Gradual Incorporation of Information into Stock Prices: An Empirical Study of Informed Trading

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Abstract

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This paper explores an environment in which the incorporation of information into stock prices is gradual, and develops appropriate estimation techniques. A large theoretical literature addresses how the trading process itself may incorporate private information into stock prices gradually. In particular, in the Kyle (1985) model, one or a small number of informed traders use their market power over their private information to maximize profits dynamically. We use the functional form predictions from Kyle in our estimation, and the results from a sample of targets of tender offers are consistent with the model. We find that price movements are sensitive to the current divergence between price and the value of the stock revealed at the announcement date. Moreover, this sensitivity grows as the announcement date approaches. In addition, we estimate the date at which the insider becomes informed, and we find a wide dispersion and a bimodal distribution in these "transition dates." The latter feature suggests two types of information structures, one where the secret is well-kept and one where significant pre-announcement leakage occurs.

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1 Introduction

Information moves stock prices. A vast literature has arisen to exploit and explain that fact. Most of that research has assumed that the information is released on a small set of observable dates, and has either assumed or established that the information is incorporated into stock prices immediately. This paper borrows from the existing theoretical literature to explore an environment in which incorporation of information into stock prices is gradual and develops an appropriate estimation technique for this setting.

The purpose of our paper is to examine the structure of price run-ups of a panel of stocks prior to tender offer announcements and to see if that specific structure is consistent with theoretical models of informed trading. In particular, models of informed trading predict that larger price increases would be associated both with a shorter time to the announcement date and a larger gap between the true value of the stock and its current trading price. Intuitively, we would expect price increases driven by informed traders to accelerate as the time to make profits dwindled and as the profit opportunity (as measured by the gap) expanded. In our sample of around 100 tender offers, we find some evidence of both and interpret those findings as broadly consistent with the theoretical work.

We draw on two main literatures to inform our study. First, Kyle (1985) offered a seminal model of how private information will be gradually incorporated into stock prices by a rational informed trader, a rational market maker, and liquidity or noise traders. Our empirical approach will be based in large part on Kyle's theoretical model. The Kyle model, of course, has sparked a large theoretical literature, which we will not supplement in any way. We will, however, selectively discuss it in our section on empirical implementation, as issues of our particular empirical setting arise to which it is relevant. Relatively little empirical work has been done examining the direct implications of the Kyle model for the pattern of price changes. Researchers have focused more on the implications for stock price volatility, as in French and Roll (1986). Recent work in market microstructure has focused on market maker behavior consistent with the presence of informed trading, as in Kavajecz (1999). One paper that directly tests the Kyle model is Cho (2007)'s analysis of the behavior of stock prices ahead of earnings announcements. Cho uses a structural model, and finds evidence of informed trading, although more consistent with Foster and Viswanathan (1996) than Kyle. Chae (2005) finds that market makers increase the price sensitivity to order flow before corporate announcements.

Second, a literature in empirical finance documents stock price run-ups prior to announcements in various settings, without connecting those run-ups to particular theoretical models. Mandelker (1974) and Halpern (1976) both documented positive run-ups in cumulative excess returns of acquired firms ahead of the announcement date of takeovers and mergers. Since they used only monthly data, they may have missed a large part of this effect. Keown and Pinkerton (1981) were the first to use daily returns to explore this pre-announcement leakage. They find that the cumulative average residual of acquired firms becomes positive (but not necessarily statistically significant) 25 trading days before the announcement date. About one half of the total increase in cumulative average residuals occurs before the announcement date. The daily average residuals "are significantly different from zero at a minimum significance level of .90 on 10 of the final 11 days prior to the announcement date, the final 5 days significant at the .995 level."[1] Keown and Pinkerton interpret their results as supporting "pervasive" insider trading. Price run-ups of this type have subsequently been verified by many authors using many samples, although the interpretation of this fact is disputed. Jarrell and Poulsen (1989) for example attribute the run-up to speculative activity based on public information rather than to illegal insider trading.

While such run-ups have been well documented in a number of settings, relatively little has been done to characterize the nature and structure of these run-ups, or to connect their structure to the theoretical literature. Are they broadly similar across announcements, or do we see a lot of heterogeneity? Are the price run-ups occurring at a constant, accelerating, or decelerating rate? What factors affect the rate? Answering these questions might be

[1]Keown and Pinkerton, p. 863.

important in interpreting the causes of the run-ups, whether insider trading or speculative activity based on public information, but our goal is not directly related to this debate. Rather, our goal is to empirically implement a simple variant of the Kyle model, therefore examining whether the price pattern is consistent with this model of informed trading. Moreover, the restrictions imposed by the model can give us a more powerful method of detecting pre-event abnormal performance than merely cumulating abnormal returns over the pre-event period.

The rest of the paper is organized into four sections. The next section discusses our empirical implementation of a model of informed trading based on Kyle (1985). We derive estimable equations from the theoretical model and discuss empirical implications of it. Section 3 describes the data set of announcements of tender offers we will be using to estimate our model of gradual diffusion, as well as our treatment of the data. Section 4 presents the results and also discusses their possible application to event study methodology. We find significant evidence of gradual incorporation of information. In addition we learn characteristics of the process through which this gradual incorporation takes place. Section 5 concludes.

