Pharmaceutical Settlements under the Hatch-Waxman Act: Stock Price Analysis of Generic Firms

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I.1 Background

Patents incentivize innovation by giving firms a period of market exclusivity during which they can earn returns to recover the high Research and Development (R&D) expenditure they incurred to develop their innovations. Market exclusivity describes the period of a time in which a firm has a monopoly over its invention. In the pharmaceutical industry, patents play an especially central role because a significant portion of costs come from R&D in laboratory work, clinical trials, and other tests to prove safety and efficacy. After a drug's composition is determined, the actual manufacturing costs are low compared to the R&D costs. After the inventing firm – which will be referred to as the "brand" firm – develops a drug, without a patent, any other company can use this formula to manufacture and sell the drugs without costly R&D expenditures. These later firms will be referred to as "generic" firms, as they manufacture generic versions of brand firm drugs. Sales lost by a brand name company after generic entry are between 14%-41%, which represents $157 billion worth of industry-wide sales.[1] In addition, prices fall an average of 85% after generic entry, with generic market penetration rates[2] of around 90%.[3] Immediate generic competition implies that a brand company cannot maintain the prices and market share needed to recover high R&D costs. Patents are essential to encourage companies to continue to invest millions of dollars into R&D and continue to innovate, giving brand firms a chance to recover some R&D costs before a generic manufacturer enters. Since the regulatory framework surrounding this topic is complex, the first section will outline how patents and patent challenges work under the Hatch-Waxman Act, the current central legal framework surrounding patents and patent challenges.

When a company develops a new drug after obtaining promising laboratory results, they will attempt to run clinical trials to prove that the drug meets Food and Drug Administration (FDA) standards. After the company discovers promising information on a drug's safety and efficacy in initial trials, they submit a New Drug Application (NDA) to the FDA. If the FDA approves the NDA, the company has the right to market the drug to the public. The firm can then apply for a patent separately at the U.S. Patent and Trademark Office (USPTO). A patent is a property right issued by the USPTO to an inventor to "exclude others from making, using,

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[1] Schacht (2012).
[2] The generic penetration rate is the total amount of sales provided by generic firms compared to the total market for the drug.
[3] FTC (2010).

offering for sale, or selling the invention throughout the United States or importing the invention into the United States" for a set period of time. Generally, patents are granted for 20 years from the date on which the application was filed. Patents are usually filed within 30 days of NDA approval. After the patent is approved, it is placed on the FDA's Approved Drug Products with Therapeutic Equivalence Evaluations, otherwise known as the Orange Book, which is a listing of drug products approved by the FDA on the basis of safety and efficacy and current standing patents.

A patent usually includes the specification of a certain compound, or pharmaceutical composition, in addition to a method of how to use the compound in the treatment or prevention of a disease. A patent can be as broad as to protect the entire compound and its use in any way or as narrow as to protect only a small modification to an existing drug. For example, a company could patent an extended-release version of an existing compound or combine two successful compounds to market as a new drug, and the patent would only protect these modifications rather than the actual compound itself. For racemate drugs that are compounds with multiple enantiomers (mirror-image molecules with the same chemical composition), companies often change the enantiomer and alter the chemical compound slightly, and some patents would only protect this new enantiomer modification. In addition, companies can also patent new uses of existing compounds and market them as a different drug. The patent protection strength is a combination of the patent length and breadth of protection.[4] Both of these components are included in the patent application that the company fills out, but ultimately determined by the USPTO at the time of patent issuance.

An important aspect of USPTO patents is that the drug is not put under intense scrutiny before the patent is granted. The USPTO simply does not have enough resources to ensure that each patent granted has the length and strength that accurately reflects the novelty of the drug it protects. Therefore, patent litigation serves to discover and establish the optimal length of a patent. When a patent is challenged, the decision that results and the entry date that prevails should reflect the optimal amount of patent protection that balances incentives for innovation with the costs of temporary monopoly. The importance of patent litigation can be seen in a Federal Trade Commission (FTC) study from 2002, where 73% of all patent cases that went to trial were won by the generic. This statistic indicates that a larger number of patents issued by

[4] Gupta et. al (2010).

the USPTO were given a stronger protective power than they should have been given, based on how beneficial the patented drug is to society. While settlements without payments may allow firms to reach a decision that would have been reached in court without costly litigation,[5] settlements with payments distort this optimality discovering process.

I.2 Intuitional Framework of the Hatch-Waxman Act

The Drug Price Competition and Patent Term Restoration Act of 1984, known as the Hatch-Waxman Act (H-W), set incentives for both brand and generic drug companies to obtain and challenge patents in the pharmaceutical industry. Among many other policies, H-W outlined a cheaper and faster process for generic companies to enter the market to encourage generic competition. This accelerated process begins with the generic filing an Abbreviated New Drug Application (ANDA) on a patented drug to the FDA. An ANDA means that a generic firm can utilize trials and data already compiled by the brand firm as long as they prove bioequivalence.[6] It is much less costly to develop a new drug through an ANDA than an NDA, as the brand firm has paid for the vast majority of R&D expenses when they filed their NDA. However, for brand drugs that are patented, an ANDA is by definition an act of patent infringement. H-W specifies four special procedures to address ANDA-related patent disputes. Generic firms must prove one of the following about the patent that their ANDA may violate:

(I) The patent has already expired
(II) The patent has not yet been filed
(III) The generic won't market their drug until the patent expires
(IV) The existing patent is invalid or not infringed

In the last clause, proving a patent is “invalid” means demonstrating that the patent should have never been issued in the first place because the invention it protects is not novel enough to warrant such a patent. Proving that a patent is “not infringed” by the ANDA generic drug involves demonstrating that the generic drug in question does not fall in the scope of exclusion specified by the patent. Proving either a patent is invalid or uninfringed allows the generic firm to enter immediately after the litigation is won. The last clause is called a Paragraph IV

[5] This idea will be investigated further later in this paper.
[6] “Bioequivalence” means that the generic drugs uses the same active ingredients and the same dosage will cause the same absorption rate into the body as the brand drug.

certification of the ANDA filing and usually results in patent litigation. These Paragraph IV patent disputes are the focus of this paper.

Drugs approved by the FDA are the only products in which a competitor must resolve conflicting patent claims before entering the market. Therefore, after the Paragraph IV ANDA is filed, if the brand firm sues within 45 days, the FDA must wait until the earliest of the following three events before approving the generic firm's ANDA:

(1) The generic wins the patent trial in court by proving that the patent is invalid or that their generic drug does not infringe upon it
(2) 30 months pass and no court decision has yet been made
(3) The patent expires

If (2) occurs and the FDA approves the ANDA without a court decision, then the generic may market their drug "at risk," which means that they must pay damages to the brand firm if a court eventually finds the patent valid or infringed by the generic drug. If the brand firm does not sue within 45 days, the FDA can approve the ANDA at any time, but the costs of damages will be up to the generic filer to pay if the brand firm eventually sues and the patent is found valid or infringed by the generic drug. By the end of 2009, 55% of all approved brand name drugs (299 out of 692 total drugs) had Paragraph IV challenges, an increase from around 20% in 1984 when H-W was first passed.[7] Paragraph IV ANDAs have become a central way in which generic firms raise patent challenges in the pharmaceutical industry.

As with any litigation, the parties can opt to "settle" on an agreed entry date before the actual hearing itself. This saves both the brand and generic firms costly litigation fees. However, in many ANDA Paragraph IV cases beginning in the 1990s, the brand firm made a payment to the generic firm as a stipulation of their settlements. These were deemed "reverse payments," as the party suing pays the party being sued. These reverse payments have been accused by the FTC of being collusive, since the brand firm "pays for the delay" of the generic firm. Reverse payment settlements could involve a cash payment, but more often involve some sort of business side deal. These non-cash side deals fall into a number of categories:

(1) Noncash business side deals: includes licenses from the brand firm to the generic to market/produce other drugs, supply of certain drugs to the generic firm, etc.

[7] Hemphill & Sampat (2011) conduct a large-sample study of patent challenges on 1,481 drugs approved by the FDA 1985-2008.

