = f_3(\alpha, \beta, \lambda)$. From the first alone, it is easy to show that $\alpha = 0$. Manipulating the other two leads to a cubic in two variables - $\beta$ and $\lambda$, instead of in $\lambda$ alone as in Kyle (1985) and Rochet and Vila (1994). Of the three solutions, only one satisfies $\lambda > 0$, which is needed to satisfy second-order conditions. So we have a unique real root. The solution is easily verified.

The intercepts being zero only reflects zero prior means of all variables. The coefficient $\tau_1$, which represents the weight the trader places on $v_F$, shows the effect of the correlation between the two payoff components. Though $v_F$ provides perfect information about one component and is public, the expression for $\tau_1$ is complex because it also yields information about the second component, as $E(v_T|v_F) = \rho\left(\frac{\sigma_T}{\sigma_F}\right)v_F$. The coefficient $\tau_1$ is increasing in the ratio $\left(\frac{\sigma_z}{\sigma_F}\right)$ for any $\rho > 0$; decreasing in that ratio, for any $\rho < 0$. It is also decreasing in $\rho$. The coefficient $\tau_2$ is increasing in the ratio $\left(\frac{\sigma_z}{\sigma_T}\right)$ for any $\rho$. As noise increases, the greater camouflage encourages the trader to be more aggressive. Also, as his information advantage is known to be greater, the market will place more weight on the order flow, and the trader tries to reveal less by becoming less aggressive.

Given $v_F$ the trader effectively faces both a different intercept and slope, and his demand reflects his information advantage, defined by the residual $v_T - E(v_T|v_F)$, which is orthogonal to $v_F$. Since the order flow is only a noisy linear transformation of this orthogonal residual, in equilibrium, the two conditioning elements in the pricing rule, $v_F$ and order flow $\omega$, are also orthogonal, regardless of the underlying parameter values. The expression for $\beta$ includes the coefficient of $v_F$ in this conditional expectation, $E(v_T|v_F)$, viz., $\rho\left(\frac{\sigma_T}{\sigma_F}\right)$. This is added to the coefficient when only $v_F$ is available as a signal in the pricing rule, namely unity. This tells us that earnings numbers not only reveal what a firm knows about its own payoff but also a bit about what traders know.

That we need $\lambda > 0$ follows from the second-order condition. If this did not hold, by buying more a trader would push the price not up but down, till he would want to hold an arbitrarily large position paying nothing. That clearly cannot be an equilibrium. Relative to the benchmark case without

$v_F$ the expression for $\lambda$ reflects here the presence of that second possibly correlated signal. When the correlation $\rho \to 0$, $\lambda$ is given by the same expression as if there was no earnings signal available. When $\rho \neq 0$, $\lambda$ is smaller because of the decline in the variance of $(\tilde{v}_T|v_F)$. In the limit, as $\rho \to \pm 1$, $\lambda$ vanishes. In other words, when $\rho \neq 0$, observing $v_T$ confers less of an information advantage to the traders, relative to market makers, who can now guess part of the traders' information. The market makers therefore set a flatter pricing rule, than they would if the information asymmetry is greater. In the limit, as all of the traders' information is anticipated, he has no information advantage.

### 3.4. Equilibrium in benchmark models

In the empirical work, we compare this main model to two simpler benchmark models[5]. In one (Regime 1) there is no FII participation, and the only signal available to market makers is $v_F$. It is obvious given our other assumptions that the following holds.

*Lemma 1*: The equilibrium price $p = v_F$, so $\beta = 1$.

In the second benchmark model (Regime 2), we have FII participation but no earnings announcements, so this reflects FII trading outside earnings announcement windows. Given our other assumptions, this model closely resembles an example in Rochet and Vila (1994), but for the component payoff structure. It is straightforward to show

*Lemma 2*: The unique equilibrium of this model is defined by

a trader (FII) strategy $x(v_T, z) = \tau_0 + \tau_1 v_T + \tau_2 z$, where

$\tau_0 = 0,\ \tau_1 = \left(\frac{\sigma_z}{2\sigma_T}\right),\ \tau_2 = -\left(\frac{1}{2}\right)$, and

a pricing rule $p = \alpha + \lambda\omega$, where

$\alpha = 0,\ \lambda = \left(\frac{\sigma_T}{\sigma_z}\right)$.

#### 3.4.1. Can $\boldsymbol{\beta}$ be negative?

[5] The sample used to analyze the main model of this paper, with observations that have both earnings and FII trading signals, is referred to as Regime 3.

Whenever $\rho \neq 0$, $\beta \neq 1$, which is the value in the benchmark model with only earnings and no trading signal. The parameter $\beta$ can even be negative. But the reason for a possible counter-intuitive sign (causing good news to be bad news) is different in this setting from the reason in Lundholm (1988) and Manzano (1999). In those papers, the multiple signals are all about the same component and correlation governs the error covariance, so $\beta$ (coefficient of the public signal in the price function) in those models can be negative when the indirect effect dominates the direct effect for sufficiently large positive error covariance. Here, $\beta < 0 \Leftrightarrow \rho\left(\frac{\sigma_T}{\sigma_F}\right) < -1$. This can arise only if we have (i) $\rho < 0$, and (ii) for sufficiently negative $\rho$, we also have $\sigma_T > \sigma_F$ by a sufficient margin. To interpret this, consider an equivalent setting where the total payoff $\tilde{v} = \tilde{v}_1 + \tilde{v}_2 + \tilde{v}_C$, $\tilde{v}_F = \tilde{v}_1 + \alpha * \tilde{v}_C$, $\tilde{v}_T = \tilde{v}_2 + (1-\alpha) * \tilde{v}_C$. Correlation arises because of the common component $\tilde{v}_C$ and will be negative when $\alpha < 0$ or $\alpha > 1$. For $\beta < 0$, besides having a significant common component between the firm and FIIs about which they disagree, it must also be the case that the FIIs' informational advantage $\sigma_T$ must be sufficiently larger than the firm's informational advantage $\sigma_F$. A practical implication of this for empirical work is that if the estimate of the shallow parameter $\beta < 0$, that immediately tells us that FIIs must know more than firms.

There is also a difference from an empirical perspective between our model here and Lundholm (1988). The correlated signals in the pricing rule here, the firm's public announcement and FII trading, are both observable. In Lundholm (1988), the private signals that are correlated with the public signal, are by definition, unobservable. So it is easier in our framework to estimate the correlation parameter, and measure its impact. Finally, because our model assumes risk neutrality, the equilibrium expressions are simpler than under risk aversion assumed in Lundholm (1988) and Manzano (1999). This simplifies and makes the estimation of primitive parameters easier.

## 4. Toward estimates of primitive parameters

Our interest in this paper is in estimating and analyzing the parameters in the pricing rule obtained under Proposition 1:

$p = \alpha + \beta v_F + \lambda\omega$, where

$$\alpha = 0,\ \beta = 1 + \rho\left(\frac{\sigma_T}{\sigma_F}\right),\ \lambda = \left(\frac{\sigma_T(\sqrt{1-\rho^2})}{\sigma_z}\right).$$

There is a property of this type of model relevant for estimation that does not appear to have previously received much attention. The above linear pricing rule is a model not for an expected price but for a conditionally expected payoff and a *realized* price. If we rewrite the above model as a pricing error $u = p - (\alpha + \beta v_F + \lambda\omega)$, under the null hypothesis that the equilibrium model holds, the pricing error $u = 0$. From this, and given observability of price $p$, earnings news $v_F$ and aggregate order flow $\omega$, it follows that we can easily derive moment restrictions for GMM estimation of the primitive parameters of the model. These are functions of the form $h(X, \Theta) = 0$, with $E\big(h(X, \Theta)\big) = 0$, where $X$ denotes data, and $\Theta$ the unknown set of parameters to be estimated. One class of restrictions has the form $E(u * Z) = 0$, where Z can be a constant or some data variable.

A more general class would be $E\big(u^k * Z\big) = 0$, $k = 1, 2, 3$ ... In the case of models like the CAPM the equilibrium relationship between returns involves expected returns, so in terms of this notation what we can take as a primitive is only $E(u) = 0$, not $u = 0$. So using powers like $u^k$ above in a moment restriction would generally be ruled out. To obtain additional moment restrictions of the form $E(u * Z) = 0$, researchers have used instruments that are plausibly orthogonal to the pricing error $u$. Here because the equilibrium pricing rule is a model for each realized price, in theory we could use any instrumental variable Z.

Of course, there are natural limits to what we can choose as Z. Completely arbitrary variables drawn from say, zoology or oceanography, may help us increase the number of moment restrictions and perhaps even yield lower asymptotic standard errors. But to learn anything useful from the rejection of the model or violation of a moment condition, there must be some plausible relationship to begin with. While there is a large literature in finance studying applications of GMM to structural estimation of asset pricing models, exactly how many and which moment restrictions to select is still at best only an art and not a science. What we have are rules of thumb. As the number of moment restrictions increases relative to the number of parameters, asymptotically valid GMM standard errors generally shrink, but finite sample performance degrades. While we need more moment restrictions than parameters to be able to define an over-identification test, using a very large number of restrictions makes model rejection more likely. Some arbitrariness seems inevitable in the choice of moment restrictions. What we aimed for was a set of at least five moment restrictions, when we estimate three parameters. We also sought to use only restrictions of the form $E(u * Z) = 0$ and to avoid higher powers of the error term. Using higher powers of the error would make an already nonlinear model even more nonlinear, and add to the complexity of any gradient search algorithm.

We also estimate an empirical model where we define moment restrictions using the linear pricing rule from not only Regime 3 where both an earnings signal $v_F$ and the FII order flow $\omega$ is available, but also from Regime 2, where only the FII trader's order flow $\omega$ is available. The extended parametrization in that setup allows us to address questions relating to whether traders gather information only in anticipation of a public announcement.

To estimate this model, we set it up as a GMM least squares minimization problem subject to certain inequality constraints on parameter values. Note that unlike the workhorse ordinary least squares linear model, our model is nonlinear in its parameters (though still linear in variables). We have to estimate four deep or primitive parameters – $\sigma_F$, $\sigma_T$, $\sigma_z$, and $\rho$, and two shallow parameters – $\beta$ and $\lambda$. Inspection of the equilibrium pricing equation reveals that the three primitive variance-related parameters, $\sigma_F$, $\sigma_T$, and $\sigma_z$, enter the equilibrium solution only in ratio form. This immediately implies that regardless of the estimation criterion we use (e.g. least squares, maximum-likelihood, GMM) we cannot identify all three variance parameters simultaneously. To see this, note that if a set of values for these three parameters optimizes any given criterion, then so will any scalar multiple of the same values.

We considered finding moment restrictions in which the variance-related parameters enter in other than the above ratio form, by using the trader's first-order condition, as in Consumption CAPM models. In those models, the representative trader's first-order conditions provide a rich source of moment conditions. In Kyle-type models like our model, because the trader's first-order condition depends on private information, no matter how we rewrite it, we cannot obtain a function of the form $h(X, \Theta) = 0$, with $E\big(h(X, \Theta)\big) = 0$, where $X$ denotes data, and $\Theta$ the unknown set of parameters to be estimated.

However, for $\sigma_F$ we can construct an independent estimate from observed values of UE, our proxy for $v_F$. We equate $\sigma_F$, the information advantage of the firm, to the overall sample estimate of the standard deviation of unexpected earnings (UE).[6] Then, in any implementation of the empirical model, we take that independently estimated $\sigma_F$ as a fixed value and estimate the remaining three primitive parameters. Because $\beta$ and $\lambda$ are defined in terms of the deep parameters, they can also be easily computed from the estimates of the deep parameters. Thus, the thrust of our empirical work is on estimating $\sigma_T$, $\sigma_Z$, and $\rho$.

Given that in the theory we have used zero-mean variables, in equilibrium, the pricing rule $p = \alpha + \beta v_F + \lambda\omega$ when evaluated at the mean $v_F = E(v_F) = 0$, $\omega = E(\omega) = 0$, yields $p = E(p) = 0$. So in the empirical work we work with mean-centered variables. To control for the various previously documented determinants of earnings announcement window returns, we first regress raw returns on various controls, and treat the resulting as our proxy for price in the model.

We also make a scale adjustment motivated by the benchmark case (Regime 1) of the relation between earnings announcement returns and UE when there is no FII trading (see section 3). Under Regime 1, the coefficient on UE has to equal one exactly ($\beta^F = 1$). Therefore, we estimate a simple linear regression of ERET on UE and control variables, for the sub-sample that has no FII trading during the earnings announcement. We then multiply centered UE by the coefficient so obtained and re-estimate the regime 1 regression; this ensures that $\beta^F = 1$. We then multiply UE for our sample of earnings announcements that have non-zero FII trading (Regime 3) by the same coefficient estimate. By doing so,

[6] We also estimate the model for sub-samples and for each firm. For these additional analyses, we use standard deviation of unexpected earnings based on the sub-samples/firms. We find that cross-sectional differences in $\sigma_F$ are substantial, causing the estimates of $\beta$ to vary across sub-samples/firms.

we can now meaningfully compare the coefficients of UE in regressions when FIITR is absent with those when it is present.[7]

A novel feature of our model is the role played by the correlation between the information advantage of the firm and that of the FIIs. Our model shows that this correlation measures how aligned are the interpretations of common information between the firm and FIIs. Although unobservable to the researcher, in our empirical work, we are able to estimate it. So our model is not just a source of predictions about regression coefficients on UE and FIITR ($\beta$ and $\lambda$), but a bridge between what we can observe – $p, v_F, \omega$ -- and the primitive parameters – $\sigma_F$, $\sigma_T$, $\sigma_z$, and $\rho$ --- that we cannot observe. A methodological contribution in this paper is to show how the underlying model of equilibrium allows us to learn more from an event study based on earnings announcements.

In our empirical analysis, we estimate parameters of the pricing error $u$ (after adjusting for control variables) corresponding to the linear pricing function defined in Proposition 1. That rule expresses the price impact $p$ (ERET) as a linear function of earnings announcement news $v_F$ $(UE)$ and the aggregate order flow $\omega$ $(FIITR)$:

$$u = ERET_{it} - (\alpha + \beta \times UE_{it} + \lambda \times FIITR_{it}) \quad (1)$$

where $\alpha = 0, \beta = 1 + \rho\left(\frac{\sigma_T}{\sigma_F}\right), \lambda = \left(\frac{\sigma_T(\sqrt{1-\rho^2})}{\sigma_z}\right)$, and

ERET = Earnings Announcement Return compounded over the day of the earnings announcement and the following day, (0,1), adjusted for control variables, firm and year effects. This is the proxy for the price impact $p$.

UE = Earnings per Share in quarter t less Earnings per Share from four quarters prior, scaled by share price two days before the earnings announcement. So UE is the empirical proxy for news in the firm's announcement, $v_F$. UE is centered and scaled as described in section 4.

[7] Note that, as with OLS regressions, scaling affects the coefficient estimates, but does not affect the t-statistics. We hasten to add that this choice of scale is obviously not a knife-edge choice. A range of scale choices all yield convergence. Adjusting the scale of UE so that in a Regime 1 regression in the aggregate sample yields $\beta^F = 1$ only makes it easier to interpret the results relating to $\beta$ when estimating the main model of this paper with both earnings and trading signals.

FIITR = Net Buying by all FIIs over the two-day earnings announcement window divided by shares outstanding. Net FII buying for a firm on a day equals number of shares bought less number of shares sold for that firm by all FIIs on that day. This is our proxy for aggregate order flow $\omega$. FIITR is centered as described earlier in this section.

In the actual empirical work we adopt a slight reparametrization of the above model for the pricing error $u$. We define $u = p - (\alpha + \beta v_F + \lambda\omega)$, with $\alpha = 0,\ \beta = 1 + \rho * \sqrt{\sigma_1^2},\ \lambda = \sqrt{\sigma_2^2} * \sqrt{1-\rho^2}$. So $\sigma_1 = \left(\frac{\sigma_T}{\sigma_F}\right)$ and $\sigma_2 = \left(\frac{\sigma_T}{\sigma_Z}\right)$. It is important to note that there is strictly no loss of information in this reparametrization, since with an independently estimated $\sigma_F$, and estimates of $\sigma_1$ and $\sigma_2$, $\sigma_T = \sigma_F * \sigma_1$, and $\sigma_Z = \left(\frac{\sigma_T}{\sigma_2}\right)$. Since our numerical algorithms search for solutions only within real values, using the radical guarantees that the variances are (almost surely) positive, and that $\rho \in [-1,1]$.

Our first set of control variables are drawn from prior work on asset pricing. Fama and French (2016) show that five factors explain a significant fraction of the cross-section of monthly returns. The factors are: market-wide return, firm size, book-to-market ratio, operating profitability scaled by assets, and prior asset growth. Our second set of controls are firm characteristics that have been shown to be related to institutional trading (Gompers and Metrick (2001); Yan and Zhang (2009)). Whether these characteristics are related to earnings announcement returns is an open question. However, we include them as regressors, for a pragmatic reason - to reduce the likelihood of any correlated omitted variable bias. Our twelve control variables are defined as follows:

1. Market-wide return (MRET) is defined as the return on the CNX Nifty Index compounded over days 0 and 1. The index daily return is calculated as the daily percentage change in the Index.
2. Firm size (LMCAP) is measured as the log of the market capitalization at the beginning of the quarter (MCAP).
3. The book-to-market ratio (BM) is obtained by dividing by the book value of equity at the end of the most recent fiscal year before the earnings announcement (year t-1) by MCAP.

4. MOM3 is the three month return during the fiscal quarter before the earnings announcement date.
5. Operating Profitability (OPROF) is measured as profit before interest, tax, and depreciation for year t-1 divided by total assets at the end of year -2.
6. Asset growth (AGRO) is the percentage change in total assets in year t-1.
7. STDRET is the standard deviation of monthly returns in the calendar year before the earnings announcement date.
8. VOL is the monthly volume divided by shares outstanding, measured for the month immediately before the fiscal quarter for which earnings is announced.
9. LAG_UE is the value of UE lagged by one quarter.
10. L_AGE is the logarithm of age of the firm at the end of the quarter measured with reference to the year of incorporation.
11. DIVY is the annual dividend in year t-1 divided by MCAP.
12. LPRC is the logarithm of beginning quarter price.

In our empirical work, we consider three sub-samples based on FII trading on the earnings announcement date and FII ownership around that date. Our first sub-sample consists of announcements during which there is no FII trading and for which FIIs owned no shares at the end of the quarter both before and after the announcement date (regime 1). We employ this sub-sample to estimate the benchmark regression of ERET on UE and control variables, when there is no FII trading, and use it to adjust the scale of the UE data in our entire sample. Our second subsample consists of those announcements that have non-zero FII trading (regime 3); our pricing equation is estimated for this sub-sample. For one analysis we augment this sample with observations that have only FII trading and no earnings announcements (Regime 2).

The third sub-sample consists of earnings announcements where there is no FII trading, but FII do own shares before and/or after the announcement. A question arises: should we treat no-trade as no-data or as a zero-trade record? Per Easley, Kiefer, O'Hara (1998), we could consider no-trade also as a signal.

In our data if we made that assumption, the sample would grow from under 18,000 to over 40,000 (see Table 1), with the entire addition being zero-trades. This would mean that FII trading variability would become close to zero, which in turn would lead to our estimate of $\sigma_T$ becoming close to zero. It seems more useful to leave the zeroes out, and acknowledge that our results hold not for the universe of all firms on India's National Stock Exchange but only for those firms that have attracted significant FII interest. These do tend to be larger firms. This is consistent with previous work on institutional trading.

## 5. Data Sources

We obtain data from two sources: the PROWESS database of the Center for Monitoring Indian Economy Private Limited and the Securities and Exchange Board of India (SEBI) website. PROWESS provides the information need to construct the dependent variable (ERET), unexpected earnings (UE), and the control variables. The SEBI website is our data source for daily FII buy and sell trades.

To measure the dependent variable ERET, we obtain the earnings announcement date (day 0) and returns on day 0 and 1. We treat the date of the board meeting on which financial results are approved as the earnings announcement date.[8] To measure unexpected earnings (UE), we obtain quarterly basic earnings per share and beginning of quarter closing prices. To measure control variables, we obtain (a) annual financial variables – book value of common equity, operating profit, total assets, and dividends[9]; (b) daily market variables – firm returns, market returns, volume, and closing prices; and (c) the year of incorporation.

To measure net FII buying on the earnings announcement date, we obtain daily FII trading data from the SEBI FII trading database.[10] On this database, the basic unit of observation is trading activity by

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[8] As per Exchange Regulations, listed firms are required to file their quarterly financial results within thirty minutes of the board meeting, presumably to reduce the likelihood of illegal insider trading. See for example, https://beta.bseindia.com/corporates/compliancecalendar.aspx.

[9] While all Indian firms report parent-only unconsolidated financial statements, some of them simultaneously report consolidated financial statements. To maximize sample size, we examine only parent-only financial statement data.

[10] We thank Mr. Shyam Benegal whose parliamentary question seeking archival FII trade data for academic research yielded the initial pilot sample. Today, the data is publicly available on the SEBI website, and some mirror sites.

an FII for a stock on a trading day. Data fields include an identifying code for each FII, the ISIN for the stock, and the exchange on which the trades were executed. It also has six measures of trading activity for each FII-stock-exchange-day quadruple: (a) the number of buys; (b) the number of sells; (c) aggregate shares bought on a day; (d) aggregate shares sold on a day; (e) value of shares bought; and (f) value of shares sold. Unfortunately, SEBI masks the FII identifying codes and changes the masks every month; consequently, FII-level analysis is difficult. Therefore, for each stock-trading day pair, we aggregate daily data across FIIs. Because we have no reason to expect exchange-related effects, we also aggregate daily trades across exchanges (primarily the BSE and the NSE).

We measure Net FII buying for a firm on a day as the number of shares bought less number of shares sold by all FIIs on that day, divided by shares outstanding. We integrate the FII trading data (SEBI) and the firm price and financial statement data (PROWESS) by matching on firms' ISINs.

# 6. Results

## 6.1. Sample Description

Our sample period consists of fourteen years; it begins in the first quarter of 2003 and ends in the fourth quarter of 2016. Table 1 describes the filters applied to our initial sample of 92,703 firm-quarters to arrive at the final sample 59,996 firm-quarters. To enter the final sample, firm-quarters are required to have non-missing data for our regression variables, announce earnings on dates that are valid and within 180 calendar-days of the fiscal quarter end date, have non-missing stock returns for at least 45 days during the 90 trading-day period centered on the earnings announcement date, and have at least two observations over the sample period. In our final sample, 18,013 (30%) had no FII ownership at all (Regime 1); 24.105 (40%) had FII ownership before, or during, or after the earnings announcement window, but no FII trading; and 17,878 (30%) had FII trading during the earnings announcement window (Regime 3). From Table 2, we see that the relative proportions of the three firm-types do not display a significant temporal shift during the sample period.

Table 3 reports univariate statistics for the regression model variables for the 17,878 firm-quarters that had non-zero FII trading during the earnings announcement period (Regime 3). The mean earnings announcement return is -0.10%, but the median is -0.32%, suggesting the influence of some large positive values on the mean. Mean unexpected earnings scaled by share price is negative at –0.19%; however, the median is slightly positive at 0.10%. The mean and median net FII buying at the earnings announcement is almost zero. The average zero net buying masks the fact that FIIs are both buying and selling on that day and their buys and sells offset each other. Figure 1 shows how median FII buying, selling, and net buying behave around earnings announcements. On day 0 and 1, both FII buying and selling spike to between 0.03% and 0.04%, higher than any other day in the sixty-day window around earnings announcements. Buying and selling offset each other, causing median FII net buying to be close to zero.

Turning to the control variables, mean market return (MRET) is positive at 0.04%, the log of mean market capitalization (LMCAP) is 10.22, and the mean book-to-market ratio (BM) is 0.61. Mean returns in the fiscal quarter before the earnings announcement (MOM3) are positive on average at 9.48%. The sample firms are profitable on average and are growing – mean operating profitability (OPROF) is 19% and mean asset growth (AGRO) is 22.41%. Mean monthly return volatility (STDRET) is 2.64% and average monthly volume as a percentage of shares outstanding (VOL) is 9.52%. The average logarithm of age (L_AGE) is 2.59, average dividend yield (DIVY) is 1.56%, and the average logarithm of price (LPRC) is 5.40.

Table 4 provides simple correlations between all our variables. The simple correlation between our two primary RHS variables, UE and FIITR is 0.01 and not significantly different from zero. However, our nonlinear model estimates of the deep parameter $\rho$ will uncover the commonality in the information advantages of the firm and the FIIs, that the simple correlation reported in Table 4 does not reveal.

### 6.2. Regression models

Our regression analysis begins with the benchmark case when the only signal available to the market is unexpected earnings (Regime 1). We estimate an OLS regression of ERET on mean centered UE and control variables for this sub-sample (n=18,013). The untabulated coefficient estimate on UE in this regression is 0.02426. We re-estimate the Regime 1 regression with mean centered UE multiplied by this scale factor and obtain a coefficient of exactly one for centered UE. Much of the remaining analysis is based on regressions for the estimation sample that corresponds to Regime 3, when both UE and FIITR are present. Before we conduct this analysis, we multiply the centered UE for the estimation sample by 0.02426.

In Table 5, we report four earnings announcement regressions for the estimation sample. The dependent variable is ERET and the main independent variables are UE and FIITR whose coefficients are $\beta$ and $\lambda$, respectively. We include firm and year fixed effects and adjust standard errors for clustering within each firm. These regressions do not use any restrictions from the underlying theory, and the coefficients $\beta$ and $\lambda$ here are estimated directly from the data, without invoking any of our equilibrium formulae. Column (1) reports the baseline regression that includes only control variables. The adjusted $R^2$ for this regression is 16.45%. The second regression (column 2) augments the model with UE. The coefficient on UE is 8.975 with a t-statistic of 13.28; the adjusted $R^2$ increases to 18.13%. In the third regression in column 3, we include FIITR without UE. FIITR is positively and significantly related to ERET with the coefficient of 4.978 and a t-statistic of 16.63. The adjusted $R^2$ in this regression is 19.41% which compares favorably to that of the regression in column 2 and suggests that FIITR is a more influential determinant of returns than is UE. The final column (4) reports the Regime 3 regression when both UE and FIITR are included. Compared to the results in columns (2) and (3), the coefficients $\beta$ and $\lambda$ are essentially unchanged and statistically significant, and the $R^2$ climbs to 21.14%. The stability of $\beta$ and $\lambda$ across regressions suggests that the variables UE and FIITR are independent of each other. Neither $\beta$ nor $\lambda$ increases or decreases because of the presence of the other signal.

Readers should recall estimation in the context of demand functions and the linear expenditure system. The application of restrictions from demand theory (such as the Slutsky sign condition and the Slutsky symmetry condition) caused the coefficients in the linear expenditure system to be different (Klein and Rubin (1947), Geary (1950), Stone (1954)), from the estimation without invoking any theory of demand. We show in what follows that we observe that kind of sharp difference only when we adjust for endogeneity of FII trades.

Thus far, our empirical model estimates assume that FII trading is exogenous to announcement returns. But not only is the theory we started out with a theory that endogenizes FII trading, it is clear that exogeneity of FII trading is easily rejected in the data. It is possible that FII trading responds to price movements during the earnings announcement period. To account for endogeneity, we employ the two-stage least squares method (2SLS). Our instruments for FIITR are: the change in the US Dollar-Rupee rate on day -3 (CH_USD_INR) and the CNX Nifty Market return on day -2 relative to the earnings announcement (L_MRET). In first-stage regressions of FIITR on the two instruments and all the other exogenous variables (UE, control variables, year and firm effects), both instruments are significantly related to FIITR. The t-statistic on the change US-Dollar Rupee rate is -1.79 and that on the lagged market return is 3.70. Importantly, these instruments are not weak. The Cragg-Donald Wald Staistic is 8.84 which exceeds the Stock-Yogo Weak ID 10% critical value (8.68). Additionally, the Hansen-Sargan J Statistic for over-identification is 0.375 with a p-value of 0.54. Thus, the two instruments are likely uncorrelated with the error term in the earnings announcement return regression. Lastly, before we discuss the estimates under FIITR endogeneity, we note that Wu-Hausman test statistic for endogeneity is 41.649 (p-value = 0.00). Thus, the null hypothesis of FIITR exogeneity is rejected.

Table 6 reports the results when we account for the endogeneity of FIITR, using two-stage least-squares, without invoking the theory. These are the 2SLS analogue to the results report in the last column of table 5. When no theory is used, $\beta = 10.312$ and $\lambda = 48.511$. The associated t-statistics are 8.58 and 3.95, respectively.

In Table 7A, we report our GMM model estimates of our primitive parameters where we account for our model structure. The empirical model is derived only from Regime 3, and we have 5 moment restrictions to estimate 3 parameters. The model is defined by the pricing error $u = p - (\alpha + \beta v_F + \lambda\omega)$, with $\alpha = 0,\ \beta = 1 + \rho * \sqrt{\sigma_1^2},\ \lambda = \sqrt{\sigma_2^2} * \sqrt{1 - \rho^2}$. So $\sigma_1 = \left(\frac{\sigma_T}{\sigma_F}\right)$ and $\sigma_2 = \left(\frac{\sigma_T}{\sigma_Z}\right)$. It is important to note that there is strictly no loss of information in this reparametrization, since with an independently estimated $\sigma_F$, and estimates of $\sigma_1$ and $\sigma_2$, $\sigma_T = \sigma_F * \sigma_1$, and $\sigma_Z = \left(\frac{\sigma_T}{\sigma_2}\right)$. The moment restrictions are given by $E(u * Z) = 0$, where the five instruments $Z$ are in turn the constant (1), $v_F$ (UE), $\omega$ (FIITR), lagged market return (L_MRET), and the change in the US$/INR exchange rate (CH_USD_INR).

The GMM objective function is nonlinear in the coefficients (though linear in the variables), and continuous and smooth. But it is clearly not globally convex. A little experimentation is sufficient to show that there are many local minima, and that the number of local minima seems to grow with sample size. The best we can hope for with a grid search, given the very large number of local minima, is to find a good local optimum. So selecting good starting values becomes important for any grid search. A first step was to simply evaluate (without any estimation) the GMM objective function, assuming an identity weight matrix, at each of a dense grid of over 4.5 million sets of parameter values. We then plotted the objective function in turn against each subset of 2 of our 3 parameters. This confirmed the ill-behavedness of the objective function. We also noticed some clustering of objective function values. From the lowest objective function values reached, we learnt about how low an objective function value we could hope for, and got some idea for appropriate starting values. For estimation purposes we used a grid of 475 sets of initial values.

We then modified the classical iterative GMM algorithm to incorporate a perturbation step proposed by Wood (2001). Define $P_k \equiv \{\rho_k, \sigma_{1_k}, \sigma_{2_k}\}$ as a set of initial parameter values. We implement 2-step GMM in the original sample to obtain a set of final parameter estimates $P_1$. We then use the same set of initial values $P_k$ with a bootstrap sample, and a weight matrix $W_k$ given by the inverse of the variance-covariance matrix of the moment conditions evaluated given the data and the parameter set $P_k$, to get another set of final parameter estimates $P_B$. We then used $P_B$ with the original sample to get another set of final parameter estimates $P_2$.We set $P_{k+1}$ equal to either $P_1$ or $P_2$ depending on which yielded the better objective function value, and updated the weight matrix $W_k$ to $W_{k+1}$. Convergence was defined as $|W_k - W_k|$ and $|P_k - P_{k+1}|$ both being within tolerance limits. The perturbation bootstrap step within each iteration reduces the chance of being trapped in a flat region of the objective function, and makes it more likely that we move to a better local minimum. The local minimum achieved was lower than the lowest from the simple evaluation of the objective function on the initial dense grid.

The striking result from Table 7A is in the magnitudes of $\sigma_1$ and $\sigma_2$. They tell us that the FII's information advantage dwarfs what the firm's information advantage ($\sigma_F$) and background noise ($\sigma_Z$) by almost an order of magnitude ($\sigma_1 = 7.509$ and $\sigma_2 = 7.4248$). This does not mean that the *total* information in the firm's report is small. That could still be large, but communication throughout the year, or close following by analysts of these relatively larger firms, could ensure that most of that information is already known to others. The coefficient $\sigma_2$ is over 5, suggesting that what FII traders know is not dwarfed by background noise. The parameter $\rho = 0.788$ so to some degree the resulting $\beta = 6.917$ reflects what the market learns about FII's private information from the firm's earnings announcement. The coefficient $\lambda = 4.5707$.

Standard errors are defined by a HAC-consistent wild cluster bootstrap procedure. We first compute residuals based on the above point estimates. Then we define observation clusters by firm, and resample with replacement to select the firms that will enter a given bootstrap sample. For these firms, the residuals of an entire firm are multiplied by an independent Rademacher random variable (+1 or -1, with equal probability). These transformed residuals are then used to define the predicted AR for the bootstrap sample, from which we get iterative GMM estimates. We used 1000 bootstrap samples to get 1000 sets of bootstrap statistics. Use of the Rademacher transformation makes the bootstrap design "wild," and provides robustness given heteroscedasticity; use of firm clusters, given serial correlation in a firm's errors. Bootstrap standard errors show that all parameters are significant.

In Table 7B, we present a set of GMM estimates where the empirical model reflects both regime 2 and regime 3. Using superscripts "T" and "FT" to denote regimes with signals of only the traders (T), regime 2, or also the firms (F), Regime 3, are available, the model is defined by the equilibrium pricing rules noted in Section 3. So we have

$u_1 = p - (\beta^{FT} * v_F + \lambda^{FT} * \omega)$, with $\beta^{FT} = 1 + \rho\left(\frac{\sigma_{T1}}{\sigma_F}\right),\ \lambda = \left(\frac{\sigma_{T1}(\sqrt{1-\rho^2})}{\sigma_z}\right)$,

$u_2 = p - (\lambda^T * \omega)$, with $\lambda^T = \left(\frac{\sigma_{T2}(\sqrt{1-\rho^2})}{\sigma_z}\right)$.

