Is good news really bad news? Event study with correlated market and non-market signals in an asset pricing model.

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Abstract:

How informed are Foreign Institutional Investors (FIIs) in Indian financial markets? We build a model of imperfect competition in a financial market, in which market makers have up to two public signals on which to define their pricing rule – firms' earnings announcements and FII trading signals. We define the payoff structure with a sum of correlated components, one known to firms, and the other, to FIIs. We estimate 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. So instead of treating multicollinearity as a problem to be resolved using more orthogonal instruments, or a better selection of regressors, we explain it using an underlying model of financial market equilibrium, and identify deep parameters that are unobservable but have economic significance.

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. We also find that correlation between the two fundamental information components is significantly positive, so that in econometric work we should consider such an environment, even beyond any correlation arising from imperfect measurement. A methodological contribution is to show how the underlying model of equilibrium allows us to learn more from the event study based on earnings announcements.

Keywords: Foreign Institutional Investors, Institutional Trading, Earnings Announcements, Investment Performance

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1. Introduction

Foreign institutional investors (FIIs) have become prominent in emerging markets. But one elementary question has not been resolved: to what degree are FIIs informed traders who use a careful optimizing strategy, and to what degree are they, like many other institutional traders, participating in the market primarily because of retail pressures to meet insurance or pension claims or to respond to portfolio rebalancing decisions made by their customers with needs of their own? This is the main 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 sometimes available. Therefore, the competitive price-setters in our model observe either or both of two signals, 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.

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. But 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.

Our study employs a database of daily stock-level trades of FIIs in India for the years 2006-2016. 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 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. We also find that correlation between the two fundamental information components is significantly positive, so that in econometric work we should consider such an environment, even beyond any correlation arising from imperfect measurement.

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 our data sources and sample selection process and section 5 presents the empirical variable definitions and main empirical models. In section 6, we present our results, and in section 7 we discuss our conclusions.

2. Prior Literature

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 portfolio diversification can arise for reasons unrelated to risk, to minimize revelation of information in a correlated environment.

Lundholm (1988), under perfect competition, and Manzano (1999), under imperfect competition, showed that 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 similar ambiguity can arise. A security's price may not rise 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, 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.

In the above examples, the asset payoff has a single component, and multiple signals are about that common component. In our work here, the payoff is defined with additive components, and corporate earnings and traders' private information are about different components. The correlation parameter can lead to an ambiguous coefficient on earnings in the pricing rule, but the exact reason is a little different. In our model the correlation parameter governs two different payoff components, and not the errors on the same component in two different signals.

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.

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 informational 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 informational 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

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

public and private signals are about the same component, yet retains parsimony in terms of the number of parameters to be estimated.

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 we will sometimes do that. But occasionally it will be more convenient to interpret it as the informational advantage of i relative to others, i.e. $\tilde{v}_i = E(\tilde{v}\,|\,\tilde{I}_i) - E(\tilde{v})$. 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 σ_F^2 and σ_T^2 serve both as prior variances and as measures of informational advantage. The variance parameter σ_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 σ_T^2.

It provides a simple way of describing whether firms know more or less than traders, without adding more notational burden. Firm 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 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 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,

[2] For a convenient summary of the algebra of informational advantages, see the remarks following assumption (A3) in Caball$\acute{e}$ and Krishnan (1994).

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 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 $p = E(\tilde{v} \,|\, v_F, \omega)$. We also assume a linear pricing

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[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.

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.

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, β and λ, instead of in λ 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 prior zero means of all variables. The coefficient τ_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 τ_1 is complex because it also yields information about the second component, as $E(v_T|v_F) = \rho\left(\frac{\sigma_T}{\sigma_F}\right)v_F$, so that given v_F the trader effectively faces both a different intercept and slope. The coefficient of v_F in this conditional expectation, $\rho\left(\frac{\sigma_T}{\sigma_F}\right)$, is added to the coefficient when only v_F is available as a signal in the pricing rule, namely unity, in this case when both v_F and v_T are available. The coefficient τ_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 ρ.

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 λ reflects here the presence of that second possibly correlated signal. When the correlation $\rho \to 0$, λ is given by the same expression as in the Model 2 benchmark. When $\rho \neq 0$, λ is smaller because of the decline in the variance of $(\tilde{v}_T|v_F)$. 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.