(2) No-AG clauses: authorized generics (AG) are the brand firm's own generic version of their drug. The brand firm may market their AG or, more often, partner with a generic manufacturer to do so. AG's are allowed during an ANDA filer's 180-day exclusivity period, so agreeing not to market an AG sacrifices brand firm profits

(3) Retained exclusivity: a third type of nonmonetary "pay for delay" settlement that may not involve direct monetary payment, but involves the brand firm allowing the generic to maintain the 180-day exclusivity period by agreeing to drop the patent fight at a later date, so that the generic first filer has a higher probability (essentially a sure chance) of getting 180 days of exclusivity than if they go to court

In a study conducted by Hemphill (2009), out of a dataset of 101 drugs with settlements, 51 (50%) drugs had settlements with payments and 48 (47%) had settlements without payments.[8] Out of the 51 drugs with payments: five were cash (~10%), 16 involved side deals (~30%), and 25 had the retained exclusivity agreement only (~50%).[9] Of the cash and side deal monetary payments, most generics also were guaranteed retained exclusivity as part of the settlement. Most deals in recent years involve complex side deal or retained exclusivity agreements. These deals are difficult to estimate in value and therefore add more difficulty when litigating antitrust consequences of reverse payment settlements.

It is important to examine these reverse payment settlements and question whether or not they have anticompetitive effects through collusive entry deterrence. If weak patents were held for significantly longer because the brand is paying the generic to stay out, these settlements would be extremely costly to consumers who must pay higher brand name prices for a longer period of time. The FTC (2010) estimates that settlements with payments have entry dates that are 17 months later than settlements without payments, using a weighted average based on drug sales. They further project that these 17 months account for an additional $20 billion in sales of brand drugs. These massive welfare consequences make it crucial to examine these settlements in detail to examine their effect on innovation and competition.

I.3 Literature Review

[8] For two drugs, the generic firm acquired the brand firm's rights to the drug and thus resolved the patent dispute through acquisition.

[9] Five drugs are other types of deals that restrict entry while the patent suit is pending but are not settlements about the outcome of the suit.

Shapiro (2003), as well as Elhauge and Krueger (2012), proposes the fundamental idea that a settlement is anticompetitive if the length of patent protection under the settlement extends beyond the patent's expected length under litigation (since litigated patent length should reflect the patent's true strength). While the ideal test for anticompetitive effects would be comparing the patent length under settlement with what would have prevailed in litigation, it is extremely difficult to compare the patent length to what *would have happened* in a normal trial. The theoretical arguments stemming from the Supreme Court case *FTC v. Actavis* attempt to evaluate the presence of antitrust concerns through the proxy of payment size. However, other economists have argued that settlements could serve functions other than entry deterrence, such as a risk premium or bridging a decision gap between players with asymmetric information. On the other hand, some empirical studies try to test this very idea by examining patent lengths established by settlements with and without payments.[10] Another study, Drake, Starr, and McGuire (2013), explores the empirical implication of this idea by examining stock price hikes of brand firms that settle with payments vs. without payments.[11] Theoretical arguments vastly outnumber empirical ones due to lack of data on the specific terms of the settlements and financial information on the firms involved.

II.1 Literature Review – Theoretical Studies

Due to the fact that settlements that involve payments occur often in litigation, one argument that these settlements are not anticompetitive is that they allow two parties with differing opinions about the strength of the patent to logistically reach an agreement without incurring litigation costs. Willig and Bigelow (2004) argue that payments may be essential for negotiating settlements when two parties have different information, expectations, and levels of risk aversion. For example, if a brand firm believes the patent is very strong, and the generic believes the patent to be very weak, then there would be no way to bridge the "gap" between their expectations without some payment:

> "The circumstances of information asymmetry, expectation asymmetry, or subsequent entry are not rare, and so it can be expected that a policy of condemnation of agreements with financial payments would be unnecessarily costly to society in repressing socially beneficial settlements, and fomenting otherwise unnecessary litigation."'

[10] FTC (2010) found that settlements with payments delayed entry by an average of 17 months longer than settlements with payments.
[11] Drake et. al (2013) will be discussed in detail in the "Empirical Studies" section of this paper.

However, this argument is limited in its treatment of the motivation for making payments. For example, since the sum of duopoly profits are proven to be less than monopoly profits, there is a strong incentive for the brand firm to pay a sum of money to delay entry in a mutually beneficial agreement with the generic firm at a cost to consumers. We can refer back to the fact that after generic entry, brand companies lose 14%-41% of their sales on the drug and therefore can be better off with a settlement as long as payments do not exceed sales lost due to generic entry. While it is true that not all settlement payments are anticompetitive, ignoring anticompetitive effects by providing only one motivation for the presence of payments is limiting.

The reasoning proposed by Willig and Bigelow could be valid when arguing against the use of *per se* illegality of reverse payment settlements. Prior to *FTC v. Actavis* in 2013, the courts were split on whether these payments should be presumed anticompetitive (*per se*) or whether the scope-of-the-patent test should be applied. The scope-of-the-patent test states that an agreement is illegal only if the agreement reduces competition and gives the brand firm more market power than what the patent originally granted. This argument assumes that the length of every patent granted by the USPTO reflects its optimal protection strength and therefore settlements are not anticompetitive as long as they set entry dates earlier than those set by the original patent. This test is deeply flawed because it does not take into account the crucial function that patent litigation serves as checking patents to make sure they actually reflect the optimal protection strengths. Therefore, while the *per se* approach could be too restrictive, the scope-of-the-patent test is also far too lenient in the antitrust examination of reverse payment settlements.

In Supreme Court case *FTC v. Actavis* (2013), the generic firm Actavis was accused of anticompetitive activity when it entered into a reverse payment settlement with brand firm Solvay. The exact settlement terms are not publicly available, but it involved Actavis agreeing not to bring a generic version of AndroGel to market for a specified number of years and promoting AndroGel to doctors in exchange for millions of dollars from Solvay.[12] The Supreme Court rejected both the *per se* approach and scope-of-the-patent test, ruling that these reverse payment settlements should be reviewed by the rule of reason antitrust standard. This marked a turning point in the litigation of reverse payment settlements, because the Court explicitly established that these payments should be treated as an antitrust issue.

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[12] *FTC v. Actavis, Inc.*, 133 S. Ct. 2223, 2227 (2013).

While the Court left the exact construction of the rule of reason test to lower courts, it did establish a few fundamental ways to examine whether a reverse payment is anticompetitive. Firstly, the Court unanimously decided that anticompetitive activity should not be determined by comparing the length that would have prevailed had there been a trial against the length of protection established by the settlement. In other words, courts should not hold a mini-trial on patent validity within an antitrust trial. This is not only time consuming and difficult, but it forces firms to go to trial on the very issue they settled on to avoid having to go to trial.[13] Secondly, to avoid this patent mini-trial, the Supreme Court proposed that there is a link between the size of the reverse payment and degree of anticompetitive effect:

> "…the likelihood of a reverse payment bringing about anticompetitive effects depends upon its size, its scale in relation to the payor's anticipated future litigation costs, its independence from other services for which it might represent payment, and the lack of any other convincing justification."[14]

Thirdly, the Court's decision more specifically states that the settlement is likely anticompetitive when the payment size exceeds the benefits that the brand firm gets out of the settlement – which the court calls "justifications" for payments to the generic. Justifications include savings on litigation costs and the value of any other services the generic may pay to the brand firm as a result of the settlement (through side business deals).[15]

Edlin, Hemphill, Hovenkamp, and Shapiro (EHHS) (2013) construct a model of the Court's decision in *Activating Actavis* based on the test outlined in Justice Breyer's opinion. This test, popularly coined as the Actavis Inference, states that anticompetitive activity is present when:

(1) The generic's entry is delayed from the date they initially intended to enter from filing the ANDA
(2) Reverse payment size is greater than the brand's litigation costs plus the value of goods and services provided by generic to the brand

If (1) and (2) are true, then the settlement must be anticompetitive because there is no other explanation or justification for this excess payment than delayed entry beyond what is optimal

[13] 2243 (Roberts, C.J., dissenting) (noting bad results if "immediately after settling, the parties would have to litigate the same issue—the question of patent validity—as part of a defense against an antitrust suit").
[14] *Ibid*, 20, Opinion of the court.
[15] *Ibid.*

for consumers. EHHS propose a mathematical model of the Actavis Inference in which a brand firm is willing to settle if:

$$E > PT + \frac{X - C_A}{M_A - D_A} \qquad [1]$$

Where E is the entry date for the generic firm under the settlement. P is the probability of the brand firm winning the patent trial and T is the remaining length of the patent, so PT is the expected patent length from going to trial, which represents the optimal length of the patent. X is the settlement payment size, C_A is the brand firm's litigation cost, M_A is the brand firm's monopoly profits, and D_A is the brand firm's duopoly profits. This model assumes that after the generic firm enters at E, the brand and generic firms compete in duopoly until the patent expires. Using the definitions of this model, a settlement is anticompetitive when the settled patent length, E, exceeds the expected patent length from going to court, PT:

$$E > PT \qquad [2]$$

The EHHS model reaches the same qualitative conclusion as the Actavis Inference: when there is a large and otherwise unexplained settlement payment (when X exceeds C_A), the settlement is anticompetitive. Therefore, for EHHS, the threshold of the settlement size is the litigation costs of the brand firm, C_A. I will develop the generic version of EHHS's model in Section VII.2 – Results: Positive Returns in No Payment Group.