2 Empirical Implementation

Planning and execution of possible corporate acquisitions and corporate control contests are usually conducted under stringent secrecy. Nevetheless, there is often a run-up of stock prices ahead of the formal public announcement. We want to apply a model which will explain and predict how this private information is incorporated into stock prices.

A small group of informed traders may not want to trade so as to instantaneously incorporate their information into the stock price, thus seeing their opportunities to profit from their information evaporate. Under general conditions, a profit-maximizing strategy would be to trade in such a way to only gradually inform the market. A well-known formalization of this idea is provided by Kyle (1985). In his model, a single informed trader uses his monopoly power over his private information to maximize profits dynamically. This results in the gradual incorporation of the private information into the stock price.

Kyle shows that it is optimal for the insider to place orders for a stock so that the market maker's price converges to the (liquidation) value only by the "end of the world," *i.e.,* the formal, public announcement of the information. One implication we take from the Kyle model is a specific functional form prediction for the expected price path and a relationship between price changes and both calendar time and the amount of information yet to be incorporated. We will look for these patterns in the price run-ups we study.

We exploit the more robust empirical implications from the Kyle model, but depart from it in some respects. First, Kyle's model is one of a single informed trader. Similar patterns of gradual incorporation of information can be derived from models with multiple informed traders, but they will typically depart from Kyle in some particulars.[2] Our empirical setting would, of course, present the possibility of multiple informed traders, so rigid adherence to particulars of the Kyle model implied by the existence of a single trader would be unwarranted. Second, Kyle's model is one of *informed* trading, not *illegal insider* trading, and so his trader only hides his information from the market to maximize his profits and does not have the additional incentive of avoiding criminal punishment. In fact, the informed trader in Kyle reveals all of his private information by the announcement date. We imagine that the incentive to avoid criminal penalties is strong in our setting, and would, in particular, make it unlikely that an informed trader would reveal all of his information by the announcement date. For these reasons, we try to formulate an econometric specification that is both tractable and robust.

Our empirical implementation is based on a discrete-time dynamic version of Kyle's model. In this model, time t runs from 0 to 1. Roughly following Kyle's notation, we denote the position in the asset of the insider at time t as x_t and the price of the asset at time t as p_t. The noise trader's position in the asset at time t is u_t, where $\Delta u_t = u_t - u_{t-1} \sim \mathcal{N}(0, \sigma_u^2)$. In addition, let v be the liquidation value of the asset (which the insider learns at time

[2] A number of authors have obtained the result of gradual incorporation of information into stock prices with extensions of the Kyle model to multiple informed traders. See, for example, Foster and Viswanathan (1996) and Back, Cao, and Willard (2000). The implications of multiple informed traders depend on the assumed information structure and the risk-aversion of the informed traders, however. Holden and Subrahmanyam (1992) find immediate incorporation of information in the limit when multiple informed traders receive identical information. Gradual incorporation occurs if informed traders receive heterogenous signals or are risk-averse, or if they collude.

0).[3] The equilibrium, in which the insider maximizes total profits, is characterized by the following linear relationships:

$$\Delta x_t = \mu_t(v - p_{t-1})$$

$$\Delta p_t = \lambda_t(\Delta x_t + \Delta u_t),$$

where μ_t and λ_t are constants which depend on time, and $\Delta x_t \equiv x_t - x_{t-1}$, $\Delta p_t \equiv p_t - p_{t-1}$.

Substituting the volume equation into the price change equation yields

$$\Delta p_t = \delta_t(v - p_{t-1}) + \epsilon_t \tag{1}$$

where $\epsilon_t = \lambda_t \Delta u_t$ and $\delta_t = \lambda_t \mu_t$. Expected price changes are positive if the previous period price is below the value of the asset, but the realization of the level of noise trading also influences realized prices. The independent error term has mean zero and a variance which may depend on t (through λ_t). See Figure 1 for a picture of the expected price path with *zero* realizations of noise trades. Still remaining is the characterization of the constants λ_t and μ_t and the nature of their dependence on t.

Intuitively, the dependence of λ_t and μ_t on t reflects an "end of the world" effect: as the end of the world (and, therefore, the end of opportunities to profit) approaches, the insider becomes more sensitive to the difference between v and p_{t-1}. Given the insider's private knowledge of v, $(v - p_{t-1})$ is a measure of how much the firm is currently undervalued. As the public announcement date approaches, the insider is about to lose his monopoly on this private information, and so there is no longer an incentive to hide behind the noise trader. So the insider should trade more aggressively, thus closing the gap between v and p_{t-1}. Clearly, we want $\delta_t = \lambda_t \mu_t$ to be positive and increase as t increases.

Were we to stay strictly within the confines of the Kyle model, we would want $\delta_t \longrightarrow \infty$ as $t \longrightarrow 1$.[4] But considerations absent from Kyle yet likely to be reflected in the data would presumably place an upper bound on δ_t. For example, the threat of prosecution for insider trading would restrain an informed trader from trading too aggressively right before the information becomes public.

[3] This is the realization of a random variable that is distributed $\mathcal{N}(p_0, \Sigma_0)$.

[4] For instance, in the continuous auction equilibrium, $\delta_t = \frac{1}{1-t}$. The equilibrium in the dynamic discrete model converges to the continuous auction equilibrium as the interval between auctions becomes small.