The moment restrictions are given by

$E(u_1 * Z) = 0$, where the five instruments $Z$ are in turn the constant (1), $v_F$ (UE), $\omega$ (FIITR), lagged market return (L_MRET), and the change in the US$/INR exchange rate (CH_USD_INR); and by $E(u_2 * Z) = 0$, where the four instruments $Z$ are in turn the constant (1), $\omega$ (FIITR), lagged market return (L_MRET), and the change in the US$/INR exchange rate (CH_USD_INR).

So we now have 9 moment conditions and 4 parameters. Notice that in the above 2-regime specification, the background noise parameter $\sigma_z$ is held constant across regimes, while the traders' information advantage $\sigma_T$ is allowed to vary across regimes. The most striking feature about the estimates in Table 7B relate to the traders' information advantage, $\sigma_T$. We find that $\sigma_{T1} = 36.75 >> \sigma_{T2}$=17.82, suggesting the traders gather more information in anticipation of a public announcement like earnings. This provides a formal structural explanation to a longstanding and well-documented empirical regularity (see Beaver et al (2018) for a recent example): trading volume increases at the time of an announcement. A public announcement should reduce dispersion of beliefs and volume should be lower, holding preferences and opportunities constant. Yet clearly other factors are not constant. When traders gather more private information at the time of a public announcement, dispersion in beliefs increases, causing volume to go up. This is also consistent with the focal point role of public announcements noted by Schelling (1960). This result also complements the results in Hirshliefer et al (2014) that traders' have finite resources of attention, that they allocate among announcing firms. We note that in the 2-regime model, the estimate for $\rho$, while still significantly positive, is now very small in absolute terms. We are currently exploring other specifications of the 2-regime model.

Is there heterogeneity in the data – i.e. firms with $\rho$ ranging from very negative to very positive – that are masked in the aggregate sample? To investigate the possibility of heterogeneity we implement the theory-based estimation with instrumental variables, on a firm-by-firm basis. For this analysis, we retain only the 366 firms that have at least twenty quarterly observations during the sample period. Additionally, we include only MRET as a control variable in each firm-specific regression. We do so to avoid model overfitting that could result if we included all twelve control variables. The coefficient on MRET is denoted as $c_1$.

Table 8 reports the distribution of firm-by-firm estimates of the primitive parameters. In Panel A we report the firm-by-firm OLS estimates of the model that does not invoke the theory. In Panel B, we report non-linear model parameter estimates. The results indicate that there is considerable variation in every parameter, deep and shallow. In particular, $\rho$ ranges from -1 to +1. To evaluate statistical significance of all the parameters, we compute the cross-sectional means of the parameters and divide these means by their standard errors (Fama and Macbeth (1973)). The t-statistics reported in Table 8 indicate that all the parameters (including $\sigma_Z$) are significant at conventional levels. What is striking is that 72 out of 366 firms have $\beta < 0$. Thus, $\rho < 0$ or disagreements in interpreting common information between firms and FIIs, is not uncommon.

### 6.3. Holdout sample model comparisons

Does our theory provide a better explanation of the world generating our data than not using any theory at all? To answer this question, we perform model comparisons. Specifically, we compare forecasts from the model that does not impose any theory with the model that does (estimates for these two models are reported in Table 7). To generate forecasts, we randomly split the sample into a training sample (80%) and a test sample (20%). We estimate both models with the training sample and then apply the coefficients thus obtained to the test sample independent variable values. This yields the “predicted” test sample values for earnings announcement returns. Based on a comparison of the actual and predicted earnings announcement returns, we compute root mean square error (RMSE) and mean absolute error (MAE). The mean with-theory RMSE is 0.0025 and the mean without-theory RMSE is 0.0031. The two-sample t-test value (with unequal variances) is 5.08 (p-value = 0.00). This suggests that invoking the theory provides a better explanation of price and trading behavior than estimating a model without the theory. Similarly, the mean with theory MAE is 0.038 and the mean without theory MAE is 0.042. The two-sample t-test is 4.80 (p-value = 0.00), confirming that the estimates that invokee the theory helps describe the data better than those without the theory.

### 6.4. Sub-sample analyses

In Table 9, we dig a little deeper into our primitive parameter estimates. Our first partition of the data is based on firm size. We measure size as the log of market capitalization at the beginning of the quarter (LMCAP). To form the three size groups, we divide the sample into ten deciles based on LMCAP. Firm-quarters in smallest three deciles are assigned to the group SMALL, those in the next four deciles are assigned to the group MEDIUM, and those in the largest three deciles are assigned to the group, LARGE.

Panel A of Table 9 reports parameter estimates across size groups. Our results indicate that while $\sigma_F$ is constant across size group (0.001), $\sigma_T$ declines sharply with size, from 0.077 for small firms to 0.0024 for large firms. Therefore, while $\sigma_T > \sigma_F$ in every case, the difference between $\sigma_T$ and $\sigma_F$ diminishes from 77 times for small firms to just 24 times for large firms. The relative information advantage of FIIs drops with firm size. A plausible explanation for this effect is that larger firms release more public information and are followed by more analysts, causing the information advantage of FIIs to decline. The market noise $\sigma_Z$ increases with firm size (from 0.007 for small firms to 0.008 and 0.015 for medium and large firms) and is larger than $\sigma_F$ for all three size classes. The correlation $\rho$ displays a slightly inverted-U pattern across firm-size groups; it increases from 0.124 for small firms to 0.153 for medium firms and then drops slightly to 0.145 for large firms. While the correlation parameter $\rho$ is not monotone in size, $\rho * \sigma_T$ is also declining in firm size.

Table 9 also reports the response coefficients to UE and FIITR for the three size classes. They are not monotone in firm size. Focusing on small versus large firms, $\beta$ is slightly larger for small firms (8.917 versus 7.443). On the other hand, $\lambda$ is significantly larger for small firms (11.375) than that of large firms (1.618). Differences in $\lambda$ are driven largely by the ratio of informed to noise trading $\left(\frac{\sigma_T}{\sigma_Z}\right)$. This ratio is 11 for small firms, but only 1.6 for large firms. An explanation for this finding is that as firm size increases, information asymmetry between firms and traders declines.

Our second partition is based on whether or not firms have just avoided reporting a loss. Beginning with Burgstahler and Dichev (1997), several studies document a sharp discontinuity around zero for various profit measures, with a disproportionate number of firms reporting profits just to the right of zero. Figure 2 presents a partial histogram of earnings per share around 0, ranging from -2.0₹ per share to 2.0₹ per share for our sample, with a bin width of 0.1. Consistent with the U.S. evidence, the Figure indicates a sharp discontinuity around zero, with a disproportionate number of firms to the immediate right of 0, compared to the number of firms to the left of zero. Loss avoiders, or small-profit firms, are defined as firms with a quarterly earnings per share (EPS) that is between 0.01₹ to 0.2₹ (inclusive). Similarly, small-loss firms are defined as firms with an EPS between -0.2₹ to -0.01₹ (inclusive). We do not include firms with an EPS that exactly equals zero, as the group to which such firms belong is ambiguous. Our interest is in examining if the deep and shallow parameters differ across the small-loss and small-profit firms.

Panel B of Table 9 reports the results. The nonlinear model estimates of β indicate that small loss firms' unexpected earnings are valued higher (β = 11.749) than that of small profit firms (β = 3.372). The deep parameter estimates can be examined to explain this result. Because $\sigma_F$ is very similar for the two sets of firms, differences in β are driven by $\sigma_T$ and $\rho$. Both $\sigma_T$ and $\rho$ are smaller for small-profit firms. That is, for small-profit firms, there is less to learn in the first place for informed traders. This may be, as prior research suggests, because small-profit firms' earnings quality is lower because these firms must have managed earnings to cross the zero line. Interestingly, the OLS estimates of β are negative (although not statistically significant) for the small-profit firms. Turning to $\lambda$, small-profit firms have a $\lambda$ that is half that of small-loss firms, again suggesting that there is a priori less information and more noise wfor small-profit firms. Again, the deep parameter estimates provide us additional insights. The ratio of $\sigma_T$ to $\sigma_Z$ – informed versus noise trading, is an important determinant of $\lambda$. Small loss firms have ten times more informed trading compared to noise trading, that ratio is only about five for small profit firms.

## 7. Additional Remarks on Substitutes or Complements

Let us return to our theoretical model and collect the equilibrium pricing rule coefficients $\beta$ and $\lambda$ under the three different regimes (using superscripts to indicate different underlying regimes), including the benchmark models described at the start of section 3.4.

| Regime | Available signals | $\beta$ | $\lambda$ |
|---|---|---|---|
| 1 | Only firm earnings $v_F$ | $\beta^F = 1$ | - |
| 2 | Only FII trades $\omega$ | - | $\lambda^T = \left(\frac{\sigma_T}{\sigma_Z}\right)$ |
| 3 | Both of the above | $\beta^{FT} = 1 + \rho\left(\frac{\sigma_T}{\sigma_F}\right)$ | $\lambda^{FT} = \left(\frac{\sigma_T(\sqrt{1-\rho^2})}{\sigma_Z}\right)$ |

By comparing the main model of this paper with benchmark models where only one signal, either earnings or FII trading, is available, sheds light on whether earnings and trading signals are substitutes or complements, or if they are independent. When there are two signals X and Y, if the weight on X increases in the presence of Y, then Y is an information complement to X. If the weight on X decreases in the presence of Y, then Y is an information substitute for X. Else X and Y are independent. Notice that if the deep parameters are constant across regimes, then $\lambda^{FT} \leq \lambda^T$, with equality only when $\rho = 0$. So except for when $\rho = 0$ (when the earnings signal $v_F$ and the FII private information $v_T$ are independent), it would always the case that for price-setting market makers, the earnings signal $v_F$ is an information substitute to the FII trading signal $\omega$. However, the converse is not necessarily true. Whether the FII trading signal is a complement to, or independent of, or a substitute for $v_F$, depends crucially on whether $\rho >, =,$ or $< 0$, as this affects whether $\beta^{FT} >, =,$ or $< \beta^F = 1$. As a practical matter, the primitive parameters are not constant across regimes.[11]

We have already estimated Regime 1, which was used to help rescale unexpected earnings for the entire sample. So we know that $\beta^F = 1$. Since all of the estimated $\beta$ in Tables 5, 6 and 7 are much larger than 1, our results suggest that FII trading serves as a complement to earnings, since the presence of that trading signal increases the weight on earnings. The reason for complementarity is not a confirmation effect as in some papers (Gonedes (1978), Allen and Ramanan (1990)). Rather it is the cross-effect from exploiting earnings to also learn about the private information of traders.

To examine if earnings are a substitute or complement for FIITR, we also estimate $\sigma_T$, $\sigma_Z$, and $\lambda^T$ under Regime 2 using data from a sample where only FII trading was observed and no earnings signals are available. Specifically, we pick four trading days from non-announcement periods for the Regime 3 sample – days -10, -20, -30, and -40 relative to the earnings announcement date. We compute the two-day returns ending on these four dates. We then estimate a regression of these two-day returns on all the control variables, and firm and year effects. The residual from these regressions is an abnormal return and is denoted as RET. Since it turns out that we can invert the equilibrium expressions for Var(P) and Var($\omega$) for the primitive parameters $\sigma_T$ and $\sigma_Z$, we obtain point estimates from $\widehat{\sigma_T} = \sqrt{2} * \sqrt{\mathrm{Var}(RET)}$ and $\widehat{\sigma_Z} = \sqrt{2} * \sqrt{\mathrm{Var}(FIITR)}$. $\lambda^T$ is obtained as the ratio of $\widehat{\sigma_T}$ to $\widehat{\sigma_Z}$. For asymptotic standard errors (SE), we used SE($\widehat{\sigma_T}$) $= \sqrt{2} * SE(\sqrt{\mathrm{Var}(RET)})$ and SE($\widehat{\sigma_Z}$) $= \sqrt{2} * SE(\sqrt{\mathrm{Var}(\omega)})$. To

[11] While the literature on product substitutes versus complements is large, and includes considerable empirical work, with respect to information substitutes and complements, the only empirical papers we have identified are Gonedes (1978) and Allen and Ramanan (1990). The two signals that both these papers focus on are unexpected earnings and insider trading; in contrast, we examine unexpected earnings and institutional trading. The significant departure that we make relative to these two papers is in identifying benchmark cases with only one signal, which makes the assessment of substitutes or complements much simpler.

obtain the standard error of a standard deviation, we used the correction factors $K_n$ and $V_n$ described in Ahn and Fessler (2003). $\lambda$, per the expression for $\lambda^T$ in the table comparing equilibria in the three models, is given by $(\frac{\sigma_T}{\sigma_Z})$.

The estimates are summarized in Table 10. We find that $\lambda$ ranges from about 24 to 26 for the four dates and is much higher (by a factor of 5) than those reported in Tables 5, 6 and 7 (except when we use instruments but do not use the theoretical restrictions). The results indicate that the relationship between earnings and trading is not symmetric. Earnings are a substitute for FII trading but FII trading is not a substitute but a complement to earnings. Earnings are a substitute for FII trading since the regime 3 $\lambda$, $\lambda^{FT}$, computed in Tables 5-7 in this paper, is less than $\lambda^T$ computed in Table 10. While the estimates for $\sigma_T$ are about 0.06 in Regime 3 and about 0.045 in Regime 2, we cannot ascribe all of this difference to $\rho$ and the availability of earnings as an additional signal, since the estimated market noise $\sigma_Z$ is also different in the two regimes. Under Regime 2 it is 0.002, which is about one-sixth its value under Regime 3 during the earnings announcement period (0.012, see Table 7).

## 8. Concluding Remarks

The contribution in this paper can be viewed from multiple perspectives. One benchmark is the vast literature on studies analyzing earnings announcements. Our work studies a case with a market-provided signal, FII trading, in addition to firm-provided earnings news. From a comparison of $\beta$ and $\lambda$ in the aggregate sample, we find that even during the earnings announcement window, the market-provided signal is relied upon more by price-setters.

It is not easy to have priors regarding parameters like the correlation $\rho$, or the traders' advantage from private information, $\sigma_T$. Our work provides empirical measures of such parameters, and so can open the way to additional questions being addressed. The empirical work in the asset pricing literature has tended to focus on Kyle's $\lambda$ or the probability of informed trading (PIN) measure derived from the Glosten-Milgrom model, or simply the bid-ask spread. Because we estimate primitive parameters, we can evaluate determinants of lambda, and because we have multiple signals in a correlated setting, our results also shed light on the role of the correlation parameter. The novel methodological contribution in our paper is to apply GMM estimation techniques to a Kyle-type model. The main insight is to see that the linear pricing rule is a convenient source of moment restrictions.

We study an Indian database that has only recently become available (and is public and free, and so allows for easy replication). Our estimates of the deep parameters of the model such as the variance governing the FIIs' informational advantage, the level of background noise, and the correlation between the two components of the payoff suggests that traders may know more about firm payoffs than firms themselves, and that the reaction to earnings is as large as it is because market participants are also using earnings to learn about the private information of traders. These are parameters of interest but cannot be directly observed or inferred, unlike the shallow parameters of an econometric model like $\beta$ and $\lambda$. The underlying model of equilibrium serves as a bridge between what we can observe, and what we are also interested in but cannot observe.

Our results indicate the information advantage of FIIs with respect to the component they have information about, exceeds the information advantage that firms have with respect to information released via earnings announcements. Also, we find that for many firms in our sample a negative $\rho$ and a large ratio of $\sigma_T$ to $\sigma_F$ causes $\beta < 0$, so that good news about firm earnings can be viewed as bad news by markets, as noted in a different setting by Lundholm (1988) and Manzano (1999). The traditional result that $\beta > 0$ may reflect omission of a key market signal, institutional trades. This is more than a theoretical curiosity, since $\beta < 0$ for 72 out of 366 firms. This conclusion is possible only because we explicitly model the underlying equilibrium in a correlated environment and confront that model with data.

Another benchmark against which to measure what this paper does is the literature on asset pricing with private information under imperfect competition. The vast literature in that area has said little about the role of correlation among signals, except to assert that with correlation there are ways to learn about signals that are not observed from signals that are observed, and that in a rational world, this would also give rise to seeking additional ways to camouflage by being cautious in trading. Learning from prices or order flows about agents' private information has been studied a lot. That other public signals, like earnings, may also reveal traders' private information, has not been sufficiently recognized so far.

The simplicity afforded by the component payoff structure can be useful in other applications. Component structure meets the test of Occam's Razor. It provides the simplest explanation of why earnings do not sufficiently account for the price reaction even within an earnings announcement window. There are significant other components of payoff, some not directly observable even to firms, that we are yet to identify.

**References**


Acharya, V., R. Anshuman, and K. Kumar. 2014. Foreign fund flows and stock returns: Evidence from India. Working Paper, New York University.

Admati. A. 1985. A noisy rational expectations equilibrium for multi-asset securities markets. *Econometrica* 53: 629-658.

Admati, A., P. Pfleiderer. 1988. A theory of intraday patterns: Volume and price variability. *Review of Financial Studies* 1: 3-40.

Ahn, S. and Fessler, J.A., 2003. Standard errors of mean, variance, and standard deviation estimators. *EECS Department, The University of Michigan*, pp.1-2.

Allen, S., R. Ramanan. 1990. Earnings surprises and prior insider trading: Tests of joint informativeness. *Contemporary Accounting Research* 6: 518-543.

Bae, S., J. Min, and S. Jung. 2011. Trading behavior, performance, and stock preference of foreigners, local Institutions, and individual investors: Evidence from the Korean stock market. Asia-Pacific Journal of Financial Studies 40: 199-239.

Bhattacharya, U., M. Krishnan. 1999. To believe or not to believe. *Journal of Financial Markets* 2: 69-98.

Burgstahler, D., I. Dichev. 1997. Earnings management to avoid earnings decreases and losses. *Journal of Accounting and Economics*, 24: 99–126.

Bushee, B. and T. Goodman. 2007. Which institutional investors trade based on private information about earnings and returns? *Journal of Accounting Research* 45: 289-321.

Caballé, J., M. Krishnan. 1994. Imperfect competition in a multi-security market with risk neutrality. *Econometrica* 62: 695-704.

Cai, F., and L. Zheng. 2004. Institutional trading and stock Returns. *Finance Research Letters* 1: 178-189.

Campbell, J.Y., Ramadorai, T. and Schwartz, A., 2009. Caught on tape: Institutional trading, stock returns, and earnings announcements. *Journal of Financial Economics*, *92*(1): 66-91.

Choe, H., B. Kho, and R. Stulz. 2005. Do domestic investors have an edge? The trading experience of foreign investors in Korea. *Review of Financial Studies* 18: 795-829

Cready, W., Kumas, A. and Subasi, M., 2014. Are Trade Size-Based inferences about traders reliable? evidence from institutional Earnings-Related trading. *Journal of Accounting Research*, *52*: 877-909.

Davidson, J., Monticini, A. and Peel, D., 2007. Implementing the wild bootstrap using a two-point distribution. *Economics Letters*, *96*: 309-315.

Daley, L.A., Hughes, J.S. and Rayburn, J.D., 1995. The impact of earnings announcements on the permanent price effects of block trades. *Journal of Accounting Research* 33: 317-334.

Dvorak, T. 2005. Do domestic investors have an informational advantage? Evidence from Indonesia. Journal of Finance 60: 817-839.

Easley, D., Kiefer, N.M. and O'Hara, M., 1997. One day in the life of a very common stock. *The Review of Financial Studies*, *10*: 805-835.

Edelen, R., O. Inze, and G. Kadlec. 2016. Institutional investors and stock return anomalies. *Journal of Financial Economics* 119: 472-488.

Efron, B., R. Tibshirani. 1998. An Introduction to the Bootstrap. Chapman & Hall/CRC: New York.

Fama, E., K. French. 2016. A five-factor asset pricing model. *Journal of Financial Economics* 116: 1–22.

Fama, E., J. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81: 607–636.

Geary, R. 1950. A note on “A constant-utility index of the cost of living”. *The Review of Economic Studies* 18: 65-66.

Gompers, P., A. Metrick. 2001. Institutional investors and equity prices. *Quarterly Journal of Economics* 116: 229-259.

Gonedes, N. 1978. Corporate signaling, external accounting, and capital market equilibrium: Evidence on dividends, income, and extraordinary items. *Journal of Accounting Research* 16: 26-79.

Griffin, J., T. Shu, and S. Topaloglu. 2012. Examining the dark side of financial markets: Do institutions trade on information from investment bank connections? *Review of Financial Studies* 25: 2155-2188.

Grinblatt, M., and M. Keloharju. 2000. The investor behavior and performance of various investor types: A study of Finland's unique data set. *Journal of Financial Economics* 55: 43-67.

Hellwig, M. 1980. On the aggregation of information in competitive markets. *Journal of Economic Theory* 22: 477-498.

Hendershott, T., D. Livdan, and N. Schurhoff. 2015. Are institutions informed about news? *Journal of Financial Economics* 117: 249-287.

Hu, G., Jo, K.M., Wang, Y.A. and Xie, J., 2018. Institutional trading and Abel Noser data. *Journal of Corporate Finance*, 52: 143-167.

Hu, G., Ke, B. and Yu, Y., 2018. Can transient institutions correctly interpret small negative earnings surprises in the absence of access to management's private information? *Journal of Accounting, Auditing & Finance*, 33: 3-33.

Huang, R., and C. Shiu. 2009. Local effects of foreign ownership in an emerging financial market: Evidence from qualified foreign institutional investors in Taiwan. *Financial Management* 38(Autumn): 567-202.

Kang, J., and R. Stulz. 1997. Why is there a home bias? An analysis of foreign portfolio equity ownership in Japan. *Journal of Financial Economics* 46: 3-28.

Ke, B. and K. Petroni. 2004. How informed are actively trading institutional investors? Evidence from their trading behavior before a break in a string of consecutive earnings increases. *Journal of Accounting Research* 42: 895-927.

Klein, L., H. Rubin. 1947. A constant-utility index of the cost of living. *The Review of Economic Studies 15*: 84-87.

Kyle, A. 1985. Continuous auctions and insider trading. *Econometrica 53*: 1315-1335.

Lundholm, R. 1988. Price-signal relations in the presence of correlated public and private information. *Journal of Accounting Research 26:* 107-118.

Mammen, E., 1993. Bootstrap and wild bootstrap for high dimensional linear models. *The Annals of Statistics* 21: 255-285.

Manzano, C. 1999. Price-signal relations in an imperfectly competitive financial market with public and private information. *Journal of Accounting Research* 37: 451-463.

Nofsinger, J., and R. Sias. 1999. Herding and feedback trading by institutional and individual investors. *Journal of Finance* 54: 2263-2295

Puckett, A. and X.Yan. 2011. The interim trading skills of institutional investors. *Journal of Finance* 66: 601-633.

Rochet, J. and Vila, J. 1994. Insider trading without normality. *The Review of Economic Studies 61*: 131-152.

Shin, H. 1994. News management and the value of the firm. *The RAND Journal of Economics* 25: 58-71.

Sias, R. 2004. Institutional Herding. *Review of Financial Studies* 17:165–206.

Stone, R. 1954. Linear expenditure systems and demand analysis: an application to the pattern of British demand. *The Economic Journal 64*: 511-527.

Wu, C. 1986. Jackknife, bootstrap and other resampling methods in regression analysis. *The Annals of Statistics* 14: 1261-1350.

Yan, X., Z. Zhang. 2009. Institutional investors and equity returns: Are short-term institutions better informed? *Review of Financial Studies* 22: 893-924.

## Appendix

Given our assumption about component payoff structure, the multinormal random vector $\tilde{y} \equiv$ tr$\{\tilde{v}_F, \tilde{v}_T, \tilde{z}\}$, where "tr" denotes the transpose, is

$$\begin{bmatrix} \tilde{v}_F \\ \tilde{v}_T \\ \tilde{z} \end{bmatrix} \sim MN \left\{ \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_F^2 & \rho.\sigma_F.\sigma_T & 0 \\ \rho.\sigma_F.\sigma_T & \sigma_T^2 & 0 \\ 0 & 0 & \sigma_Z^2 \end{bmatrix} \right\}.$$ Let us call this 3x3 variance-covariance matrix

$\Sigma$, and let tr(j) $\equiv \{1,1\}$. Let $\tilde{y}_1 \equiv$tr$\{\tilde{v}_F, \tilde{v}_T\}$, and $\Sigma_{11}$ be the leading 2x2 minor of $\Sigma$. Then total payoff $\tilde{v} \equiv$ tr(j).$\tilde{y}_1$, and $\tilde{v} \sim N(0,$ tr(j).$\Sigma_{11}$.j).

We now define the FII trader's optimization problem. Since the trader can observe announced earnings $v_F$, her own private information $v_T$, and FII noise trade $z$, and faces the pricing rule $p = \alpha + \beta v_F + \lambda \omega$, where aggregate FII order flow $\omega = x + z$, the problem of the trader is to choose a demand $x$ to maximize profit, defined by $((v_F + v_T) - (\alpha + \beta v_F + \lambda(x + z)))x$ which yields the first-order condition $-\alpha + (1 - \beta)v_F + v_T - \lambda z = 2\lambda x$. Solving for $x$ yields $\tau_0 = \frac{-\alpha}{2\lambda}$, $\tau_1 = \left(\frac{(1-\beta)}{2\lambda}\right)$, $\tau_2 = \left(\frac{1}{2\lambda}\right)$, $\tau_3 = -\left(\frac{1}{2}\right)$.

Then aggregate order flow $\omega = x + z = \frac{-\alpha}{2\lambda} + \tau_1 v_F + \tau_2 v_T + \left(\frac{1}{2}\right)$z.

We then compute the expectation $E(\tilde{v}|v_F, \omega)$ where $\tilde{v} = \tilde{v}_F + \tilde{v}_T$. Define the multinormal random vector $\tilde{h} \equiv$ tr$\{\tilde{v}, \tilde{v}_F, \tilde{\omega}\}$, where "tr" denotes the transpose.

$$\begin{bmatrix} \tilde{v} \\ \tilde{v}_F \\ \tilde{\omega} \end{bmatrix} \sim MN \left\{ \begin{bmatrix} 0 \\ 0 \\ \frac{-\alpha}{2\lambda} \end{bmatrix}, \begin{bmatrix} \text{tr(j)}.\Sigma_{11}.\text{j} & \sigma_F^2 + \rho.\sigma_F.\sigma_T & 0 \\ \sigma_F^2 + \rho.\sigma_F.\sigma_T & \sigma_F^2 & 0 \\ 0 & 0 & \boldsymbol{Var}(\tilde{\omega}) \end{bmatrix} \right\},$$

where $Var(\tilde{\omega}) = Var(\tilde{x} + \tilde{z}) = Var(\tilde{x}) + Var(\tilde{z}) + 2Cov(\tilde{x}, \tilde{z})$.

Because of multinormality, the expectation $E(\tilde{v}|v_F, \omega)$is linear in the conditioning arguments. Recall that by virtue of market efficiency we have $p = E(v|v_F, \omega)$. Therefore, we equate corresponding coefficients to get three equations of the form, $\alpha = f_1(\alpha, \beta, \lambda)$, $\beta = f_2(\alpha, \beta, \lambda)$, $\lambda = f_3(\alpha, \beta, \lambda)$. From the first alone, it is easy to show that $\alpha = 0$. Manipulating the other two leads to a cubic in two variables, $\beta$ and $\lambda$, instead of in $\lambda$ alone as in Kyle (1985) and Rochet and Vila (1994). We obtain three candidate solutions of which only one satisfies $\lambda > 0$, which is needed to satisfy second-order conditions. So we have a unique real root. The solution is easily verified. Plugging the equilibrium values of $\beta$ and $\lambda$ into the trader's strategy coefficients yields Proposition 1.

**Figure 1**
*FII Buying and Selling Around Earnings Announcements*

In this Figure, we plot median FII buying, FII selling, and *net* FII buying around earnings announcements. FII buying (selling) on a day aggregates all buys (sells) for that day and divides that sum by shares outstanding. Net FII buying for each firm-day equals the number of shares bought less the number of shares sold by all FIIs for that firm on that day, divided by shares outstanding. The sample consists of only those firm-quarters for which FII trading during the earnings announcement period is non-zero. Data on FII trading are obtained from the SEBI website: http://www.sebi.gov.in. Earnings announcement dates are from the PROWESS database.

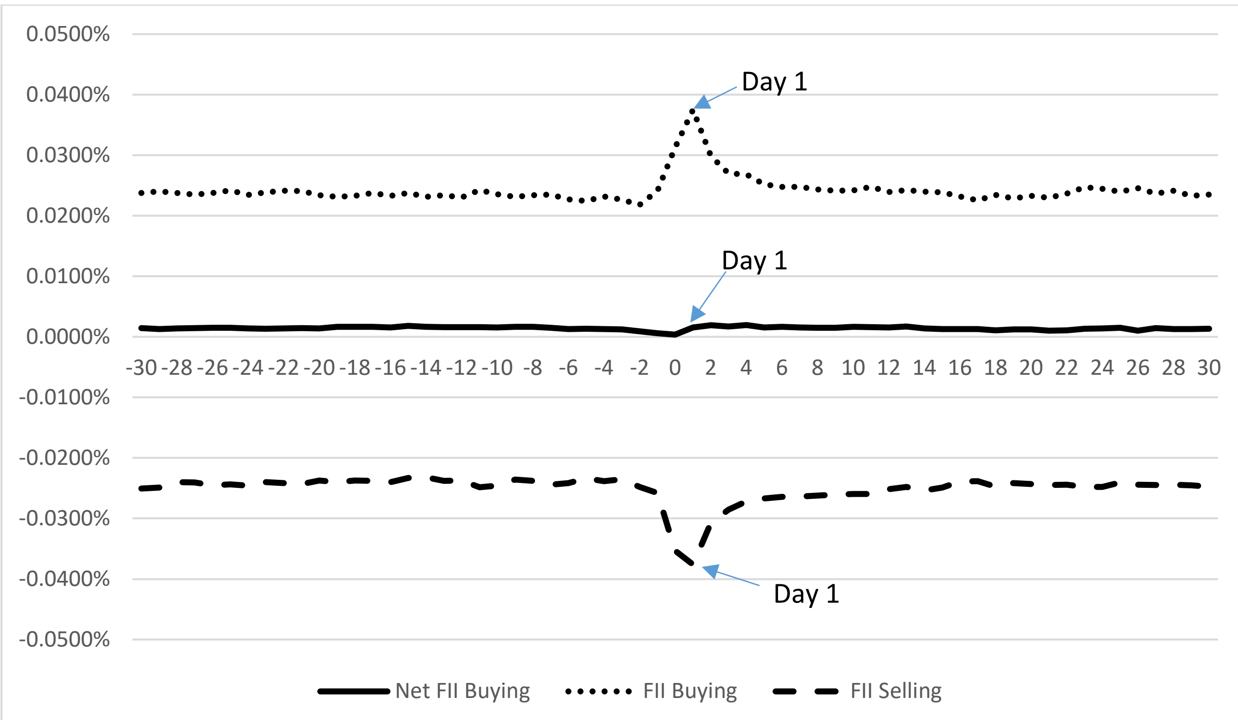

**Figure 2**
*Histogram of Basic Earnings per share around zero*

In this Figure, we present a partial histogram of earnings per share frequencies around zero, ranging from -2.0 ₹ per share to 2.0₹ per share. The sample consists of listed Indian firms for the years 2003-2016. Data on Earnings per share are from Prowess.