3.4. Equilibrium in benchmark models

In our empirical strategy, a crucial role is played by comparing this main model to two simpler benchmark models. In one 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, we have FII participation but no earnings announcements, so this reflects FII trading outside earnings announcement windows. Given our other assumptions this model resembles closely 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

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

Let us collect the equilibrium pricing rule coefficients β and λ under the three different regimes (using superscripts to indicate different underlying regimes):

Model	Available signals	β	λ

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

3.4.1. Substitutes or complements

The above table immediately sheds light on whether the two public signals available in general to market makers are information 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 for Y. 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 ω. 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.[5]

The parameter β^{FT} 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

[5] 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.

same component and correlation governs the error covariance, so β (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 ρ, we also have $\sigma_T > \sigma_F$ by a sufficient margin. To interpret this, consider a setting where the total payoff $\tilde{v} = \tilde{v}_1 + \tilde{v}_2 + \tilde{v}_C$, $\tilde{v}_F = \tilde{v}_1 + \gamma_F \tilde{v}_C$, $\tilde{v}_T = \tilde{v}_2 + \gamma_T \tilde{v}_C$, with $\gamma_F + \gamma_T = 1$ to preserve our original assumption about payoff structure, that $\tilde{v} = \tilde{v}_{\boldsymbol{F}} + \tilde{v}_{\boldsymbol{T}}$. Correlation arises because of the common component $\tilde{v}_C$, and will be negative when the coefficients γ_F and γ_T have different signs. For $\beta < 0$, besides having a significant common component between the firm and FIIs, it must also be the case that the FIIs' informational advantage σ_T must exceed the firm's informational advantage σ_F. A practical implication of this for empirical work is that if the estimate of the shallow parameter β is negative, that immediately tells us that FIIs must know more than firms.

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

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

To estimate this model, we set it up as a least squares minimization problem subject to certain inequality constraints (defined below). In our empirical work, we equate p to returns on the earnings announcement date (ERET); v_F to unexpected earnings (UE) and ω (aggregate order flow) to net FII buying on that date (FIITR). Note that, importantly, the model is non-linear in its parameters. This brings two additional estimation considerations (when compared to the workhorse ordinary least squares model) – constraints on parameters and scale of the observed independent variables. We describe how we take into account these two factors in the following paragraphs.

We have to estimate four deep or primitive parameters – σ_F, σ_T, σ_Z, and ρ, and two shallow parameters – β and λ. Inspection of the equilibrium pricing equation reveals that the three primitive variance parameters, σ_F, σ_T, and σ_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) 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. However, for σ_F we can construct an independent estimate from observed values of unexpected earnings (UE, our proxy for v_F). We equate σ_F, the information advantage of the firm, to the sample estimate of the average standard deviation of unexpected earnings (UE), across firms.[6] Then, in any implementation of the empirical model, we take that independently estimated σ_F as a fixed value, and estimate the remaining three primitive parameters. Because β and λ 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 σ_T, σ_Z, and ρ.

To obtain meaningful parameter estimates we need the following constraints: $\sigma_i > 0, i = T, Z$ and $\rho \in (-1,1)$. Additionally, to facilitate model convergence, we impose two additional restrictions on σ_T and σ_Z: $\sigma_T \leq 2$ and $\sigma_Z \leq 0.1$. The primary reason for these restrictions is to make the hill-climbing grid search algorithm more efficient. It was implemented in SAS using PROC OPTMODEL. This procedure uses our initial starting guesses for

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[6] In addition to reporting estimates for the overall sample, we also estimate the model for sub-samples and for each firm. What we have notice is that cross-sectional differences in σ_F are substantial, especially when we compute estimates at more disaggregate levels, like the level of the firm. We find that, consequently, the estimates of β vary across sub-samples, though the estimates of λ generally do not change significantly.

the parameters, but augments these with additional starting points of its own, which are determined in part by the definition of the parameter region. Defining these upper bounds on σ_T and σ_z, neither of which is binding, speeds up the estimation. The restriction on σ_T is guided by (a) the observation that the sample estimate of σ_F is about 0.0013 and (b) the expectation that σ_T should be approximately of the same order of magnitude as σ_F. A value of two is about 1,500 times the estimated σ_F. Turning to σ_z, our model defines the variance of the aggregate order flow (ω) as the sum of the variances of the informed order flow and that of the noise trader order flow. Therefore, σ_z has to be less than the sample standard deviation of FIITR, which is about 0.001. We set the bound for σ_z to be 0.01, which is about ten times the theoretical bound.