So instead we assume the following functional form for δ_t, letting $\delta_t = \gamma_1 + \gamma_2 t$. This simple specification is tractable and econometrically robust, and yet allows us to capture the dependence of δ_t on t. Then

$$\Delta p_t = \gamma_1(v - p_{t-1}) + \gamma_2(v - p_{t-1})t + \epsilon_t \tag{2}$$

Note that we do not specify a functional form for λ_t alone, even though it multiplies Δu_t to give us the error term in the equation. Instead we allow for heteroskedasticity when estimating the equation to accommodate different types of dependence of ϵ_t on t.[5]

We now have an equation that can be estimated econometrically given values for p_t and v. We observe p_t, of course, and will use the price of the asset at the announcement date for v.

A few additional issues remain in the empirical implementation of the model. First, the correspondence between the timing in the model and in the empirical setting must be established. Time 1, the announcement date (or "end of the world"), is clear, but time 0, the date at which the insider becomes informed, is unknown to the econometrician. We will need to estimate it.

The date at which the insider becomes informed triggers a shift between two regimes. What we call regime A is one in which there is no private information or informed trading. Price changes will therefore reflect only new public information about the asset's value, which we assume is white noise. We can accommodate this regime within the previous notation by noting that before time 0, $\gamma_1 = \gamma_2 = 0$ and $\lambda = 1$. In other words, price change in regime A, before information leakage, will be determined by the following equation:[6]

$$\Delta p_t = \Delta u_t \tag{3}$$

Price change in regime B, after the insider becomes informed, will just be given by equation (2).

[5] In the continuous auction equilibrium, λ_t is a constant, and therefore heteroskedasticity would not arise. It need not be constant in the sequential auctions equilibrium, however.

[6] We assume here that the insider is not a noise trader before he becomes informed. Otherwise, Δp_t will be the sum of *two* independent errors and will have a variance greater than that of Δu_t alone.

In this formulation, we let realizations of Δu_t represent new public information in Regime A but only noise trades in Regime B. We could instead introduce two separate random variables. In either case, we estimate heteroskedasticity-robust standard errors to allay concern about misspecification.

We translate the timing in the model into calendar time. Calendar time covers days $t = 1, 2, 3 \ldots T$, having re-scaled t. The insider becomes informed on date t_0, $1 \leq t_0 \leq T$, and the information is publicly announced on date T. Finally, we have to specify the transition from regime A to regime B. We use a logistic function $f(t, t_0)$ as a continuous approximation to an indicator function for the shift to regime B, which maintains differentiability with respect to all the parameters.

Given these adjustments, if X stands for the matrix of all the explanatory variables and θ for the vector of parameters, then the conditional mean function

$$m(X, \theta) = \xi_0 + \gamma_1 (v - p_{t-1}) f(t, t_0) + \gamma_2 (v - p_{t-1}) (\frac{t - t_0}{T - t_0}) f(t, t_0) \tag{4}$$

where $f(t, t_0) = \frac{e^{(t-t_0)}}{1+e^{(t-t_0)}}$. Finally,

$$\Delta p_t = m(X, \theta) + \epsilon_t \tag{5}$$

where $\epsilon_t \sim \mathcal{N}(0, \lambda_t^2 \sigma_u^2)$. We estimate the parameters by Non-Linear Least Squares (NLLS).

Since we estimate the time at which the insider becomes informed, we allow the data to reject the Kyle model completely by estimating a $t_0 = T$. In other words, we do not impose the Kyle model *a priori*, but we allow the data to tell us if observed price patterns are consistent with the model's predictions. The important features we take from the Kyle model are the relevant variables and the functional form of the relationship among them. These features then guide our estimation and provide us with additional power to the extent they are correct.

3 Data

3.1 Sample of Targets

In some cases, public information about a merger or corporate control contest is widely disseminated well before the formal announcement. For our purposes here, it is useful to study a sample in which the researcher can identify *a priori* when the public announcement of information occurred.

Our sample of targets consists of a 107-firm subsample from Jarrell and Poulsen's (1989) study of tender offers. These firms are shown in Tables 1-3. Jarrell and Poulsen's sample consists of 172 (successful) cash tender offers from 1981 to 1985 in which the target was traded on the AMEX or NYSE.

Jarrell and Poulsen identify and distinguish the "news-adjusted date" from the formal announcement date. "Specifically, the news-adjusted date is the earlier of:

1. the day before the formal *Wall Street Journal* announcement of a 14D-1 filing or tender offer proposal, or the day of the ticker announcement if before close of trading (the "formal" date), or

2. the public disclosure (usually over the Dow Jones ticker) of a Schedule 13D filing with a possible intention to seek a change of control, or

3. the public announcement of merger talks naming the target firm."[7]

For our sample, we use 107 of the 108 tender offers in which the "news-adjusted date" was the same as the formal announcement date.[8] In other words, we estimate the gradual incorporation of information in an environment in which we can be reasonably confident of the date at which the information became public.

It will be convenient to discuss briefly our treatment of the data. In particular, we indicate how we take market movements into account.

3.2 Data Treatment

Although much of the literature in financial economics concerns equity *returns*, in our environment it is clearer if we speak in terms of *prices*. Since we nevertheless wish to control for movements in a security's price that are generated by its comovements with the overall stock market, we compute *market-adjusted* prices in the following way.