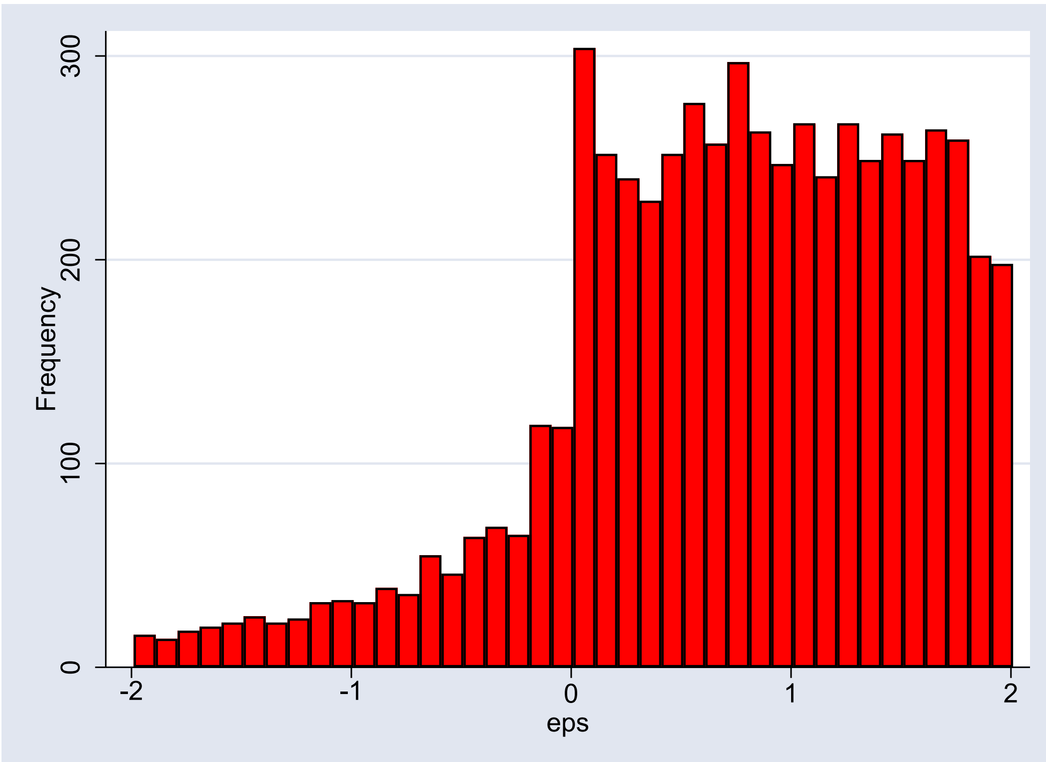

**Table 1**
*Sample Selection*

Our initial sample consists of all listed Indian firms with non-missing quarterly earnings announcement dates and non-missing earnings per share for the years 2003-2016. To enter the final sample, firm-quarters are required to have non-missing data for our regression variables, announce earnings on dates that are valid and within 180 calendar-days of the fiscal quarter end date, have non-missing stock returns for at least 45 days during the 90 trading-day period centered on the earnings announcement date, and have at least two observations over the sample period. Data on daily FII trades are obtained from the SEBI website: http://www.sebi.gov.in. Quarterly earnings announcement dates and earnings per share, stock prices and returns, annual financial data, industry codes, and quarterly FII ownership levels are obtained from the PROWESS database.

| | |
|---|---|
| **Initial Sample of Firm-quarters (2003-2016)** | 92,703 |
| Less: Firm-quarters with missing data for unexpected earnings and its four-quarter lagged value | 19,094 |
| Less: Firm quarters with erroneous earnings announcement dates or dates that are more than 180 days after the fiscal quarter end | 354 |
| Less: Firm-quarters with more than 45 missing returns during the 90 trading-day period centered on the earnings announcement date | 3,323 |
| Less: Firm-quarters with missing returns on the earnings announcement days (0,1) | 1,745 |
| Less: Firm-quarters with missing data on control variables | 8,006 |
| Less: Singleton firm-quarters | 185 |
| **Final Sample** | 59,996 |
| **Composition of Final Sample:** | |
| Firm-quarters with trading during earnings announcements (30%) | 17,878 |
| Firm-quarters with no trading during earnings announcements and with FII ownership (40%) | 24,105 |
| Firm-quarters with no trading during earnings announcements and with *no* FII ownership (30%) | 18,013 |

**Table 2**
*Yearly Distribution of FII Trading during Earnings Announcements*

This Table reports the sample distribution by year for three types of firm-quarters: (a) firm-quarters with FII trading during earnings announcements and (b) firm-quarters with no FII trading during earnings announcements, when FIIs own shares, and (c) Zero FII Ownership. The sample period consists of the years 2003 to 2016. Data on FII trading are obtained from the SEBI website: http://www.sebi.gov.in. Quarterly earnings announcement dates and earnings per share, stock prices and returns, annual financial data, industry codes, and quarterly FII ownership levels are obtained from the PROWESS database.

| | Trading During Earnings Announcements | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Non-Zero | | Zero | | Zero FII ownership | | Total | |
| Year | Num. | % | Num. | % | Num. | % | Num. | % |
| 2003 | 386 | 14% | 1,222 | 44% | 1,187 | 42% | 2,795 | 100% |
| 2004 | 543 | 19% | 1,166 | 42% | 1,098 | 39% | 2,807 | 100% |
| 2005 | 1,105 | 28% | 1,567 | 40% | 1,288 | 33% | 3,960 | 100% |
| 2006 | 1,317 | 31% | 1,709 | 41% | 1,193 | 28% | 4,219 | 100% |
| 2007 | 1,449 | 33% | 1,734 | 39% | 1,251 | 28% | 4,434 | 100% |
| 2008 | 1,038 | 31% | 1,394 | 42% | 903 | 27% | 3,335 | 100% |
| 2009 | 1,156 | 28% | 1,760 | 43% | 1,160 | 28% | 4,076 | 100% |
| 2010 | 1,356 | 32% | 1,623 | 39% | 1,205 | 29% | 4,184 | 100% |
| 2011 | 1,394 | 32% | 1,697 | 40% | 1,202 | 28% | 4,293 | 100% |
| 2012 | 1,415 | 29% | 1,998 | 41% | 1,442 | 30% | 4,855 | 100% |
| 2013 | 1,594 | 31% | 2,154 | 42% | 1,385 | 27% | 5,133 | 100% |
| 2014 | 1,703 | 30% | 2,300 | 40% | 1,683 | 30% | 5,686 | 100% |
| 2015 | 1,913 | 33% | 2,260 | 39% | 1,655 | 28% | 5,828 | 100% |
| 2016 | 1,509 | 34% | 1,521 | 35% | 1,361 | 31% | 4,391 | 100% |
| **Total** | 17,878 | 30% | 24,105 | 40% | 18,013 | 30% | 59,996 | 100% |

**Table 3**
*Descriptive Statistics*

This Table presents descriptive statistics for the variables used in our analysis. ERET is the earnings announcement return obtained by compounding raw returns over days (0, +1) relative to the earnings announcement date. UE equals earnings per share for quarter t less earnings per share for quarter t-4 divided by closing price at the beginning of quarter t. FIITR is net FII buying over the earnings announcement period, days (0, +1), divided by shares outstanding. Net FII buying for a firm on a day equals number of shares bought less number of shares sold for that firm by all FIIs on that day. Market-wide return (MRET) is defined as the return on the CNX Nifty Index compounded over days 0 and 1. The index daily return is calculated as the daily percentage change in the Index. Firm size (LMCAP) is measured as the log of the market capitalization at the beginning of the quarter (MCAP). The book- to-market ratio (BM) is obtained by dividing by the book value of equity at the end of the most recent fiscal year before the earnings announcement (year t-1) by MCAP. MOM3 is the three month return during the fiscal quarter before the earnings announcement date. Operating Profitability (OPROF) is measured as profit before interest, tax, and depreciation for year t-1 divided by total assets at the end of year -2. Asset growth (AGRO) is the percentage change in total assets in year t-1. STDRET is the standard deviation in monthly returns in the calendar year before the earnings announcement date. VOL is the monthly volume divided by shares outstanding, measured for the month immediately before the fiscal quarter for which earnings is announced. LAG_UE is the value of UE lagged by one quarter. L_AGE is the logarithm of age of the firm at the end of the quarter measured with reference to the year of incorporation. DIVY is the annual dividend in year t-1 divided by MCAP. LPRC is the logarithm of beginning quarter price. The sample consists of 17,878 earnings announcements for the years 2003 to 2016 for which net FII buying is non-zero on the earnings announcement date. Data on FII trading are obtained from the SEBI website: http://www.sebi.gov.in. Earnings announcement dates, quarterly earnings per share, shares outstanding, firm stock prices, returns, trading volume, market capitalization, book value of equity, profit before interest, tax, and depreciation, total assets, dividends, and the year of incorporation are obtained from the PROWESS database.

| | # of obs. | Mean | Median | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|---|---|
| ERET | 17,878 | -0.10% | -0.32% | 5.86% | -27.24% | 24.89% |
| UE | 17,878 | -0.19% | 0.10% | 3.75% | -45.99% | 24.59% |
| FIITR | 17,878 | -0.003% | 0.002% | 0.21% | -1.33% | 1.28% |
| MRET | 17,878 | 0.04% | 0.07% | 2.52% | -15.70% | 12.86% |
| LMCAP | 17,878 | 10.24 | 10.16 | 1.64 | 5.78 | 14.70 |
| BM | 17,878 | 0.61 | 0.41 | 0.63 | -0.04 | 4.96 |
| MOM3 | 17,878 | 9.48% | 4.95% | 29.87% | -63.51% | 190.38% |
| OPROF | 17,878 | 19.00% | 16.32% | 12.37% | -2.18% | 90.99% |
| AGRO | 17,878 | 22.41% | 15.30% | 33.14% | -33.31% | 364.31% |
| STDRET | 17,878 | 2.64% | 2.43% | 1.03% | 0.88% | 8.09% |
| VOL | 17,878 | 9.52% | 4.11% | 17.32% | 0.13% | 352.46% |
| LAG_UE | 17,878 | -0.30% | 0.11% | 3.86% | -35.79% | 23.32% |
| L_AGE | 17,878 | 2.59 | 2.77 | 0.83 | 0.00 | 4.58 |
| DIVY | 17,878 | 1.56% | 1.10% | 1.58% | 0.00% | 10.51% |
| LPRC | 17,878 | 5.40 | 5.41 | 1.23 | 1.84 | 9.15 |

**Table 4**
*Pearson Correlations*

This Table presents Pearson correlations for the variables used in our analysis. The estimation sample consists of 17,878 earnings announcements for the years 2003 to 2016 for which net FII buying is non-zero during the earnings announcement period (0,+1). Data on FII trading are obtained from the SEBI website: http://www.sebi.gov.in. Earnings announcement dates, quarterly earnings per share, shares outstanding, firm stock prices, returns, trading volume, market capitalization, book value of equity, profit before interest, tax, and depreciation, total assets, dividends, and the year of incorporation are obtained from the PROWESS database. Variable definitions are contained in Table 3. Correlations that are significant at the 1% level are marked with an asterisk (*).

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) ERET | 1.00 | | | | | | | | | | | | | | |
| (2) UE | 0.14* | 1.00 | | | | | | | | | | | | | |
| (3) FIITR | 0.19* | 0.01 | 1.00 | | | | | | | | | | | | |
| (4) MRET | 0.37* | -0.02 | 0.02* | 1.00 | | | | | | | | | | | |
| (5) LMCAP | -0.03* | 0.06* | -0.03* | -0.05* | 1.00 | | | | | | | | | | |
| (6) BM | -0.01 | -0.17* | -0.03* | 0.02 | -0.31* | 1.00 | | | | | | | | | |
| (7) MOM3 | 0.12* | 0.16* | 0.09* | 0.03* | -0.01 | 0.07* | 1.00 | | | | | | | | |
| (8) OPROF | 0.01 | -0.03* | 0.03* | 0.02* | 0.07* | -0.35* | 0.02 | 1.00 | | | | | | | |
| (9) AGRO | 0.01 | -0.04* | 0.02 | 0.03* | -0.06* | -0.14* | -0.02* | 0.43* | 1.00 | | | | | | |
| (10) STDRET | 0.01 | -0.07* | -0.04* | 0.04* | -0.35* | 0.21* | 0.21* | -0.08* | 0.13* | 1.00 | | | | | |
| (11) VOL | -0.02* | 0.00 | -0.03* | 0.01 | -0.12* | 0.05* | 0.02* | -0.02* | 0.04* | 0.24* | 1.00 | | | | |
| (12) LAG_UE | 0.01 | 0.40* | 0.02 | -0.02 | 0.07* | -0.22* | 0.11* | 0.03* | -0.00 | -0.07* | -0.01 | 1.00 | | | |
| (13) L_AGE | -0.02 | 0.01 | 0.01 | -0.03* | 0.14* | 0.01 | 0.00 | -0.02 | -0.19* | -0.16* | -0.09* | 0.00 | 1.00 | | |
| (14) DIVY | 0.01 | -0.13* | -0.00 | 0.01 | -0.07* | 0.23* | -0.15* | 0.08* | -0.09* | -0.07* | -0.09* | -0.10* | 0.05* | 1.00 | |
| (15) LPRC | 0.01 | 0.09* | 0.03* | -0.02* | 0.49* | -0.50* | 0.13* | 0.33* | 0.08* | -0.31* | -0.09* | 0.13* | 0.16* | -0.18* | 1.00 |

**Table 5**
*Earnings Announcement Return Regressions*

The dependent variable is ERET, the two-day (0, +1) earnings announcement return. The main independent variables are UE, unexpected earnings, and FIITR, net FII buying on the earnings announcement days. Firm and year effects are included in the estimation but not reported to conserve space. Standard errors are clustered by firm. The estimation sample consists of 17,878 earnings announcements for the years 2003 to 2016 for which net FII buying is non-zero during the earnings announcement period. Data on FII trading are obtained from the SEBI website: http://www.sebi.gov.in. Earnings announcement dates, quarterly earnings per share, shares outstanding, firm stock prices, returns, trading volume, market capitalization, book value of equity, profit before interest, tax, and depreciation, total assets, dividends, and the year of incorporation are obtained from the PROWESS database. Variable definitions are contained in Table 3.

| | (1) | | | (2) | | | (3) | | | (4) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. | t-stat. | p-value | Coef. | t-stat. | p-value | Coef. | t-stat. | p-value | Coef. | t-stat. | p-value |
| Intercept | 0.013 | 1.71 | 0.09 | 0.014 | 1.89 | 0.06 | 0.013 | 1.80 | 0.07 | 0.014 | 1.97 | 0.05 |
| UE | | | | 8.975 | 13.28 | 0.00 | | | | 9.114 | 13.49 | 0.00 |
| FIITR | | | | | | | 4.978 | 16.63 | 0.00 | 5.022 | 17.00 | 0.00 |
| MRET | 0.856 | 36.94 | 0.00 | 0.858 | 37.04 | 0.00 | 0.847 | 37.87 | 0.00 | 0.849 | 37.93 | 0.00 |
| LMCAP | -0.047 | -8.38 | 0.00 | -0.047 | -8.49 | 0.00 | -0.045 | -7.83 | 0.00 | -0.044 | -7.90 | 0.00 |
| BM | -0.024 | -5.54 | 0.00 | -0.019 | -4.45 | 0.00 | -0.023 | -5.43 | 0.00 | -0.018 | -4.28 | 0.00 |
| MOM3 | 0.031 | 16.16 | 0.00 | 0.028 | 14.90 | 0.00 | 0.028 | 14.74 | 0.00 | 0.025 | 13.44 | 0.00 |
| OPROF | -0.009 | -2.89 | 0.00 | -0.004 | -1.47 | 0.14 | -0.010 | -3.31 | 0.00 | -0.006 | -1.88 | 0.06 |
| AGRO | -0.001 | -0.38 | 0.70 | 0.000 | -0.01 | 0.99 | -0.001 | -0.55 | 0.58 | 0.000 | -0.18 | 0.86 |
| STDRET | -0.005 | -2.49 | 0.01 | -0.004 | -2.02 | 0.04 | -0.004 | -2.00 | 0.05 | -0.003 | -1.52 | 0.13 |
| VOL | -0.005 | -2.24 | 0.03 | -0.005 | -2.25 | 0.03 | -0.006 | -2.47 | 0.01 | -0.006 | -2.48 | 0.01 |
| LAGUE | 0.003 | 2.13 | 0.03 | -0.003 | -1.88 | 0.06 | 0.003 | 2.04 | 0.04 | -0.003 | -2.02 | 0.04 |
| L_AGE | 0.021 | 2.09 | 0.04 | 0.018 | 1.77 | 0.08 | 0.023 | 2.22 | 0.03 | 0.019 | 1.90 | 0.06 |
| DIVY | 0.009 | 2.97 | 0.00 | 0.011 | 3.83 | 0.00 | 0.008 | 2.70 | 0.01 | 0.010 | 3.59 | 0.00 |
| L_PRC | -0.011 | -2.98 | 0.00 | -0.011 | -3.06 | 0.00 | -0.012 | -3.27 | 0.00 | -0.012 | -3.36 | 0.00 |
| Firm and Year effects | | | Yes | | | Yes | | | Yes | | | Yes |
| Number of Clusters | | | 1,135 | | | 1,135 | | | 1,135 | | | 1,135 |
| # of Obs. | | | 17,878 | | | 17,878 | | | 17,878 | | | 17,878 |
| Adjusted $R^2$ | | | 16.45% | | | 18.13% | | | 19.41% | | | 21.14% |

**Table 6**
*2SLS Estimates that Account for Endogeneity of FII Trading (restrictions from the theory ignored).*

The dependent variable is ERET, the two-day (0, +1) earnings announcement return. The main independent variables are UE, unexpected earnings, and FIITR, net FII buying on the earnings announcement days. Columns (1)-(3) report two-stage least-squares estimates that account for the endogeneity of FIITR. The instruments for FIITR are the quintile rank of the change in the rupee-dollar rate on day -2 relative to the earnings announcement date and the quintile rank of the market return on day -1 relative to the earnings announcement date. Standard errors are clustered by firm. The estimation sample consists of 17,878 earnings announcements for the years 2003 to 2016 for which net FII buying is non-zero on the earnings announcement date. Data sources and variable definitions are described in Table 3. In addition, rupee-dollar exchange rates are from the Federal Reserve of New York web site. The estimates are from estimating the following model:

$$ERET_{it} = \alpha + \beta UE_{it} + \lambda \widehat{FIITR}_{it} + \text{Control Variables} \qquad (1)$$

$\widehat{FIITR}_{it}$ is the predicted value from a first stage regression of FIITR on the two instruments, and other exogenous variables. Firm and year effects are included but not reported to conserve space.

| | Two-Stage Least Squares | | |
|---|---|---|---|
| Parameter/Variable | Coef. | t-stat. | p-value |
| UE | 10.312 | 8.58 | 0.00 |
| FIITR | 48.511 | 3.95 | 0.00 |
| MRET | 0.767 | 17.66 | 0.00 |
| LMCAP | -0.018 | -1.36 | 0.17 |
| BM | -0.009 | -0.96 | 0.34 |
| MOM3 | -0.002 | -0.28 | 0.78 |
| OPROF | -0.003 | -0.80 | 0.43 |
| AGRO | -0.016 | -2.43 | 0.02 |
| STDRET | 0.006 | 1.43 | 0.15 |
| VOL | -0.009 | -2.07 | 0.04 |
| LAGUE | -0.005 | -1.56 | 0.12 |
| L_AGE | 0.031 | 1.41 | 0.16 |
| DIVY | 0.002 | 0.38 | 0.70 |
| L_PRC | -0.020 | -2.61 | 0.01 |
| Adjusted $R^2$ | | | 12.87% |
| # of Obs. | | | 17,878 |
| | | | |
| Wu-Hausman Test of Endogeneity (p-value) | | | 41.649 (0.000) |

| | |
|---|---|
| Weak Identification Test: Cragg-Donald Wald F Statistic | 8.841 |
| Stock-Yogo Weak ID critical values (10% maximal LIML size) | 8.68 |

**Table 7A**

*GMM Estimates of Primitive Parameters and Shallow Parameters: Full Sample*

The Table reports estimates of primitive parameters from estimating the following model based on Regime 3 alone, defined by the pricing error

$$u = p - (\alpha + \beta v_F + \lambda\omega), \text{with } \alpha = 0, \beta = 1 + \rho * \sqrt{\sigma_1^2}, \lambda = \sqrt{\sigma_2^2} * \sqrt{1-\rho^2}. \text{ So } \sigma_1 = \left(\frac{\sigma_T}{\sigma_F}\right), \sigma_2 = \left(\frac{\sigma_T}{\sigma_Z}\right).$$

It is important to note that there is strictly no loss of information in this reparametrization, since with an independently estimated $\sigma_F$, and estimates of $\sigma_1$ and $\sigma_2$, $\sigma_T = \sigma_F * \sigma_1$, and $\sigma_Z = \left(\frac{\sigma_T}{\sigma_2}\right)$. The moment restrictions are given by $E(u * Z) = 0$, where the five instruments $Z$ are in turn the constant (1), $v_F$ (UE), $\omega$ (FIITR), lagged market return ($L_{MRET}$), and the change in the US$/INR exchange rate (CH_USD_INR).The four primitive parameters are $\sigma_T$, $\sigma_Z$, $\rho$, and $\sigma_F$. Of the four, we equate $\sigma_F$, the information advantage of the firm, to the sample estimate of the standard deviation of unexpected earnings (UE) of all firms. We first estimate the primitive parameters, and then derive the two parameters $\beta$ and $\lambda$ (referred to as shallow parameters) from the formulae above. The estimation sample consists of 17,878 earnings announcements for the years 2003 to 2016 for which net FII buying is non-zero on the earnings announcement date. Data on FII trading are obtained from the SEBI website: http://www.sebi.gov.in. Earnings announcement dates, quarterly earnings per share, shares outstanding, firm stock prices, returns, trading volume, market capitalization, book value of equity, profit before interest, tax, and depreciation, total assets, dividends, and the year of incorporation are obtained from the PROWESS database. Variable definitions are contained in Table 3. The t-statistics are based on bootstrap standard errors. Firm and year effects are included in the estimation but not reported to conserve space.

Table 7A -- GMM results with bootstrap errors
Number of parameters = 4
Number of moments = 9
Initial weight matrix: Identity Number of obs = 17,765
GMM weight matrix: Cluster (cnum)
(Replications based on 1,132 clusters in cnum; singleton clusters dropped)

| | Observed Coef. | Bootstrap Std. Err. | P>\|z\| |
|---|---|---|---|
| /rho | 0.428946 | 0.06466 | 0 |
| /sigma1 | 13.64262 | 7.211335 | 0.059 |
| /sigma2 | 5.041628 | 0.233508 | 0 |

**Table 7B**
*GMM Estimates of Primitive Parameters and Shallow Parameters: Full Sample*

The Table reports estimates of primitive parameters from estimating the following model based on Regimes 2 and 3 alone, defined by the pricing error

$u_1 = p - (\beta^{FT} * v_F + \lambda^{FT} * \omega)$, with $\beta^{FT} = 1 + \rho\left(\frac{\sigma_{T1}}{\sigma_F}\right),\ \lambda = \left(\frac{\sigma_{T1}(\sqrt{1-\rho^2})}{\sigma_z}\right)$,

$u_2 = p - (\lambda^T * \omega)$, with $\lambda^T = \left(\frac{\sigma_{T2}(\sqrt{1-\rho^2})}{\sigma_z}\right)$.

The moment restrictions are given by

$E(u_1 * Z) = 0$, where the five instruments $Z$ are in turn the constant (1), $v_F$ (UE), $\omega$ (FIITR), lagged market return (L_MRET), and the change in the US$/INR exchange rate (CH_USD_INR); and by

$E(u_2 * Z) = 0$, where the four instruments $Z$ are in turn the constant (1), $\omega$ (FIITR), lagged market return (L_MRET), and the change in the US$/INR exchange rate (CH_USD_INR). The four primitive parameters are $\sigma_T$, $\sigma_z$, $\rho$, and $\sigma_F$. Of the four, we equate $\sigma_F$, the information advantage of the firm, to the sample estimate of the standard deviation of unexpected earnings (UE) of all firms. We first estimate the primitive parameters, and then derive the two parameters $\beta$ and $\lambda$ (referred to as shallow parameters) from the formulae above. The estimation sample consists of 17,878 earnings announcements for the years 2003 to 2016 for which net FII buying is non-zero on the earnings announcement date. Data on FII trading are obtained from the SEBI website: http://www.sebi.gov.in. Earnings announcement dates, quarterly earnings per share, shares outstanding, firm stock prices, returns, trading volume, market capitalization, book value of equity, profit before interest, tax, and depreciation, total assets, dividends, and the year of incorporation are obtained from the PROWESS database. Variable definitions are contained in Table 3. The t-statistics are based on bootstrap standard errors. Firm and year effects are included in the estimation but not reported to conserve space.

Table 7B -- GMM estimation

Number of parameters = 4
Number of moments = 9
Initial weight matrix: Identity Number of obs = 17,765
GMM weight matrix: Cluster (cnum)

(Std. Err. adjusted for 1,126 clusters in cnum, singletons dropped)

| | Coef. | Robust[12] Std. Err. | P>\|z\| |
|---|---|---|---|
| /rho | .0002684 | .0000199 | 0.000 |
| /sigma_t1 | 36.75789 | .05? | 0.000 |
| /sigma_z | 3.853109 | .2183623 | 0.000 |
| /sigma_t2 | 17.82408 | 1.346009 | 0.000 |

[12] Bootstrap standard errors being computed.

**Table 8**
*Cross-sectional Distribution of Estimates of Primitive Parameters and Shallow Parameters*

The Table reports the distribution of firm-by-firm estimates of primitive parameters from estimating the following model based on Regime 3 alone. The four primitive parameters are $\sigma_T$, $\sigma_z$, $\rho$, and $\sigma_F$. Of the four, we equate $\sigma_F$, the information advantage of the firm, to the sample estimate of the standard deviation of unexpected earnings (UE), for each firm in the sample. We first estimate the primitive parameters, and then derive the two parameters $\beta$ and $\lambda$ (referred to as shallow parameters) from the formulae in Eq. (2), above. We retain only the 366 firms that have at least twenty quarterly observations during the sample period. Additionally, we include only MRET as a control variable in each firm-specific regression. The coefficient on MRET is $c_1$. Variable Definitions are described in Table 3.

Panel A: OLS Estimates (primitive parameters cannot be estimated)

| | # of obs. | Mean | Median | Std. Dev. | t-stat | Min | Max |
|---|---|---|---|---|---|---|---|
| Intercept | 366 | -0.002 | -0.002 | 0.001 | -3.488 | -0.089 | 0.043 |
| $\beta$ | 366 | 36.639 | 19.374 | 4.116 | 8.901 | -210.298 | 889.583 |
| $\beta < 0$ | 366 | 0.197 | 0.000 | 0.021 | 9.455 | 0.000 | 1.000 |
| $\lambda$ | 366 | 14.679 | 10.091 | 2.159 | 6.798 | -94.365 | 157.894 |
| c1 | 366 | 0.877 | 0.855 | 0.032 | 27.210 | -1.513 | 3.212 |
| # of obs. per firm | 366 | 33.054 | 32.000 | 0.503 | | 20.000 | 53.000 |

Panel B: Non-linear Model Estimates (uses theory, primitive parameters estimated)

| | # of obs. | Mean | Median | Std. Dev. | t-stat | Min | Max |
|---|---|---|---|---|---|---|---|
| $\sigma_T$ | 366 | 0.053 | 0.060 | 0.001 | 44.170 | 0.000 | 0.090 |
| $\sigma_Z$ | 366 | 0.041 | 0.008 | 0.003 | 13.256 | 0.000 | 0.165 |
| $\sigma_F$ | 366 | 0.001 | 0.000 | 0.000 | 19.331 | 0.000 | 0.003 |
| $\rho$ | 366 | 0.248 | 0.134 | 0.026 | 9.646 | -1.000 | 1.000 |
| c1 | 366 | 0.889 | 0.867 | 0.028 | 31.890 | -0.758 | 2.661 |
| $\sigma_T/\sigma_F$ | 366 | 202.424 | 113.941 | 13.001 | 15.569 | 0.002 | 2505.334 |
| $\sigma_T/\sigma_Z$ | 366 | 58.457 | 7.173 | 17.202 | 3.398 | 0.000 | 3544.626 |
| $\beta$ | 366 | 22.656 | 16.438 | 2.085 | 10.868 | -114.354 | 171.837 |
| $\beta < 0$ | 366 | 0.197 | 0.000 | 0.021 | 9.455 | 0.000 | 1.000 |
| $\lambda$ | 366 | 8.333 | 6.628 | 0.461 | 18.083 | 0.000 | 60.919 |
| # of obs. per firm | 366 | 33.054 | 32.000 | 0.503 | | 20.000 | 53.000 |

**Table 9**
*Estimates of Primitive Parameters and Shallow Parameters: Sub-samples*

The Table reports estimates of primitive parameters from the following model for sub-samples: The four primitive parameters are $\sigma_T$, $\sigma_z$, $\rho$, and $\sigma_F$. Of the four, we equate $\sigma_F$, the information advantage of the firm, to the sample estimate of the standard deviation of unexpected earnings (UE) of each sub-sample. Panel A reports model estimates for three size sub-groups – small, medium, and large. We measure size based on the log of market capitalization at the beginning of the quarter (LMCAP). To form the three size groups, we divide the sample into ten deciles based on LMCAP. Firm-quarters in smallest three deciles are assigned to the group SMALL, those in the next four deciles are assigned to the group MEDIUM, and those in the largest three deciles are assigned to the group, LARGE. Panel B compares deep and shallow parameters for firms with small profits with those with small losses. Small profit firms, are defined as firms with a quarterly earnings per share (EPS) that is between 0.01₹ to 0.2₹ (inclusive). Similarly, small loss firms are defined as firms with an EPS between -0.2₹ to -0.01₹ (inclusive). We do not include firms with an EPS that exactly equals zero, as the group to which such firms belong is ambiguous. All regressions include control variables and firm and year effects; we suppress reporting their estimates to conserve space. Variable definitions are contained in Table 3.

Panel A: Size-based Sub-samples

| | Small Firms | | | Medium Firms | | | Large Firms | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coef. | t-stat. | p-value | Coef. | t-stat. | p-value | Coef. | t-stat. | p-value |
| $\sigma_T$ | 0.077 | 8.81 | 0.00 | 0.044 | 2.92 | 0.00 | 0.024 | 1.99 | 0.05 |
| $\sigma_Z$ | 0.007 | 1.69 | 0.09 | 0.008 | 1.47 | 0.14 | 0.015 | 2.23 | 0.03 |
| $\sigma_F$ | 0.001 | 39.95 | 0.00 | 0.001 | 28.94 | 0.00 | 0.001 | 20.45 | 0.00 |
| $\rho$ | 0.124 | 2.66 | 0.01 | 0.153 | 1.34 | 0.18 | 0.145 | 0.43 | 0.67 |
| # of Obs. | | | 5,363 | | | 7,152 | | | 5,363 |
| Nonlinear Model-based Shallow Parameter Estimates: | | | | | | | | | |
| β | 8.917 | 9.23 | 0.00 | 10.636 | 3.05 | 0.00 | 7.443 | 4.06 | 0.00 |
| $\lambda$ | 11.375 | 2.57 | 0.01 | 5.517 | 1.59 | 0.11 | 1.618 | 0.62 | 0.54 |
| OLS-based Shallow Parameter Estimates: | | | | | | | | | |
| β | 8.924 | 10.02 | 0.00 | 10.669 | 8.52 | 0.00 | 8.165 | 4.69 | 0.00 |
| $\lambda$ | 3.121 | 7.00 | 0.00 | 4.761 | 11.52 | 0.00 | 9.701 | 19.12 | 0.00 |

Panel B: Small Loss versus Small Profit Firms

| | Small Loss Firms | | | Small Profit Firms | | |
|---|---|---|---|---|---|---|
| | Coef. | t-stat. | p-value | Coef. | t-stat. | p-value |
| $\sigma_T$ | 0.064 | 2.61 | 0.01 | 0.053 | 2.11 | 0.04 |
| $\sigma_Z$ | 0.006 | 0.69 | 0.49 | 0.011 | 1.32 | 0.19 |
| $\sigma_F$ | 0.001 | 5.00 | 0.00 | 0.001 | 10.73 | 0.00 |
| $\rho$ | 0.159 | 0.44 | 0.66 | 0.042 | 0.10 | 0.92 |
| # of Obs. | | | 230 | | | 556 |
| Nonlinear Model-based Shallow Parameter Estimates: | | | | | | |
| β | 11.749 | 2.15 | 0.03 | 3.372 | 1.25 | 0.21 |
| $\lambda$ | 10.580 | 0.83 | 0.40 | 5.024 | 0.65 | 0.51 |
| OLS-based Shallow Parameter Estimates: | | | | | | |
| β | 26.331 | 1.94 | 0.05 | -2.568 | -0.66 | 0.51 |
| $\lambda$ | 9.351 | 2.10 | 0.04 | 7.888 | 4.12 | 0.00 |

**Table 10**

*Estimates of $\sigma_T$ and $\sigma_Z$ from Non-Announcement Periods (Regime 2)*

In this Table, we examine if earnings are a substitute for or complement to FIITR. To do so we estimate $\sigma_T$, $\sigma_Z$, and $\lambda^T$ under Regime 2 using data from a sample where only FII trading was observed and no earnings signals are available. Specifically, we pick four trading days from non-announcement periods for the Regime 3 sample – days -10, -20, -30, and -40 relative to the earnings announcement date. We compute the two-day returns ending on these four dates. We then estimate a regression of these two-day returns on all the control variables, and firm and year effects. The residual from these regressions is an abnormal return and is denoted as RET. Since it turns out that we can invert the equilibrium expressions for Var(P) and Var($\omega$) for the primitive parameters $\sigma_T$ and $\sigma_Z$, we obtain point estimates from $\widehat{\sigma_T} = \sqrt{2} * \sqrt{\text{Var}(RET)}$ and $\widehat{\sigma_Z} = \sqrt{2} * \sqrt{\text{Var}(FIITR)}$. $\lambda^T$ is obtained as the ratio of $\widehat{\sigma_T}$ to $\widehat{\sigma_Z}$. For asymptotic standard errors (SE), we used SE($\widehat{\sigma_T}$) $= \sqrt{2} * SE(\sqrt{\text{Var}(RET)})$ and SE($\widehat{\sigma_Z}$) $= \sqrt{2} * SE(\sqrt{\text{Var}(\omega)})$. To obtain the standard error of a standard deviation, we used the correction factors $K_n$ and $V_n$ described in Ahn and Fessler (2003). $\lambda$, per the expression for $\lambda^T$ in the Table comparing equilibria in the three models, is given by $(\frac{\sigma_T}{\sigma_Z})$.

| Day Relative to Earnings Announcement | # Obs. | $\sigma_T$ | t-stat. | p-value | $\sigma_Z$ | t-stat. | p-value | $\lambda$ |
|---|---|---|---|---|---|---|---|---|
| -10 | 17,869 | 0.0460 | 189.04 | 0.00 | 0.0017 | 189.04 | 0.00 | 26.50 |
| -20 | 17,869 | 0.0458 | 189.04 | 0.00 | 0.0019 | 189.04 | 0.00 | 24.13 |
| -30 | 17,864 | 0.0464 | 189.01 | 0.00 | 0.0018 | 189.01 | 0.00 | 25.82 |
| -40 | 17,866 | 0.0455 | 189.02 | 0.00 | 0.0019 | 189.02 | 0.00 | 24.31 |

**Murgie Krishnan Vita – Brief Summary of Recent Activities**

Teaching

- Taught several sections of financial accounting, managerial accounting, intermediate accounting -- undergrad, MBA (regular, professional and online), Professional MS in Accounting.
- Taught introductory finance and a senior elective on international finance.
- Was invited by IIM Bangalore in January 2015 and July 2018 to give 4 PhD lectures on asset pricing with private information. Taught a 2-week PhD course in June-July 2017 at IIT-Kharagpur. (External member on PhD committee for Indian universities.)