For the iterative algorithm we defined the following stopping rule: stop when both the objective function and all of the parameter estimates stay the same to the 4th decimal place. As in any gradient search with an objective function that is not globally convex, we cannot be sure we have a global minimum, but only a local minimum. Making the parameter region for the grid search large improves the chances of identifying a global minimum.

The model for error is given by

$(ERET - (1 + \rho(\sigma\_T/\sigma\_F\ )) * UE - ((\sigma\_T\ (\sqrt{}(1 - \rho\hat{}2)))/\sigma\_z\ ) *\ FIITR)$

where $\rho \in (-1,1);\ \sigma_i > 0, i = T, Z;\ \sigma_T <\ 2;\ \sigma_Z < 0.1.$

$\sigma_i > 0, i = T, Z;\ \sigma_T <\ 2;$

In the empirical analysis, we choose to change the scale of our key independent variables, UE and FIITR, for two reasons. First, we require that our empirical proxies for these two variables conform as closely as possible to their definitions in the theoretical model. Second, models that are non-linear in parameters tend to have better convergence properties when independent variables are in the same scale. Note that, as with OLS regressions, scaling affects the coefficient estimates, but does not affect the t-statistics.

Our first transformation is that all variables (including UE and FIITR) are winsorized at the 1% level; this is quite standard in the literature in accounting and finance and reduces the sensitivity of our estimates to outliers. Second, recall from section 3.1 that $\tilde{v}_i \sim N(0, \sigma_i^2), i = F, T$; that is, both UE and FIITR are mean zero variables. Accordingly, we subtract the respective sample means from both these variables to obtain centered UE and FIITR, respectively. Third, our benchmark case of the relation between earnings announcement returns and UE when there is no FII trading, requires that the coefficient on UE equals 1 exactly ($\beta^F = 1$, see Lemma 1 in section 3.4). Therefore, we estimate a simple linear regression of ERET on UE and control variables, for the sub-sample that has no FII trading and find that the coefficient on UE is about 0.04. We multiply centered UE by this coefficient estimate to ensure that $\beta^F = 1$. This allows us to meaningfully compare the coefficients of UE in regressions when FIITR is absent with those when it is present. Fourth, a well-known numerical analysis rule of thumb recommends rescaling independent variables such that they are on the same scale. This rule is meant to help convergence and stability in gradient-based algorithms. Accordingly, for our overall sample, we further divide the scaled and centered UE by 2 to render its scale comparable to that of FIITR. In our section on results, we our careful to re-calibrate our comparisons of σ_T and σ_F to account for these scaling adjustments.[7]

Lastly, a few words about ρ. From the theory, the right-hand side variables UE ($\tilde{v}_F$) and FIITR ($\tilde{\omega}$) are correlated: Cov($\tilde{v}_F, \tilde{\omega}$) $=$ $\tau_1 *$ Var($\tilde{v}_F$) $+$ $\tau_2 *$ Cov($\tilde{v}_F, \tilde{v}_T$). Without an economic model that defines correlation as a parameter that influences the decisions of agents, this correlation would be a *mere statistical artifact* (most likely ascribed to measurement error) that has to be dealt with. Specifically, it would require that both UE and FIITR be included on the

[7] 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 β.

right-hand side of the regression to avoid a correlated omitted variable bias. In contrast, our model shows that the correlation parameter has *economic content*; it is not merely a statistic that has to be accommodated through a multiple regression. Specifically, our model shows that this correlation measures the commonality in the information advantages of the firm and the informed traders. Further, although unobservable to the researcher, in our empirical work, we are able to estimate it.

Our model is not just a source of predictions about regression coefficients on UE and FIITR (β and λ), but a direct bridge between what we can observe – p, v_F, ω, and the primitive parameters – σ_F, σ_T, σ_z, and ρ, 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.

5. Empirical Design

5.1. Model

In our empirical analysis, we estimate the pricing function defined in Proposition 1 that expresses the price impact (p) as a linear function of earnings announcement news (v_F) and aggregate order flow (ω):

$$ERET_{it} = \alpha + \beta * UE_{it} + \lambda * FIITR_{it} + \text{Control Variables} \qquad (1)$$

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). 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.