Using the returns on the individual 107 target firms, we first estimate an OLS market model over the 250 trading days from 310 trading days before to 61 trading days before the

[7] Jarrell and Poulsen, pp. 231-232.

[8] We excluded one additional firm, Breeze Corp. (BRZ), since trading in its stock was suspended well before its announcement date.

announcement date. We use the formal announcement date in the Jarrell-Poulsen appendix for each target.[9] We estimate

$$R_{it} = \alpha_i + \beta_i R_{mt} + \nu_{it} \tag{6}$$

where R_{it} is the return on stock i and R_{mt} is the return on the CRSP equally weighted index for day t.[10]

Then for the period from 60 trading days before the announcement up to the day after the announcement, we form prediction errors over the potential leakage period:

$$A_{it} \equiv R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \tag{7}$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are OLS estimates from the market model estimation period. A_{it} is an indicator of abnormal performance on day t, a standard measure used in many stock market studies.

We translate A_{it} into a market-adjusted price $p_{i,t}$ by the formula:

$$p_{i,t} = (1 + A_{it}) p_{i,t-1} \tag{8}$$

after having normalized $p_{i,1} = 1$.

Intuitively, if all fluctuations in a stock's price during the potential leakage period could be accounted for by market movements, there would be no abnormal performance and no information incorporation. Therefore A_{it} would equal zero each day, and the market adjusted price $p_{i,t}$ would be flat, equal to 1 each day.[11]

[9] In five cases, the target did not trade on its announcement day. For these five (CEQ, CNG, DWR, RED, and TG), we substitute the next day each stock traded.

[10] Employing the CRSP value weighted index as the market measure had negligible effects on the estimated market model parameters.

[11] This market adjusted price avoids some measurement problems raised in the literature. The standard measure of long run abnormal performance is the buy-and- hold abnormal return (BHAR), which is the difference between a firm's multi-period compounded gross return and the multi-period compounded gross return on a benchmark portfolio, such as the market. Mitchell and Stafford (2000) point out that the compounding in the BHAR formula means that the BHAR is increasing in the holding period, the number of days of compounding, even if true abnormal performance exists over a short time interval. Our measure avoids this problem since we compound only the indicator of single period abnormal performance. A separate concern is that if $\hat{\alpha}$ was substantially removed from zero, then compounding could impart erroneous drift to our market adjusted prices. This is not a problem here, since $\hat{\alpha} = 0.00095$, and a similar pattern emerges if we constrain $\alpha = 0$.

4 Results

In our implementation of Kyle, the dependent variable is the change in market-adjusted prices, Δp_t. We use the market-adjusted price the day after the formal announcement as our estimate of the liquidation value v, since by that date all investors should know the news conveyed by the tender offer. By beginning estimation of the Kyle model at 60 days before the announcement date, we include more pre-announcement days than is typical in event studies of targets.[12] This choice is designed to accommodate a reasonably lengthy diffusion process while attempting to avoid including extraneous innovations far removed from the announcement date.

The central prediction of the Kyle model is that price changes should depend positively on $(v - p_{t-1})$, and that this dependence should grow more pronounced as the public announcement date grows near. Before we estimate our formal econometric specification, we present an initial, descriptive regression. So we regress Δp_t on the variable $(v - p_{t-1})$ interacted with dummy variables for the six 10-day periods preceding the announcement date. This reveals how strong an explanatory variable $(v - p_{t-1})$ is in different time periods leading up to the announcement date. The OLS estimates are reported in Table 4, and the pattern is consistent with a gradual and increasing leakage of information about the true liquidation value of the stock, and with predictions of the Kyle model. In fact, the coefficient estimates increase *monotonically* as the announcement date approaches, and the estimates are statistically significant in each time period. For example the coefficient of .0358 on $(v - p)_{51-60}$ is over 7 times the coefficient on $(v - p)_{1-10}$. Thus price changes are much more sensitive to $(v - p)$, or potential insider profits, in days 51-60, the last 10 trading days before the formal announcement.

These results are very suggestive, but the formal econometric specification allows for more structure and hence greater efficiency. So we return to the conditional mean function in equation (4). We first restrict this model by setting $\gamma_2 = 0$. We estimate this restricted model by constraining the remaining parameters to be equal for all the firms. This includes

[12] Bradley, Desai and Kim (1988) and Jarrell and Poulsen use 20 days, Dodd (1980) uses 40 days. Keown and Pinkerton (1981) use up to 125 days, but their results suggest that the run-up in the target's price does not begin until 25 days before the announcement.

constraining all firms to have the same transition time t_0. The results of NLLS estimation of the restricted Kyle model are reported in Table 5.

The theory predicts a zero constant term, but we allow for a non-zero constant term to serve as a specification test. The estimated constant term, ξ_0, is small and is not statistically significantly different from zero, which is reassuring. The coefficient γ_1, which measures the sensitivity of price changes to $v - p_{t-1}$, is positive and very statistically significant, also as predicted by the theory. Note that this establishes more than just that price changes are positive over the sample period, but that these price changes are sensitive to $(v - p_{t-1})$, the extent to which the target is currently undervalued given the insider's private information. Finally, t_0, the estimated date at which the insider receives his information, is just under 47.8 in this 60-day sample period, corresponding to 12.2 trading days before the public announcement. The 95 percent confidence interval around the estimated t_0 ranges from day 46.6 to day 49.0. Both the point estimates and the confidence interval involve days that are somewhat closer to the announcement date than one might expect from some of the existing literature on merger targets, but are nonetheless reasonable. Meulbroek (1992) provides direct evidence on trading activity from public and non-public SEC data from illegal insider trading cases. In her sample, "on average, insider trading takes place 13.2 trading days (median=6.0) before the inside information is publicly announced," quite close to our estimate of 12.2 days.