Since the EHHS model was published, two other theoretical models have been published in response. One model, proposed by Harris, Murphy, Willig, and Wright (HMWW) (2014) states that since brand firms are risk-averse, the EHHS model does not account for larger payment sizes due to risk aversion and therefore ignores a wide spectrum of settlements that are large but not anticompetitive. Many other authors, including Willig and Bigelow (2004) as well as Yu and Chatterji (2011), have also written about the brand firm's risk aversion as a justification for large reverse payments. However, it is possible that EHHS left this out on purpose, as the Supreme Court in *Actavis* addresses the risk aversion argument:

> "The owner of a particularly valuable patent might contend, of course, that even a small risk of invalidity justifies a large payment. But, be that as it may, the payment (if otherwise unexplained) likely seeks to prevent the risk of competition. And, as we have said, that consequence constitutes the relevant anticompetitive harm"[16]

[16] *Ibid*, page 19, Opinion.

Therefore, if payments due to risk aversion also mitigate risks that the patent will be proved invalid or not infringed in court the firm effectively pays to avoid risks of competition and any instances of this should be treated as anticompetitive. In other words, payments due risk aversion could be anticompetitive depending on the type of risk that the firm attempts to avoid with the payment.

Kobayashi, Wright, Ginsburg, and Tsai (KWGT) (2014) propose an alternative model in response to EHHS. This model suggests that the link between settlement payment size and anticompetitive activity is weak because EHHS assume monopoly to duopoly profits once entry occurs. KWGT state that a more accurate occurrence is monopoly to competitive market with multiple generic entrants. Under this model, the generic firm has less of an incentive to enter into the settlement because they get lower competitive profits while more entry imposes a greater loss on revenues for the brand firm and gives them a higher incentive to enter into a settlement. This makes the generic firm more receptive to a later entry date and the brand firm to an earlier one. This opens up the range of possible settlement payment amounts and entry dates, some of which would be deemed anticompetitive under the EHHS model. Therefore, KWGT argue that the EHHS model is too restrictive and is likely to trigger Type I error of falsely rejecting the null that no anticompetitive activity is present.

EHHS have responded to KWGT and argue that if the brand firm is avoiding even lower revenues from multiple generic competitors than just one generic competitor, they will have an even greater incentive to increase settlement payment size. A settlement rides on the amount of payment *the brand firm* is willing to pay and should be analyzed from their perspective, because there is no reason for the generic to accept a smaller payment if the brand firm is offering a large one. EHHS make a critical point that feasible settlements are not all relevant, as most are not optimal and would not be chosen in equilibrium. The set of welfare-increasing settlements proposed by KWGT that would be deemed anticompetitive are not equilibria and therefore do not play a role in undermining the Actavis Inference. EHHS have also produced a new theoretical model in which multiple generic entries serve an even greater incentive for anticompetitive payments.[17]

The EHHS, HMWW, and KWGT models form much of the theoretical debate on how to establish whether a reverse payment settlement is anticompetitive, especially after the Actavis

[17] Edlin et. al (2015).

case. However, the authors do not go into an empirical calibration of their models with previous settlements that have occurred between 1984 and today. This could be due to the fact that it is extremely difficult for an outside analyst to know the terms of the settlements (only a handful of settlements have terms released to the public) and it is even more difficult to estimate the value of side deals and non-AG payments. These theoretical models serve as instruction to courts on how to implement the *Actavis* decision when full terms of the deals are known.

II.2 Literature Review – Empirical Studies

In contrast, there have been two types of empirical studies that study whether settlements with payments are anticompetitive. One type investigates the average additional months of delayed competition in settlements with payments versus settlements without payments. Another, which will be the focus of this paper, analyzes brand firm stock price jumps on the settlement day to predict abnormal profits and therefore anticompetitive activity.

The first type of empirical study is conducted by the FTC in its 2010 report, *Pay for Delay*. The FTC examined a sample of 218 final patent settlements from 2004 to 2009, with 66 settlements with payments and 152 settlements without payments. The study examines the average sales-weighted length of delayed entry (due to the settlement) for settlements with and without payments, and determined that settlements with payments delayed entry for an average of 17 months longer at the 99% confidence level. While this is a statistically significant result, it assumes that the samples of settlements with delays and settlements without delays are similar in terms of sales-weighted averages. However, the study could be ignoring additional traits of drugs that settle with payment, and merely looking at average delays does not directly imply anticompetitive activity has taken place.

The second type of empirical study focuses on stock price movements of brand firms that settle. Drake, Starr, and McGuire’s (DSM) 2014 paper argues that if a settlement is considered anticompetitive when the expected entry delay with the settlement is greater than the expected entry delay with litigation, then the empirical implication is a stock price hike for the brand firm at the time of settlement. The firm gets more monopoly time than expected under litigation, higher profits, and therefore experiences a jump in their stock price. DSM use settlements without payments in their control group to acknowledge that “settling litigation can be motivated by reasons other than extending monopoly or avoiding managerial risk…These cost savings with settlement might cause the stock price to rise with settlement.” Therefore, DSM assume that if settlements with payments raise stock prices more than settlements without payments, it should only be due to the payment and thus suggest anticompetitive effects. DSM utilize earlier event study methods by Panattoni (2009) and Jacobo-Rubio, Turner, and Williams (2014), who analyze stock price fluctuations of patent litigation decisions. These event study procedures will be described extensively in the Event Study Methodology section.

DSM examine a set of 110 settlements between 1993 and 2013 and narrowed it down to 68 settlements that had the qualifications for an event study, including a clear announcement date, a publicly traded brand firm, and no other significant news that came out around the settlement date. They conducted event studies for the 27 settlements with payments and 41 settlements without payments with event windows that begin and end one, two, and three days before and after the event. Using the Constant Mean Model, Market Model, and Fama-French Model to measure stock price returns, they calculated average abnormal returns across their samples and summed them across their event windows to obtain Cumulative Average Abnormal Returns (CAAR's). They then tested the null hypothesis that the CAAR's for every window in both samples are equal to 0, as well as the null that they are not significantly different from each other. They were able to reject both null hypotheses. In the settlements with payments, CAAR's ranged from 5.9% to 6.6% in all three models on the three symmetric event windows, all of which are significant at the 99% confidence interval. Settlements without payments all had CAAR's less than 1% and were statistically insignificant. DSM concluded that settlements with payments caused a 6% abnormal return in brand drug prices and therefore empirically show that reverse payment settlements are anticompetitive.

III. Questions

My paper builds upon empirical studies conducted by DSM by using stock price movements of generic firms to determine the presence of anticompetitive activities in reverse payment settlements. My research is guided by three questions:

I. Are there positive abnormal stock returns of generic firms in settlements with payments and settlements without payments from 1993 to 2015?

    Ib. Do these results suggest that the settlements are anticompetitive?

II. Do other factors in addition to indications of payments influence abnormal returns during settlements? Other factors that I investigate include:

- The reputation of the generic firm characterized by how frequent they settle

- The drug's sales as a percentage of firm revenue

III. How do the stock returns of generic firms differ from brand firms during settlements? How do these differences describe the anticompetitive and possibly collusive nature of reverse payment settlements?