FIITR = Net Buying by all FIIs over the two-day earnings announcement window divided by shares outstanding on day -2. 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 ω. FIITR is centered as described in section 4.

Our first set of control variables are drawn from prior work on asset pricing. Fama and French (2015) 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 (2000); 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 summed 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 volume divided by shares outstanding, measured for the month prior to the beginning of the quarter of the earnings announcement.
9. LAG_UE is the value of UE lagged by one quarter.
10. L_AGE is the 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 the fiscal year before the earnings announcement divided by MCAP.
12. LPRC is the logarithm of beginning quarter price.

While our empirical model resembles a classical linear regression model, the linear coefficients of interest are themselves related nonlinearly to the primitive parameters. In a Gaussian environment, least-squares estimators are equivalent to MLEs. Asymptotic properties are easy to invoke in case of MLEs. So our primary estimates are based on the least-squares criterion applied to our nonlinear model.

In our empirical work, we consider three sub-samples based on FII trading on the earnings announcement date and FII ownership around that date. This is motivated by the idea that lack of FII trades may have value as a market signal when it is more likely that FIIs a priori had some interest in a firm. Our first subsample consists of those announcements that have non-zero FII trading; our pricing equation is estimated for this sub-sample. Our second 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. For this sub-sample we do not code FII trades as zero but as not available. Recall, from section 4, as a benchmark case that we wish to estimate a regression of ERET on UE and control variables, when there is no FII trading (Lemma 1). We employ this sub-sample to estimate this regression. 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.[8] For this sub-sample absence of FII trades is coded as zero.

5.2. 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. 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 is from the SEBI FII trading database.[10] On this database, the basic unit of observation is trading activity by 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

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[8] In this draft, we do not analyze this third sub-sample, but plan to do so in future revisions.

[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 non-consolidated financial statement data.

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

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. We integrate the FII trading data (SEBI) and the firm- earnings announcement data (PROWESS) by matching on firms' ISINs and dates.

6. Results

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 281,183 firm-quarters to arrive at the final aggregate sample 85,918 firm-quarter observations. Of these 21% had FII trading during the earnings announcement window; 30% had FII ownership before, or during, or after the earnings announcement window, but no FII trading; and 49% had no FII ownership at all. 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 variables in the regression model for the sub-sample for which FII trading is non-zero on the earnings announcement date (0,1), n=16,103. The mean and median earnings announcement return are small and negative at -0.2% and -0.5%, respectively. Mean unexpected earnings scaled by share price is also negative at -0.07%; however, the median is slightly positive at 0.01%. The average net FII buying at the earnings announcement is almost zero - FII trading as a fraction of shares outstanding is very small; . The FII net buying ranges from -0.45% to 0.44% as a percentage of shares outstanding. Turning to the control variables, mean market return is positive at 0.3%, the log of mean market capitalization is about ₹7 Billion, and the mean book-to-market ratio is 1.1. The sample firms are profitable on average and are growing – mean operating profitability is 14.3% and mean asset growth is 16.7%.

Table 4 provides simple correlations between all our variables. The correlation between our two primary RHS variables, UE and FIITR is 0.08 and significant. So there is a prima facie suspicion of significant collinearity between them when used in the regression.

We obtain Table 5 reports on classical earnings announcement event study regressions, by focusing first only on UE (with coefficient β = 2.209), then only on FIITR (with coefficient λ = 0.78), and finally with both together (with $\beta = 2.210$, and $\lambda = 0.780$). These regressions do not use any restrictions from the underlying theory, and the coefficients β and λ here are estimated directly from the data, without invoking any of our equilibrium formulae. The Regime 1 regression where only UE is available is like a classical event study using earnings announcements. It shows that there is nothing special about our sample. So this sample from an Indian financial market is like most other samples from round the world. But when we look at Regime 3 where both UE and FIITR are available, what is noteworthy is that even within an earnings announcement window, it is FII trading rather than the firm's earnings announcement that is more significant. We compare the estimates of β and λ in the regressions under Regimes 1 and 2 where UE or FIITR enter without the other, and in Regime 3 where they both enter. These comparisons suggest that the variables UE and FIITR are independent of each other. Neither β nor λ increases or decreases because of the presence of the other signal. Yet we know from Table 4 that these two regressors are significantly correlated. This is what makes modeling of the correlation potentially informative.