In the next specification, we include both $(v-p)$ and $(v-p)t$ as regressors, and constrain t_0 to be the same for all firms. The results are reported in Table 6, and they are further confirmation of the implications of the Kyle model.[13] In particular, γ_2, the coefficient on $(v - p)$ interacted with time, is positive and statistically significant. The coefficient γ_1 is also positive but is not statistically significant. Note however that the two explanatory variables are highly collinear and the F-test on the joint hypothesis that both γ_1 and γ_2 are zero is overwhelmingly rejected.[14] This pattern is directly implied by the Kyle model; the theoretical parameter δ_t, the coefficient on $v - p_{t-1}$ in the model, is increasing in t.

[13] The results we report were obtained from a wide range of reasonable starting parameter values. For large starting t_0 values, the estimates converge to the degenerate case of $t_0 \simeq 60$.

[14] The value of $F(2, 6416) = 67.36$, with a p-value of 0.0000.

Intuitively, the informed trader should trade more aggressively on his private information on how much the target is undervalued as his monopoly on that private information is about to evaporate. The other results are robust. The estimate of t_0, at 46.05, is not far removed from that found in the restricted model, although the precision is reduced. And the constant term ξ_0 remains the same, small and not significantly different from zero, as predicted by the theory.

These specifications have imposed that t_0 be equal across all firms, and so what we have estimated could be interpreted as the average value of t_0. One may, however, be interested in the dispersion of t_0 across targets. Our final model, then, is analogous to the Table 5 specification, except we estimate a separate transition time t_0 for each firm. First, our estimates of ξ_0 and γ_1 are fairly robust to this change in specification. The estimate of ξ_0 is still small ($\hat{\xi}_0 = -0.0008$) and not statistically significant at the 5 percent level ($SE = .0004$). The estimate of γ_1 is close to that in Table 5 ($\hat{\gamma}_1 = 0.0325$) and is very significant ($SE = .0021$).

The 107 remaining estimated parameters from this model, hard to interpret in table form, are presented in Figure 2 as a histogram.[15] Before interpreting these results, it should be noted that this is a histogram of *estimated* firm-specific transition times, as distinct from a histogram of *true* firm-specific transition times. Therefore, the underlying distribution of estimated times will have a higher variance than the underlying distribution of true times because each has a positive standard error associated with it. Our estimated times have an average standard error of 6.46.

With that caveat in mind, we point out a few interesting features of this histogram. First, we have significant heterogeneity in our estimated times. Second, the bulk of our estimated times lie between approximately day 30 to day 45, or 30 to 15 days before the announcement. Most of the existing merger literature assumes or finds that leakage begins in that range. Finally and perhaps most interestingly, the histogram has two significant modes, the main one slightly after day 40 and the second one much closer to the announce-

[15] In estimating this 109 parameter model with NLLS, we obtained convergence according to standard default criteria. However, the objective function was sufficiently flat in the directions of some of the parameters that standard errors could not be obtained for them. We have omitted those estimates from the histogram.

ment date. This feature suggests two types of information structures, one where the secret is well-kept and one where significant pre-announcement leakage occurs.

Our results have a number of interesting implications. First, we find evidence (as have others before) of significant leakage of information ahead of corporate control announcements. Despite using quite different techniques, our findings are fairly consistent with that previous empirical literature. Second, we find evidence of significant heterogeneity across firms as to when this leakage begins, and, in particular, a bimodal distribution of these estimated transition times. Third, we find features of these data consistent with theoretical models of informed trading, such as the increasing sensitivity of the value-price gap over time. Taken as a whole, we think these results add significantly to our knowledge of the nature and structure of preannouncement price run-ups.

We should note that while the researcher would usually lack independent information identifying t_0, an exception comes from prosecuted illegal insider trading cases.[16] We could, therefore, identify such as case, add that firm to our sample, and compare its estimated t_0 with the relevant transition date identified in trial documents. To do this, we use the high profile case of Martha Stewart, CEO of Martha Stewart Living Omnimedia, and Sam Waksal, CEO of ImClone Systems (IMCL), concerning their trades in IMCL.[17] When we perform this additional estimation, our estimated transition date is 40.99 (with $SE = 5.68$). The actual trading date from trial documents is 58, and so beyond our 95 percent confidence interval. This estimation does not provide the corroboration we might have hoped for, suggesting that more weight should be placed on the broader and more robust features of the estimation and less on individual $\hat{t}_0$s, perhaps.

In addition to supplementing our qualitative knowledge of these run-ups, our methodology could have broader applicability, in particular to the execution of event studies with event date uncertainty or gradual diffusion or revelation of information. Applied researchers employ a number of methods to address this situation. For example, they may produce

[16] We thank an anonymous referee for suggesting this avenue.