Question I poses a similar question that DSM set out to answer for the brand firm in their 2013 study: whether there is a stock price jump in response to the settlement announcement in the news and whether this jump shows that the settlement is anticompetitive. DSM make two underlying assumptions in their study:

(1) Settlements without payments are not anticompetitive because they represent a fair negotiation of the settlement terms between the brand and generic firms and serve as a proxy for the expected patent length from a trial

(2) A positive abnormal stock return indicates that an anticompetitive settlement has taken place

DSM's results show that settlements with payments have a positive abnormal stock return while settlements with payments do not, which is constituent with the two assumptions that they make. In addition, DSM find a significant difference between abnormal stock returns for payment and non-payment settlements in all event windows. From these results and the two assumptions above, DSM conclude that settlements with payments are anticompetitive while settlements without payments are not.

My initial hypothesis for Question I is that the generic firms' stock returns will behave in a similar way, with positive abnormal returns for settlements with payments that are significantly different from no payment settlement stock returns in all windows. However, since my study explores generic settlements, I believe that assumption (1) no longer holds and will therefore answer Question I keeping assumption (2), but proposing a different interpretation of settlements without payments as assumption (1). This interpretation is based on the EHHS model and is developed in Section VII.2.

Question II attempts to find different factors that influence stock price jumps at the time of settlement besides the announcement of a payment. This question originates from the recent string of settlements that involve complex side deals instead of simple transfers of cash. This trend likely materialized as a result of close FTC antitrust scrutiny of cash payments. They may serve as a way to obscure large payments through complicated settlement terms. While most courts post-*Actavis* have treated side deals like cash payments,[18] these deals add another layer of complexity to the Actavis Inference because courts have to value deals that may be worth different amounts depending on the business structure of the company involved. In addition, many deals in the last few years are announced as "confidential" instead of specifying payments or no payments. For a public company, the terms of the settlement constitute as material information that could significantly move the stock price but are obscured from shareholder knowledge. In light of these trends that add more layers of opacity to settlements, it is important to search for alternative means to gauge anticompetitive activity when payment and no payment terms and classifications are unclear.

A second component of Question II relates to investor conceptions of different types of deals. While this may involve using larger event windows, it would be interesting to evaluate whether there are certain settlements that the market takes longer to understand. As settlement terms get more and more complex, perhaps investors themselves do not truly understand the full effects of some deals right away. This would add valuable discussion to the methodology of short event study windows to determine whether there are anticompetitive effects of reverse payment settlements. I attempt to answer this by comparing the differences between stock returns on the event date and days after the event date to see if there's a delay in responding to the settlement announcement.

To answer Question III, I compare my results qualitatively with DSM's results for the brand firm. While there is currently no literature about the generic firm's stock returns after reverse payment settlements, my initial hypothesis is that generic stock prices should also jump at news of settlement. If both the brand and generic stock prices jump at the news of a settlement with payment, it would further reinforce the collusive nature of these reverse payment settlements – they benefit both brand and generic firms at the cost of consumers. However, if the generic stocks do not jump when the brand stocks do for settlements with payments, it would mean that either:

- Settlements do not produce higher future profits for generic firms and therefore the benefits of settlements are asymmetrically distributed to brand firms
- Expectations of the settlements are better built into the generic's stock prices prior to the settlement announcements

[18] With the exception of two recent court cases.

Conversely, if stock returns of generic firms jump while brand firms do not in the case of settlements without payments, it may provide a different interpretation of how settlements without payments work for the generic firm than the brand firm (DSM's assumption (1) from above). All three cases of empirical results provide insight for the interactions between the generic and brand firm during patent settlement and help add to the discussion of antitrust issues within reverse payment settlements.

A motivating study for the method of using event studies as a way to determine the presence of anticompetitive activity is Panattoni (2009). After conducting event studies on 37 Paragraph IV litigation decisions, she found that the average announcement cumulative abnormal return (CAAR) for the brand upon winning the patent suit was 3.84% and upon losing was -5.20% (both abnormal returns were significantly different from zero at the 1% level). In showing that stock prices jump significantly at wins and losses of patent litigation, Panattoni showed that the pre-event stock price reflected stockholders' expected outcome of the litigation trial that factors in both possible outcomes and their probabilities. The post-event outcome follows a binomial outcome space of a positive stock return jump upon winning the trial and a negative stock return jump upon losing. By extension, DSM also assume that pre-settlement stock prices reflect investors' expectations of litigation. Therefore, if a stock price jump occurs after a settlement, it indicates that (1) the patent length as agreed upon in the settlement is higher than the expected patent length from litigation (2) the stock market underestimated the expected litigation exclusion period, or (3) another unknown cause that is not necessarily anticompetitive but has influenced investors has occurred. In analyzing stock prices, I attempt to examine which of the previous three causes produced the stock price jumps.

IV.1 Data – Collection

My data is a panel data set that consists of all ANDA settlements between 1993 and 2015 that fit three requirements of the event study approach:

(i) The generic firm involved is public and trades on the New York Stock Exchange (NYSE) or NASDAQ Stock Market

(ii) There is one clear announcement date that can be seen in multiple news articles

(iii) There is no other major news by the generic firm(s) involved in the settlement within the widest event window, (-3,3)

Requirement (ii) is fulfilled if most of the news articles announcing the settlement are from the same date. To check whether requirement (iii) is fulfilled, I conducted a search on the firm's name and/or stock ticker on Google, Lexis Nexis, and Factiva in the date range of three days before (t=-3) and three days after (t=3) the event date (t=0), defined as the four-day window, (-3,3). More explanation for the selection of event windows will be given in the Event Study Methodology section. I sorted the search results for relevancy and looked through the first 60-70 results, counting earnings releases, mergers and acquisitions, major lawsuit outcomes (including ANDA litigation for other patents), and major changes in management as "other major news" that would also move the stock price and contaminate my results. However, since many generic firms that engage in Paragraph IV settlements are large and multinational, it is impossible to exclude every settlement simply due to an event that coincides with the event window. A large generic firm often announces a new drug, global licensing agreement, supply agreement, and lab results all in one week. Therefore, in order to gauge the relevancy and importance of a news event, I looked at the number of articles about it on the three databases. On average, there are about 3-4 articles for every given event so I counted an event with 6-7 articles or more as a major news event and excluded the settlement from my dataset.

My data can be broken into three portions, one from a secondary data source and two novel datasets that I collected:

(1) Non-novel: Settlements between 1993 and 2013 collected by DSM

(2) Novel, dropped: Settlements between 1993 and 2013 dropped by DSM because the brand firm wasn't public and/or there was another major news announcement about the brand firm that could have affected their stock prices

(3) Novel, new: Settlements between 2013 and 2015 (DSM's study ends in 2013)

To obtain part (1) of my dataset, I took DSM's list of 68 settlements with clear announcement dates and checked that they fit my two requirements (i) and (iii), which narrowed the dataset down to 46 settlements: 22 settlements with payment and 24 settlements without payments. However, DSM also applied the same requirements and dropped 52 settlements that did not meet the requirements from the perspective of the brand firm. Therefore, there is a subsection of data dropped by DSM that may meet my data requirements about the brand firm involved. For part (2) of my dataset, I was able to recover 38 settlements with a clear announcement date out of the 52 settlements dropped by DSM from doing searches on Google, Lexis Nexis, and Factiva of combinations and variations of "settle," "patent settlement," "Abbreviated New Drug

Application," "ANDA," etc. for 1993-2013. Keith Drake, one of the authors of the DSM 2013 paper, also sent me a list of 39 dropped settlements, 25 with a clear announcement date, and I checked to make sure that I had all of the settlements on their partial list of the settlements that they dropped. An important note is that my dataset retrieved 38 out of 52 settlements that were thrown out because the brand firm was private or had other news and can therefore still analyze anticompetitive effects with the generic stock price. Lastly, part (3) of my data involved looking for any settlements that occurred between 2013 and 2015. I looked through the three databases with similar search terms and narrowed my results down to 2013 through 2015. I sorted by relevance on each database and looked through the first 200 search results (in some cases, the relevancy of the results diminished long before the 200 result mark) to find a list of 41 settlements with a clear announcement date.