Service

Spent significant time in 2014-2015 on the Graduate Studies Task Force which is reviewing the MBA curriculum, trying to align with the school's goals for expansion, and coordinating between the committee and the department. Participated in activities relating to AACSB accreditation.

Research

- Obtained 2 very competitive research grants, NSE-NYU Stern Initiative (controlled by NYU) and the NSE-IGIDR Initiative (controlled by IGIDR). These are worldwide research grant competitions, in which applications are received even from the very best research schools. They also involve a condition to meet various deadlines – for an initial draft to be sent to referees appointed by NYU or IGIDR, responses to referees' comments, submission of a revised draft before an international conference deadline, and for a subsequent draft after the conference.
- Papers accepted at Contemporary Accounting Research, the top Canadian accounting research journal, and at Applied Economics Letters.
- Have also been working on revisions of four papers listed on my vita. Three of these are related to grants received, and have been presented at competitive research conferences, and are in advanced review at major accounting, finance and economics journals.
- Best Paper Award, 2018 ICFMCF Conference (for "A theory of analyst forecast bias")

<u>**Summary of CUNY (Baruch College) Evaluations**</u>

ACC 9110 is the MBA core course. It used to be a mix of financial accounting (about 2/3) and managerial accounting (1/3). Right after 9/11 for a while the entire MBA cohort was taught in one section.

| Year | Semester | Level | Discipline | Course | Q8 | Q9 | Q11 | Q12 | Q16 | Class size |
|---|---|---|---|---|---|---|---|---|---|---|
| 2003 | Fall | MBA | ACC | 9110 | 3.13 | 3.32 | **3.22** | 3.82 | 3.35 | **250** |
| 2004 | Spring | MBA | ACC | 9110 | 3.67 | 3.70 | **3.80** | 3.37 | 3.72 | **250** |
| 2004 | Fall | MBA | ACC | 9110 | 3.97 | 4.11 | **3.97** | 4.42 | 4.23 | **250** |
| 2005 | Spring | MBA | ACC | 9110 | 4.05 | 4.35 | **4.09** | 4.46 | 4.23 | **110** |
| 2005 | Spring | MBA | ACC | 9110 | 4.15 | 4.23 | **4.04** | 4.46 | 4.19 | **110** |

<u>**Key for questions (all responses on a 5-point scale, 5 = best):**</u>

Q8 – Is the instructor's material presented in an interesting manner? (Very Dull – Very Interesting)
Q9 – Does instructor generate enthusiasm for the subject matter? (Very Boring – Very Stimulating)
**Q11 – Overall, how would you rate this instructor with other instructors you have had? (Worst – Best)**
Q12 – Does instructor encourage students to ask questions, disagree, and express ideas? (Very Encouraging – Very Discouraging)
Q16 – Does instructor pose interesting and stimulating questions in class? (Never – Always)

Murugappa (Murgie) Krishnan -- Summary of Rutgers Student Evaluations

| Course Information | | | | | | | | | Course Evaluation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | Teaching Effectiveness (Max = 5) | | Course Quality (Max = 5) | |
| S/yr | Course Title | Course Number | Cr | MOI | Audience | Resp | Enrl | Evaluation Responses | Instructor | Dept Mean | Instructor | Dept Mean |
| F-02 | Acctg for Managers | 22:010:577 (41) | 3 | Lec | MBA | Total | 42 | 41 | 4.15 | 4.01 | 3.92 | 3.92 |
| F-02 | Acctg for Managers | 22:010:577 (61) | 3 | Lec | MBA | Total | 59 | 54 | 4.24 | 4.01 | 4 | 3.92 |
| S-02 | Acctg for Managers | 22:010:577 (41) | 3 | Lec | MBA | Total | 25 | 21 | 4.48 | 4.13 | 4.14 | 4.03 |
| S-02 | Acctg for Managers | 22:010:577 (61) | 3 | Lec | MBA | Total | 57 | 45 | 3.82 | 4.13 | 3.67 | 4.03 |
| F-01 | Acctg for Managers | 22:010:577 (41) | 3 | Lec | MBA | Total | 21 | 16 | 4.06 | 3.95 | 3.88 | 3.93 |
| F-01 | Acctg for Managers | 22:010:577 (61) | 3 | Lec | MBA | Total | 59 | 54 | 4.02 | 3.95 | 3.92 | 3.93 |
| Sum-01 | Acctg for Managers | 22:010:577 (41) | 3 | Lec | MBA | Total | 13 | 11 | 4.73 | 4.27 | 4.45 | 4.23 |
| Sum-01 | Acctg for Managers | 22:010:577 (61) | 3 | Lec | MBA | Total | 18 | 17 | 4.41 | 4.27 | 4.29 | 4.23 |
| F-00 | Acctg for Managers | 22:010:577 (61) | 3 | Lec | MBA | Total | 51 | 28 | 3.71 | 4.13 | 3.57 | 4.02 |
| F-00 | Intermediate Acct-II | 22:835:502 | 3 | Lec | MBA | Total | 38 | 29 | 2.68 | 4.13 | 2.74 | 4.02 |
| S-00 | Info and Fin Mkts | 26:010:685 | 3 | Lec-Sem | PhD | Total | 5 | 4 | 5 | 4.92 | 5 | 5 |
| S-00 | Acct Principles - II | 33:010:274 (10)* | 3 | Lec | UM | Total | 47 | 20 | 4.05 | 4 | 3.83 | 3.86 |
| S-00 | Acct Principles - II | 33:010:274 (9)* | 3 | Lec | UM | Total | 66 | 31 | 3.13 | 4 | 3 | 3.89 |
| F-99 | Acc Prin and Prob-2 | 22:835:502 | 3 | Lec | MBA | Total | 29 | 25 | 4.8 | 4.01 | 4.72 | 3.9 |
| S-99 | None (full load in fall, as was assigned by Dept Chair to fill in for recently departed faculty). | | | | | | | | | | | |
| F-98 | Intro to Acct | 29:010:203 (10) | 3 | Lec | UNM | Total | 59 | 28 | 4.37 | 4.17 | 4.28 | 4.12 |
| F-98 | Intro to Acct | 29:010:203 (02) | 3 | Lec | UNM | Total | 60 | 25 | 3.96 | 4.17 | 4.04 | 4.12 |
| F-98 | Intro to Acct | 29:010:203 (01) | 3 | Lec | UNM | Total | 69 | 32 | 3.29 | 4.17 | 3.19 | 4.12 |
| F-98 | Advanced Acctg | 29:010:402 | 3 | Lec | UM | Total | 21 | 19 | 4.11 | 4.17 | 4.06 | 4.12 |

**Note:** In Spring 2000, these 2 sections of 274 were part of a 12-section course coordinated by Jim Baratta of New Brunswick. The understanding was that the syllabus was common but otherwise my sections were run independently. **I was also nominated by the dept for the school-wide teaching award in Summer 2000**.

**Student comments from SET Evaluation Forms (transcribed by Jackie Adams, Secretary, Accounting Dept)**

Krishnan Fall 1999 22:835:502:10 23957

20. **What do you like best about this course?**

- The teacher made it easy to understand.
- I felt Prof. Krishnan's teaching methods were excellent. - he generated interest in the material and always encouraged further thought and learning.
- The notes professor passed out were excellent! Professor was very thorough in his teaching skills. I learned a great deal. I wish he could be my next semester's accounting teacher!!
- The handout from the professor help us to prepare very well for the subjects
- Instructor's preparedness for the class
- I think Prof. Krishnan taught the course perfectly. He is very easy to follow and if you could not follow he was more than happy to explain. He was always very prepared and organized.
- The instructor was well prepared and presented the material clearly.
- Professor Krishnan was always prepared and sent emails informing students of changes.
- The case studies encourage application of theory. Focus on fundamentals.
- Detailed explanation of accounting concepts and examples.
- The instructor is patient, well prepared and inspiring, also he lets students get prepared before class.

21. **If you were teaching this course, what would you do differently?**

- Nothing.
- Put less emphasis on cold calling it's stressful on the students.
- No.
- Nothing.
- The approach to the course is good.
- Couldn't do better.
- Don't be so anile.

22. **In what ways, if any, has this course or the instructor encouraged your intellectual growth and progress?**

- He has a great attitude, he loves what he teaches and it affects the students.
- Yes.
- I understand accounting principles much better than before.
- Case study.

23. **Other comments or suggestions.**

- He was fantastic.
- I truly enjoyed this course and feel I learned a great deal from Prof. Krishnan. He is an excellent instructor and I would take another course with him in the future if given the opportunity.
- Great teacher! Highly recommend to teach again!

- Thanks very much for the instructor.
- Great job!
- Excellent instructor!
- Your analogies are very confusing. You go into such sorry detail on every minor point that you make simple ideas complicated. Drop the details. We are grad students, not freshmen but we're freshmen is how you treated us.
- Prof. Krishnan was excellent.

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Krishnan Summer 2001 22:010:577:61 91467

20. **What do you like best about this course?**
    - The professor presented the material in a non-threatening manner and was always available to students.
    - Instructor method.
    - Prof. Krishnan made the course easy to understand.
    - Subject material is logical and makes sense.
    - Material presented in a manner that's easy to understand. Good practical application. Enthusiastic about accounting.
    - He was a fair grader.
    - Professor's positive attitude.
    - The use of accounting in the real world. Example from the textbooks made me motivated.
    - How to read the acc's books / statements etc.
    - Material was very clear.
    - He was kind and always willing to help.

21. **If you were teaching this course, what would you do differently?**
    - Nothing
    - Nothing
    - Spend more time on Acct. for Managers. We spent too much time on basic accounting journal entries, statements. Should have spent more time on application of acct. info.
    - Stick to the text. Handouts are more difficult to learn on own. (For students that travel, etc)
    - Give text examples. Try to make the students work on the how.
    - I think the MBA program must do a stronger job a monitoring students who have prior acctg. Experience and enforce the rules on these students to not take this course.

22. **In what ways, if any, has this course or the instructor encouraged your intellectual growth and progress?**
    - Great knowledge
    - By constantly asking 'Q' and homework
    - Encouraged questions

23. **Other comments or suggestions**.
    - Great Prof. will take again if opportunity exists

- Very nice & fair professor. Very enthusiastic about a boring (my opinion) topic. Thanks.
- No comment
- Exam questions were tough! I went over homework problems and felt confident in my knowledge yet felt the exam went over and above

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Krishnan Summer 2001 22:010:577:41 90754

20. **What do you like best about this course?**

- Use of internet and email
- The professor!
- The instructor's knowledge of the topic and enthusiasm of the topic. The instructor's enthusiasm for the topic. The instructor's respect for the students. The instructor's organized, clear, and concise instructional method.
- Prof. Krishnan presentation of the material was understandable and even made accounting somewhat interesting.
- The professor had a great deal of interest in the class.
- The topics selected for teaching helped a lot.

**21. If you were teaching this course, what would you do differently?**

- Focus less on finishing all chapters, and focus more on making sure students fully understand.
- Get more real life company examples.
- Add more high-level management decision-making examples.
- Add more cases.

22. **In what ways, if any, has this course or the instructor encouraged your intellectual growth and progress?**

- Provide rationale for general practices in accounting.

23. **Other comments or suggestions.**

- Hermits have no peer pressure.
- Best prof. I've had so far.

## Teaching Related Testimonials From Previous Appointments

1. Report of Prof. Glen Berryman, then Chairman, Department of Accounting, University of Minnesota, based on a visit to a class in the MBA core course, on October 6, 1994. (This course is essentially like 'Accounting for Managers' at many schools.)
2. Report of Prof. Susan Ambrose, Teaching Excellence Center, Carnegie-Mellon University (counterpart of Teaching Excellence Center here at Rutgers), after visits to 3 different sections of an undergraduate class in Introductory Financial Accounting. (This course is like the introductory financial accounting classes I've taught at many schools.)
3. Letter from Prof. Glenn Hueckel, Professor of Economics and Director, Undergraduate Programs, Krannert School of Management, Purdue University. It was written in support of my application for a teaching innovation award, based on work I did in an undergraduate Intermediate Financial Accounting course.

Report of Prof. Glen Berryman, then dept chairman, based on visit to MBA class, at Minnesota.

2k

October 6, 1994

Report of visit to class taught by Murgie Krishnan.

MBA 8130 is the basic financial accounting class for entering MBA students. It meets in Blegen 425 from 1:15 p.m. to 3:00 p.m. on Tuesdays and Thursdays. I visited the class for the entire session on October 6, 1994.

A. Presence in the Class

Professor Krishnan was in full charge of the class at all times. He commanded the respect of the students and managed the classroom time well. His opinions and analytical statements were recognized as having validity by the members of the class.

B. Organization of the Presentation

The class session proceeded at an orderly rate of speed and was well organized. It was clear that specified amounts of time had been allocated to each of the topics and that each had been given reasonable amounts of time to assure substantial coverage. The subject matter was amply covered in a substantial ten-page handout, which had been prepared and organized by Murgie. He used the overhead projector effectively as a supplement to the handout and to emphasize key points. Also, he used the overhead to respond in-depth to certain student concerns with respect to accounting procedure.

C. Clarity

The subject matter was introduced clearly and appropriately delineated. The comments made by the instructor were direct and to the point. The illustrations selected added to the specificity and applicability of the concepts presented. Students seemed to gain understandings of the material that was being presented, which indicated that they had been presented clearly.

D. Responsiveness to Students

A substantial number of questions were raised by the students. Murgie understood the questions and responded substantively and directly to each question asked. He handled questions of limited value in a direct manner. He could have, on one occasion, pointed out that the question was beyond the scope of the course and not taken the class time to respond to it. On another question, there was a gap in the student's knowledge base; Murgie very appropriately laid out the specific response, including the applicable journal entries, to help the student gain needed understanding.

E. Substance of the Subject Matter

Coverage was substantial and in-depth on revenue recognition. This is one of the most important issues in financial accounting and must be addressed in an introductory MBA financial accounting course. In addition, there was time spent on a particular illustration which focused on application of the cost principle and cost allocations. In the latter case, there was only limited depth presented, whereas in the revenue recognition area real depth was achieved.

F. Mannerisms

There were no negative aspects in the presentation which detracted in anyway from its effectiveness.

G. Distracting Influences (if any)

A minor amount of hallway noise crept into the room, but it was not distracting. The use of the overhead, on a ongoing basis, was effective and maintained the attention of the students on a ongoing basis.

H. Timeliness

The class started on time and finished on time. Students became a little restless about five minutes before the class ended. This is not at all unusual and was appropriately handled by Murgie.

In summary, the class was well planned and well executed. It was presented in such fashion as to provide students with a first class learning experience. With respect to specific suggestions for change. I submit the following:

1. Improve the transitional statements that are given when a move is made from one topic to another topic. In particular, this applied in this class in the transition from revenue recognition as the primary focus to the application of the cost principle and cost allocations.

2. The application of the percentage completion concept in revenue recognition could be enhanced by further focus on the effect of changes in accounting estimates on incomplete contracts; particularly the focus of their effect on gross margin recognition in succeeding periods would be helpful.

3. The completed contract method was passed over very lightly and a very brief illustration would have been helpful to illustrate that method.

In summary, this was an effective class and students and instructor interactions were substantial and positive.

Note: — Ms. Ambrose attended 4 classes of mine in all during my Fall '92 teaching stint at CMU. This feedback was written as she had attended 3 sessions.
— As indicated in the ~~notes~~ the CMU syllabus that I used, by force of circumstances (and no one's fault) I had to adopt the Text, syla etc. already in place.
MK

**Carnegie Mellon**
**University Teaching Center**

**To:** Murugappa Kirshnan, GSIA

**From:** Susan Ambrose, Director, UTC

**Date:** September 15, 1992

**Subject:** 70-121 Financial Accounting

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I have enjoyed reviewing the syllabus and observing classes for your Financial Accounting course. Let me first comment on your syllabus and then discuss my perceptions of the consistencies, inconsistencies, strengths and weaknesses of the course. As we discussed, we can then compare my perceptions with the students' feedback per their responses on the early course evaluations administered on September 14 and the small group instructional diagnoses which we've scheduled for October 7.

Syllabus as Representative of the Course

Overall, your syllabus is well-constructed: you include all of the necessary technical information about the course and the instructor, the purpose of the course, the way time will be spent in the course (both your time and the students' time), scheduling information about course readings, assignments, quizzes, grading information, policy on academic honesty, and a daily class outline.

I would suggest, however, that you think about stating objectives in the course in terms of what students will be able to do at the end of the course (often these are called behavioral objectives). These specific and concrete items often help students to clearly understand what they will learn, should be learning, and learned in a course. We can talk about these in our meeting on September 16 and I will provide you with some examples.

I have a concern about homework assignments, which I note you do not collect or grade. You mention in the syllabus the "class assignments" which will help you and students to assess learning -- that's a great idea. My only concern is that it may be necessary to include some motivator in the syllabus (and reiterate in class) because students often claim that they prioritize work according to "what is due" next. If, indeed, nothing is "due" in Financial Accounting, they may hope to get to the homework problems but this may never actually happen. Let's discuss some kind of statement which, for example, might explain that the exam problems will be similar to those assigned but not collected. Also, in the class outline, is there a difference between "prepare" and "homework?"

Finally, I'm not sure what your statement about grading on the bottom of page 2 / top of page 3 means. Do you grade on the curve with the class determining what the curve will be?

Again, we can discuss these issues on Wednesday, September 16.

3

Class Observations

You are an excellent classroom teacher! You are very consistent in your classroom behaviors, and I didn't really notice any differences in your behaviors or the students' among the 8:30, 11:30, and 1:30 sections. On the days on which I observed, you seemed to have as much energy, enthusiasm, and patience during the 1:30 class as during the 8:30. Overall, you are an excellent classroom instructor -- let me be specific in what it is you do which I believe facilitates students' learning:

• You always provide an introduction to the day's session: you tell students what you will be doing for the next fifty minutes.

• Similarly, you always end the class session reporting on what you will do in the next class.

• You provide a lot of opportunity for active learning and student involvement, and you do it in a very non-threatening, non-intimidating way.

- You ask a lot of questions and you call on students to respond. Most of the students did well in this area. I was impressed with the number of students you called on and the number who responded either correctly or almost correctly.
- When they were unsure or wrong, you did one of two things -- you simply went to someone else and didn't provide an opportunity for the student to feel embarrassed or stupid or you took part of what the student said and posed another question to help the student along. Once you even said "take another shot, you're on the right track." You did all of this very skillfully.
- Often you asked a question in a way in which students felt like they could take a risk. For example, you said things like "xxx, do you want to try this?" or "xxx, do you have an idea of . . . " In both of these instances, students would feel that it was alright to take a shot at responding.
- You make sure to call on students from all over the room -- you don't favor one section over another. This helps students in all areas (even the back) to realize that they must pay attention.
- You called on an equal number of males and females in the room, and your questions to the them did not differ based on sex.

• You provide a lot of positive feedback and reinforcement which helps students to feel both comfortable responding and that their contributions to the class are important and appreciated.

- You often tell someone that the question they asked was "good" or "important." This really encourages students to ask questions.
- You credit students with their contributions from previous classes (which shows that you really listen). For example, on one day you said "in the last class Martin gave an alternative which . . . " Even if you don't do this often, it sends a message that you do listen to student contributions.
- When students say something that doesn't quite fit in with the current discussion, you effectively stay on track by saying something like "we'll get to that later and then remind us" or " what you said falls under merits of the alternatives, so let's exhaust the list first and then come back and discuss merits and problems with each alternative."

• You respond effectively to all questions. You answered every question with a sense that it was an important one, and often you verbally responded and then wrote the "equation

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version" on the board (the "equation" I jotted down was A=L+PIC+BRE+R-X-D and then you broke down the PIC variable).

• Your use of overheads was great: it enabled you to look at and talk to the students more than when you used the board, and it enabled you to refer back to previous sheets (which doesn't happen when you erase the board). I didn't have any problem reading your writing.

• You provide nice periodic summaries within the fifty minute period. For example, you reviewed the accounting cycle once you worked through it with an example. At another point, you said "so how many sets of journal entries have we seen?" and you proceeded to outline them.

• The Frequent Flier case seemed to work beautifully in the 11:30 section. The students all seemed familiar with the case (due to your assigning a one page write-up) and thus were able to respond to your higher level analysis questions.

• You provide effective cues or hints to students to help them learn the material. For example, you strongly suggested that students work in groups on the case assignment and you provided some suggestions for working with the case. You mentioned that the upcoming quiz would be similar to exercises one and two. You said things to remind students of previous material which they probably needed reminding of -- "if you remember our discussion from last class, we said that . . . " All of these things help students in the long run.

• In one session you were working from a handout which students had and they were filling it in as the discussion progressed: This seemed to work very nicely in terms of students not spending too much time writing at the expense of listening.

<u>Suggestions</u>

• At one point on September 14, you used an overhead which would have worked better as an handout (information on the AB Co.). Students had to write from the overhead and that seemed to take important and valuable time. Think carefully about what to hand out to facilitate effective use of classroom time.

• I did not have any trouble hearing you in any of the three rooms, but in all three rooms there were times when I couldn't hear a student's question, answer, or comment. Either remind students to speak loudly or repeat their inputs.

The above comments represent my perceptions based on the observations I did of your three classes. There are many elements and/or aspects of the course which I cannot address (pace, level, coherency of parts, and so on), but we can gather and analyze that data from the early course evaluations and the small group instructional diagnoses.

I will read your early course evaluations immediately upon receipt of them and begin to analyze students' perceptions of their learning experience. Then we can sit down and discuss the issues which arise and ways to work with/through identified problems. I look forward to our meeting on September 16.

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# PURDUE UNIVERSITY

SCHOOL OF MANAGEMENT
KRANNERT GRADUATE SCHOOL OF MANAGEMENT

23 March 1992

Selection Committee
"Helping Students Learn" Award
Executive Vice President for Academic Affairs
CAMPUS

Dear Colleagues:

I have just learned that Professor Murugappa Krishnan has submitted for the consideration of your committee his very effective class innovation in the "Critical Analysis of Accounting Standards," and I have taken it upon myself to write in support of his nomination.

Professor Krishnan's exercise is the most effective means I have seen to encourage in our accounting students a critical and questioning cast of mind as they approach those technical accounting standards that will guide their professional judgment throughout their careers. I am aware of no other Intermediate Accounting course that puts into the students' hands the actual "Original Pronouncements"--the very documents that convey the official statements of those standards. However, the point of Professor Krishnan's exercise goes beyond a simple, unquestioning memorization of those standards to a critical analysis of the rationale behind those standards and an informed judgment regarding the range of discretion permitted the professional accountant in applying those standards. Students who complete this exercise are the beneficiaries of a carefully structured exposure to the very questions of judgment and discretion that will face them throughout their professional lives.

It is that care with which Professor Krishnan has structured his exercise that, I think, makes it so effective. The committee has no doubt already noticed with approval the close attention given to the forms provided the students to guide their responses. But I am particularly moved by his insistence on a private meeting with each of this over 150 students to discuss personally the student's work. As one who also makes heavy use of written exercises (particularly term papers and essay exams), I am both shamed and impressed by his diligence in this matter.

In my opinion, Professor Krishnan's very great care and diligence in devising and carrying out his "Accounting Standards" exercise carries our students to an uncommonly high level of critical understanding, and it is therefore most deserving of recognition as an "Outstanding Innovation in 'Helping Students Learn.'"

Respectfully,

Glenn Hueckel

Glenn Hueckel
Director
Undergraduate Programs

KRANNERT BUILDING • WEST LAFAYETTE, IN 47907

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## Summary of Research Statement

- My research relates to asset pricing with private information, under both perfect and imperfect competition; accounting and disclosure policy; and industrial organization.
- Most of my efforts have been in theoretical modeling, and includes work published in Econometrica, RAND Journal of Economics, Journal of Financial Markets, and Contemporary Accounting Research.
- I have also done empirical work, mostly predicated on a formal underlying equilibrium model. Some of this deals with analyst forecasts.
- This work is at the intersection of accounting, finance and economics.
- In recent years I have also become interested in questions arising in Indian financial markets. Some of these are also relevant to audiences elsewhere, as in the current working paper looking at how price-setters in financial markets are influenced during an earnings announcement window, not only by what the firm releases but also by what one class of institutional investors learns on its own.
- In analyst forecast papers, forecast errors in general are partly a function of how posterior beliefs are distorted by psychological factors, and partly by how given posterior beliefs, strategic factors lead to herding or bias. To date, papers have assumed either one or the other. In ongoing work we study analyst forecast errors that allow us to look both at a factor distorting posterior beliefs (over-confidence or under-confidence) and a strategic feature given posterior beliefs (herding) in the same model, and provide estimates of both of these parameters together.

Research Statement*
Murugappa Krishnan
January 2019

1. Introduction

Financial accounting consists principally of corporate reporting to the financial market, and hence most research into financial accounting questions necessarily has to consider issues involving the production and supply of information to a financial market. While my research has addressed different questions using diverse methods, these questions have been driven by some common themes, and this statement is intended to explain these. I have taken the following to be reasonable and easily justifiable premises.

- *While public information is available in a wide variety of economic settings, in most financial markets such information is made available only by self-interested agents.*

In particular, in financial markets public information, whether provided by the firm and its managers or auditors, or by other agents, such as analysts, or traders, seems eminently manipulable, and a fundamental question is: how do agents manipulate public information, and how do agents extract information from variables they know to be manipulable?

- *Modern financial markets exhibit features of imperfect competition.*

Perfect competition or price-taking behaviour has long held a central place in economic theory, and for a long time financial markets were considered one real-world example that closely resembled the idealized features of such models. Over the last two decades, however, there has been a growing realization that imperfect competition may provide better explanations in many markets. Even in financial markets, since the insider trading scandals of the 80's there is now a belief that agents with private information may also be big players relative to the market. So the notion that strategic behaviour is important has steadily taken root.

- *Research bridging theory and data is important, and as yet somewhat limited.*

While there has been a fair amount of theory in asset pricing, disclosure policy, and more generally, on information in financial markets, and a fair amount of empirical work, research helping us to prune at least some existing theories or suggesting sharper testable restrictions, has been relatively scarce.

* I am assuming that whoever gets this document will also get to see a copy of my vita, hence some details (such as abstracts of papers) are omitted here. Copies of most papers are also downloadable from the links indicated on the vita, or my SSRN page. Am also assuming that citation information will be available directly to the committee, from SSCI, Google Scholar, etc. Some of my papers have also been included in PhD reading lists at Stanford, MIT and the London Business School.

Some of my research (studying shopfloor productivity) has been driven by an additional premise:

- *Even for incentive issues within a firm, the noncooperative approach can yield useful insights beyond the cooperative or contractual paradigm.*

My work includes both theoretical and empirical research. Before identifying different (overlapping) streams into which I would classify my own papers, let me mention that in each theoretical paper I have tried to achieve some subset of the following targets:

- offer a new candidate answer to an old question or help raise a new question (as in "To Believe Or Not To Believe," with Utpal Bhattacharya, which suggests that managers may disclose bad news to minimize suspicion and suspicion-induced reliance on alternative sources of information; or "Preemptive Investment With Resalable Capacity," with Lars-Hendrik Rö1ler, which shows that an inability to commit can sometimes help rather than hurt a first-mover, suggesting that it is important to investigate into the sources of limited commitment; or "Theory of Analyst Forecast Bias," which suggests that analysts engage in bias to raise the cost of silence for managers and induce them to reveal information),

- achieve a significant generalization, critical also in enabling further applications, evidenced by the citation report, as in "Insider Trading in an Imperfectly Competitive Multi-Security Market with Risk Neutrality," with Jordi Caballé, which generalizes the Kyle (1985) framework to the case of N assets and K traders, and shows that diversification and risk-reduction need not necessarily be linked (which was the sole dominant presumption in the profession at one point): *agents may also diversify purely for strategic reasons, to minimize revelation of information*),

- lay a basis for applications and empirical work (as in the above paper, which can be useful for studying repackaging of assets, liabilities, and related issues in security design, and disclosure regulation; or "Skewness and the Believability Hypothesis," with Hyun-Song Shin and Srinivasan Sankaragurswamy, which shows that the min-max measure of skewness can help sidestep measurement problems associated with measuring discretionary accruals; or "Sources of Volatility in a Multi-Security Market with Imperfect Competition," with Jordi Caballé, which derives closed-form solutions to the maximum-likelihood estimators of primitive parameter matrices governing private information precision, liquidity noise, underlying values, and moment restrictions useful for implementing G\IM estimation).

With respect to empirical work, I have been driven by a desire to not only document statistical regularities (which I do regard as also important) but also to establish a tight connection between data and a model of equilibrium behaviour. To this end, I have been interested in

- structural estimation (i.e. estimation of primitive parameters from detailed trade and quote data, such as the precision of private information, or the level of background noise in a market), as in “Prices as Aggregators of Private Information: Evidence from S&P 500 Futures Data,” with Jin-Wan Cho, “Measuring Informational Efficiency Without Conditioning On A Public Announcement,” with Yu Cong, or in “Analysts’ Herding Propensity, “ with Lim, Shon and Zhou, where a first-order condition in the analyst optimization problem serves as the estimating equation for the unobservable herding propensity parameter, to learn about parameters that are not directly observable but are interesting and interpretable in the context of an economic model, or

- testing restrictions that flow directly from necessary conditions for an equilibrium, as in “To Herd or Not To Herd, “ with Huang, Shon and Zhou, in the hope of learning more by helping prune at least some theories.

Despite the inevitability of some overlap, it is probably convenient to classify my papers under the following heads.

1. Strategic disclosure in financial markets.

2. Asset pricing theory, explaining how information is incorporated into stock prices.

3. Structural estimation and tests of asset pricing models, with a significant recent emphasis on Indian financial markets.

4. Industrial organization and market structure.

5. Shopfloor productivity.

In the sections that follow, I discuss published and unpublished work in each area, together with brief notes on other work in progress.

## 2. Strategic disclosure in financial markets

While public information is available in a wide variety of economic settings, in most markets such information is made available only by self-interested agents. My work has focused on equilibrium models of how public information is manipulated. and how agents seek to learn from manipulable information. I feel the distinctive feature of my work in this area, relative to the large amount of theory, and the large amount of empirical work in this area, is the stress on relating theory to data.

While there is a tradition of assuming that participants in a financial market are rational, and that managers are rational, it seems to be less common to assume that *both can be rational in equilibrium at the same time, and in the same model.* Recognizing that a larger set of agents can be rational, which also seems very plausible, raises sharp questions about several strands of existing literature. For example, there is a rather large and growing empirical literature (McNichols and Wilson (1988), Jones (1991), Dechow (1994), Subrahmanyam (1996)) assessing how the market prices discretionary accrual choices by managers. Typically some measure of surprise in prices or security returns will be regressed against some measure of discretionary accruals chosen by managers. The market is assumed (explicitly or implicitly) to be rational, and a significant coefficient is interpreted as signifying 'valuable' information.

If we explicitly recognize that managers can also be rational - *so that the discretionary accruals chosen by managers are not regarded as mechanically generated signals* - several questions arise. Why would rational managers convey even bad news without distortion or camouflage? If they do not, how do they report, and how would a rational market adjust its inferences if it acknowledged the possibility of self-interested reporting? If cheating, exaggeration or bias is fully unravelled, a manager could be indifferent; so some source of noise that prevents unravelling by the market seems essential for a plausible story. If they do engage in self-interested reporting, and this is camouflaged by some source of noise, why should any econometrician's measure of the information in a discretionary accrual, or any other report, be better than that of rational agents in the model?

In "To Believe or Not to Believe," with Utpal Bhattacharya, we develop a theory of corporate disclosure under moral hazard, and show why managers may have an incentive to tell the truth even if their reports are necessarily like cheap talk (based on soft data), allowing them to manipulate reports with impunity. Thus we offer one explanation for the observed association between abnormal returns and unexpected earnings that is well-documented in the accounting literature, which is consistent with the notion that accounting earnings numbers are pieces of public information provided by opportunistic managers. This is of special relevance because given "safe harbour" rules governing disclosure of forward-looking statements, the fear of lawsuits due to a precipitous drop in share price is no longer as credible a mechanism for inducing managers to reveal even bad news.

In a non-cooperative setting we show that they may do so to minimize suspicion (aroused when the public news is good) and suspicion-induced reliance on alternative sources of information by financial market participants. By construction in our setting, there is no opportunity for managers to develop a reputation, yet the suspicion effect can be sufficient to alleviate moral hazard. There is a tension between the incentive compatibility conditions for the manager (to reveal even bad news) and the trader (to engage in costly search only when the public news is good) which can be resolved in equilibrium if fundamental values are skewed to a degree that seems plausible on empirical grounds. We also develop a testable distinction between the hard data hypothesis and the soft data hypothesis regarding the nature of corporate disclosure: *the spread given good news should exceed the spread given bad news.*

Besides the manager providing information about the firm, in an active financial market there are also a variety of information professionals such as securities analysts who provide information about the firm. In "A Theory of Analyst Forecast Bias," we show that a strategic analyst concerned with the combined accuracy of his sequence of forecasts, can benefit from an initial biased forecast in order to gain access to management's private information - by raising the cost of silence for the manager - and improve his subsequent forecast, even if both the manager and the financial market are rational, provided there is also a fraction of non- strategic analysts whose presence provides camouflage for the strategic analyst. Besides explaining documented declining positive bias, our theory also suggests a new testable prediction. While empirical papers have long documented analyst forecast bias, we believe our model is the first to provide an equilibrium explanation for this bias.