[17] Associated Press, "Timeline of Events in the Martha Stewart Stock Scandal," USA Today, accessed from www.usatoday.com/money/industries/retail/2004-07-15-stewart-timeline.htm

graphs of Cumulative Average Abnormal Returns (CARs) over multiple days before and after an event, or they may widen the event window so as not to miss the impact of the event. As Salinger (1992, 1994) notes, the latter procedure as typically applied results in incorrect standard errors, and he provides an appropriate correction.

Our method suggests two alternatives.[18] First, rather than assuming a particular event window, the researcher could estimate it, just as we have estimated the transition time for when the insider became informed. Second, in some settings the researcher may be concerned about heterogeneity in pre-announcement leakage across the sample. So one may estimate different event windows across different firms, corresponding to the differing transition times summarized in Figure 2. We offer these suggestions with a couple of caveats, however. As the IMCL example above demonstrates, estimating separate transition dates sacrifices degrees of freedom and produces results that will not be as robust as those from more parsimonious specifications. In addition, the estimation algorithm may have difficulty recovering all parameter estimates. The researcher should weigh these factors.

5 Conclusion

In this paper, the price movements ahead of tender offers were shown to be characterized by a gradual incorporation of information. Accounting for this gradual incorporation revealed elements of the price process. These elements are broadly consistent with the implications of the Kyle model of informed trading.

Since corporate control transactions generate valuable private information, this is a natural setting in which to implement a model of informed trading. But there is also possible gradual incorporation of information ahead of other corporate events, such as an earnings announcement, or an important regulatory decision, such as FDA approval for a drug. Price run-ups may precede some of these events, and the techniques used in this

[18] There is a small literature on event-study methodology that is related, but nonetheless differs significantly from this problem. Ball and Torous (1988) address the situation of event-date uncertainty, in which the researcher knows that an event took place on a single day within some time period, but does not know which date. But in their setting the news event and its incorporation into stock prices occurs at a single, albeit unknown, date, rather than occurring gradually. Ellison and Mullin (1995, 2001) examine settings where one finds gradual incorporation of information into stock prices, both quite distinct from this one, and discuss appropriate empirical techniques for addressing the gradual incorporation.

paper could be applied to these other environments.

Table 1: Tender Offer Targets Sample

Company	Ticker Symbol
Aegis Corp.	AO
Amalgamated Sugar Co.	AGM
American Nat. Res.	ANR
ANTA Corp.	ANA
Applied Data Resh. Inc.	ADR
ARO Corp.	ARO
Bache Group Inc.	BAC
Brunswick Corp.	BC
Burgess Inds. Inc.	BGS
Cannon Mills Inc.	CAN
Cardiff Equities Corp.	CEQ
Caressa Group Inc.	CSA
Carnation Co.	CMK
Cenco Inc.	CNC
Cessna Aircraft Co.	CEA
Chieftain Development Corp.	CID
Chilton Corp.	CHN
Clausing Corp.	CLA
Coldwell Banker & Co.	CBC
Compugraphic Corp.	CPU
Connecticut Nat. Gas. Corp.	CNG
Conoco Inc.	CLL
Continental Airlines Corp.	CAL
Cox Communications Inc.	COX
Criton Corp.	CN
Dean Witter Reynolds Inc.	DWR
Delhi Intl. Oil Corp.	DLH
Donaldson, Lufkin & Jenrette Inc.	DLJ
Enstar Corp.	EST
Esmark Corp.	ESM
Faberge Inc.	FBG
Franks Nursery & Crafts Inc.	FKS
Friona Inds. Inc.	FI
Garfickel Brooks Bros Miller	GBM
Gas Svc. Co.	GSV
General Portland Inc.	GPT
General Steel Inds. Inc.	GSI
Getty Oil Co.	GET
G F Corp.	GFB
Giddings & Lewis Inc.	GID
Grand Central Inc.	GC
Gray Drug Stores	GRY

Table 2: Tender Offer Targets Sample, continued

Company	Ticker Symbol
Harsco Corp.	HSC
Heublein Inc.	HBL
Hobart Corp.	HOB
Informatics General Corp.	IG
Itek Corp.	ITK
James Fred S. & Co. Inc.	JMS
Juniper Petroleum Corp.	JUN
Kentron Intl. Inc.	KTN
Lane Bryant Inc.	LNY
Levi Strauss & Co.	LVI
Lowenstein M. Corp.	LST
MGM Grand Hotels Inc.	GRH
Malone & Hyde Inc.	MHI
Marathon Oil Co.	MRO
Marshall Field & Co.	MF
McGraw Edison	MGR
Mesa Royalty Trust	MTR
Mite Corp.	MTE
N I Industries Inc.	NIN
Nabisco Inc.	NB
Narco Scientific Inc.	NAO
Northwest Energy Co.	NWP
Northwest Inds. Inc.	NWT
Northwestern Mutual Life	NML
Norton Simon Inc.	NSI
Opelike Mfg. Corp.	OPK
Pacific Lumber Co.	PL
Pay Less Drug Stores NW	PAY
Peoples Drug Stores Inc.	PDG
Petrolane Inc.	PTO
Puritan Fashions Corp.	PFC
Real Estate Investment Trust America	REI
REDM Inds. Inc.	RED
Revlon Inc.	REV
Richardson Vicks Inc.	RVI
Rio Grande Inds. Inc.	RGI
SCA Services Inc.	SCV
SCM Corp.	SCM
Schlitz Jos. Brewing Co.	SLZ
St. Joe Minerals Corp.	SJO
St. Regis Corp.	SRT
Schrader Abe Corp.	AMS
Scovill Inc.	SCO