Table 6 reports non-linear least-squares estimates of the primitive parameters from a regression using the aggregate sample. The estimate for σ_T (0.0508) is much larger than for σ_F (0.0028). So even within the earnings announcement window the information advantage that FIIs have is much greater than what firms have. So the market learns more from FII trades than from the firm announcement. Since $\sigma_Z = 0.0067$, background market noise is only of the same order of magnitude as the firms' information advantage. The correlation parameter $\rho = -0.0620$. Because this is negative, and because the ratio of σ_T to σ_F is more than 18, the β estimate from using the theoretical restrictions turns out to be negative. So we have a case where good news can turn into bad news, as noted by Lundholm (1988) and Manzano (1999). This conclusion in this event study is possible only because we explicitly model the underlying equilibrium in a correlated environment.[11]

The crux of the empirical work to date represents an effort at assessing the stability of these comparisons between Table 5 and Table 6. The broad conclusion so far (based on some variations in how each empirical variable is measured, and in the exact options used during estimation) is that these qualitative results are very stable. Using our equilibrium model as an explanation for the correlation causes the β estimate to be very different. We are in the process of attempting a formal out of sample comparison between the models in Table 5 and the model in Table 6, to check if the predictive power of using a theory is greater than using no theory. 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

[11] We also examined measures of informativeness. In our context we can define various measures of ex ante and ex post measures. For example, an ex ante measure of informativeness is $\frac{\sigma_T}{\sigma_F}$, which measures the information advantage of FIIs at the time of an earnings announcement, relative to the information advantage of firms about what is released in the earnings announcement. For ex post measures, we look at the total variance of abnormal returns (adjusted for control variables), and ask what percentage of this variance is explained by unexpected earnings or FII trading? We find that both unexpected earnings and FII trading each explain slightly less than 1% of the total variation at the time of earnings announcement.

in the linear expenditure system to be very different (Klein and Rubin (1947), Geary (1950), Stone (1954)) from the estimation without invoking any theory of demand.

This suggests that even in well-studied data sets such as the US, the traditional positive Earnings Response Coefficient may be due to ignoring the effect of a prominent market signal from institutional trades, and not adjusting for the correlation between these market signals and the earnings announcement. In the model we develop in this paper, institutional traders not only have distinct private information, but they can also observe the earnings announcement when they choose their trades.

In Tables 7, 8 and 9, we dig a little deeper into our primitive parameter estimates. Table 7 examines sub-samples based on capitalization (and compares small, medium and large market-cap sub-samples). Table 8 compares profitable firms and loss firms. Table 9 summarizes firm-level estimates. While this work is preliminary, it is clear that our assessment of the earnings response coefficient β is what is really questioned by the application of theory. The estimate of λ, the order flow response coefficient, does not change much. Table 7 suggests that in small firms with more limited institutional trading the β estimate is positive. Table 8 suggests that a positive β holds for loss firms. Table 9 which reports on firm-level estimates shows that there is huge variation in β estimates across firms. We are planning to explain this cross-sectional variation using firm characteristics.

In ongoing work, we are examining robustness of our results to alternative estimation methods (one alternative is 2SLS where the FII trades will be regarded as a function of exchange rates). We are also calculating measures of informativeness, and examining if UE and FIITR are substitutes or complements to each other.

7. Remarks on Contribution

The contribution in this paper can be viewed from multiple perspectives. One benchmark is the vast literature on event studies analyzing earnings announcements. Our work studies a case with an additional market-provided signal, FII trading, in addition to the firm-provided earnings news. From a comparison of β and λ in the aggregate sample, we find that even during the earnings announcement window, the market-provided signal is relied upon more by price-setters. This offers a new explanation for the well-documented result while earnings numbers matter to financial market participants, and move prices, they explain only a small portion of the earnings window price variation. Other information – here FII trading – matters more.

Also, a negative ρ and a large ratio of σ_T to σ_F causes $\beta < 0$, so that good news can be actually bad news. The traditional result that $\beta > 0$ may reflect omission of a key market signal, institutional trades.