In current work, I am trying to develop an alternative explanation of positive bias in analyst forecasts, based on the intuition that while analysts compete with one another in building a forecasting reputation, they share an incentive to make their industry look attractive and thereby enhance the value of their own human capital. We hope to set up an empirical contest between the two different explanations for positive forecast bias.

In “To Herd Or Not To Herd,” we measure the pressure that analysts face to introduce strategic bias and herd with the prevailing consensus. This paper makes an important contribution in several respects. Herding is treated as an unobservable parameter to be estimated assuming optimizing behavior by analysts. We measure herding propensity also at the level of each individual analyst, so that it is now possible to examine the extent to which previous aggregate results are driven by a few analysts making a lot of forecasts. An inherent major difficulty in this entire literature has been the difficulty in disentangling herding behavior from behavior that reflects only ‘slow learning” by later forecasters. We develop a metric to measure where ‘slow learning” is more likely to be an explanation and show that our estimates of herding propensity are uncorrelated with ‘slow learning.”

A technical remark: one feature common to all of the above work involving strategic disclosure to financial markets is that agents are concerned with manipulating the posterior *mean.* In models of *direct disclosure* (as opposed to signaling models, or of disclosure via choices of costly variables) for technical reasons it has generally been more common to consider manipulation of the posterior *variance,* though on purely economic grounds, in many settings manipulation of the mean (making things seem more rosy) seems at least as important.

## 3. Asset pricing theory

For a long time research in asset pricing was dominated exclusively models which assumed perfect competition and only public information (such as the CAPM, consumption CAPM, APT, etc.). The growing realization that in modern financial markets agents with private information might also have some market power led to a variety of models since the early 80’s (Gale and Hellwig, Laffont and Maskin, Kyle (1985; 1989), Glosten and Milgrom (1985)), with a large literature based on the Kyle (1985) and Glosten and Milgrom (1985) models, which captured the intuition that the bid-ask spread was a way in which an uninformed specialist may protect himself given an information disadvantage relative to some traders.

In “Equivalence of the Kyle (1985) and the Glosten-Mugrom (1985) Models” I develop a discrete version of the Kyle (1985) model, and show that the distinction that in the latter, that agents know the exact price at which they trade while in the former they only have an expect price to go by, is unimportant, for all traditional questions dealing with informativeness of market aggregates, expected profits, etc. This becomes transparent once distributional assumptions and strategy spaces are made identical under both extensive forms. Even the negative correlation in orderflows between the informed and liquidity traders in the discrete version of Kyle (1985) is analogous to what obtains under the Glosten-Milgrom setting via the concept of a waiting line that limits only one trader to be at the window' at any time, so that if one trader has an opportunity to trade it implies that another does not.

The original Kyle (1985) paper studied a model with a single asset and a single informed trader. While that paper yielded important insights, in "Insider Trading in an Imperfectly Competitive Multi-Security Market with Risk Neutrality." with Jordi Caballé, we consider an economy with $N$ assets and $K$ traders, with general correlation structure governing returns, errors in private signals. and liquidity noise terms, with price-setting market makers who can observe multiple orderfiows in setting each price, to assess if such a general model will still yield any predictive content. A rich correlation structure is not only likely to be descriptively more valid, but it also can give rise to richer patterns of strategic behaviour. While diversification for reasons of risk reduction has been the cornerstone of accounting and finance for many years, this model, which rules out risk reduction incentives by construction - by assuming risk neutrality - *shows that agents may wish to diversify purely for strategic reasons, to minimize information revelation.*

We also obtain some predictive content: regardless of the underlying correlation structure, it turns out that the equilibrium matrix relating prices and order flows must be symmetric and positive definite. Symmetry means that the influence asset $i's$ orderfiow has on asset $j's$ price is the same as the influence that asset $j's$ orderfiow has on asset $i's$ price. Positive definiteness implies that nevertheless asset $i's$ price is most influenced only asset $i's$ orderfiow. The surpising aspect is that this result does not appear to depend on any underlying symmetry in the exogenous elements of the model.

We believe it is the first explicit solution to a multisecurity version of a model of this kind, and that it is even today the most general model in this literature (stemming from Kyle (1985)). Where Kyle (1985) suggested that a unique linear equilibrium was "fortuitous" our analysis made clear that the problem of finding an equilibrium is equivalent to finding a positive definite squareroot of a positive definite matrix, and hence uniqueness (of the linear equilibrium) follows.

This paper also clarified that a well-cited result about ambiguous comparative statics in the perfect competition noisy rational expectations model of Admati (Econometrica 1985) was essentially due to what econometricians call the correlated-regressors effect. In contrast to Admati (1985), in our setting despite allowing the same general correlation structure, we were able to identify one robust prediction: given a linear pricing rule, the coefficient matrix governing the relationship between the price vector and the orderfiow vector must be symmetric and positive definite, for *any* underlying set of parameter values. Thus, even without being able to estimate primitive parameter values (elements of the three different covariance matrices governing returns, errors in private signals, and liquidity noise), we still obtain an *empirically refutable prediction,* enabling one to consider going beyond theorizing to see if we could accept or reject the theory.

Our expressions for equilibrium profits and the general correlation structure also makes our model convenient as a vehicle for studying security design. In work in progress, we examine a closely related lognormal version of the model (in which the pricing rule relates percentage change in price [i.e. returns] to dollar-value orderfiow) to study security design.Under this setup liquidity needs are defined in cash, which is more easy to interpret, and enables us to find a meaningful way of "keeping noise constant".

As the citation report will show, these papers have not just been cited by many, but cited by leading scholars in accounting, finance, and economics, in their papers that appear in major journals, which in turn have been cited heavily. So the impact of these articles has been significant. They continue to be cited heavily in recent years. They have also been used in PhD syllabi in top schools (including Stanford, Yale, NYU, Indiana at Bloomington, London Business School, etc).

4. Structural estimation and tests of asset pricing models

Being able to estimate primitive parameters such as the precision of private information, the level of background noise, and the quality of priors, also raises the possibility of studying factors these parameters may be correlated with. In ongoing research we are examining an *event study* under imperfect competition, in which the primary focus is on the impact of public earnings announcements on these parameters. It also allows us to test necessary conditions for an equilibrium expressed in terms of these primitive parameters.

In “Prices as Aggregators of Private Information: Evidence from S&P 500 Futures Data?” with Jin-Wan Cho (lead paper, Journal of Financial and Quantitative Analysis), we show that a version of the *perfect competition* model due to Hellwig (1980) model has the property that the parameters of the (price, terminal value) joint distribution can be inverted to obtain its primitive parameters. Using S&P futures data, in which case terminal values can be treated as observable, we provide estimates of primitive parameters such as the precision of private information and supply noise. We also provide estimates of ancillary quantities such as the weights on different types of information in the agents’ expectation function, and estimates of the signal-to-noise ratio. This is another example of *structural estimation,* in which the equilibrium model plays an important role in building a bridge between what we can observe, and what we cannot observe but still regard as interesting.

In “Measuring Informational Efficiency Without Conditioning On a Public Announcement,” we exploit the availability of active single-stock futures markets in India (they do not exist in the US where they were banned in 1980, restarted in 2001 and shut down soon after). This allows us estimate firm-level primitive parameters of the Hellwig (1980) model, and so compute informational efficiency as a function of those parameters. We then relate the cross-section of these informational efficiency measures to measures of corporate governance, which are also important in determining transparency. It raises questions about conclusions reached previously by using discretionary accrual proxies or earnings response coefficients as parameters governing informational efficiency.

In “Event Study With Imperfect Competition and Private Information,” we use this technology to extend traditional event studies that focus exclusively on the price reaction to a public announcement, to also address questions relating to *private information before, during, and soon after a public announcement window*.

In “Herding, Momentum, and Investor Over-reaction,” with Ran Hoitash, we propose an empirical measure of noise in prices arising from mimicking or herding behavior beyond what is justified by correlated information. To the best of our knowledge this is the first measure at the level of an individual firm-quarter of a parameter governing noise in prices. We show that its market aggregate is well-correlated with aggregate measures of a bubble such as Shiller’s Bubble Expectations Index. We then apply this measure to a contemporary question in accounting: has the relevance of accounting earnings declined? Our answer: it is the noise in prices that has increased over time, and it is the omission of this variable that has made some researchers conclude that earnings numbers have deteriorated.

The recent availability of very detailed databases from the India's National Stock Exchange has caused me to allocate substantial time and attention in recent years to studying this market. Unlike the data available from the New York Stock Exchange (e.g. Trades and Quotes) in which we have to guess whether a trade is buyer or seller-initiated, India's National Stock Exchange is an open electronic limit-order market providing data that directly reveals buy and sell orders. India's recent history as a significant emerging market with unique history makes this interesting. Three working papers explore different aspects of this market, dealing with liquidity, informational efficiency and price discovery. I anticipate working intensively in this area for the short- and medium-term future. Part of the challenges in working with Indian data has been that while stock market data has been plentiful and of very good quality, related financial statement information has been more scarce.

Also for some questions of natural interest in today's India – e.g what is the role played by foreign institutional investors (FIIs) – lack of transparency and the intransigence of a few regulators has been a stumbling block. Instead of only limiting myself to questions that can be conveniently analyzed with existing data, I also spent time and effort trying to identify ways to improve the data availability in some critical areas, in order to address more important questions. This took me on the overlap between research and service activity, in using India's Right To Information Act (2005) and related avenues, to try and alleviate this problem. This has begun to bear some fruit, as I have indicated in my vita.

I have also been working with an Indian Member of Parliament (Shyam Benegal) to use the parliamentary process to help gain access to this data. This is an activity for which I have received encouragement from several senior academics in India and the US (including Prof. Shyam Sunder of the Accounting Dept at Yale University, and former Editor-in-Chief of the Accounting Review).

5. Industrial organization and market structure

This area contains papers that each contain a model of imperfect competition designed to address a particular question. Except for one exception, we use models consistent with noncooperative game theory"

In "Preemptive Investment and Resalable Capacity," with Lars-Hendrik Röller, (lead paper, RAND) we consider an entry game with resalable capacity. While there is a vast literature on entry and entry deterrence games, the literature has almost without exception assumed that the incumbent or first mover can make an *irreversible investment.* This confers a degree of power to make a commitment *for* which we find no significant practical examples. In the real world most investments can at least have value to other agents who wish to enter the industry: they are resalable to potential competitors. Given the pervasiveness of this attribute of investment, for a theory to be meaningful, we argue that we must explore fully the implications of investment being resalable, and of the incumbent's ability to make commitments being consequently much more limited.

In the context of an entry game a la Spence (1979) and Dixit (1980) we show that *this inability to commit can nevertheless help rather than hurt.* Resalability increases the complexity of the incumbent's choice problem but also furnishes her with an additional strategic variable. This shows that in an analysis of limited commitment the nature of the source of such limits can be important.

In "Regulating Price-Liability Choices to Improve Welfare," with Lars-Hendrik Röller, we study regulation in markets where firms choose price-liability combinations. This is of considerable contemporary significance given auditors' concerns over liability regimes. Our work implies that a recently suggested regulatory rule, restricting the maximum liability that can be assumed, does not increase consumer welfare. We also study a rule inspired by the German audit market, in which maximum liability is restricted but only as a multiple of the price, and show that this rule can also reduce consumer welfare, and even be Pareto inferior.

In "Setting Accounting Standards," with Lynda Thoman, we study standard-setting in the private sector and compare control of the standard-setting process by auditors with that by their clients. To capture the notion of a private sector agency like the FASB controlling standard setting, we assume the first stage is cooperative, followed by a non-cooperative competition among auditors. This is similar to the R & D literature dealing with research joint ventures. Standard- setting is modeled as *collective choice of the level of fuzziness in the rule* which affects amount of discretion that a preparer is allowed.

> While some results depend on who controls the process (e.g. when switching costs are small, auditors are more likely to set standards that allow for discretion than clients) interestingly many results do not depend on who - big auditors or big business has control. In particular, auditor independence holds for a wide variety of parameter values under both regimes. We also show that clear standards do not imply auditor independence, and nor do fuzzy standards imply non-independence.

6. Shopfloor productivity

One premise I have believed in is that even for problems within the firm the non-cooperative aproach may yield useful insights. While principal-agent or contract theoretic approaches are also useful, especially for studying, say, top-management compensation, at lower levels of the typical organization are several problems, such as maintenance and production scheduling, for which a non-cooperative formulation appears more useful than either the traditional single decision maker framework, or a contract-theoretic approach.
In "How Do Shop-Floor Supervisors Allocate Their Time," with Ashok Srinivasan, we consider a setting where a shop floor worker's productivity can be enhanced by on-the-job training by a first-line supervisor, and where targets (production, quality, etc.) are set from above. Within the context of a simple noncooperative sequential game designed to capture salient incentives of worker and supervisor, we show that for training activity to emerge in equilibrium, targets should be sufficiently high that it is credible for the worker to believe that the supervisor will not have idle time just because the worker's own contribution to output increases from participation in training. We also validate the model using data obtained from a Japanese manufacturing plant in the Midwest. The combination of theory and empirical work in this area is somewhat limited.

At the core of the problem is how a supervisor allocates his time between direct contribution to productivity on the line, and indirect contribution via helping coworkers, taking into account the best response or reaction function of the workers. What is surprising is the impact of labour even in a capital intensive environment. We used data from the same site as in the above paper, to estimate a flexible (parametric) production function, assuming a single decision-maker. This appears in “Do Supervisory Inputs Matter In A Capital Intensive Industry? - Some Evidence From A Japanese Car Transplant”.

We estimate a translog production function based on the same data from a Japanese automobile plant in the Midwest where output is determined by capital and different supervisory time inputs. The model allows for heteroskedastic errors, where this heteroskedasticity is a function of various variables affecting perceived target severity. We find that while as expected capital inputs are important, each supervisory time input is also significant in this capital intensive industry. Linear homogeneity in these inputs is rejected. We find evidence of asymmetry in substitution (using Morishima elasticities) among different components of supervisory time. This asymmetry has implications for the design and allocation of supervisory tasks.

In continuing work, we are exploring a slightly different functional form, which nests the Cobb-Douglas, and which in the context of our sequential game, allows us to explicitly calculate choices at each stage of the game. We are also planning to implement generalized method of moments estimation of primitive parameters in this context.

## 7. Ongoing agenda and concluding remarks

I have studied the connection between information and the behaviour of financial markets, which is central to financial accounting, which consists in the production and provision of public information by self-interested agents.

I expect this focus of my research in the medium term to continue, and to be involved in both theoretical and empirical research. Extensive trade and quote data bases have only recently become available. Detailed non-US data (in particular from India) are of even more recent origin. These would enable me to pursue even more empirical research dealing with market microstructure. My interest in applied non-cooperative game theory as a tool has only grown over time, and consequently I expect to be interested in issues pertaining to imperfect competition and industrial organization also, and their application to financial markets, for a long time to come.

# Summary of Teaching Statement

- Experience includes all accounting classes at introductory, intermediate and advanced levels barring auditing and tax. Introductory and international finance. Doctoral level courses in asset pricing and disclosure. I have taught different age groups from college freshmen to mid-career executives; and in different formats – traditional in-class, online, hybrid, executive and professional. Have taught outside the US in Poland and India, besides teaching at a wide variety of schools, and classes varying in size even at the undergrad or master's levels from under ten to over 250.
- In introductory classes my objectives have been to introduce business language, provide adequate practice, show connections to other courses, and to provide multiple ways for a student to demonstrate learning, besides just exams, such as group research into one company.
- In graduate classes I have emphasized more a user than a preparer perspective, both in financial and managerial accounting, to show that numbers can be manipulated often even within the rules, and therefore to understand incentives and opportunities that arise, and to be skeptical.
- In my doctoral classes I have tried to develop the mathematical tools to make students comfortable with important classes of models in the theory of asset pricing with private information, and disclosure to a financial market. And to show that empirical work can be predicated on underlying models of equilibrium.
- Besides numerical student evaluations and student comments, I think it is important to also look at the reports of in-class or other observations (by Susan Ambrose, Carnegie-Mellon; Prof. Glen Berryman, U of Minnesota; and prof. Glenn Hueckel, Purdue University). I consider these important pieces of evidence.
- For MBA classes like in managerial accounting where I've used discussions based on contemporary questions (health care, defense contracts, the Wells Fargo scam) to understand the role of incentives, even a sampling of a copy of my online discussion boards will be useful. Those who have taught online and face to face will recognize that these online discussion boards are like a qualitative lower bound on the kinds of discussions that take place in face-to-face classes. Therefore I think this evidence is important.

# Teaching Statement

Murugappa Krishnan

## 1. Philosophy

Over the years I have taught financial accounting, financial statement analysis, cost accounting, at introductory, intermediate and advanced levels; PhD courses in asset pricing with private information and disclosure; introductory finance and international finance. My primary effort in the introductory classes I have taught has been to try and increase enthusiasm among the class, and help develop an understanding of business language. At the intermediate level I have made a serious effort to get students to spend time with the original pronouncements themselves and appreciate that even within GAAP there is substantial discretion. At the MBA and MS level I have consciously tried to relate what we do in class to contemporary controversies involving financial accounting.

My methods have centered around providing structure while yet challenging students to strive for more. Because students tend to be diverse even in how they respond to teaching methods and types of tests I have tried to offer a mix of coursework, some individual and some group work, to help discover how a student does well and help them learn something in that way. The rest of this document provides background for understanding the teaching-related credentials I am submitting as part of my packet.

## 2. Introduction

In this document I have tried to briefly explain what I regard as my contribution to teaching. I also present some evidence pertaining to undergraduate, MBA. MS-Accounting, and PhD teaching at all of the schools where I've taught. While these documents were mostly created for various different purposes, and in the case of the first two items below, were meant solely as feedback for me, I think the obvious candor in some of them make them useful in getting a more complete picture of classroom performance. Enclosed are unedited copies of

- Report of Prof. Glen Berryman based on visit to MBA class at Minnesota.
- Report of Ms. Susan Ambrose, Director, Teaching Center, Carnegie-Mellon University, who attended 9 sessions in all. This report was written after 3-4 sessions. (You may contact her for more information ... she told me keeps written records of all her impressions.)
- Letter of recommendation written by Prof. Glenn Hueckel, then Undergraduate Chairman at Purdue University, in suport of my application for a Teaching Innovation Award.
- Formal numerical teaching ratings

## 3. Undergraduate and MBA teaching

Over the years I have taught financial accounting at the introductory, intermediate and advanced levels. My primary effort in the introductory classes I have taught has been to try and increase enthusiasm among the class, and help develop one particular set of skills, sometimes by adapting the well-known Monopoly game to the course.

At the introductory level one problem students face is simply understanding business language (‘what does *accrue* mean ... who's giving money to whom’). The initial exercises in recording business transactions with journal entries stump students because business itself − let alone business language − seems unfamiliar. Playing Monopoly (a game familiar to most students, even international students) helped to overcome this since students were required to first simply write a brief informal verbal description of each transaction as they played; later these transactions were recorded in the journal, and then used as a basis for the entire accounting cycle from initial journal entries, to ledger entries, trial balance, adjustments, and preparation of income statement and balance sheet.

The rules of the traditional Monopoly game were modified to ensure that we had a greater variety of transactions, besides buying and selling property, paying and receiving rent, paying taxes, etc. and to ensure that more transactions − similar to those in the early chapters of the text − were generated within a given period. So Chance, Community Chest and Jail were ignored, and students simply played on. At each board was a group of 5-7 students, with one student being the designated banker, and another, and half of the cash and most of the property was distributed (the latter by shuffling cards and having students pick an equal number) at the start. Property construction was permitted even with one card of a colour.

Having a student be the banker in each group had one great benefit. Students got to see both sides of virtually all transactions. So a common question in introductory financial accounting, ‘Why do you say *debit* cash when my cash increases, when the bank tells me it is *crediting* my account?’ is virtually answered by the students themselves. They realize quickly that the bank is describing the transaction from its perspective, and not that of its depositor’s.

I also allowed students or the government (holder of all residual property) auction property off. This helped teach students that historical cost to the new acquirer is whatever he or she paid for it, and not the board number or what was paid by the initial acquirer.

In a little over one class period we played Monopoly, during which time transactions were recorded only informally, but where I insisted that everyone record every transaction. This led to discussion within most groups, and I think students learnt from each other as well. Later, these descriptions of transactions became the ‘word problems’ that they used for going through the accounting cycle, on which we spent another 2-3 weeks.

While my initial target was only to overcome the hurdle of unfamiliar business language, while breaking the monotony of a lecture and the tension of a large class, in retrospect I think the greatest gain was in enthusiasm and attendance over the entire term. Reviewers should note that my introductory accounting classes, like introductory calculus classes have been large, and a lot of time and effort outside of class (in setting up for class, and in cleaning up after class) is also involved.

Years ago I taught introductory financial accounting at Carnegie-Mellon where I was a visitor. Ms. Susan Ambrose, Director of the Teaching Center attended nine classes of mine and wrote the report that I attach. Nine classes (on 3 different days) is a fair amount of watching, and for that reason I consider her testimony valuable. She also told me she keeps careful records, so interested reviewers could contact her if they would like more details.

Among the supplementary evidence (over and above ratings) that I have included is the letter written by Prof. Glenn Hueckel of Purdue University, proposing my name for a teaching award there. He was impressed by a project I required of students in intermediate accounting, in which they had to confront the Original Pronouncements, and answer some challenging questions. It also involved a final one-on-one chat with each student (of large sections).

In the advanced financial accounting class I taught, I had to cope with students whose backgrounds were not only diverse, but whose last previous experience with accounting sometimes went back some years. It required refreshing their knowledge of introductory and intermediate accounting, while at the same time leaving adequate time for special topics like partnerships, segment reporting, governmental accounting, and accounting for foreign currency transactions. All students wrote a term paper in which they had to critically examine the financial statements of a small town over two years. It helped them see the differences between governmental accounting and corporate reporting, and appreciate the political nature of reports better. For some students it was also a new experience to learn how much they could learn from the web about their own town.

My experience includes MBA teaching both in the US and at the Warsaw School of Economics in Poland. In the supplementary material is a formal report written by Prof. Glen Berryman, then chairman of the Minnesota accounting department, to meet the University of Minnesota requirements that faculty be evaluated using not only numerical teaching ratings but also reports of class visits. The particular class he attended dealt with revenue recognition, and all of the features he liked continue to be part of my teaching strategy, and I've used the material in other courses as well.

I have also made a conscious effort in my MBA classes to relate what we do in class to contemporary accounting controversies. The best example I can give of this is the assignment based on Enron that I have used. Besides this teaching statement I include a copy of that Enron assignment with its solution and some further notes.

**4. MS Accounting teaching**

At Yeshiva I was involved in the MS Accounting program since its inception. In "Contemporary Topics in Accounting" I have endeavored to introduce students to
(a) contemporary controversies in accounting
(b) the roles of various agents besides accountants and regulators who affect the information environment in which accounting operates

(c) the differences between US Generally Accepted Accounting Principles (GAAP) and the increasingly adopted International Financial Reporting Standards (IFRS).

In this connection given the feedback from potential employers of our students, I use a variety of cases from the FASB Cases on Recognition and Measurement, to give our students practice in making an argument (a) based on first principles (b) searching for support in the FASB Accounting Standards Codification (c) searching through International Financial Reporting Standards. For non-accountant reviewers I should note that US GAAAP runs into about 25,000+ pages, IFRS into about 2,000+ pages, and these can sometimes lead to contradictions or allow for diverse judgments. So skill in not just searching but making an argument based on proper justification is valued in practice. Our students also learn to make a case in writing and orally, and get more used to making presentations in public.

## 5. PhD teaching

I have taught a course on information and financial markets, covering material which is taught at some of the best accounting research programs. Where I've offered a similar course before, it has usually been taken by PhD students in accounting, finance and economics. The structure of the PhD program in some places where I've taught does not ensure that accounting students will have the requisite background in economics and probability theory by the time they take my course. So I have voluntarily offered classes over summer to students interested in taking the course this fall but concerned about their economics preparation. We covered some technical material more slowly. Those students may also be contacted for their perception of the benefit from the course.

Reviewers should realize that a big chunk of research in accounting pertains to information in financial markets. Even empirical researchers feel preparation in theory can help them pose questions more precisely. Since many of the students registered for my course have a strong interest in empirical work, I have also covered some empirical literature in this course.

In Jan 2015, and in July 2018, I taught 4 PhD classes at IIM Bangalore, and in the summer of 2017 a 2-week short course at IIT Kharagpur. I have also taken PhD classes at IIT Madras several times. This is also evidence of my contribution and reputation as a teacher.

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 52: 010: 202: 90MANAGEMENTACCOUNTNG: 2017SP - MANAGEMENT ACCOUNTNG 52: 010: 202: 90

**Instructor:** Murugappa Krishnan *

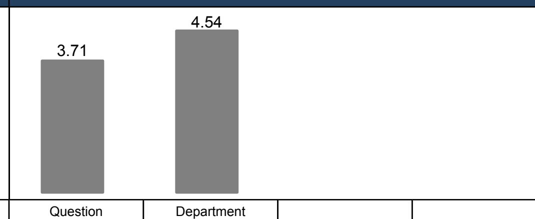
**Response Rate:** 19/36 (52.78 %)

### 1 - The instructor was prepared for class and presented the material in an organized manner.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent | Percent Responses |
|---|---|---|---|---|
| Strongly Disagree | (1) | 1 | 5.26% | |
| Disagree | (2) | 2 | 10.53% | |
| Neutral | (3) | 4 | 21.05% | |
| Agree | (4) | 4 | 21.05% | |
| Strongly Agree | (5) | 6 | 31.58% | |
| N/A | (0) | 2 | 10.53% | |
| | | | | 0 25 50 100 |

**Means**



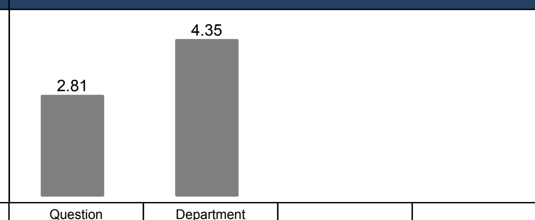

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 19/36 (52.78%) | 3.71 | 1.26 | 4.00 | 284 | 4.54 | 0.96 | 5.00 |

### 2 - The instructor generated interest in the course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent | Percent Responses |
|---|---|---|---|---|
| Strongly Disagree | (1) | 2 | 11.11% | |
| Disagree | (2) | 7 | 38.89% | |
| Neutral | (3) | 2 | 11.11% | |
| Agree | (4) | 2 | 11.11% | |
| Strongly Agree | (5) | 3 | 16.67% | |
| N/A | (0) | 2 | 11.11% | |
| | | | | 0 25 50 100 |

**Means**



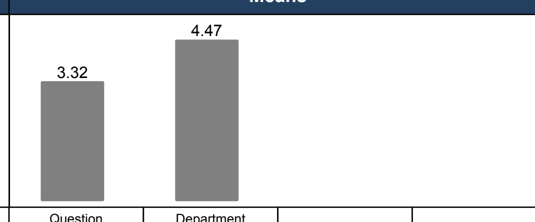

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 18/36 (50.00%) | 2.81 | 1.38 | 2.00 | 283 | 4.35 | 1.03 | 5.00 |

### 3 - The instructor responded effectively to student comments and questions.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent | Percent Responses |
|---|---|---|---|---|
| Strongly Disagree | (1) | 2 | 10.53% | |
| Disagree | (2) | 5 | 26.32% | |
| Neutral | (3) | 2 | 10.53% | |
| Agree | (4) | 5 | 26.32% | |
| Strongly Agree | (5) | 5 | 26.32% | |
| N/A | (0) | 0 | 0.00% | |
| | | | | 0 25 50 100 |

**Means**



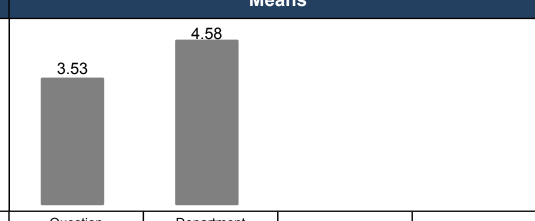

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 19/36 (52.78%) | 3.32 | 1.42 | 4.00 | 282 | 4.47 | 0.99 | 5.00 |

### 4 - The instructor had a positive attitude toward assisting all students in understanding course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent | Percent Responses |
|---|---|---|---|---|
| Strongly Disagree | (1) | 2 | 10.53% | |
| Disagree | (2) | 1 | 5.26% | |
| Neutral | (3) | 5 | 26.32% | |
| Agree | (4) | 4 | 21.05% | |
| Strongly Agree | (5) | 5 | 26.32% | |
| N/A | (0) | 2 | 10.53% | |
| | | | | 0 25 50 100 |

**Means**




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 19/36 (52.78%) | 3.53 | 1.33 | 4.00 | 284 | 4.58 | 0.90 | 5.00 |

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 52: 010: 202: 90MANAGEMENTACCOUNTNG: 2017SP - MANAGEMENT ACCOUNTNG 52: 010: 202: 90

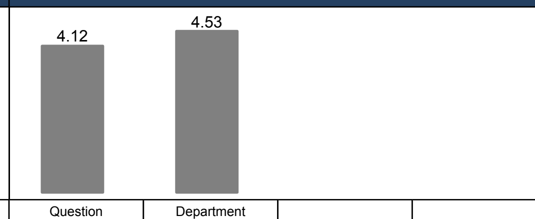
**Instructor:** Murugappa Krishnan *

**Response Rate:** 19/36 (52.78 %)

### 5 - The instructor assigned grades fairly.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 2 | 10.53% |
| Agree | (4) | 11 | 57.89% |
| Strongly Agree | (5) | 4 | 21.05% |
| N/A | (0) | 2 | 10.53% |

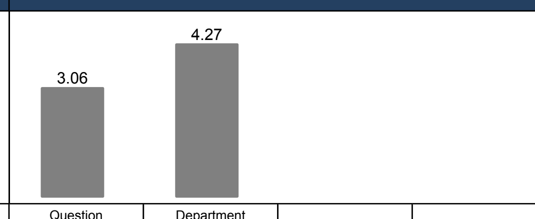



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 19/36 (52.78%) | 4.12 | 0.60 | 4.00 | 284 | 4.53 | 0.84 | 5.00 |

### 6 - The instructional methods encouraged student learning.

**Murugappa Krishnan**

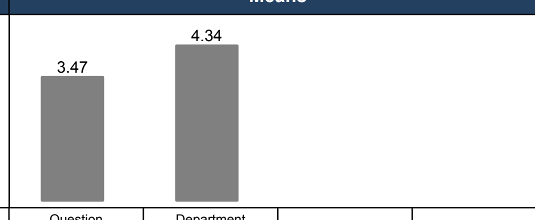
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 10.53% |
| Disagree | (2) | 5 | 26.32% |
| Neutral | (3) | 4 | 21.05% |
| Agree | (4) | 4 | 21.05% |
| Strongly Agree | (5) | 3 | 15.79% |
| N/A | (0) | 1 | 5.26% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 19/36 (52.78%) | 3.06 | 1.30 | 3.00 | 284 | 4.27 | 1.07 | 5.00 |

### 7 - I learned a great deal in this course.

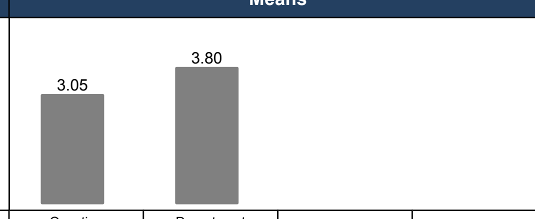
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 10.53% |
| Disagree | (2) | 1 | 5.26% |
| Neutral | (3) | 6 | 31.58% |
| Agree | (4) | 6 | 31.58% |
| Strongly Agree | (5) | 4 | 21.05% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 19/36 (52.78%) | 3.47 | 1.22 | 4.00 | 283 | 4.34 | 0.99 | 5.00 |

### 8 - I had a strong prior interest in the subject matter and wanted to take this course.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 10.53% |
| Disagree | (2) | 5 | 26.32% |
| Neutral | (3) | 4 | 21.05% |
| Agree | (4) | 6 | 31.58% |
| Strongly Agree | (5) | 2 | 10.53% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 19/36 (52.78%) | 3.05 | 1.22 | 3.00 | 283 | 3.80 | 1.23 | 4.00 |

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 52: 010: 202: 90MANAGEMENTACCOUNTNG: 2017SP - MANAGEMENT ACCOUNTNG 52: 010: 202: 90

**Instructor:** Murugappa Krishnan *

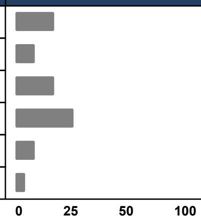
**Response Rate:** 19/36 (52.78 %)

### 9 - I rate the teaching effectiveness of the instructor as:

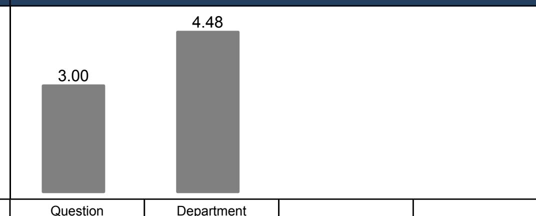
**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 4 | 21.05% |
| 2 | (2) | 2 | 10.53% |
| 3 | (3) | 4 | 21.05% |
| 4 | (4) | 6 | 31.58% |
| 5 = Excellent | (5) | 2 | 10.53% |
| N/A | (0) | 1 | 5.26% |

Percent Responses




Means

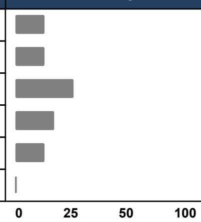



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 19/36 (52.78%) | 3.00 | 1.37 | 3.00 | 282 | 4.48 | 0.87 | 5.00 |

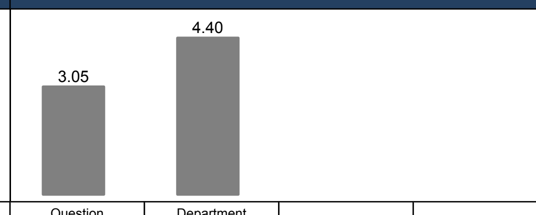
### 10 - I rate the overall quality of the course as:

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 3 | 15.79% |
| 2 | (2) | 3 | 15.79% |
| 3 | (3) | 6 | 31.58% |
| 4 | (4) | 4 | 21.05% |
| 5 = Excellent | (5) | 3 | 15.79% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 19/36 (52.78%) | 3.05 | 1.31 | 3.00 | 281 | 4.40 | 0.88 | 5.00 |

### 11 - What do you like best about this course?

| Response Rate | 8/36 (22.22%) |
|---|---|

- N/A
- Unfortunately, I did not enjoy this course. Although because of this course my math skills are much stronger.
- N/A
- N/A
- this course shouldn't be offered online. There so so many fine nuances in accounting that are extremely difficult for a student to pick up on online without a professor to help immediately when an issue arises. At my satellite campus in freehold simple classes like abnormal psychology and digital marketing have in class sessions which are an easy A. Classes like that are that easy should be the ones online and others such as accounting, fiance, and statistics should be offered in classrooms. this would increase student success as i have talked to many students who struggle with courses such as this. Why are we paying so much money to Rutgers to teach ourselves? i really hope professors aren't getting paid extra to be assigned to an online class since the professor did absolutely nothing to help me pass this course. All effort came from myself alone. I hope other students take the time to write their honest opinions too because this needs to change.
- N/A
- The ability to take the class from home
- I enjoyed the flexibility of the schedule.

| | |
|---|---|
| **Course:** | 52: 010: 202: 90MANAGEMENTACCOUNTNG: 2017SP - MANAGEMENT ACCOUNTNG 52: 010: 202: 90 |
| **Instructor:** | Murugappa Krishnan * |
| **Response Rate:** | 19/36 (52.78 %) |

**12 - If you were teaching this course, what would you do differently?**

| Response Rate | 9/36 (25%) |
|---|---|

• Actually teach something rather relying solely on Connect.