In total, I found 145 settlements with a clear announcement date between 1993 and 2015. I excluded 47 settlements for having a private or internationally traded generic firm and 14 more settlements for having other major news announcements within the period (-3,3). I ended up with 84 settlements between 1993 and 2015 that fit my event study requirements: 33 with payments and 51 without payments. Since there were some settlements that involved more than one generic firm, these 84 settlements yielded 90 generic firms – or 90 "events" – in total.[19] Of my initial list of 90 events, 37 were settlements with payments and 53 were settlements without payments.

There were two settlements that happened on the same day between the same firms – Teva and Barr Labs settling with Sanofi SA on Allegra/Allegra D-12 and Nasacort on November 19, 2008. The two settlements both involved payments and had similar terms; since it would difficult to distinguish the positive abnormal returns between the two settlements, I treated them as one event. In addition, two settlements with payments by Impax Labs coincided with the period between 2007 and 2008 when it was delisted by the SEC for not filing annual earnings reports, so the two settlements were thrown out. Five settlements without payments settled by Actavis occurred after September 2015, for which CRSP had not yet updated their fourth quarter data for 2015 when I downloaded the database in January 2016. After excluding the nine

[19] Out of the 85 settlements, four settlements involved two public generic firms and 1 settlement involved three public generic firms.

settlements described, my final sample size had **81 settlements: 33 settlements with payments and 48 settlements without payments.**

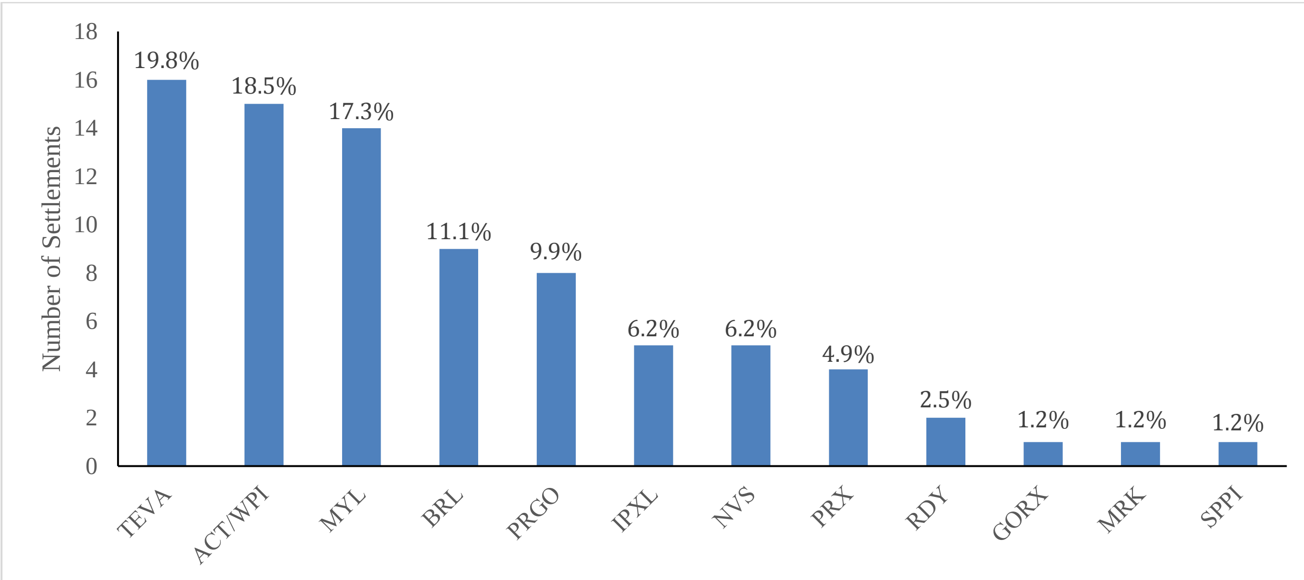
Data on the annual sales of a particular drug or a company were taken from www.drug.com's lists of top-selling drugs and their annual sales[20]. If a drug's annual sales could not be found from drug.com, I conducted searches for the drug's name and combinations of the words "revenue," "sales," and the year in question on Google, Lexis Nexis, and Factiva. Company sales figures were downloaded from Computstat Industrial Files and checked against their annual 10-K filings to the Securities and Exchange Commission (SEC). All drug sales and company sales data were obtained for the year that the settlement took place or the closest year with available data[21] and adjusted by the Consumer Price Index (CPI) All Urban Consumers index to be expressed in 2015 dollars. Any foreign currencies for drug sales or company sales were converted to U.S. dollars using the Yearly Average Currency Exchange Rates for the year in question from the U.S. Internal Revenue Service (IRS) website.[22]

IV.2 Data – Sample Categorization

In Question I, I investigate whether settlements with payments and settlements without payments lead to positive abnormal stock returns by separating my data into "Payments" and "No Payments." However, in order to answer Question II and examine whether firm reputation or drug sales percentage plays a role in abnormal returns, I separated my data again into settlements by "frequent settlers" and "infrequent settlers" – referred to in this paper simply by "Frequent" and "Infrequent." I define a "frequent settler" as a firm that settles more than 10% of all the settlements in the total sample. Firms in the Frequent group are Teva (TEVA), Actavis/Watson Pharmaceuticals (ACT/WPI), Mylan (MYL), and Barr Laboratories (BRL). They collectively settle 54 out of 81 settlements, which constitutes around 66.67% of the data. Firms in the Infrequent group are Perrigo (PRGO), Impax Laboratores (IPXL), Novartis (NVS), Par Pharmaceuticals (PRX), Reddy Laboratories (RDY), GeoPharma (GORX), Merck (MRK), and Spectrum Pharmaceuticals (SPPI). The Infrequent group collectively settle 27 out of 81 settlements, or about a third of all settlements in the data set. Figure 1 displays the frequencies at which each firm settles within the entire data set:

[20] Drug.com publishes lists of 200 or 100 top-selling brand-name drugs and their sales every year.
[21] Five out of 81 events included drug sales percentages up to two years earlier than the settlement year. Another four only had nine-month or three-month sales, which I pro-rated to estimate sales for the full year.
[22] https://www.irs.gov/Individuals/International-Taxpayers/Yearly-Average-Currency-Exchange-Rates.

Figure 1. Frequencies of Firm in Settlement Data



While I could merely include dummy variables of "Payment/No Payment" and "Frequent/Infrequent Settler" in my regression of abnormal returns onto sales % to answer the second part of Question II, I decided to separate the data into four different groups to allow for interaction between the dummies (Payment/No Payment and Frequent/Infrequent Settler) and the continuous variable (Sales %). The following diagram represents the breakdown of the four subcategories of my data:

Figure 2. Subcategories and number of samples (N) in each group

	Frequent (F=1)	Infrequent (F=0)
Payment (P=1)	Payment/Frequent (P/F) N=27	Payment/Infrequent (P/IF) N=6
No Payment (P=0)	No Payment/Frequent (NP/F) N=27	No Payment/Infrequent (NP/IF) N=21

V.1 Event Study Methodology – Daily Returns and Selection of Windows

Event studies examine the impact of an event on a company's stock price to gauge whether the event had a significant effect on the company. All event studies assume that the stock market responds quickly to news of an event bearing on the expected profits of a firm.[23] Changes in stock prices are expressed as stock returns, which is essentially defined as the percentage change of the stock price from the previous day. To obtain daily stock return data, I extracted the adjusted stock returns from the Center for Research in Security Prices (CRSP) database through the Wharton Research Data Services (WRDS). I imported the data into SAS with Eventus software to sort the data and calculate my performance variables based on different expected returns models. I will also use Eventus to conduct my hypothesis tests for Question I and I use base SAS without Eventus to conduct regressions for Question II. CRSP defines a stock return as the change in the total value of an investment in a security over some period of time per dollar of initial investment, calculated as:

$$r_{it} = \frac{p_t f_t + d_t}{p_{t-1}} - 1 \qquad [3]$$

p_t = price of security i at time t
p_{t-1} = price of security i at time $t-1$
d_t = dividend of security i at time t, assumed to be re-invested in the security post-distribution
f_t = factor to adjust prices of security i based on any stock splits that may have occurred

Abnormal returns in an event study are calculated as the difference between the actual daily stock return on a given day in the event window and the expected stock return on that day:

$$AR_{it} = r_{it} - E(r_{it}) \qquad [4]$$

where i is a given security and t is a given day in the event window. In my paper, the event date occurs on date t=0 when the settlement is first announced in the news, while negative values of t indicate days before the event date and positive values of t indicate days after the event date. For example, t=-3 is the date that is three days before the event date.