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. The empirical work in that literature has tended to focus on Kyle's λ 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 which are unobservable, and because we have multiple signals in a correlated setting, our results also shed light on the role of the correlation parameter.

In terms of methodology, this view of correlation as a fundamental determinant of the underlying equilibrium marks a departure from treating collinearity in the data as a nuisance to be minimized or adjusted for.

8. Conclusion

How informed are Foreign Institutional Investors (FIIs) in Indian financial markets? We build a model of imperfect competition in a financial market, in which market makers have up to two public signals on which to define their pricing rule – firms' earnings announcements and FII trading signals. We define the payoff structure with a sum of correlated components, one known to firms, and the other, to FIIs. We then estimate 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. These are parameters of interest but cannot be directly observed, or inferred from the shallow parameters of an econometric model. The underlying model of equilibrium serves as a bridge between what we can observe, and what we are also interested in but cannot observe. So instead of treating multi-collinearity as a problem to be resolved using more orthogonal instruments, or a better selection of regressors, we harness it by explaining it using an underlying model of financial market equilibrium, and identify deep parameters that are unobservable but have economic significance.

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. We also note that correlation between the two fundamental information components is significant, and often negative, so that in econometric work we should allow for such correlation, even beyond any correlation arising from imperfect measurement.

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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

Σ, and let tr(j) $\equiv \{1,1\}$. Let $\tilde{y}_1 \equiv$tr$\{\tilde{v}_F, \tilde{v}_T\}$, and Σ_{11} be the leading 2x2 minor of Σ. Then total payoff $\tilde{v} \equiv$ tr(j).$\tilde{y}_1$, and $\tilde{v} \sim N(0,$ tr(j).Σ_{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, β and λ, instead of in λ 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 β and λ into the trader's strategy coefficients yields Proposition 1.

Table 1
Sample Selection

Our initial sample consists of all firms with non-missing quarterly earnings announcement dates from the CMIE prowess database. We require that firms should have non-missing data for our regression variables, should have traded at least one day in the 200 calendar-days around the earnings announcement date, and that earnings announcement dates are within 180 calendar-days of the fiscal quarter end date. Data for our regression variables (market data, financial statement items, and FII ownership) are from CMIE Prowess. Table 3 contains variable definitions.

Initial Sample of Firm-quarters (2003-2016)	**281,883**
Less: Firm-quarters with missing data for UE and LAGUE	143,162
Less: Firm quarters with erroneous earnings announcement dates or dates that are more than 180 days after the fiscal quarter end	692
Less: Firm-quarters with no price data over the entire 200 calendar-days around the earnings announcement date	30,501
Less: Firm-quarters with no price data on the earnings announcement date alone	3,158
Less: Firm-quarters with missing data on control variables	18,452
Final Sample	**85,918**
Composition of Final Sample:	
Firm-quarters with trading during earnings announcements (21%)	18,098
Estimation Sample (2003-2014):	14,573
Holdout Sample (2015-2016):	3,575
Firm-quarters with no trading during earnings announcements and with FII ownership (30%)	25,965
Firm-quarters with no trading during earnings announcements and with *no* FII ownership (49%)	41,855

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. Earnings announcement dates and earnings per share, stock prices and returns, 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	326	13%	845	33%	1,370	54%	2,541	100%
2004	541	16%	1,125	32%	1,797	52%	3,463	100%
2005	1,128	22%	1,752	33%	2,356	45%	5,236	100%
2006	1,332	22%	1,927	32%	2,852	47%	6,111	100%
2007	1,489	23%	1,968	30%	3,139	48%	6,596	100%
2008	1,061	21%	1,650	32%	2,390	47%	5,101	100%
2009	1,116	19%	1,930	33%	2,859	48%	5,905	100%
2010	1,374	21%	1,902	29%	3,250	50%	6,526	100%
2011	1,420	21%	1,892	28%	3,447	51%	6,759	100%
2012	1,435	20%	2,110	29%	3,768	52%	7,313	100%
2013	1,620	23%	2,258	31%	3,315	46%	7,193	100%
2014	1,731	22%	2,414	30%	3,801	48%	7,946	100%
2015	1,943	23%	2,477	29%	4,172	49%	8,592	100%
2016	1,582	24%	1,715	26%	3,339	50%	6,636	100%
Total	18,098	21%	25,965	30%	41,855	49%	85,918	100%