• This Professor was organized, but at the same time disorganized. I think he is so intelligent that he expects his students to be on the same level. Each week along with the readings he would provide lectures and notes, which most of the time was very confusing. The lectures and notes did not pertain to the material for that week, or for the entire course to this date. For example, early in the semester (week 3) he provided us with notes on quadratic functions which was strange. I spent time studying these notes only to discover that quadratic functions had nothing to do with the course material. His lecture notes were of no help and only made things more confusing. If I were teaching this course, I would not make the course material more challenging than it already was.

• N/A

• I can honestly say this was the worst experience I've ever had in any college course. I understand that online classes are more so an "on your own" kind of thing and a lot of the responsibility lies on the student. However, Murugappa Krishnan's "mini-lectures" were pretty much useless and had little applicability with the weekly assignments. I felt like I had to teach myself all of the course content and whenever I asked Krishnan a specific question about a problem he would never give me a straight answer or include any steps on how to solve it. So all in all I feel that Krishnan didn't do his job as a University Professor and actually "teach" the course material adequately.

• get the teacher in the classroom, regardless of the commute. if they really care about teaching and not just collecting a paycheck they wont mind. and if they do, get more dedicated staff.

• Having the professor actually answer questions that we have rather than telling us to refer to the text and the course sections on the bottom of Connect.

• N/A

• I would not rely on the book publishers homework assignments in order to educate and grade students. I understand that online classes can require that, however, the McGraw Hill homework assignments were incredibly tough, due to lack of feedback. The other issue is that the teacher cannot - so far as I am aware - access the assignment in order to assist the student if they need help.

• The course was very self taught. The lecture videos only somewhat pertained to the subject matter. I would have posted more in depth lectures.

**13 - In what ways, if any, has this course or the instructor encouraged your intellectual growth and progress?**

| Response Rate | 7/36 (19.44%) |
|---|---|

• None.

• None.

• N/A

• N/A

• it hasn't

• N/A

• N/A

**14 - Other comments or suggestions:**

| Response Rate | 7/36 (19.44%) |
|---|---|

• The assignments take far too long.

• This Professor is so intelligent, but maybe not all of his students are able to comprehend some of the notes/lectures he provides. His lectures should be more transparent and related to the course material.

• First thing I would suggest is to have utilize a different site for the homework problems, other then the Connect site. Intro to Financial Accounting had the homework on the Pearson site which is great because it gives feedback when a question is wrong and it shows you how to solve it, which I cannot say the same for Connect. While I did enjoy watching a video about an example problem I was disappointed that the video was not offered for every question. Students learn in different ways and I believe that watching example problems being done is great. So I strongly suggest another site besides Connect be used for students in the future. If that cannot be done, then I suggest that the professor works out an example problem straight from the homework and puts it on a video so the entire class can see it. Again, it will help to see an exact problem being done so students can learn to do it themselves.

• If I was to make any suggestions to Krishnan one would be to actually go through PowerPoint slides and explain the course content clearly. His method of using a piece of paper to solve a random problem is not effective in the least and actually generates more confusion than anything. Also I would suggest the he answer student questions effectively and without the "figure it out on your own" attitude whenever one is asked.

• increase Rutgers' presence in satellite campuses such as Freehold. Why bother to have a partnership if it is just going to be understaffed, and under funded. There is now just ONE Rutgers counselor at the Freehold location to hand hundred of students. Does that make sense?

• N/A

• The homework program, as stated before, was atrocious. I have never, in the entire time that I have been going to school, dealt with such poor programming. It makes it easy for the teacher because they do not need to do anything at all. However, it gives no feedback on what I did wrong, only that I did something wrong. It does not show how to do it correctly, there is nothing. Add that in with the difficulty of the assignments, and the fact that it was weighted the same as exams. It should have made the course easier, but instead I was stuck spending 6-8 hours a week on a single homework assignment, and still not getting 100% on it, and being left with little to no idea on how I solved it in the first place. I even went so far as to try to hire tutors online, and they were unable to solve the equations, or come up with a method for solving the equations, so that I could actually learn what to do, which makes me wonder the accuracy of the program itself.

**Course:** 52: 010: 202: 90MANAGEMENTACCOUNTNG: 2017SP - MANAGEMENT ACCOUNTNG 52: 010: 202: 90

**Instructor:** Murugappa Krishnan *

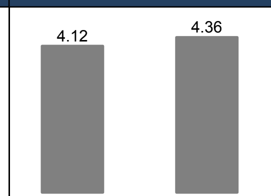
**Response Rate:** 19/36 (52.78 %)

### 15 - The course met the objectives in the syllabus.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 4 | 22.22% |
| Agree | (4) | 7 | 38.89% |
| Strongly Agree | (5) | 6 | 33.33% |
| N/A | (0) | 1 | 5.56% |

Percent Responses: 0 25 50 100

Means




Question Department

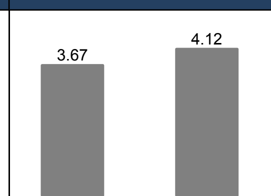
| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 18/36 (50.00%) | 4.12 | 0.78 | 4.00 | 51 | 4.36 | 0.83 | 5.00 |

### 16 - Given the subject of the course, there was good balance between the readings, online discussions, and assignments.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 5.56% |
| Disagree | (2) | 2 | 11.11% |
| Neutral | (3) | 4 | 22.22% |
| Agree | (4) | 6 | 33.33% |
| Strongly Agree | (5) | 5 | 27.78% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means




Question Department

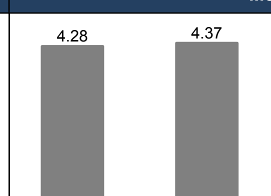
| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 18/36 (50.00%) | 3.67 | 1.19 | 4.00 | 52 | 4.12 | 1.02 | 4.00 |

### 17 - I now feel comfortable using the online learning system.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 2 | 11.11% |
| Neutral | (3) | 2 | 11.11% |
| Agree | (4) | 3 | 16.67% |
| Strongly Agree | (5) | 11 | 61.11% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means




Question Department

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 18/36 (50.00%) | 4.28 | 1.07 | 5.00 | 52 | 4.37 | 1.01 | 5.00 |

### 18 - I was satisfied by the technical support services for this course.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 5.88% |
| Disagree | (2) | 1 | 5.88% |
| Neutral | (3) | 4 | 23.53% |
| Agree | (4) | 6 | 35.29% |
| Strongly Agree | (5) | 3 | 17.65% |
| N/A | (0) | 2 | 11.76% |

Percent Responses: 0 25 50 100

Means


Question Department

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/36 (47.22%) | 3.60 | 1.12 | 4.00 | 50 | 3.91 | 1.01 | 4.00 |

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 52: 010: 202: 90MANAGEMENTACCOUNTNG: 2017SP - MANAGEMENT ACCOUNTNG 52: 010: 202: 90

**Instructor:** Murugappa Krishnan *

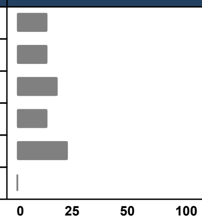
**Response Rate:** 19/36 (52.78 %)

**19 - The instructor effectively made use of the online environment to support classroom learning.**

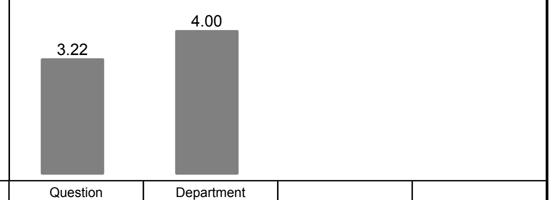
**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 3 | 16.67% |
| Disagree | (2) | 3 | 16.67% |
| Neutral | (3) | 4 | 22.22% |
| Agree | (4) | 3 | 16.67% |
| Strongly Agree | (5) | 5 | 27.78% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means

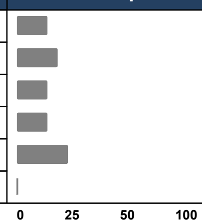



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 18/36 (50.00%) | 3.22 | 1.48 | 3.00 | 51 | 4.00 | 1.26 | 4.00 |

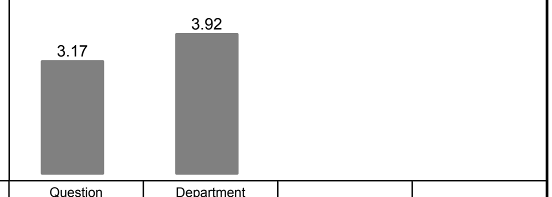
**20 - I would recommend this course to others.**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 3 | 16.67% |
| Disagree | (2) | 4 | 22.22% |
| Neutral | (3) | 3 | 16.67% |
| Agree | (4) | 3 | 16.67% |
| Strongly Agree | (5) | 5 | 27.78% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means

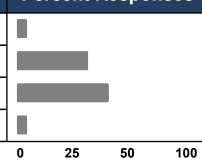



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 18/36 (50.00%) | 3.17 | 1.50 | 3.00 | 52 | 3.92 | 1.33 | 4.00 |

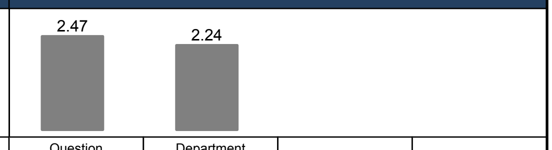
**21 - Do you think you would have received a lower, the same, or a higher grade if you had been in a regular classroom?**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Lower | (1) | 1 | 5.56% |
| The Same | (2) | 7 | 38.89% |
| Higher | (3) | 9 | 50.00% |
| N/A | (0) | 1 | 5.56% |

Percent Responses




Means

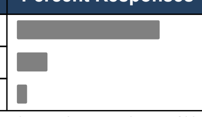



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 18/36 (50.00%) | 2.47 | 0.62 | 3.00 | 52 | 2.24 | 0.63 | 2.00 |

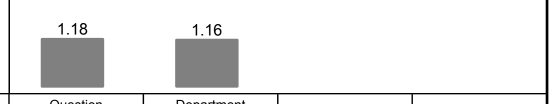
**22 - If you had the opportunity to take another course online, rather than in-class, would you do so?**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Yes | (1) | 14 | 77.78% |
| No | (2) | 3 | 16.67% |
| N/A | (0) | 1 | 5.56% |

Percent Responses




Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 18/36 (50.00%) | 1.18 | 0.39 | 1.00 | 52 | 1.16 | 0.37 | 1.00 |

| | |
|---|---|
| **Course:** | 52: 010: 202: 90MANAGEMENTACCOUNTNG: 2017SP - MANAGEMENT ACCOUNTNG 52: 010: 202: 90 |
| **Instructor:** | Murugappa Krishnan * |
| **Response Rate:** | 19/36 (52.78 %) |

### 23 - What were some of the positive aspects of taking this course online?

| Response Rate | 8/36 (22.22%) |
|---|---|

- N/A
- The ability to do the work and readings around my schedule is a beautiful thing. Between working full time and raising a child, I am so thankful for the opportunity to study online.
- N/A
- Flexibility to complete assignments on my own time.
- I work full time so taking classes online allow me to take the class and I can do the work when I have time (nights, weekends)
- nothing.
- N/A
- I didn't need to go into a classroom and sit through a three hour lecture that doesn't apply to the homework assigned, as has been an issue with other teachers in the past.

### 24 - What were some of the negative aspects of taking this course online?

| Response Rate | 8/36 (22.22%) |
|---|---|

- N/A
- Not being able to meet face to face with your instructor for a bit more guidance/instruction.
- N/A
- I had a hard time understanding the teacher.
- Lack of communication/explanation of course material.
- way too time consuming and frustrating with nothing to reference but the book and even so, there aren't even practice problems with ANSWERS. the amount of time it take to complete just the homework 100% correct took me 5+ hours every week. not to mention the reading. I don't even need to spend 5 hours a week on all my other classes combined and i still have A's in all of them.
- N/A
- The website used for the homework was, as stated before, an extremely bad experience overall. As a suggestion, use MyAccountingLab in the future. It is more user friendly, and will at least tell the student what they're doing wrong.

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 01ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 01

**Instructor:** Murugappa Krishnan *

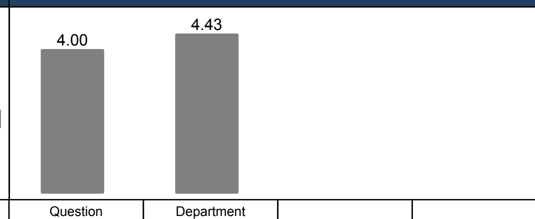
**Response Rate:** 4/11 (36.36 %)

### 1 - The instructor was prepared for class and presented the material in an organized manner.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 0 | 0.00% |
| Agree | (4) | 4 | 100.00% |
| Strongly Agree | (5) | 0 | 0.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100



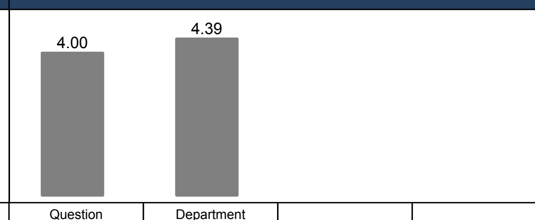

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 4.00 | 0.00 | 4.00 | 54 | 4.43 | 0.79 | 5.00 |

### 2 - The instructor generated interest in the course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 1 | 25.00% |
| Agree | (4) | 2 | 50.00% |
| Strongly Agree | (5) | 1 | 25.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100



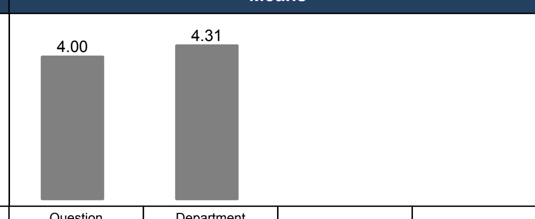

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 4.00 | 0.82 | 4.00 | 54 | 4.39 | 0.90 | 5.00 |

### 3 - The instructor responded effectively to student comments and questions.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 1 | 25.00% |
| Agree | (4) | 2 | 50.00% |
| Strongly Agree | (5) | 1 | 25.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100



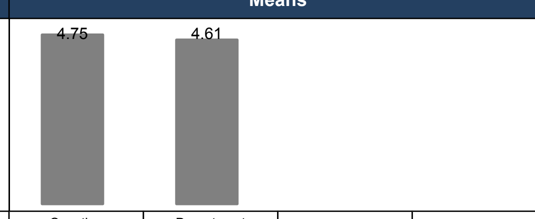

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 4.00 | 0.82 | 4.00 | 54 | 4.31 | 1.08 | 5.00 |

### 4 - The instructor had a positive attitude toward assisting all students in understanding course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 0 | 0.00% |
| Agree | (4) | 1 | 25.00% |
| Strongly Agree | (5) | 3 | 75.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 4.75 | 0.50 | 5.00 | 54 | 4.61 | 0.86 | 5.00 |

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 01ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 01

**Instructor:** Murugappa Krishnan *

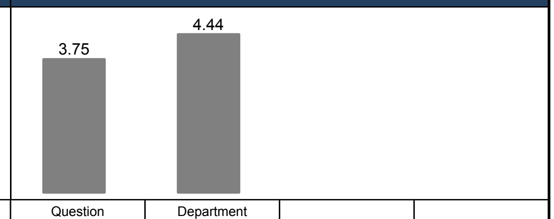
**Response Rate:** 4/11 (36.36 %)

### 5 - The instructor assigned grades fairly.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 1 | 25.00% |
| Agree | (4) | 3 | 75.00% |
| Strongly Agree | (5) | 0 | 0.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100



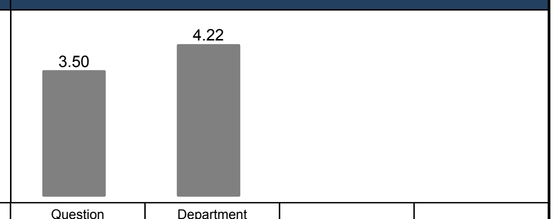

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 3.75 | 0.50 | 4.00 | 54 | 4.44 | 0.82 | 5.00 |

### 6 - The instructional methods encouraged student learning.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 1 | 25.00% |
| Neutral | (3) | 1 | 25.00% |
| Agree | (4) | 1 | 25.00% |
| Strongly Agree | (5) | 1 | 25.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

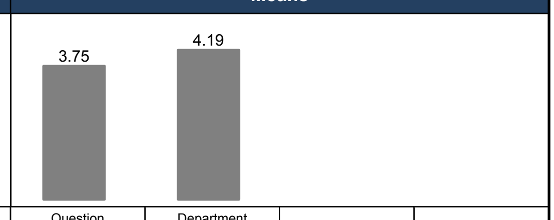



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 3.50 | 1.29 | 3.50 | 54 | 4.22 | 1.02 | 5.00 |

### 7 - I learned a great deal in this course.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 1 | 25.00% |
| Agree | (4) | 3 | 75.00% |
| Strongly Agree | (5) | 0 | 0.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

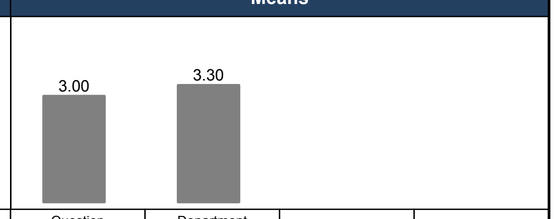



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 3.75 | 0.50 | 4.00 | 54 | 4.19 | 0.93 | 4.00 |

### 8 - I had a strong prior interest in the subject matter and wanted to take this course.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 1 | 25.00% |
| Neutral | (3) | 2 | 50.00% |
| Agree | (4) | 1 | 25.00% |
| Strongly Agree | (5) | 0 | 0.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 3.00 | 0.82 | 3.00 | 54 | 3.30 | 1.19 | 3.50 |

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

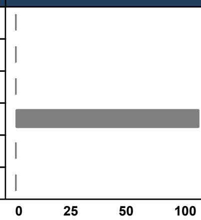
| | |
|---|---|
| **Course:** | 53: 010: 503: 01ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 01 |
| **Instructor:** | Murugappa Krishnan * |
| **Response Rate:** | 4/11 (36.36 %) |

### 9 - I rate the teaching effectiveness of the instructor as:

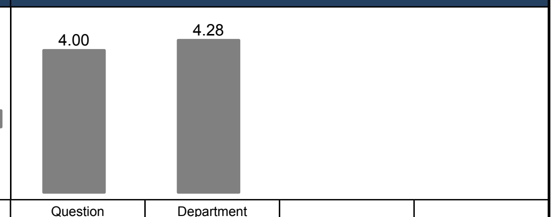
**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 0 | 0.00% |
| 2 | (2) | 0 | 0.00% |
| 3 | (3) | 0 | 0.00% |
| 4 | (4) | 4 | 100.00% |
| 5 = Excellent | (5) | 0 | 0.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means

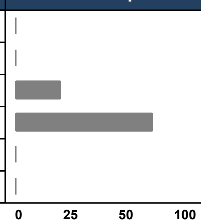



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 4.00 | 0.00 | 4.00 | 54 | 4.28 | 0.90 | 5.00 |

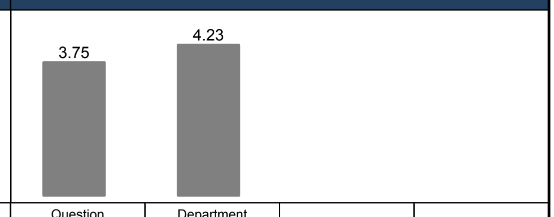
### 10 - I rate the overall quality of the course as:

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 0 | 0.00% |
| 2 | (2) | 0 | 0.00% |
| 3 | (3) | 1 | 25.00% |
| 4 | (4) | 3 | 75.00% |
| 5 = Excellent | (5) | 0 | 0.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 3.75 | 0.50 | 4.00 | 53 | 4.23 | 0.87 | 4.00 |

### 11 - What do you like best about this course?

| | |
|---|---|
| **Response Rate** | 1/11 (9.09%) |

- Professor Krishnan brings tremendous energy to the course, which is essential in getting students to stay engaged in accounting on a Saturday morning. He's got a great personality.

### 12 - If you were teaching this course, what would you do differently?

| | |
|---|---|
| **Response Rate** | 2/11 (18.18%) |

- The use of Connect was a detriment to this course. The fact that it marks questions wrong without any indication of why cost every student unnecessary hours in reworking problems, not realizing that all they needed to do was add a minus sign, or round the answer differently.
- I would NOT use the McGraw Hill CONNECT online program. While I appreciate that using CONNECT is convenient because it generates a unique set of numbers for each homework problem for each student, I respectfully submit that any "convenience" is substantially outweighed by the amount of time spent trying to determine why CONNECT marked answers incorrect that were correctly calculated using the methodology that Dr. Krishnan taught in class. I think it's reasonable to infer that there are other Accounting textbooks and/or online programs available that accomplish the same intended ends, but do not require, unlike CONNECT, spending additional class time to discuss how questions in CONNECT were poorly phrased and to determine why CONNECT is marking answers as incorrect. This is particularly frustrating given that Accounting for Managerial Decisions is considered to be one of the fundamental core courses of the MBA program. Dr. Krishnan is remarkably intelligent and offers a lot of valuable insight about Accounting for Managerial Decisions; hence, I implore Dr. Krishnan to remove the one, albeit substantial, component of the class that is counterproductive and undermines what would otherwise be a rewarding and enriching course: McGraw Hill CONNECT.

### 13 - In what ways, if any, has this course or the instructor encouraged your intellectual growth and progress?

| | |
|---|---|
| **Response Rate** | 0/11 (0%) |

### 14 - Other comments or suggestions:

| | |
|---|---|
| **Response Rate** | 1/11 (9.09%) |

- Dr. Krishnan offers valuable and insightful commentary on many of the accounting principals discussed in class, but this commentary is undermined, as discussed above, by McGraw Hill CONNECT---a program that is perhaps best described as the antithesis of a helpful Accounting for Managerial Decisions program. Thus, I emphatically encourage Dr. Krishnan to select a different accounting book/program for future classes.

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 01ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 01

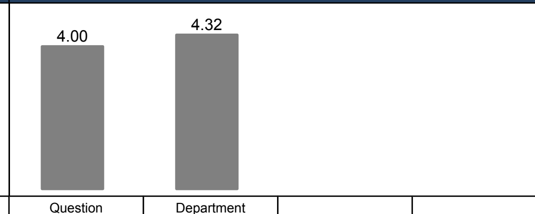
**Instructor:** Murugappa Krishnan *

**Response Rate:** 4/11 (36.36 %)

**15 - The course met the objectives in the syllabus.**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 1 | 33.33% |
| Agree | (4) | 1 | 33.33% |
| Strongly Agree | (5) | 1 | 33.33% |
| N/A | (0) | 0 | 0.00% |

Means

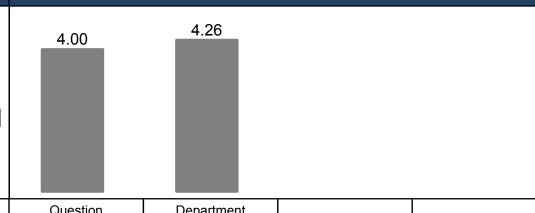



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 3/11 (27.27%) | 4.00 | 1.00 | 4.00 | 31 | 4.32 | 0.79 | 4.00 |

**16 - Given the subject of the course, there was good balance between the readings, online discussions, and assignments.**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 0 | 0.00% |
| Agree | (4) | 3 | 100.00% |
| Strongly Agree | (5) | 0 | 0.00% |
| N/A | (0) | 0 | 0.00% |

Means

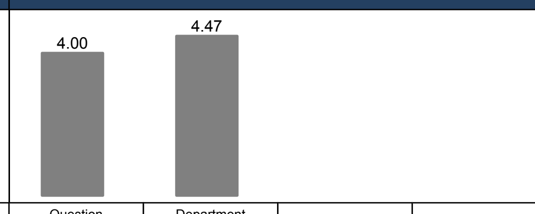



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 3/11 (27.27%) | 4.00 | 0.00 | 4.00 | 31 | 4.26 | 0.82 | 4.00 |

**17 - I now feel comfortable using the online learning system.**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 1 | 25.00% |
| Neutral | (3) | 0 | 0.00% |
| Agree | (4) | 1 | 25.00% |
| Strongly Agree | (5) | 2 | 50.00% |
| N/A | (0) | 0 | 0.00% |

Means

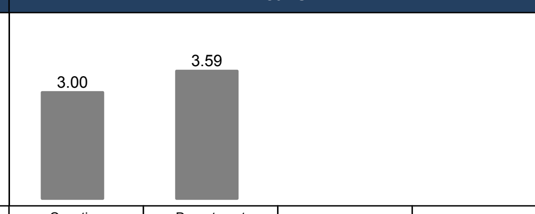



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 4.00 | 1.41 | 4.50 | 32 | 4.47 | 0.82 | 5.00 |

**18 - I was satisfied by the technical support services for this course.**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 2 | 50.00% |
| Neutral | (3) | 1 | 25.00% |
| Agree | (4) | 0 | 0.00% |
| Strongly Agree | (5) | 1 | 25.00% |
| N/A | (0) | 0 | 0.00% |

Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 3.00 | 1.41 | 2.50 | 32 | 3.59 | 1.15 | 4.00 |

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 01ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 01

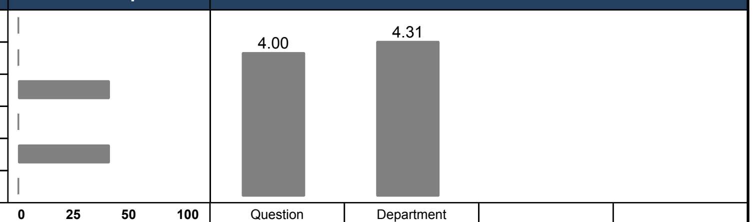
**Instructor:** Murugappa Krishnan *

**Response Rate:** 4/11 (36.36 %)

**19 - The instructor effectively made use of the online environment to support classroom learning.**

**Murugappa Krishnan**

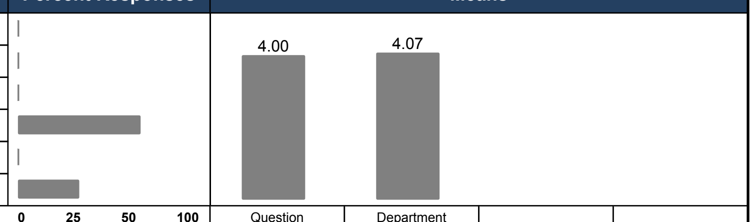
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 2 | 50.00% |
| Agree | (4) | 0 | 0.00% |
| Strongly Agree | (5) | 2 | 50.00% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 4.00 | 1.15 | 4.00 | 32 | 4.31 | 0.97 | 5.00 |

**20 - I would recommend this course to others.**

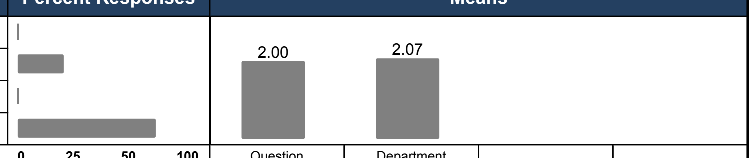
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 0 | 0.00% |
| Agree | (4) | 2 | 66.67% |
| Strongly Agree | (5) | 0 | 0.00% |
| N/A | (0) | 1 | 33.33% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 3/11 (27.27%) | 4.00 | 0.00 | 4.00 | 31 | 4.07 | 0.98 | 4.00 |

**21 - Do you think you would have received a lower, the same, or a higher grade if you had been in a regular classroom?**

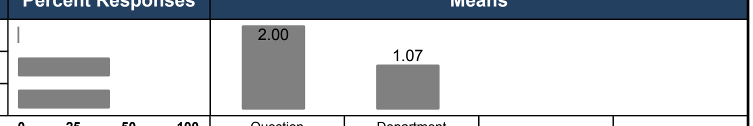
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Lower | (1) | 0 | 0.00% |
| The Same | (2) | 1 | 25.00% |
| Higher | (3) | 0 | 0.00% |
| N/A | (0) | 3 | 75.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 2.00 | 0.00 | 2.00 | 32 | 2.07 | 0.54 | 2.00 |

**22 - If you had the opportunity to take another course online, rather than in-class, would you do so?**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Yes | (1) | 0 | 0.00% |
| No | (2) | 2 | 50.00% |
| N/A | (0) | 2 | 50.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 4/11 (36.36%) | 2.00 | 0.00 | 2.00 | 32 | 1.07 | 0.25 | 1.00 |

**23 - What were some of the positive aspects of taking this course online?**

| Response Rate | 0/11 (0%) |
|---|---|

**24 - What were some of the negative aspects of taking this course online?**

| Response Rate | 1/11 (9.09%) |
|---|---|

- McGraw Hill Connect

# Rutgers University
## Fall 2016 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2016FA - ACCTG FOR MGRL DEC 53: 010: 503: 90-2016FA | ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 17/42 (40.48 %)

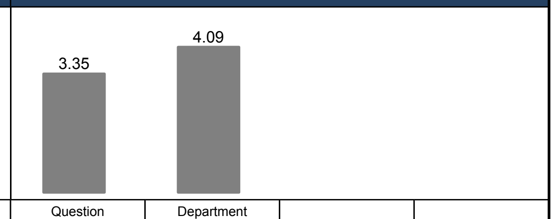
### 1 - The instructor was prepared for class and presented the material in an organized manner.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 5.88% |
| Disagree | (2) | 6 | 35.29% |
| Neutral | (3) | 2 | 11.76% |
| Agree | (4) | 2 | 11.76% |
| Strongly Agree | (5) | 6 | 35.29% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.35 | 1.46 | 3.00 | 33 | 4.09 | 1.31 | 5.00 |

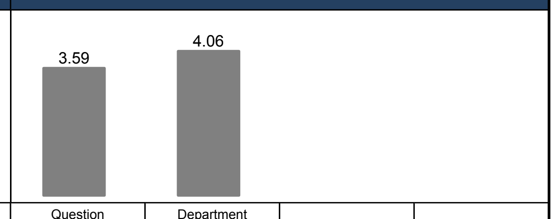
### 2 - The instructor generated interest in the course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 5.88% |
| Disagree | (2) | 1 | 5.88% |
| Neutral | (3) | 6 | 35.29% |
| Agree | (4) | 5 | 29.41% |
| Strongly Agree | (5) | 4 | 23.53% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.59 | 1.12 | 4.00 | 33 | 4.06 | 1.03 | 4.00 |

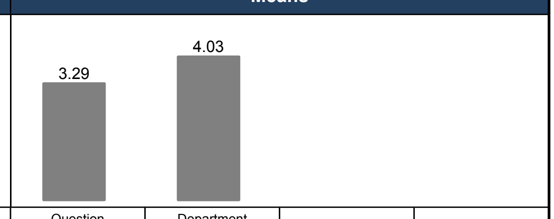
### 3 - The instructor responded effectively to student comments and questions.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 11.76% |
| Disagree | (2) | 5 | 29.41% |
| Neutral | (3) | 1 | 5.88% |
| Agree | (4) | 4 | 23.53% |
| Strongly Agree | (5) | 5 | 29.41% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.29 | 1.49 | 4.00 | 33 | 4.03 | 1.33 | 5.00 |