Table 3: Tender Offer Targets Sample, continued

Company	Ticker Symbol
Searle G. D. & Co.	SRL
Signal Cos. Inc.	SGN
Southland Rty. Co.	SRO
Spectro Inds. Inc.	SPO
Speed O Print Bus. Mach.	SBM
Sta Rite Inds. Inc.	SRE
Stauffer Chemical Co.	STF
Suburban Propane Gas Corp.	SPG
Sunbeam Corp.	SMB
Technicolor Inc.	TK
Texas Gas Res. Corp.	TXG
Texasgulf Inc.	TG
Thiokol Corp.	THI
Torin Corp.	TOR
Transway Intl. Corp.	TNW
Uniroyal Inc.	R
United Energy Res. Inc.	UER
United Rlty Invs. Inc.	URT
United States Inds. Inc.	USI
Unocal Corp.	UCL
Vulcan Inc.	VX
Walbar Inc.	WBR

Table 4: Kyle Model, Reduced Form

Regressor	Estimate	Stand Err	T Stat
$(v-p)_{1-10}$	0.0060	0.0021	2.94
$(v-p)_{11-20}$	0.0076	0.0023	3.26
$(v-p)_{21-30}$	0.0090	0.0027	3.31
$(v-p)_{31-40}$	0.0131	0.0032	4.11
$(v-p)_{41-50}$	0.0149	0.0039	3.85
$(v-p)_{51-60}$	0.0361	0.0052	6.90
constant	-0.0026	0.0007	-3.59

Dependent Variable is Δp_t, change in market adjusted prices. Estimated by OLS over $T = 60$ trading days. The standard errors are heteroskedasticity-robust.

Table 5: Results, Restricted Kyle Model

Parameter	Estimate	Stand Err	T Stat
ξ_0	0.0004	0.0004	0.86
γ_1	0.0293	0.0025	11.75
t_0	47.7859	0.6174	77.39

Dependent Variable is Δp_t, change in market adjusted prices. Estimated by Non-Linear Least Squares over $T = 60$ trading days. The standard errors are heteroskedasticity-robust.

Table 6: Results, Kyle Model

Parameter	Estimate	Stand Err	T Stat
ξ_0	0.0004	0.0004	0.89
γ_1	0.0005	0.0198	0.03
γ_2	0.0505	0.0210	2.41
t_0	46.0479	4.6414	9.92

Dependent Variable is Δp_t, change in market adjusted prices. Estimated by Non-Linear Least Squares over $T = 60$ trading days. The standard errors are heteroskedasticity-robust.

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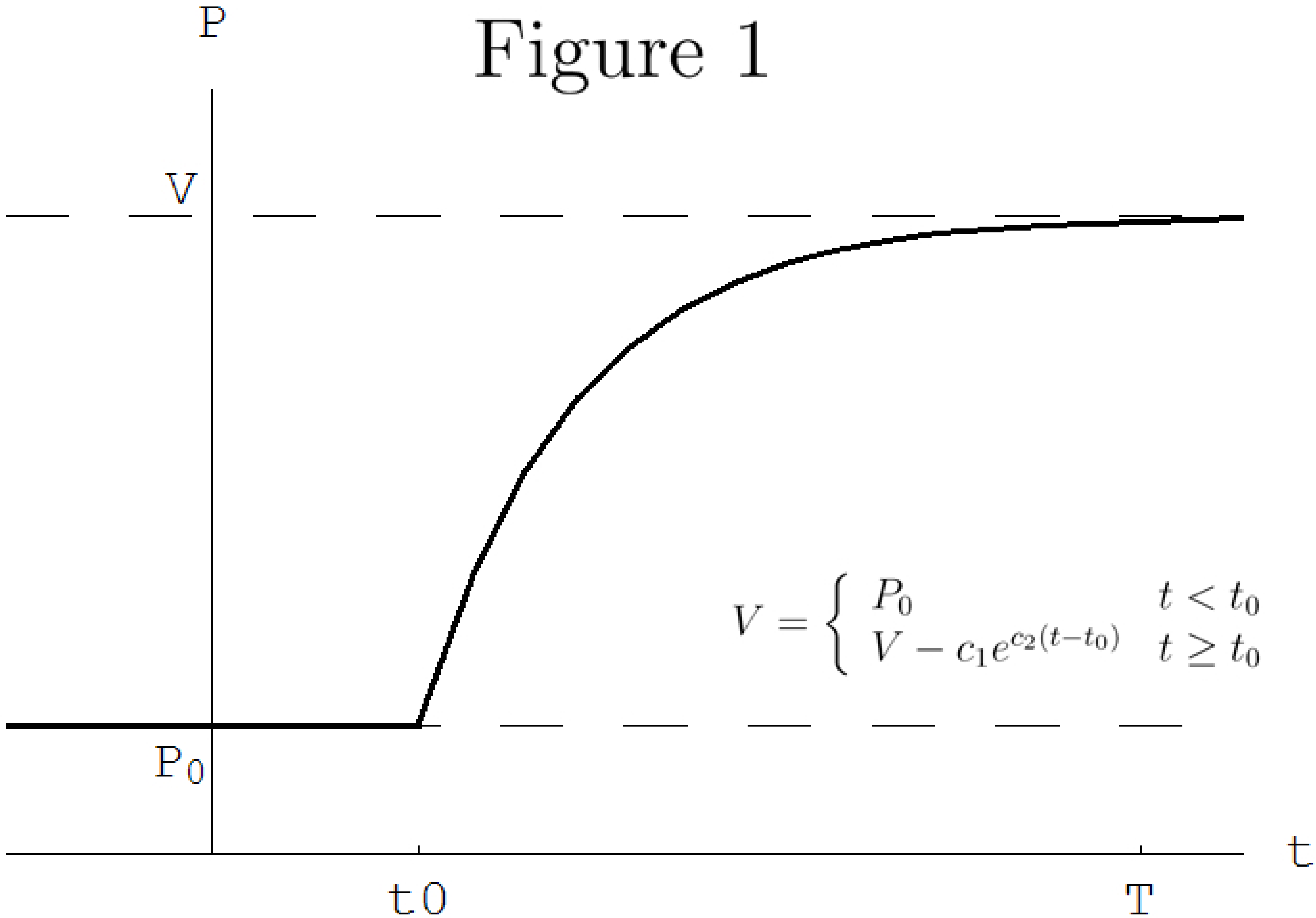
Figure 1