Abnormal returns are often aggregated into “Cumulative Abnormal Returns”[24] across “event windows”, which define the days across which the market is assumed to be responding to news of the event. It often takes multiple days to adequately capture the effects of an event because of differences in announcement time of day, news leakage, and imperfect news dissemination. Usually, the event window is chosen as the day of the event and one day after (Panattoni 2011), and sometimes a few days before and after (Drake et. al 2013). It’s important

[23] Drake et. al (2013) and Brown and Warner (1985).
[24] The Performance Variables section later in the paper will describe the exact calculation of Cumulative Abnormal Returns ($CAR_{i,T2-T1}$) and Cumulative Average Abnormal Returns ($CAAR_{T2-T1}$).

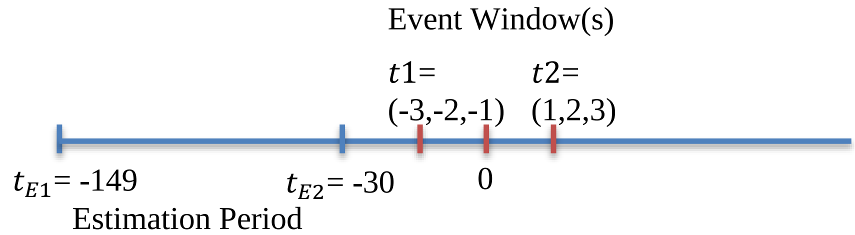
to balance an event window wide enough to adequately capture the effects of an event but narrow enough to avoid excess noise of other events (MacKinlay 1997, Brown and Warner 1985). For events like settlement announcements, negotiations regarding settlement terms have been going on for months or years before the announcement date, so returns on the days prior to the announcement date 0 are necessary to account for any news leakage or capture any trading based on expectations about the event that are not captured in the estimated returns $E(r_{it})$. At the same time, the period after the event could capture any delayed responses to complex and opaque settlement terms. To capture effects before and after the event date, I consider symmetric and asymmetric windows that begin (and end) one, two, and three day(s) before (and after) the event. For example, an event window (-3,0) represents the three-day period from t=-3 to t=0. My event windows are: (0,0), (-3,3), (-2,2), (-1,1), (-3,0),(-2,0),(-1,0), (0,1), (0,2), and (0,3). My windows are also intentionally similar to DSM's windows in order to evaluate any differences between the generic and brand firm stock movements when answering Question III.

V.2 Event Study Methodology – Estimating $E(r_{it})$

While the abnormal return itself is calculated during the event windows, the expected stock return is calculated by inputting a market-wide return observation for date t into a model with coefficients that are estimated during the estimation period. These coefficients are estimated using the Ordinary Least Squares (OLS) method and the estimation period is typically the 120 days ending 30 days before the event date, t=0.

There are a number of different approaches used to estimate $E(r_{it})$ with different estimation windows. While DSM used the estimation period 120 days ending 30 days prior to the start of the event window, MacKinlay (1997) and Brown and Warner (1985) use 250 and 239 days prior to the event window. A sufficiently large estimation period is needed to capture the 'normal' behavior of the security. I use two different expected returns models to calculate my AR_{it} observations to provide a robustness check to each model. I also compare the R^2 of both models to compare the effectiveness of the models in explaining variance of the stock return during the estimation window. The R^2 values will give a sense of the fit for each model. I use the same estimation window as DSM, the 120-day period ending 30 days prior to the start of my event date. See the diagram below for a description of the relationship between the event windows, event date 0, and estimation period:

Figure 3. Timeline of Event Study



In this paper, date t_E denotes a date in the estimation period while date t denotes a date in the event window(s).

My first model and the main model used in most event studies literature is the Market Model (see Brown and Warner, 1985), in which OLS is used to estimate the coefficients of the regression of a security's return on the market index return during the estimation period. These coefficient estimates are then used to calculate the expected return estimate $E(r_{it})$ during the event window. I used the CRSP Equally Weighted index as my market index, which weights all stocks on the CRSP database equally, because it is a common index used in event studies and has been proven to be as effective as other popular market indices.[25] The Market Model describes the expected return of security i on date t as a function of the market index return on date t:

$$E(r_{it}) = \hat{\alpha} + \hat{\beta}\, r_{mt} \qquad [5]$$

Where r_{mt} is the daily market return for date t and $\hat{\alpha}$ and $\hat{\beta}$ are the OLS estimates of the actual coefficients α and β, calculated over the estimation period. $\hat{\alpha}$ and $\hat{\beta}$ from equation [5] are calculated by regressing r_{it_E}on the market index $r_{mt_E}$for the 120 observations collected from the estimation window, t_{E1}=-149 to t_{E2}=-30:

$$r_{it_E} = \alpha + \beta r_{mt_E} + \varepsilon_{it_E} \qquad [6]$$

MacKinlay (1997) states that usually, adding additional factors to the market model does not increase the R^2 and thus the explanatory power of the model. Brown and Warner (1985) have also stated the Market Model is well specified for an event study and under most conditions, relatively powerful in rejecting the null hypothesis that abnormal returns are equal to zero when

[25] MacKinlay (1997) describes the S&P 500 and CRSP Value Weighted Index as other popular indices. Brown and Warner (1980) compare the Value Weighted and Equally Weighted Index and find no significant differences between the rejection rates of the null that abnormal returns are equal to zero of either index for the Market Model and Fama-French Model, discussed below.

abnormal returns are actually present. However, I add another popular event study model as a robustness check to the Market Model.

The Fama-French Model (Fama and French 1996) is the second expected returns model used, and adds two additional factors to the Market Model: the difference in returns between big-cap and small-cap stocks on date t and the difference between stocks with high and low book-to-market ratio on date t. The expected return from the Fama-French Model for security i on date t is calculated as:

$$E(r_{it}) = \hat{\alpha} + \hat{\beta}_{i1} r_{mt} + \hat{\beta}_{i2} smb_t + \hat{\beta}_{i3} hml_t \quad [7]$$

where r_{mt} is the market return, using the CRSP Equally Weighted Index on day t and smb_t ("small minus big") is the difference in returns between big-cap and small-cap stocks on date t.[26] hml_t ("high minus low") is the difference between the returns of high book-to-market value stocks and low book-to-market value stocks on date t.[27] Similar to the market model, coefficients $\hat{\alpha}$, $\hat{\beta}_{i1}$, $\hat{\beta}_{i2}$, an$\hat{\beta}_{i3}$d are the OLS estimates of the coefficients in [8] below, calculated over the estimation period by regressing the stock return for firm i on date t_E on the factors r_{mt_E}, smb_{t_E}, and hml_{t_E} on date t_E:

$$r_{it_E} = \alpha + \beta_{i1} r_{mt_E} + \beta_{i2} smb_{t_E} + \hat{\beta}_{i3} hml_{t_E} + \varepsilon_{it_E} \quad [8]$$

The Fama-French model takes into account the empirical observation that small-cap stocks and large book-to-market ratio (or "undervalued," see footnote 27) stocks on average have a higher return than the market. In Buchheim et al.'s study, the R^2 went up by nearly 25% when they used the Fama-French model instead of the Market Model. It is included as a robustness check to ensure that my results do not depend on the expected returns model used.

Table 1 provides the values of the OLS estimates for coefficients of factors in the Market Model and Fama-French Model for different subsets of the data and the R^2 of both models. It also includes the mean squared error term (the sum of squared ε_{it} in equations [6] and [8]). The Fama-French model increases the R^2 for every sample and subsample by an average of 0.0328, so I will include it as a robustness check for my abnormal returns calculations in my event

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[26] Small-cap and big-cap refer to the size of a company's market capitalization, which is defined as the number of total shares outstanding multiplied by the share price.