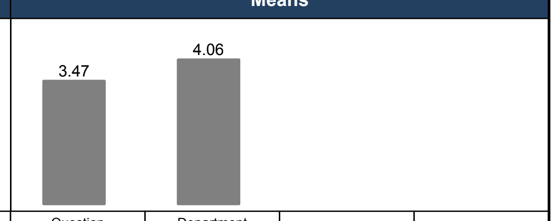
### 4 - The instructor had a positive attitude toward assisting all students in understanding course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 5.88% |
| Disagree | (2) | 2 | 11.76% |
| Neutral | (3) | 7 | 41.18% |
| Agree | (4) | 2 | 11.76% |
| Strongly Agree | (5) | 5 | 29.41% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.47 | 1.23 | 3.00 | 33 | 4.06 | 1.12 | 4.00 |

# Rutgers University
## Fall 2016 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2016FA - ACCTG FOR MGRL DEC 53: 010: 503: 90-2016FA | ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 17/42 (40.48 %)

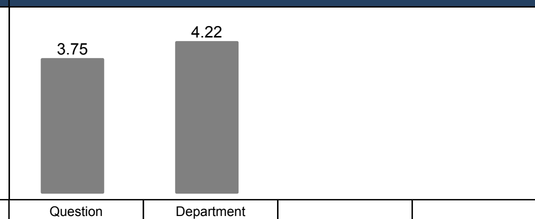
### 5 - The instructor assigned grades fairly.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 2 | 11.76% |
| Neutral | (3) | 4 | 23.53% |
| Agree | (4) | 6 | 35.29% |
| Strongly Agree | (5) | 4 | 23.53% |
| N/A | (0) | 1 | 5.88% |

Percent Responses: 0 25 50 100

Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.75 | 1.00 | 4.00 | 33 | 4.22 | 1.01 | 5.00 |

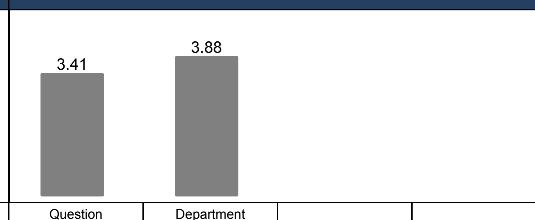
### 6 - The instructional methods encouraged student learning.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 11.76% |
| Disagree | (2) | 2 | 11.76% |
| Neutral | (3) | 4 | 23.53% |
| Agree | (4) | 5 | 29.41% |
| Strongly Agree | (5) | 4 | 23.53% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means



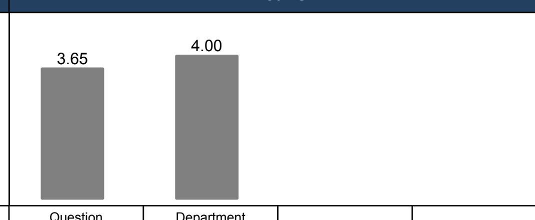

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.41 | 1.33 | 4.00 | 33 | 3.88 | 1.19 | 4.00 |

### 7 - I learned a great deal in this course.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 5.88% |
| Disagree | (2) | 1 | 5.88% |
| Neutral | (3) | 6 | 35.29% |
| Agree | (4) | 4 | 23.53% |
| Strongly Agree | (5) | 5 | 29.41% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means



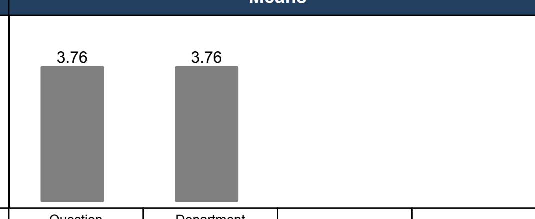

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.65 | 1.17 | 4.00 | 33 | 4.00 | 1.15 | 4.00 |

### 8 - I had a strong prior interest in the subject matter and wanted to take this course.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 3 | 17.65% |
| Neutral | (3) | 3 | 17.65% |
| Agree | (4) | 6 | 35.29% |
| Strongly Agree | (5) | 5 | 29.41% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.76 | 1.09 | 4.00 | 33 | 3.76 | 1.17 | 4.00 |

# Rutgers University
## Fall 2016 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2016FA - ACCTG FOR MGRL DEC 53: 010: 503: 90-2016FA | ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 17/42 (40.48 %)

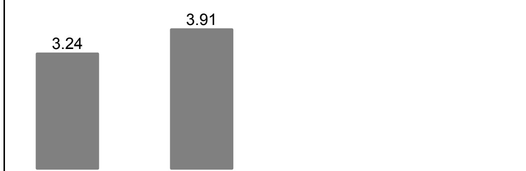
### 9 - I rate the teaching effectiveness of the instructor as:

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 2 | 11.76% |
| 2 | (2) | 5 | 29.41% |
| 3 | (3) | 2 | 11.76% |
| 4 | (4) | 3 | 17.65% |
| 5 = Excellent | (5) | 5 | 29.41% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means



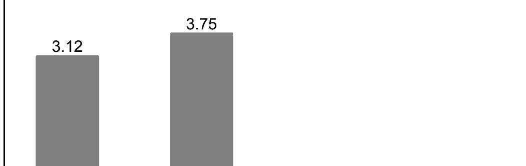

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.24 | 1.48 | 3.00 | 33 | 3.91 | 1.35 | 5.00 |

### 10 - I rate the overall quality of the course as:

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 4 | 23.53% |
| 2 | (2) | 3 | 17.65% |
| 3 | (3) | 2 | 11.76% |
| 4 | (4) | 3 | 17.65% |
| 5 = Excellent | (5) | 5 | 29.41% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.12 | 1.62 | 3.00 | 32 | 3.75 | 1.55 | 4.50 |

### 11 - What do you like best about this course?

| Response Rate | 8/42 (19.05%) |
|---|---|

- I think the homework platform is a great way to continually learn how to process the equations. I also like the lecture layout, however the lectures could be a bit more streamlined/presented more efficiently as seen in some other courses.
- I like the easy to use Canvas and connection to McGraw Hill learning
- It was online
- The material is useful in the realm of business.
- I think the homework assignments were very good. The problems from the book, encouraged leaning the material in a practical way.
- The best part of the course was the online assignments to facilitate learning.
- The steady and timely feedback from the instructor
- I thought the topics were relevant and interesting. The discussions were good in the sense that there was a lot of interaction amongst the class.

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2016FA - ACCTG FOR MGRL DEC 53: 010: 503: 90-2016FA | ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 17/42 (40.48 %)

## 12 - If you were teaching this course, what would you do differently?

| Response Rate | 10/42 (23.81%) |
|---|---|

• Be more involved with the students. Accounting is a tricky subject and i feel as though learning the material was simply put on our shoulders. I can handle it, but i know from interactions with other students, some struggled with this.

• I would take it easy on student responses, there are some strong opinions coming from the instructor, which have encouraged students to hold their tongues in critical discussions that an MBA should be having. It comes across a bit intimidating and demeaning on the online platform.

• I would let my students know, ahead of time, what type of textbook needs to be ordered for the course. It was a brand a new book, which was on back-order, it was available through Rutgers bookstore only and was only available about 3 weeks into the course. Also, this is a managerial accounting course, which is all about numbers and formulas, so I would put less discussions and give more time on reading on material. Discussions are not related to textbooks or homeworks and I was pretty confused by those.

• Use a different textbook instead of a hybrid.

• I would permit the students to have access to the 'hint' option on their homework. It works very well when its able to be used and I learn from it.

• I feel that the material is not well-organized nor is the Canvas system utilized to its fullest extent.

• I would be more upfront about the grading of the assignments. I have no idea how the posting are graded, when they count for 25% of the grade. It's hard to understand where you are at during the semester when a big chunk of the work has not been graded.

• If I were teaching the course, I'd have set deadlines to have weeks learning materials posted. I'd have more information posted in one area instead of scattered through emails, posts, and weekly tasks.

• No idea

• I would have given more relevant instruction for the HW assignments. The textbook format of weekly answering is tough to learn and follow. The assignment questions are hard to find similar examples in the text or video help. I would provide students with excel templates or help in formulating excel templates so they could compute the problems at hand.

## 13 - In what ways, if any, has this course or the instructor encouraged your intellectual growth and progress?

| Response Rate | 6/42 (14.29%) |
|---|---|

• The instructor encouraged reading the material, and taking advantage of the Connect resources - which really helped to understand the material. The instructor also presented very insightful knowledge and discussion questions, which helped with analytical thinking.

• His feedback

• The instructors choice of homework problems were very good. It really drove the chapters subject, and prepared the students for the exam. I think that doing problems are the best way to learn material in accounting/math.

• There was minimal learning over and above previous knowledge.

• The instructor encouraged dialogue and original ideas by constantly tasking students with the responsibility of formulating their in individual opinion.

• I think the discussions were challenging and relevant to the current news environment.

## 14 - Other comments or suggestions:

| Response Rate | 5/42 (11.9%) |
|---|---|

• Take it easy on strong opinions on student posts. Modify presentations for better quality, instead of scanned notes. And send announcements more condensed than multiple times in one or two days.

• It would be useful to get grades for discussions we did because I don't even know if my comments were correct or not. I never received a grade for my discussions from September. Same goes for group project, we never received a grade for that either.

• Because this is an online course, the course material should also be available offline when internet connectivity is intermittent or not available.

• I disagree with the amount of "postings". I don't think this is such much an applicable way to measure the students understanding of the accounting topics. Also when providing the amount of postings, but lacking the timely grading, it leaves the students confused on whether their postings are sufficient through out the semester. I'd prefer more group or a writing project rather then weekly postings, that really do not create the discussions they are intended to do.

• First, the custom text was a waste. I'd rather have a book that I can download to my iPad. The chapters from financial accounting could be covered in a few power points. Having the actual text would allow me to look in other chapters for information. Second, there is a certain blatant disrespect for students not grading any posts through the semester. Before filling out this evaluation on December 11, week 1 posts have not been graded... we are now in week 15. I'd really like to know why the only grades that have been given were the automated ones from the Connect homework. Third, the posts seemed to not be in relation to the material in the course and appeared to potentially be more of topics from other classes. As they were not graded, it was difficult to see if they were meeting the rubric or not.

# Rutgers University
# Fall 2016 Student Instructional Rating Surveys

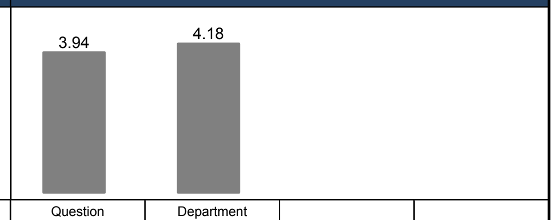
**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2016FA - ACCTG FOR MGRL DEC 53: 010: 503: 90-2016FA | ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 17/42 (40.48 %)

### 15 - The course met the objectives in the syllabus.

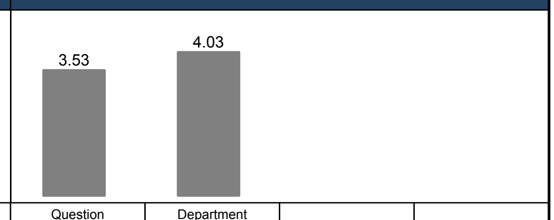
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 1 | 5.88% |
| Neutral | (3) | 4 | 23.53% |
| Agree | (4) | 7 | 41.18% |
| Strongly Agree | (5) | 5 | 29.41% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.94 | 0.90 | 4.00 | 33 | 4.18 | 1.07 | 5.00 |

### 16 - Given the subject of the course, there was good balance between the readings, online discussions, and assignments.

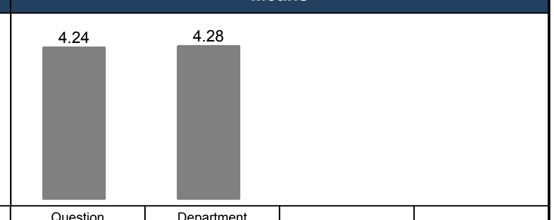
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 4 | 23.53% |
| Neutral | (3) | 4 | 23.53% |
| Agree | (4) | 5 | 29.41% |
| Strongly Agree | (5) | 4 | 23.53% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.53 | 1.12 | 4.00 | 33 | 4.03 | 1.10 | 4.00 |

### 17 - I now feel comfortable using the online learning system.

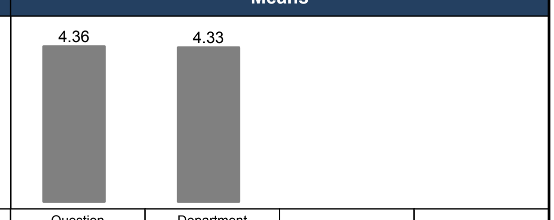
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 1 | 5.88% |
| Neutral | (3) | 2 | 11.76% |
| Agree | (4) | 6 | 35.29% |
| Strongly Agree | (5) | 8 | 47.06% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 4.24 | 0.90 | 4.00 | 33 | 4.28 | 0.99 | 5.00 |

### 18 - I was satisfied by the technical support services for this course.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 1 | 6.25% |
| Agree | (4) | 5 | 31.25% |
| Strongly Agree | (5) | 5 | 31.25% |
| N/A | (0) | 5 | 31.25% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 16/42 (38.10%) | 4.36 | 0.67 | 4.00 | 32 | 4.33 | 0.92 | 4.50 |

# Rutgers University
## Fall 2016 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2016FA - ACCTG FOR MGRL DEC 53: 010: 503: 90-2016FA | ACCTG FOR MGRL DEC 53: 010: 503: 90

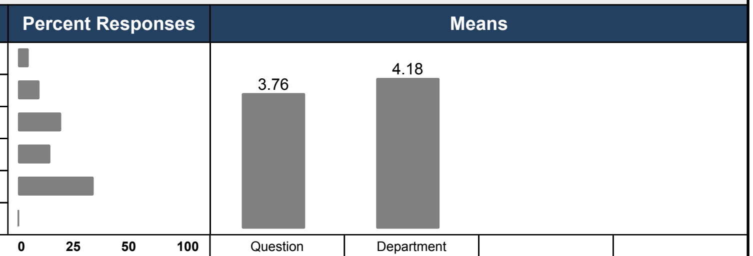
**Instructor:** Murugappa Krishnan *

**Response Rate:** 17/42 (40.48 %)

### 19 - The instructor effectively made use of the online environment to support classroom learning.

**Murugappa Krishnan**

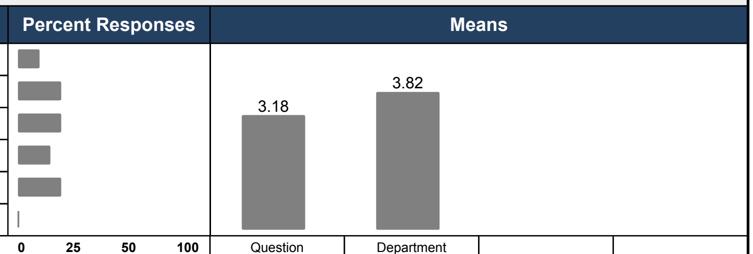
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 5.88% |
| Disagree | (2) | 2 | 11.76% |
| Neutral | (3) | 4 | 23.53% |
| Agree | (4) | 3 | 17.65% |
| Strongly Agree | (5) | 7 | 41.18% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.76 | 1.30 | 4.00 | 33 | 4.18 | 1.13 | 5.00 |

### 20 - I would recommend this course to others.

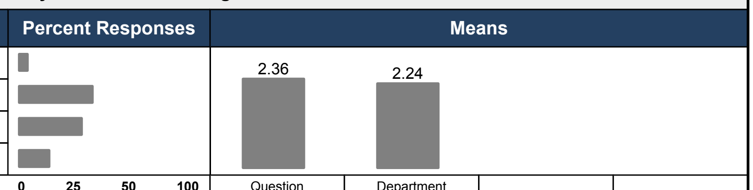
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 11.76% |
| Disagree | (2) | 4 | 23.53% |
| Neutral | (3) | 4 | 23.53% |
| Agree | (4) | 3 | 17.65% |
| Strongly Agree | (5) | 4 | 23.53% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 3.18 | 1.38 | 3.00 | 33 | 3.82 | 1.38 | 4.00 |

### 21 - Do you think you would have received a lower, the same, or a higher grade if you had been in a regular classroom?

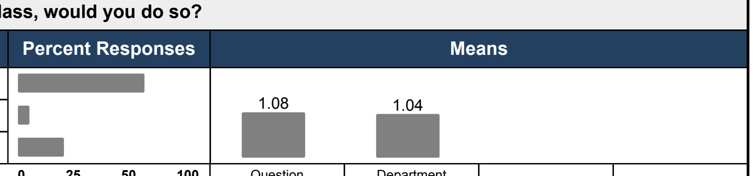
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Lower | (1) | 1 | 5.88% |
| The Same | (2) | 7 | 41.18% |
| Higher | (3) | 6 | 35.29% |
| N/A | (0) | 3 | 17.65% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 17/42 (40.48%) | 2.36 | 0.63 | 2.00 | 33 | 2.24 | 0.58 | 2.00 |

### 22 - If you had the opportunity to take another course online, rather than in-class, would you do so?

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Yes | (1) | 11 | 68.75% |
| No | (2) | 1 | 6.25% |
| N/A | (0) | 4 | 25.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 16/42 (38.10%) | 1.08 | 0.29 | 1.00 | 32 | 1.04 | 0.20 | 1.00 |

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2016FA - ACCTG FOR MGRL DEC 53: 010: 503: 90-2016FA | ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 17/42 (40.48 %)

| 23 - What were some of the positive aspects of taking this course online? | |
|---|---|
| **Response Rate** | 7/42 (16.67%) |

• Flexibility, availability, better discussions. In class short discussions are had by MBA's and more papers. Encouraging online input in length, and responses helps to provide critical and analytical thinking skills growth.

• The positives were taking it on line as I am a full time mom who works full time. Homework with hints was useful as this course is pretty hard.

• Interacting with students of various backgrounds and experiences that are not confined geographically to the school.

• Ease of access.

• Again the book and learning through the problems assigned were a great tool. The videos provided by the book were very helpful.

• Work when you can.

• Individual responsibility of turning in assignments before their deadline each week.

| 24 - What were some of the negative aspects of taking this course online? | |
|---|---|
| **Response Rate** | 9/42 (21.43%) |

• Interaction with the professor

• Nothing, just the learning curve of the new platform for Canvas.

• The negatives aspects was the confusing discussions, never received grades for them so not sure even if I answered correctly. Tests are confusing in terms of length and time. Professor mentioned that test will be 3 hours long, but when I logged in they were 2 hours long.... we were told that finishing test is not necessarily.... that is confusing as if I spend whole 2-3 hours on 1 problem and get it right, does it mean I pass the test? This wasn't clear to me.

• The coursebook is not available offline and neither are the learning modules. An online course should have the option of accessing materials with or without internet.

• teacher did not grade discussions. We had discussions throughout the course and they are still not graded and this is 25% of our overall grade.

• Application of Connect system resources was highly uneven – sometimes book materials would be very easily accessible and pertinent and other times, homework didn't remotely resemble assigned readings. The trouble of a custom textbook is almost too much to write about. I would NEVER take another class in which an instructor specified a custom text.

• I have no idea what my grade is, and that makes it hard to make it through the course. When a portion of your grade is dependent on 25% of the class, but the instructor has not provided any grades, it can be more nerve racking then it should be. The added stress does not help in completing the class. Also due to the textbook being new, and overpriced...the chapter 1 homework was extended. Since the new web layout was introduced, my completion of HW 1 was not recorded in the grade book. The instructor did mention this could happen in an initial class posting. I emailed the the professor twice to make sure it is incorporated in my overall grade, but he did not respond. I can only hope the completed Chapter 1 homework is part of my overall grade.

• Instructor was very against communication other than email. We should be able to call and talk to the professor when needed.

• N/A

# Rutgers University
## Fall 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2017FA - ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 26/38 (68.42 %)

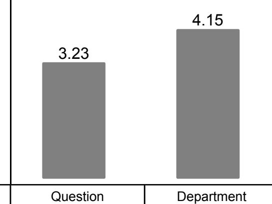
### 1 - The instructor was prepared for class and presented the material in an organized manner.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 3.85% |
| Disagree | (2) | 7 | 26.92% |
| Neutral | (3) | 6 | 23.08% |
| Agree | (4) | 9 | 34.62% |
| Strongly Agree | (5) | 3 | 11.54% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

**Means**




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 3.23 | 1.11 | 3.00 | 183 | 4.15 | 1.13 | 5.00 |

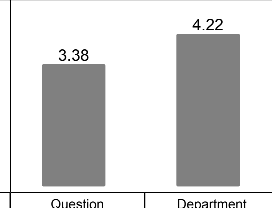
### 2 - The instructor generated interest in the course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 8 | 30.77% |
| Neutral | (3) | 5 | 19.23% |
| Agree | (4) | 8 | 30.77% |
| Strongly Agree | (5) | 5 | 19.23% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

**Means**




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 3.38 | 1.13 | 3.50 | 184 | 4.22 | 1.07 | 5.00 |

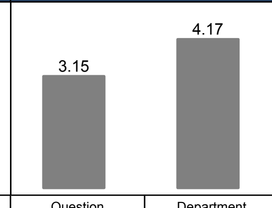
### 3 - The instructor responded effectively to student comments and questions.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 7.69% |
| Disagree | (2) | 6 | 23.08% |
| Neutral | (3) | 9 | 34.62% |
| Agree | (4) | 4 | 15.38% |
| Strongly Agree | (5) | 5 | 19.23% |
| N/A | (0) | 0 | 0.00% |

Percent Responses: 0 25 50 100

**Means**




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 3.15 | 1.22 | 3.00 | 184 | 4.17 | 1.10 | 5.00 |

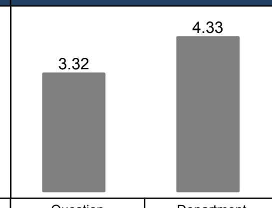
### 4 - The instructor had a positive attitude toward assisting all students in understanding course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 7.69% |
| Disagree | (2) | 4 | 15.38% |
| Neutral | (3) | 7 | 26.92% |
| Agree | (4) | 8 | 30.77% |
| Strongly Agree | (5) | 4 | 15.38% |
| N/A | (0) | 1 | 3.85% |

Percent Responses: 0 25 50 100

**Means**




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 3.32 | 1.18 | 3.00 | 184 | 4.33 | 1.02 | 5.00 |

# Rutgers University
# Fall 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2017FA - ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

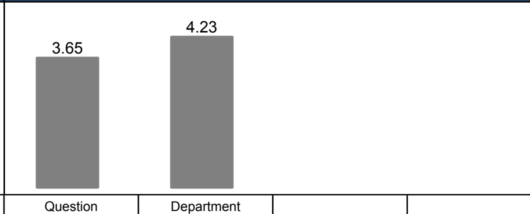
**Response Rate:** 26/38 (68.42 %)

**5 - The instructor assigned grades fairly.**

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent | Percent Responses |
|---|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% | |
| Disagree | (2) | 2 | 7.69% | |
| Neutral | (3) | 8 | 30.77% | |
| Agree | (4) | 13 | 50.00% | |
| Strongly Agree | (5) | 3 | 11.54% | |
| N/A | (0) | 0 | 0.00% | |
| | | | | 0 25 50 100 |

**Means**



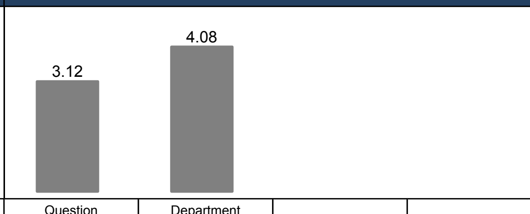

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 3.65 | 0.80 | 4.00 | 185 | 4.23 | 0.99 | 5.00 |

**6 - The instructional methods encouraged student learning.**

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent | Percent Responses |
|---|---|---|---|---|
| Strongly Disagree | (1) | 5 | 19.23% | |
| Disagree | (2) | 1 | 3.85% | |
| Neutral | (3) | 8 | 30.77% | |
| Agree | (4) | 8 | 30.77% | |
| Strongly Agree | (5) | 3 | 11.54% | |
| N/A | (0) | 1 | 3.85% | |
| | | | | 0 25 50 100 |

**Means**

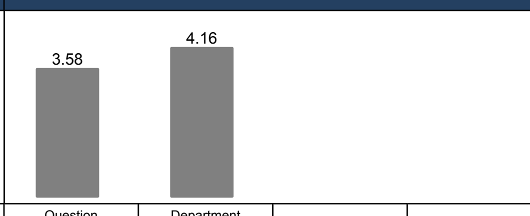



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 3.12 | 1.30 | 3.00 | 182 | 4.08 | 1.17 | 4.00 |

**7 - I learned a great deal in this course.**

| Response Option | Weight | Frequency | Percent | Percent Responses |
|---|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% | |
| Disagree | (2) | 2 | 7.69% | |
| Neutral | (3) | 11 | 42.31% | |
| Agree | (4) | 9 | 34.62% | |
| Strongly Agree | (5) | 4 | 15.38% | |
| N/A | (0) | 0 | 0.00% | |
| | | | | 0 25 50 100 |

**Means**

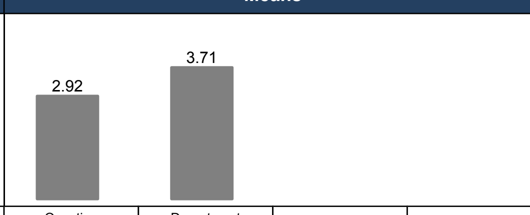



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 3.58 | 0.86 | 3.50 | 184 | 4.16 | 1.04 | 4.00 |

**8 - I had a strong prior interest in the subject matter and wanted to take this course.**

| Response Option | Weight | Frequency | Percent | Percent Responses |
|---|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% | |
| Disagree | (2) | 10 | 38.46% | |
| Neutral | (3) | 10 | 38.46% | |
| Agree | (4) | 4 | 15.38% | |
| Strongly Agree | (5) | 2 | 7.69% | |
| N/A | (0) | 0 | 0.00% | |
| | | | | 0 25 50 100 |

**Means**




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 2.92 | 0.93 | 3.00 | 183 | 3.71 | 1.21 | 4.00 |

# Rutgers University
## Fall 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2017FA - ACCTG FOR MGRL DEC 53: 010: 503: 90

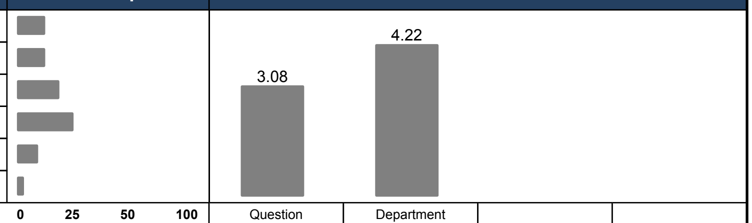
**Instructor:** Murugappa Krishnan *

**Response Rate:** 26/38 (68.42 %)

**9 - I rate the teaching effectiveness of the instructor as:**

**Murugappa Krishnan**

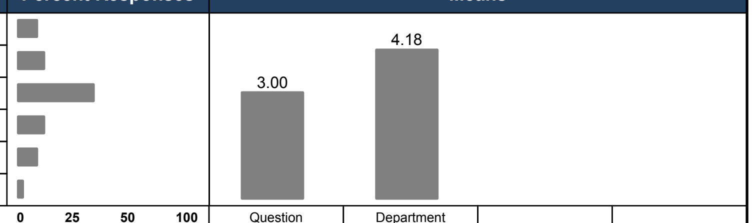
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 4 | 15.38% |
| 2 | (2) | 4 | 15.38% |
| 3 | (3) | 6 | 23.08% |
| 4 | (4) | 8 | 30.77% |
| 5 = Excellent | (5) | 3 | 11.54% |
| N/A | (0) | 1 | 3.85% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 3.08 | 1.29 | 3.00 | 185 | 4.22 | 1.06 | 5.00 |

**10 - I rate the overall quality of the course as:**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 3 | 11.54% |
| 2 | (2) | 4 | 15.38% |
| 3 | (3) | 11 | 42.31% |
| 4 | (4) | 4 | 15.38% |
| 5 = Excellent | (5) | 3 | 11.54% |
| N/A | (0) | 1 | 3.85% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 26/38 (68.42%) | 3.00 | 1.15 | 3.00 | 181 | 4.18 | 1.05 | 5.00 |

**11 - What do you like best about this course?**

| Response Rate | 9/38 (23.68%) |
|---|---|

- Professor was very encouraging throughout the course.
- I did not enjoy any aspect of this course. It has been the worst course in my undergrad and grad school experience.
- I like the use of McGraw Hill, it makes homework and tests easy.
- The content went deep. I was surprised at how much I learned from the course.
- Not much. It was frustrating, at best. I spent more hours on this course than any other course in the MBA program including the capstone!
- Simulated problems are helpful to learn mechanics.
- Online
- I was able to get answers correct on homework assignments when it was explained in the textbook. Exams were related to what was learned from homework assignments.
- Discussions

# Rutgers University
# Fall 2017 Student Instructional Rating Surveys

| | |
|---|---|
| **Course:** | 53: 010: 503: 90ACCTGFORMGRLDEC: 2017FA - ACCTG FOR MGRL DEC 53: 010: 503: 90 |
| **Instructor:** | Murugappa Krishnan * |
| **Response Rate:** | 26/38 (68.42 %) |

**12 - If you were teaching this course, what would you do differently?**

| Response Rate | 14/38 (36.84%) |
|---|---|

• Some of the topics could still be a little confusing and in this case, additional further explanation beyond the text would have benefited the class. Additionally, I appreciated that the discussions were not blanket discussions to describe the text and were instead "real world engaging". However, sometimes had trouble linking the purpose of the discussions and they could be a bit controversial for an accounting course. I would choose different and more applicable discussion topics for some (but not all) discussions.

• This course lacked connection between the textbook chapters and the online assignments. Based off of emails, it seemed like a majority of the class was clueless on how to complete the assignments. I had to fully teach myself every aspect of this course using guess and check via the online homework modules and outside resources. The syllabus was lacking a great deal of detail. The online module was a horrible experience and it was impossible to plan for this semester via grades or assignments (extra assignments were in the grade book, weeks were not labeled and were locked until the start of the week). This class lacked engagement in every way and was a miserable experience each week to read the chapters and complete the assignments.

• The homework in this course was very time consuming with little guidance. Every week my classmates would complain on the discussion boards about how it was impossible to complete the assignments.

• There were often message threads of a lot of students who were having trouble with hw. I think having a few more example problems would have helped tremendously.

• Homework was very challenging, and sometimes text didn't help. Took significant time on many occasions.

• I would provide more access to things that were being asked of us on the online tool for homework. I felt like I was ill prepared for a lot of the questions on the website and got low homework scores because of that.

• I would not use the "Connect" website. It is faulty and wastes students' time. The answers are too particular so students will spend hours playing with decimals and numbers to find the perfect answer without learning anything.

• Clean up all the old modules from previous classes. This made the expectations rather confusing.

• I would align the text and learning concepts to the homework. People were taking out old accounting books and googling resources. There was no clear correlation between assignments and homework.

• Clearer presentation of subject matter, perhaps use a case study for a group project.

• Improve video lectures

• Post should have been relevant to material. Relating textbook learning to real world happenings. No just having arbitrary discussions about random topics.

• Post grade distributions and deadlines accurately on syllabus and on canvas 'Grades' section. Provide additional resources related concepts on homework assignments.

• The modified text do not provide adequate examples and explanations to assist student learning. Furthermore, some of the chapters do not match the problems given on the homework portal. Instructure needs to ensure that chapters in the book coincide with the homework problems. In one instance a chapter was completed eliminated from the modified textbook that was assigned in class. I would also provide more video lectures that explains the chapter and go through problems step by step. That would aide in the learning process.

**13 - In what ways, if any, has this course or the instructor encouraged your intellectual growth and progress?**

| Response Rate | 6/38 (15.79%) |
|---|---|

• This course has not helped me progress or grow, other than to begin to regret my decision to accept my placement in the Rutgers online MBA program.

• Giving us current even instructions.

• I now have a deeper appreciation for accounting and managerial decisions.

• I gained patience. When asked for help, the instructor declined, stating he had no office hours and would provide no additional assistance. We were encouraged to seek out other students for help.

• The course has provided a rigorous review of financial accounting.

• n/a

**14 - Other comments or suggestions:**

| Response Rate | 10/38 (26.32%) |
|---|---|

• The professor responded to emails, though the responses were usually inadequate, even to point me in the correct direction to complete homework assignments. This class/instructor should be audited due to the lack of quality. I was expecting, due to the reputation of the Rutgers MBA program and the amount of money charged for tuition to this online program, a more informative and well structured course.

• Unfortunately, Professor Krishnan's course structure was very unorganized. Overlapping homework and assignments from previous semesters made deadlines and due dates very confusing. Also, despite outreach from various students regarding degree of difficulty on homework assignments, content covered on homework had no relevance to textbook or video lecture content. Very difficult to communicate with through email as well. Course was essentially a full-time online class with heavy reliance on self-teaching approach to learning material.

• While McGraw Hill is useful it is too expensive. My other class used and older cost effective edition.

• The professor needs to assign homework assignments from the book and have students send him a PDF for him to grade. The online website "Connect" is horrible and does not promote learning whatsoever.

• Please clean up all the old modules. Maybe offer more discussions. Make the weekly homework assignments smaller. Some weeks I spent 6 hours on homework. This is hard as a grad student with full-time job and family.

• I found the discussions to be unclear in what the professors expectations were. I also did not understand the connection of the discussions to the course subject matter.

• n/a

• Exams required more time than allowed. As much as I was prepared and studied....it still wasn't enough time to complete exams in its entirety. Too many calculations which take considerable time.

• The course could have been more interesting if so much time wasn't spent trying to figure out the correct answers to the homework assignments - which had to be more self taught.