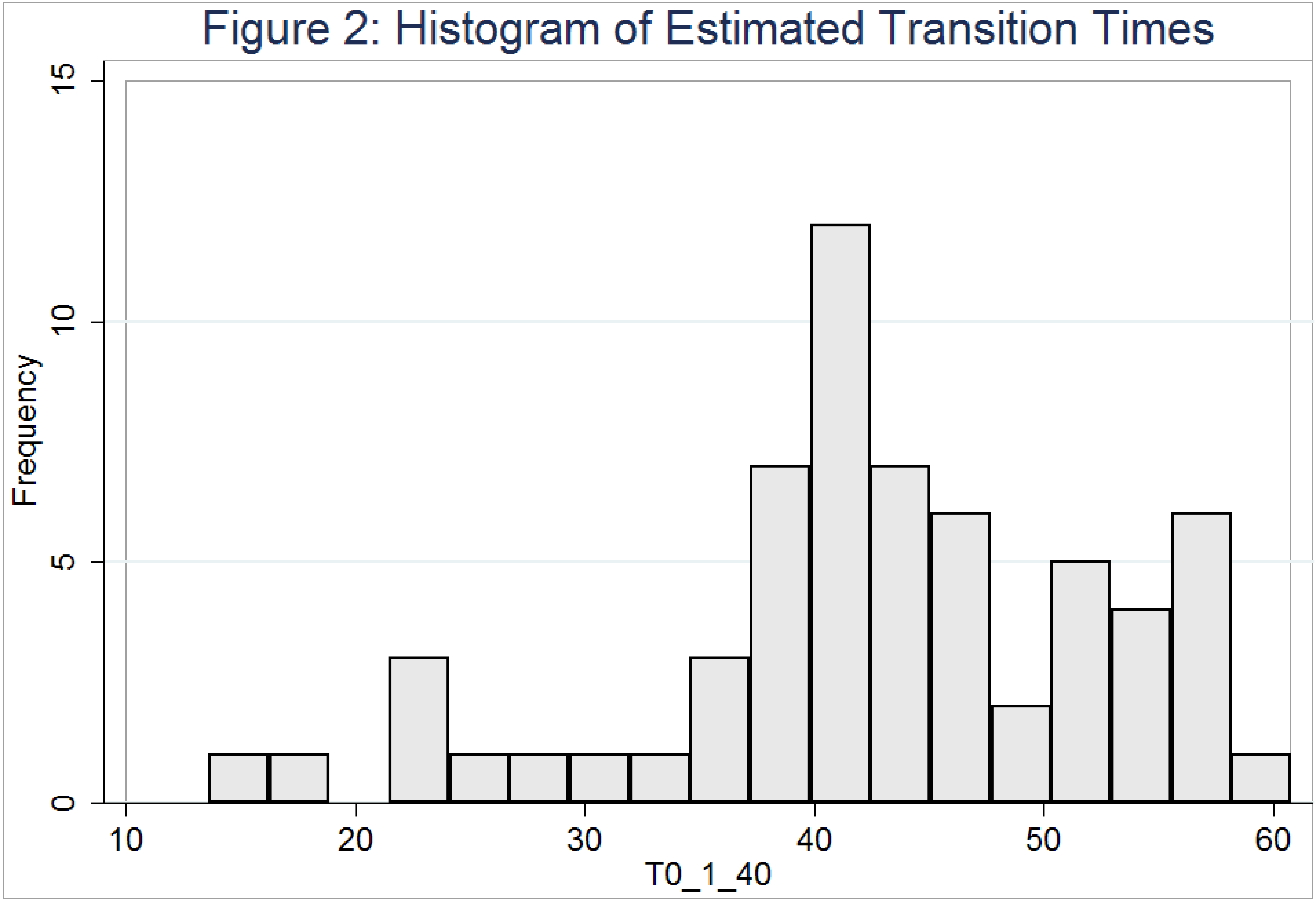


Figure 2: Histogram of Estimated Transition Times
Frequency
0
5
10
15
10
20
30
40
50
60
T0_1_40