[27] Book value is the company's assets minus its liabilities and market value has the same definition as market capitalization in footnote 26. Stocks with a high book-to-market value are often called "undervalued" because its balance sheet equity is greater than the value of its equity in the stock market. The stock market is therefore "undervaluing" the company's equity. The reverse is true for stocks with low book-to-market value, which are "overvalued."

studies. As described in the IV.2 Data – Sample Categorization Section above, since I separate my data into two samples “Payment” and “No Payment” and four subsamples “Payment – Frequent,” “Payment – Infrequent,” “No Payment – Frequent,” and “No Payment – Infrequent,” I also separate data into these six samples/subsamples when estimating the coefficients used to calculate $E(r_{it})$. These categories and their respective OLS estimated coefficients are displayed in Table 1.

Table 1. Estimation period average OLS estimates for coefficients in Market and Fama-French Models for all Samples and Subsamples

Market Model							
Average	$\hat{\alpha}$	$\hat{\beta}$(mr)	Root MSE	R Squared	N		
Payment	0.0004	0.6734	0.0180	0.1825	33		
No Payment	0.0005	0.8413	0.0181	0.2210	48		
Frequent	0.0004	0.7402	0.0159	0.2113	54		
Infrequent	0.0005	0.8381	0.0224	0.1932	27		
Payment /Frequent	0.0004	0.6656	0.0179	0.1754	27		
Payment /Infrequent	0.0004	0.7083	0.0184	0.2146	6		
No Payment /Frequent	0.0004	0.8149	0.0139	0.2472	27		
No Payment /Infrequent	0.0005	0.8752	0.0139	0.2472	21		
Fama-French Model							
Average	$\hat{\alpha}$	$\hat{\beta}_{i1}$(mr)	$\hat{\beta}_{i2}$(SMB)	β_{i3} (HML)	Root MSE	R Squared	N
Payment	0.0004	0.7200	-0.2643	-0.3387	0.0178	0.2131	33
No Payment	0.0005	0.9371	-0.3262	-0.4138	0.0178	0.2667	48
Frequent	0.0004	0.8603	-0.3977	-0.4448	0.0156	0.2480	54
Infrequent	0.0007	0.8254	-0.1075	-0.2600	0.0221	0.2387	27
Payment /Frequent	0.0004	0.7313	-0.2522	-0.3287	0.0177	0.2027	27
Payment /Infrequent	0.0007	0.6695	-0.3187	-0.3835	0.0182	0.2602	6
No Payment /Frequent	0.0003	0.9893	-0.5431	-0.5609	0.0135	0.2933	27
No Payment /Infrequent	0.0007	0.8699	-0.0472	-0.2247	0.0232	0.2326	21

V.3 Event Study Methodology – Calculating AR_{it}

To reiterate equation [4], the abnormal return for security i on date t is the difference between its actual return r_{it} and its expected return $E(r_{it})$ on date t (which will be different depending on which expected return model used):

$$AR_{it} = r_{it} - E(r_{it}) \quad [4]$$

where $E(r_{it})$ could be calculated by either the Market Model or the Fama-French Model. The abnormal return for both the Market Model and the Fama-French Model are as follows:

Market Model Abnormal Return:

$$MMAR_{it} = r_{it} - (\hat{\alpha} + \hat{\beta} r_{m_t}) \quad [9]$$

Fama-French Model Abnormal Return:

$$FFMAR_{it} = r_{it} - (\hat{\alpha} + \hat{\beta}_{i1} r_{mt} + \hat{\beta}_{i2} smb_t + \hat{\beta}_{i3} hml_t) \quad [10]$$

In this section, $MMAR_{it}$ and $FFMAR_{it}$ are simply written as "AR_{it}" for simplicity.

V.4 Event Study Methodology – Calculating Performance Variables

After calculating the abnormal returns for each date t={-3,-2,-1,0,1,2,3} in the event windows from both the Market Model and Fama-French Model, I calculate three descriptive variables from these abnormal returns: (1) Average Abnormal Returns (AAR_t) (2) Cumulative Average Abnormal Returns ($CAAR_{t2-t1}$) and (3) Cumulative Abnormal Returns ($CAR_{i,t2-t1}$). These will be referred to as "performance variables" throughout my paper. Usage of these three variables is common in event studies (see Brown and Warner 1985, MacKinlay 1997, and Buchheim et al. 2001) because they take into account the change in stock returns of a given sample both across securities in the sample and across days of the event window.

The average abnormal returns (AAR_t) are the average daily returns of all stocks in a sample on date t in the event window. This is commonly called a cross-sectional return calculation in event study literature:

$$\mathrm{AAR_t} = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \quad [11]$$

where N is the number of securities in each given sample and AR_{it} is the return of stock i on day t. The AAR_t is used to calculate the Cumulative Average Abnormal Returns ($CAAR_{t2-t1}$) by summing the AAR_t's across different event windows when they are more than one day long. This allows us to capture the cross-sectional effects over the entire window:

$$\mathrm{CAAR_{t2-t1}} = \sum_{t=t1}^{t2} \mathrm{AAR_t} \quad [12]$$

where $t1$ to $t2$ represents event window (t1,t2) and AAR_t is the average abnormal return across securities in a sample on date t, as defined above. To answer Question I and determine if there is an abnormal return across days of the event window as a result of the settlement announcement, I test whether or not $CAAR_{t2-t1}$ is significantly greater than zero in different event windows. If there was no stock price jump as a result of the settlement announcement in a sample, then the performance variables AAR_t and $CAAR_{t2-t1}$ for the sample should equal zero. The Cumulative Abnormal Returns ($CAR_{i,t2-t1}$) are the daily returns of stock i summed over the event window:

$$\mathrm{CAR}_{\mathrm{i,t2-t1}} = \sum_{t=t1}^{t2} AR_{it} \qquad [13]$$

where $t1$ to $t2$ represents event window (t1,t2) and AR_{it} is the return of stock i on day t, as defined above. To answer the second part of Question II regarding the effect of drug sales percentage on abnormal returns, I regress $CAR_{i,t2-t1}$ onto each settlement's drug sales percentage of generic firm annual sales.

VI. Hypothesis Testing – t-test

To answer Question I, I test whether or not the performance variable, $CAAR_{t2-t1}$, for each window (t1,t2) for each sample is significantly different from zero. I will use three parametric tests (t-test, Patell test, and BMP test) and two non-parametric tests (sign test and rank test) as a robustness to check to ensure that the significance of my results does not depend on the statistical test I choose. For detailed calculations for the Patell test, BMP test, sign test, and rank test, please see the Appendix A. It is important to remember that parametric tests assume that the distribution stock returns r_{it} and therefore AR_{it} ($AR_{it} = r_{it} - E(r_{it})$) are independent and identically distributed (i.i.d.) random variables.

The first set of null and alternative hypotheses that I test relate to the variable $CAAR_{t2-t1}$, the cumulative average abnormal returns of all securities across my event windows:

H_0: $CAAR_{t2-t1} = 0$ [14]

H_1: $CAAR_{t2-t1} > 0$

Since $CAAR_{t2-t1}$ is constructed by summing AAR_t across event window(s) (t1,t2), as described in [12], I use the mean, variance, and distribution assumptions of AAR_t to construct the test statistics regarding $CAAR_{t2-t1}$. In Brown and Warner's simulation (1985) of 250 samples with 50 securities in each sample, the abnormal returns for individual securities did not resemble a normal distribution, with a higher skewness and kurtosis than typically seen under normality. However, taking the sample means of the 250 samples, Brown and Warner (1985) found that "departures from normality are less pronounced for cross-sectional mean excess returns than for individual security excess returns, as would be expected under the Central Limit Theorem (CLT)." The CLT states that if sample observations are i.i.d. with finite mean and variance, then the distribution of the sample mean converges to a normal distribution no matter what the underlying distribution of the data is, as long as the sample size is large enough. Therefore, the above H_0 tests whether or not the sample mean across a window – the average abnormal return across all securities in a sample – is equal to zero and can be tested using typical t-test/z-tests as with any normal distribution. Assuming all of my sample sizes are large enough, the CLT allows us to assume that the distribution of $\text{CAAR}_{t2\text{-}t1}$ follows a normal distribution, $N(0, \sigma^2(\text{CAAR}_{t2\text{-}t2})$.