• I recommend the professor being more engaging and respond to student concerns and questions with details and explanations, instead of one word responses and blanket statements.

# Rutgers University
# Spring 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

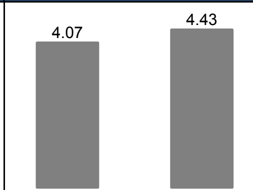
**Instructor:** Murugappa Krishnan *

**Response Rate:** 14/34 (41.18 %)

### 1 - The instructor was prepared for class and presented the material in an organized manner.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 3 | 21.43% |
| Agree | (4) | 7 | 50.00% |
| Strongly Agree | (5) | 4 | 28.57% |
| N/A | (0) | 0 | 0.00% |

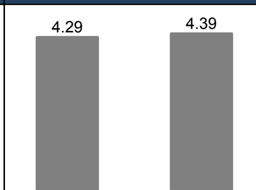



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.07 | 0.73 | 4.00 | 54 | 4.43 | 0.79 | 5.00 |

### 2 - The instructor generated interest in the course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 3 | 21.43% |
| Agree | (4) | 4 | 28.57% |
| Strongly Agree | (5) | 7 | 50.00% |
| N/A | (0) | 0 | 0.00% |

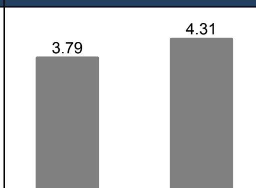



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.29 | 0.83 | 4.50 | 54 | 4.39 | 0.90 | 5.00 |

### 3 - The instructor responded effectively to student comments and questions.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 7.14% |
| Disagree | (2) | 2 | 14.29% |
| Neutral | (3) | 2 | 14.29% |
| Agree | (4) | 3 | 21.43% |
| Strongly Agree | (5) | 6 | 42.86% |
| N/A | (0) | 0 | 0.00% |

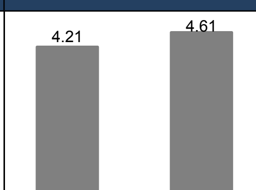



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 3.79 | 1.37 | 4.00 | 54 | 4.31 | 1.08 | 5.00 |

### 4 - The instructor had a positive attitude toward assisting all students in understanding course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 2 | 14.29% |
| Neutral | (3) | 1 | 7.14% |
| Agree | (4) | 3 | 21.43% |
| Strongly Agree | (5) | 8 | 57.14% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.21 | 1.12 | 5.00 | 54 | 4.61 | 0.86 | 5.00 |

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

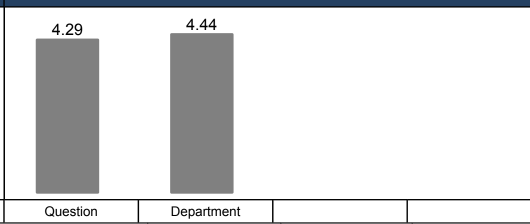
**Instructor:** Murugappa Krishnan *

**Response Rate:** 14/34 (41.18 %)

### 5 - The instructor assigned grades fairly.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 3 | 21.43% |
| Agree | (4) | 4 | 28.57% |
| Strongly Agree | (5) | 7 | 50.00% |
| N/A | (0) | 0 | 0.00% |

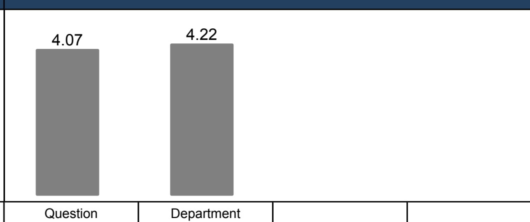



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.29 | 0.83 | 4.50 | 54 | 4.44 | 0.82 | 5.00 |

### 6 - The instructional methods encouraged student learning.

**Murugappa Krishnan**

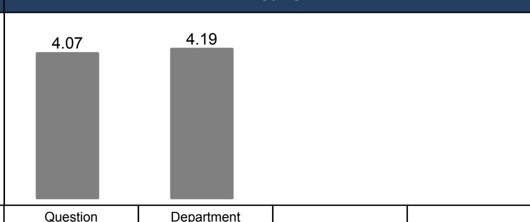
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 2 | 14.29% |
| Neutral | (3) | 1 | 7.14% |
| Agree | (4) | 5 | 35.71% |
| Strongly Agree | (5) | 6 | 42.86% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.07 | 1.07 | 4.00 | 54 | 4.22 | 1.02 | 5.00 |

### 7 - I learned a great deal in this course.

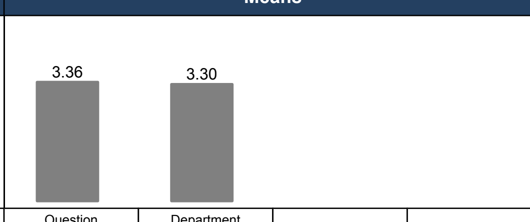
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 2 | 14.29% |
| Neutral | (3) | 1 | 7.14% |
| Agree | (4) | 5 | 35.71% |
| Strongly Agree | (5) | 6 | 42.86% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.07 | 1.07 | 4.00 | 54 | 4.19 | 0.93 | 4.00 |

### 8 - I had a strong prior interest in the subject matter and wanted to take this course.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 3 | 21.43% |
| Neutral | (3) | 4 | 28.57% |
| Agree | (4) | 6 | 42.86% |
| Strongly Agree | (5) | 1 | 7.14% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 3.36 | 0.93 | 3.50 | 54 | 3.30 | 1.19 | 3.50 |

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

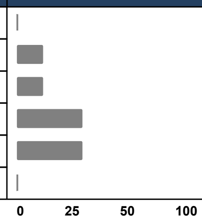
**Instructor:** Murugappa Krishnan *

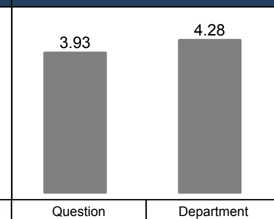
**Response Rate:** 14/34 (41.18 %)

### 9 - I rate the teaching effectiveness of the instructor as:

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 0 | 0.00% |
| 2 | (2) | 2 | 14.29% |
| 3 | (3) | 2 | 14.29% |
| 4 | (4) | 5 | 35.71% |
| 5 = Excellent | (5) | 5 | 35.71% |
| N/A | (0) | 0 | 0.00% |

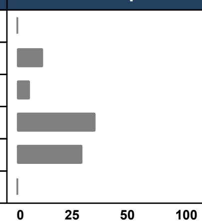


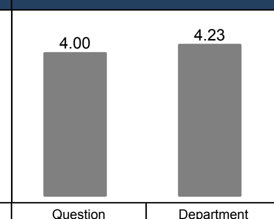




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 3.93 | 1.07 | 4.00 | 54 | 4.28 | 0.90 | 5.00 |

### 10 - I rate the overall quality of the course as:

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 0 | 0.00% |
| 2 | (2) | 2 | 14.29% |
| 3 | (3) | 1 | 7.14% |
| 4 | (4) | 6 | 42.86% |
| 5 = Excellent | (5) | 5 | 35.71% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.00 | 1.04 | 4.00 | 53 | 4.23 | 0.87 | 4.00 |

### 11 - What do you like best about this course?

**Response Rate** 6/34 (17.65%)

- The learning tools online
- it was challenging and rewarding at the same time. a good approach to learning some complicated concepts.
- n/a
- Ability to do multiple homework submissions - If I got a wrong answer, it encouraged me to continue working on the problem until I learned the correct homework solution.
- Online
- I enjoyed that it allowed us to incorporate the topics learned into everyday applications, which assisted in reinforcing the material.

### 12 - If you were teaching this course, what would you do differently?

**Response Rate** 7/34 (20.59%)

- Discussions would be graded on a different scale. 1 -3 doesnt leave much room for success.
- I would potentially exclude one or two of the homework results from the final grade achieved. It does take some getting used to and some flexibility there would help encourage the student a bit to not worry too much if they don't grasp the process and content completely in a few cases.
- Give more guided tutorials as opposed to just sending the students to the textbook.
- Provide additional resources for students struggling with homework (For the ROI homework, the chapters referenced in Connect were incorrect)
- Nothing
- Provide better chapter notes to further elucidate and explain the topics discussed in the book, as some of the concepts were very challenging. I would welcome any opportunity to help students in learning the material, instead of responding coldly when they came to me for help. A number of times I felt incredibly frustrated by the homework, but after I asked him for help I just felt worse by his responses and they were not helpful.
- I would try to relay personal information and previous work experience to my students when applicable. Compared to other courses, I do not feel like the professor had much interaction with the class other than turning on assignments.

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 14/34 (41.18 %)

### 13 - In what ways, if any, has this course or the instructor encouraged your intellectual growth and progress?

| Response Rate | 5/34 (14.71%) |
|---|---|

- He took some important and complicated material and really taught me a substantial amount of usable techniques and concepts.
- n/a
- Learning how to apply material to business setting.
- Assigned all types of homework
- He has chosen a textbook for the course that was a great resource.

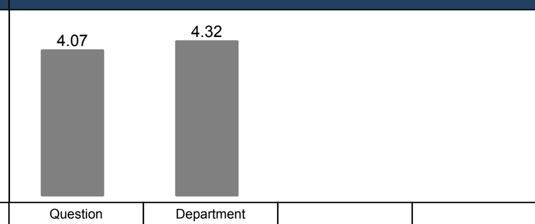
### 14 - Other comments or suggestions:

| Response Rate | 1/34 (2.94%) |
|---|---|

- I felt as though I was taught by the textbook, and not by an instructor throughout the duration of the course, which was incredibly frustrating. When I would reach out for help, he provided little to none without exception, which was also extremely frustrating. His emails were frequently confusing and unclear, as well. I felt as though the instructor was disengaged and apathetic, and invariably came off as though I was bothering him when I came to him for help, even when I had explained that I appreciated his time and was only reaching out because I had been struggling on my own unsuccessfully for hours upon hours. I know that these issues were difficult for my other classmates as well, because we discussed our frustrations, and they essentially echoed my experience.

### 15 - The course met the objectives in the syllabus.

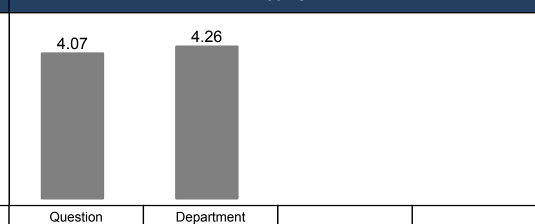
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 1 | 7.14% |
| Neutral | (3) | 2 | 14.29% |
| Agree | (4) | 6 | 42.86% |
| Strongly Agree | (5) | 5 | 35.71% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.07 | 0.92 | 4.00 | 31 | 4.32 | 0.79 | 4.00 |

### 16 - Given the subject of the course, there was good balance between the readings, online discussions, and assignments.

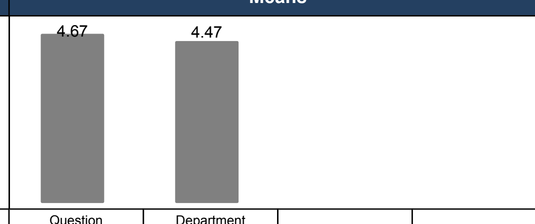
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 2 | 14.29% |
| Neutral | (3) | 1 | 7.14% |
| Agree | (4) | 5 | 35.71% |
| Strongly Agree | (5) | 6 | 42.86% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.07 | 1.07 | 4.00 | 31 | 4.26 | 0.82 | 4.00 |

### 17 - I now feel comfortable using the online learning system.

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 1 | 7.14% |
| Agree | (4) | 2 | 14.29% |
| Strongly Agree | (5) | 9 | 64.29% |
| N/A | (0) | 2 | 14.29% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.67 | 0.65 | 5.00 | 32 | 4.47 | 0.82 | 5.00 |

# Rutgers University
# Spring 2017 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

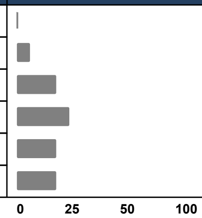
**Instructor:** Murugappa Krishnan *

**Response Rate:** 14/34 (41.18 %)

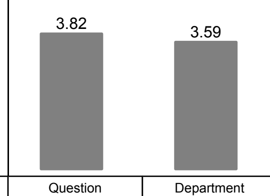
**18 - I was satisfied by the technical support services for this course.**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 1 | 7.14% |
| Neutral | (3) | 3 | 21.43% |
| Agree | (4) | 4 | 28.57% |
| Strongly Agree | (5) | 3 | 21.43% |
| N/A | (0) | 3 | 21.43% |

Percent Responses




Means



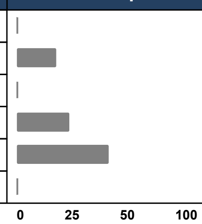

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 3.82 | 0.98 | 4.00 | 32 | 3.59 | 1.15 | 4.00 |

**19 - The instructor effectively made use of the online environment to support classroom learning.**

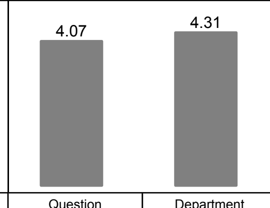
**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 3 | 21.43% |
| Neutral | (3) | 0 | 0.00% |
| Agree | (4) | 4 | 28.57% |
| Strongly Agree | (5) | 7 | 50.00% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means

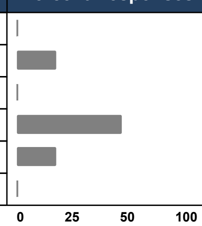



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 4.07 | 1.21 | 4.50 | 32 | 4.31 | 0.97 | 5.00 |

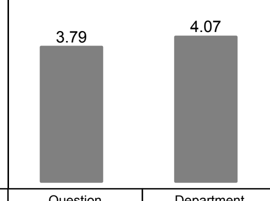
**20 - I would recommend this course to others.**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 3 | 21.43% |
| Neutral | (3) | 0 | 0.00% |
| Agree | (4) | 8 | 57.14% |
| Strongly Agree | (5) | 3 | 21.43% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means

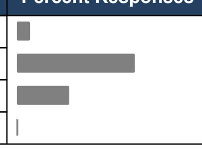



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 3.79 | 1.05 | 4.00 | 31 | 4.07 | 0.98 | 4.00 |

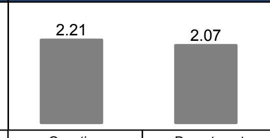
**21 - Do you think you would have received a lower, the same, or a higher grade if you had been in a regular classroom?**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Lower | (1) | 1 | 7.14% |
| The Same | (2) | 9 | 64.29% |
| Higher | (3) | 4 | 28.57% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 2.21 | 0.58 | 2.00 | 32 | 2.07 | 0.54 | 2.00 |

# Rutgers University
## Spring 2017 Student Instructional Rating Surveys

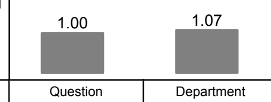
**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2017SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 14/34 (41.18 %)

**22 - If you had the opportunity to take another course online, rather than in-class, would you do so?**

| Response Option | Weight | Frequency | Percent | Percent Responses | Means |
|---|---|---|---|---|---|
| Yes | (1) | 14 | 100.00% | | |
| No | (2) | 0 | 0.00% | | |
| N/A | (0) | 0 | 0.00% | | |
| | | | | 0 25 50 100 | Question / Department |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 14/34 (41.18%) | 1.00 | 0.00 | 1.00 | 32 | 1.07 | 0.25 | 1.00 |

**23 - What were some of the positive aspects of taking this course online?**

| Response Rate | 4/34 (11.76%) |
|---|---|

- Flexibility
- Flexibility
- It allowed for greater convenience and flexibility, as well as the ability to utilize resources throughout, which reinforced my learning.
- Flexibility

**24 - What were some of the negative aspects of taking this course online?**

| Response Rate | 4/34 (11.76%) |
|---|---|

- Lack of engagement
- If I need to speak to professor, we can only send an email. Sometimes I feel like in-person interactions help with understanding coursework material better. When course first started there were some confusing course assignments showing up in the assignments section twice. Although this issue was fixed later, it created confusion for the first 2-3 weeks of the semester.
- Some of the topics were very challenging, and I know I would have benefited greatly from having an actual person explaining things, versus working just from the textbook.
- I do not feel that the professor gave insights or personal perspectives on the material. Online courses miss out on interaction from the professor and classmate. Discussions attempt to connect the class but it is more forced than natural flow of conversation that occurs in a classroom. I feel that on-campus programs offer more of a robust learning experience inside and outside of the courses than online courses do.

# Rutgers University
# Spring 2018 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2018SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

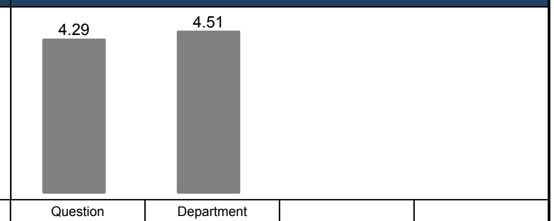
**Instructor:** Murugappa Krishnan *

**Response Rate:** 34/42 (80.95 %)

### 1 - The instructor was prepared for class and presented the material in an organized manner.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 0 | 0.00% |
| Neutral | (3) | 4 | 11.76% |
| Agree | (4) | 16 | 47.06% |
| Strongly Agree | (5) | 14 | 41.18% |
| N/A | (0) | 0 | 0.00% |

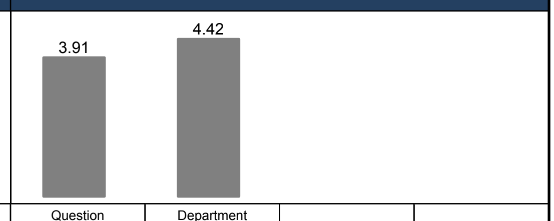



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 34/42 (80.95%) | 4.29 | 0.68 | 4.00 | 130 | 4.51 | 0.77 | 5.00 |

### 2 - The instructor generated interest in the course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 6.06% |
| Disagree | (2) | 2 | 6.06% |
| Neutral | (3) | 6 | 18.18% |
| Agree | (4) | 10 | 30.30% |
| Strongly Agree | (5) | 13 | 39.39% |
| N/A | (0) | 0 | 0.00% |

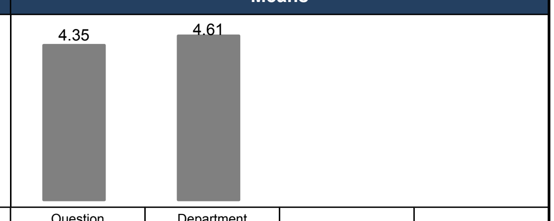



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 33/42 (78.57%) | 3.91 | 1.18 | 4.00 | 129 | 4.42 | 0.89 | 5.00 |

### 3 - The instructor responded effectively to student comments and questions.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 2 | 5.88% |
| Neutral | (3) | 2 | 5.88% |
| Agree | (4) | 12 | 35.29% |
| Strongly Agree | (5) | 18 | 52.94% |
| N/A | (0) | 0 | 0.00% |

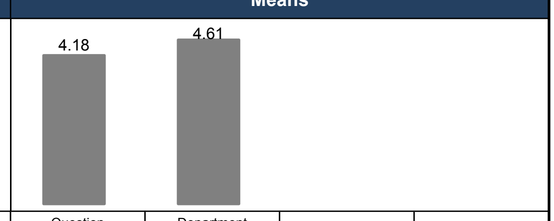



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 34/42 (80.95%) | 4.35 | 0.85 | 5.00 | 130 | 4.61 | 0.70 | 5.00 |

### 4 - The instructor had a positive attitude toward assisting all students in understanding course material.

**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 0 | 0.00% |
| Disagree | (2) | 2 | 6.06% |
| Neutral | (3) | 5 | 15.15% |
| Agree | (4) | 11 | 33.33% |
| Strongly Agree | (5) | 15 | 45.45% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 33/42 (78.57%) | 4.18 | 0.92 | 4.00 | 129 | 4.61 | 0.72 | 5.00 |

# Rutgers University
## Spring 2018 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2018SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

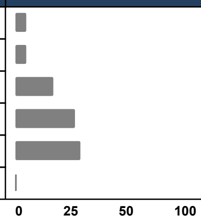
**Response Rate:** 34/42 (80.95 %)

**5 - The instructor assigned grades fairly.**

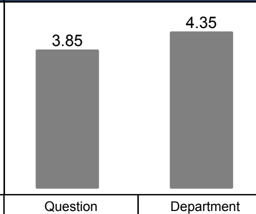
**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 5.88% |
| Disagree | (2) | 2 | 5.88% |
| Neutral | (3) | 7 | 20.59% |
| Agree | (4) | 11 | 32.35% |
| Strongly Agree | (5) | 12 | 35.29% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means



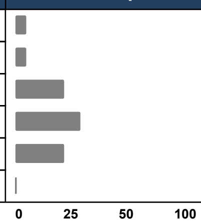

| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 34/42 (80.95%) | 3.85 | 1.16 | 4.00 | 130 | 4.35 | 0.96 | 5.00 |

**6 - The instructional methods encouraged student learning.**

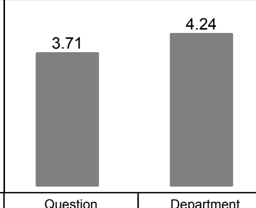
**Murugappa Krishnan**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 5.88% |
| Disagree | (2) | 2 | 5.88% |
| Neutral | (3) | 9 | 26.47% |
| Agree | (4) | 12 | 35.29% |
| Strongly Agree | (5) | 9 | 26.47% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means

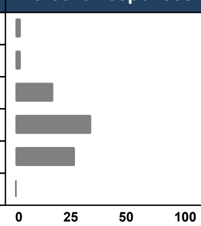



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 34/42 (80.95%) | 3.71 | 1.12 | 4.00 | 129 | 4.24 | 1.01 | 5.00 |

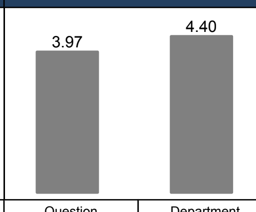
**7 - I learned a great deal in this course.**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 1 | 2.94% |
| Disagree | (2) | 1 | 2.94% |
| Neutral | (3) | 7 | 20.59% |
| Agree | (4) | 14 | 41.18% |
| Strongly Agree | (5) | 11 | 32.35% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means

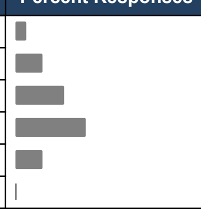



| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 34/42 (80.95%) | 3.97 | 0.97 | 4.00 | 130 | 4.40 | 0.79 | 5.00 |

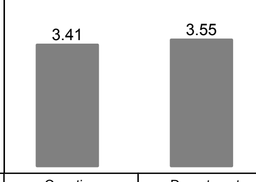
**8 - I had a strong prior interest in the subject matter and wanted to take this course.**

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| Strongly Disagree | (1) | 2 | 5.88% |
| Disagree | (2) | 5 | 14.71% |
| Neutral | (3) | 9 | 26.47% |
| Agree | (4) | 13 | 38.24% |
| Strongly Agree | (5) | 5 | 14.71% |
| N/A | (0) | 0 | 0.00% |

Percent Responses




Means




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 34/42 (80.95%) | 3.41 | 1.10 | 4.00 | 129 | 3.55 | 1.06 | 4.00 |

# Rutgers University
## Spring 2018 Student Instructional Rating Surveys

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2018SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

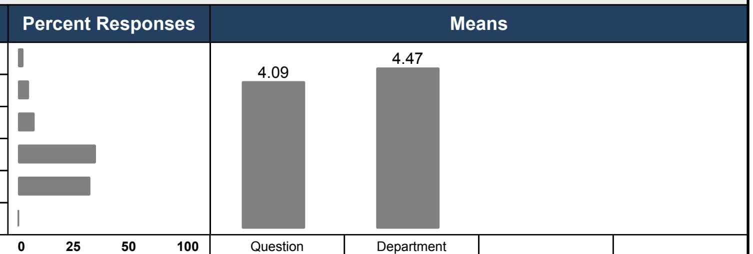
**Instructor:** Murugappa Krishnan *

**Response Rate:** 34/42 (80.95 %)

### 9 - I rate the teaching effectiveness of the instructor as:

**Murugappa Krishnan**

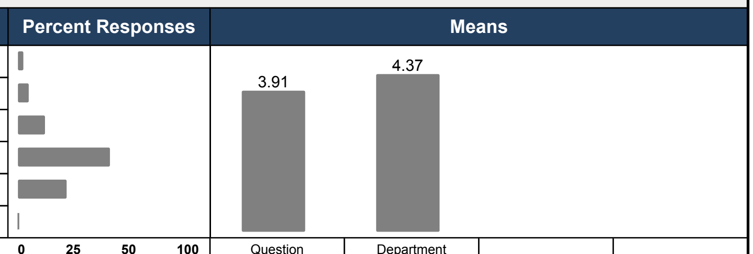
| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 1 | 3.03% |
| 2 | (2) | 2 | 6.06% |
| 3 | (3) | 3 | 9.09% |
| 4 | (4) | 14 | 42.42% |
| 5 = Excellent | (5) | 13 | 39.39% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 33/42 (78.57%) | 4.09 | 1.01 | 4.00 | 128 | 4.47 | 0.83 | 5.00 |

### 10 - I rate the overall quality of the course as:

| Response Option | Weight | Frequency | Percent |
|---|---|---|---|
| 1 = Poor | (1) | 1 | 2.94% |
| 2 | (2) | 2 | 5.88% |
| 3 | (3) | 5 | 14.71% |
| 4 | (4) | 17 | 50.00% |
| 5 = Excellent | (5) | 9 | 26.47% |
| N/A | (0) | 0 | 0.00% |




| Response Rate | Mean | STD | Median | Department | Mean | STD | Median |
|---|---|---|---|---|---|---|---|
| 34/42 (80.95%) | 3.91 | 0.97 | 4.00 | 130 | 4.37 | 0.81 | 5.00 |

### 11 - What do you like best about this course?

| Response Rate | 16/42 (38.1%) |
|---|---|

- Dealing with Connect is frustrating and things must be improved. When a student have a test and the tool is not working well and you run out of time and nothing is done, I simply feel it's unfair to the student.
- Great pace and interesting concepts!
- Other than learning the material that will assist me in my career, I enjoyed the foundational layout of the course and the instruction from Professor Murgie. The course was structured in such a manner that combined an inherent sense of fairness in learning and receiving grades on assignments. The weighted averages and % breakdown of Homework / Tests and Course Discussions was a thoughtful approach to help each student be successful if they worked hard. The discussion questions were challenging, not of average discussion and content I have seen in other courses. Professor Murgie challenged us to be better, to work harder in these discussions - and I did. Although sometimes frustrating, learning can sometimes be. I would not change a thing in the discussion part of the course - continue to provoke critical thinking and challenge students to try harder. Benign posting is for an undergraduate program.
- This course went smoothly and all assignments were well designed. Professor Krishnan responded to any question very promptly and he was extremely accomodating.
- It is applicable to current business situations.
- The thinking outside of the box teaching. I've been in courses that were really dry because the instructor strictly followed what was in the book. Professor Murgie really made the course interesting by including real life business cases and pushed me to think about complex topics. I find myself fully engaged and challenged which I love.
- The instructor by far. I wouldn't have been able to complete this semester had he not been so informative and helpful.
- I really liked the modules, they were very helpful and the weekly assignment problems.
- I liked the use of Connect. I feel that is a good tool to learn a subject like accounting. doing the homework in Connect also was good as it would tell you when your answer was incorrect, forcing you to think more and generate another answer.
- I learned more about cost accounting
- The online videos.
- I enjoyed the discussion questions that came along the accounting HW. It made the accounting work more relevant.
- Access to the correct homework answers (following the due date) when I was unable to calculate the correct answer.
- Management accounting.
- The homework problems were fun and very helpful.
- I greatly enjoyed the threaded discussions. They really prompted us to think outside the box on important topics and to relate them to our business and managerial knowledge.

**Course:** 53: 010: 503: 90ACCTGFORMGRLDEC: 2018SP - ACCTG FOR MGRL DEC 53: 010: 503: 90

**Instructor:** Murugappa Krishnan *

**Response Rate:** 34/42 (80.95 %)

### 12 - If you were teaching this course, what would you do differently?

| Response Rate | 15/42 (35.71%) |
|---|---|

• This a graduate course, we should not totally base our focus on homework problem solving and timed exams. In the real world, nothing we do is designed this way so we need to design the course to be more like the real working environment. The course must be designed to better bring out more thinking and dialog than problem solving.

• n/a

• The timeliness of feedback and grading on the discussion issues could have been just a little more timely. In essence, sans quicker feedback in order to employ and use to improve on subsequent discussions I enjoyed the material, they structure and Professor Murgie's instruction.

• I would give only one midterm test.

• Nothing.

• Sometimes Canvas is very confusing with rounding etc...I think on a couple of occasions there were glitches in the system. But this is not fault of the course.

• NA

• Only change that needs to be made is more instructions on the discussion questions. How the grading is calculated and in more detail of discussion question instructions for content. Assignment questions, we should have a weekly review, if students had some difficulty with answering problems.

• I'm not sure that the discussion questions were relative to the course subject matter. How does the compensation fraud at Wells Fargo relate to pricing variance or materials costing?

• I would utilize a weighted grading system that was easily communicated through Canvas so students could feel at ease as to where they stood at any given point in the semester. I would also not weigh three subjective discussion posts on 25% of the student's grades for a managerial accounting course. If discussion boards are necessary, which I can understand for online learning, I would almost prefer less weighted weekly posts for students to gain an understanding of the professors grading preferences overtime.

• I wouldn't be so harsh on the students. Grading was extremely unfair and when we ask questions about grading, it is not clear on how to improve.

• N/A

• A Kahn Academy type white board demonstration may better support learning when giving examples.

• 1) Completely eliminate the discussion posts. They are useless in any accounting class unless clearly and distinctly related to accounting or business accounting management topics. Could have easily expanded on the book case studies and really enhanced management accounting, even for non-accounting/business MBA's. 2) Have better lecture notes. Several instances, the notes did not even match to the chapter material, so what was the purpose of them? Examples - quadratic functions - they are not used anywhere in accounting, I asked accountants. After the second exam the material skipped around so much and the chapters did not align with the lecture notes I got lost as to the chapter we were supposed to read. 3) Have homework line up to exam material. In an online class, students rely on the book and lecture notes. In the first exam one problem wasn't even covered in lecture or homework.

• Nothing, i found the assignments to be a good balance

### 13 - In what ways, if any, has this course or the instructor encouraged your intellectual growth and progress?

| Response Rate | 11/42 (26.19%) |
|---|---|

• See above.

• This course was a real challenge for me. From homework, to discussions and tests, I came into this course 7 classes deep with a 4.0. To date I believe I worked harder in this class than those that have preceded it - including Stats. As I have previously stated the best part of this course was the fine balance Professor Murgie struck between challenging, teaching and mentoring students, which he did extremely well. He was timely in responding to all concerns or inquiries and fair in all of assessments. When things didn't go as expected he encouraged me to try harder and I did. He pushed me to dig deeper, try harder and think more analytically.

• The discussions are related to the industry and we learn a great deal when we get involved in these discussions and read what others have posted.

• The instructor helped me to think more critically.

• I think Professor Murgie has a passion for teaching and really inspiring his students to look at a scenario from many different viewpoints. I think the biggest challenge in the real world is that there are not so many straightforward answers and scenarios change very fast. This course and it's instructor really opened my mind in terms of thinking about business problems from many angles.

• the professor

• Professor used current relatable topics for the discussion questions

• The group discussion questions encouraged my intellectual growth.

• It has helped the manner in which I approach analytical problems in my current position.

• Liked the different management accounting concepts, good in any business environment.

• through the discussions he was highly engaged and drove better discussion.

### 14 - Other comments or suggestions:

| Response Rate | 5/42 (11.9%) |
|---|---|

• Rutgers is extremely fortunate to have someone like Murgie on the faculty. He is demanding and yet helps assist you in meeting the objectives of the course. If given the opportunity I would take another of his courses if it crosses my MBA path again!

• Keep up the good work! The Rutgers business school and us students are blessed to have someone like Professor Murgie. He makes Managerial Accounting fun and I actually look forward to studying and participating in discussions everyday. That's not a light compliment considering the nature of the course : )

• I am a fan of the CONNECT learning. I like how the homework gives us an opportunity to learn prior to submitting and that we are presented with similar problems during our exams.

• N/A

• Eliminate or change the discussion posts. The professor did not follow or rely on the rubric to grade. How can the opening remarks say keep it short, then praise a dissertation with no references? Makes no sense. Seemed he was more interested in attaching he students than promoting a learning environment/critical thinking.

Murugappa (Murgie) Krishnan
(908)376-9795 (cell)
(908)739-0917 (fax)

90 New England Ave Apt 6
Summit, NJ 07901-1830
7th May 2021

Search Committee
University of Washington at Bothell

Dear Sir/Madam:

RE – my application for a part-time position.

I just realized that I had applied for a non-research and purely teaching and service position. I wish to withdraw my application for this position.

I do have a strong interest in your school, and in the area, and would very much like to be considered for a position that also encourages some research. It is to that end that I submitted samples of also recent research work.

I hope you will be able to consider me for such a position. Thank you.

Sincerely,

Murugappa Krishnan

Murgie Krishnan

# Application Forms

## Please tell us how you first heard about this position.

**Please tell us how you first heard about this position.**

Chronicle of Higher Education

# Sexual Misconduct Declaration

**Are you the subject of any substantiated findings of sexual misconduct in any current or past employment?**

No

**Are you currently being investigated for sexual misconduct at any current or past employer?**

No

**Have you left a position during an investigation into a violation of any sexual misconduct policy at any current or past employers?**

No

**Name**

Murugappa Krishnan

**Date**

5th May 2021