To construct the variance of cumulative average returns across window (t1,t2), $\sigma^2(\text{CAAR}_{t2\text{-}t2})$., I first construct the variance of AAR_t on date t. Since AAR_t is the cross-sectional mean of AR_{it}, assuming that r_{it} and therefore AR_{it} is i.i.d. for large samples, the variance of AAR_t can be written as:

$$\sigma^2(\text{AAR}_t) = \frac{\sum_{i=1}^{N} \sigma^2(AR_{it})}{N^2} \qquad [15]$$

The actual variance $\sigma^2(AR_{it})$ can be approximated with the sample variance of AR_{it} on date t_E during the estimation period: ${S_{AR_{it_E}}}^2$. The variance of AAR_t can therefore be estimated as:

$$\sigma^2\widehat{(\text{AAR}_t)} = \frac{{S_{AR_{it_E}}}^2}{N} \qquad [16]$$

where N is the number of observations in the sample and ${S_{AR_{it_E}}}^2$ is the variance of the sample of stock returns over the estimation period. I acknowledge that there may be some additional variance in addition to the term above due to the sampling error of my $E(r_{it})$ model and estimating coefficients, but if the estimation period is large enough, the sampling error should approach zero and can be ignored in the calculation of the test statistic (MacKinlay 1997). It is also possible to calculate the variance of AAR_t directly with the standard error of AAR_t observations over the estimation period. To calculate the standard deviation of the sample mean:

$$\sigma(\widehat{\text{AAR}}_t) = S_{\text{AAR}_{t_E}} = \sqrt{\sum_{t_{E1}=-149}^{t_{E2}=-30} (\text{AAR}_{t_E} - \overline{\text{AAR}})^2/120} \qquad [17]$$

where $\overline{\text{AAR}} = \frac{1}{120}\sum_{-149}^{-30} \text{AAR}_{t_E}$, which is the average per-day abnormal return during the estimation period (average across all securities in a sample and average across all days of the estimation period) and $S_{AAR_{t_E}}$ is the average per-day standard deviation of the sample during the estimation period (Brown and Warner 1985, Buchheim et al 2001).[28] This method calculates the variance of AAR_t based on its daily standard deviation from the mean of AAR_t across all days of the estimation period, using this standard error as a proxy for the true standard of the AAR_t distribution. Buchheim et al. calls this the "time series method" of calculating variance.

Since $CAAR_{t2\text{-}t1}$ is the sum of the AAR_t terms across the days of the event window, the variance of $CAAR_{t2\text{-}t1}$ equals the sum of $\sigma^2(\text{AAR}_\text{t})$across the event window (t1,t2), assuming that the AR_{it}'s, and therefore AAR_t's, are i.i.d:

$$\sigma^2(\text{CAAR}_{\text{t2-t1}}) = \sum_{\text{t=t1}}^{\text{t2}} \sigma^2(\text{AAR}_\text{t}) \quad [18]$$

The standard deviation of $CAAR_{t2\text{-}t1}$ can be written as (using the equation for $\sigma(\widehat{\text{AAR}}_\text{t})$ from above):

$$\sigma(\text{C}\widehat{\text{AAR}}_{\text{t2}-\text{t1}}) = \sigma(\text{AAR}_\text{t}) * \sqrt{(t_{E2} - t_{E1} + 1)} \quad [19]$$

$$= \sqrt{\sum_{t_{E1}=-149}^{t_{E2}=-30} \frac{\left(\text{AAR}_{\text{t}_\text{E}} - \overline{\text{AAR}}\right)^2}{120}) * (t_{E2} - t_{E1} + 1)}$$

where $(t_{E2} - t_{E1} + 1)$ is the number of days in estimation window (t_{E1},t_{E2}). I can write test statistic to test the null hypothesis regarding $CAAR_{t2\text{-}t1}$ in [14] as:

$$test\ statistic_1 = \frac{\text{CAAR}_{\text{t2-t1}}}{\sigma(\text{CAAR}_{\text{t2-t1}})} \quad [20]$$

This test is called the "Crude Dependence Adjustment" by Brown and Warner (1980) because it averages the abnormal return of all securities in a sample for a given day t, testing AAR_t, and thus accounting for correlation between securities and cross-sectional dependence by using the averages of abnormal returns across all securities in a sample.

In addition, to test whether or not there is a significant difference in the $CAAR_{t2\text{-}t1}$ observations between two different samples, the second set of null and alternative hypothesis can be written as:

H_0: $CAAR_{t2\text{-}t1,\ Sample\ 1} - CAAR_{t2\text{-}t1,\ Sample\ 2} = 0$ [21]

H_1: $CAAR_{t2\text{-}t1,\ Sample\ 1} - CAAR_{t2\text{-}t1,\ Sample\ 2} > 0$

[28] See Brown and Warner (1985, 7) or Brown and Warner (1980, 251) for this calculation.

Assuming that the two samples are not correlated, the standard error of the difference of $CAAR_{t2\text{-}t1}$ between the two samples can be calculated as:

$$\sigma\left(\widehat{\mathrm{CAAR}_{t2-t1,\mathrm{Sample\ 1}} - \mathrm{CAAR}_{t2-t1,\mathrm{Sample\ 2}}}\right) \quad [22]$$

$$= S\left(\mathrm{CAAR}_{t2-t1,\mathrm{Sample\ 1}} - \mathrm{CAAR}_{t2-t1,\mathrm{Sample\ 2}}\right)$$

$$= \sqrt{\frac{\sigma^2(\mathrm{CAAR}_{t2-t1,\mathrm{Sample\ 1}})}{N_{Sample\ 1}} + \frac{\sigma^2(\mathrm{CAAR}_{t2-t1,\mathrm{Sample\ 2}})}{N_{Sample\ 2}}}$$

where $\sigma^2(\mathrm{CAAR}_{t2-t1})$ for each sample is calculated in the same way as in [18] and [19]. The test statistic to test the difference in $CAAR_{t2\text{-}t1}$ between samples can be written as:

$$test\ statistic_2 = \frac{\mathrm{CAAR}_{\mathrm{t2\text{-}t1,\ Sample\ 1}} - \mathrm{CAAR}_{\mathrm{t2\text{-}t1,\ Sample\ 2}}}{\sigma\left(\mathrm{CAAR}_{\mathrm{t2\text{-}t1,\ Sample\ 1}} - \mathrm{CAAR}_{\mathrm{t2\text{-}t1,\ Sample\ 2}}\right)} \quad [23]$$

Finally, to answer Question II regarding whether or not the drug sales percentage of annual firm sales at the time of settlement is significant on the abnormal returns after the announcement of a settlement, I regress the $CAR_{i,t2\text{-}t1}$ observations onto the drug sales percentage for each settlement:

$$CAR_{i,t2-t1} = \beta_0 + \beta_1(Sales_t) + \epsilon_i \quad [24]$$

Where $Sales_t$ is equal to the percentage of the firm's annual sales that the drug's annual sales make up:

$$Sales_t = \frac{Drug\ Sales_t}{Firm\ Sales_t} \quad [25]$$

OLS estimators, $\widehat{\beta_0}$ and $\widehat{\beta_1}$, are used to estimate the true coefficients, β_0 and β_1: The null and alternative hypotheses regarding whether the estimated coefficient of sales, $\widehat{\beta_2}$, is significantly different from zero are:

H_0: $\widehat{\beta_2} = 0$ [26]

H_1: $\widehat{\beta_2} > 0$

The test statistic to test the hypotheses above can be written as:

$$test\ statistic_3 = \frac{\widehat{\beta_2}}{SE(\widehat{\beta_2})} \quad [27]$$

Where $SE(\widehat{\beta_2})$ can be calculated as:

$$SE(\widehat{\beta_2}) = \sqrt{\frac{Var(\epsilon_i)}{\sum_{i=1}^{N} CAR_{i,t2\text{-}t1}^2}} \quad [28]$$

VII.1 Results – Payment Group and Asymmetric Timing

This section presents test statistics for the hypotheses described above. In addition to t-tests/z-tests, two other parametric tests, the Patell Test and BMP Test, and two non-parametric tests, the Sign Test and Rank Test, are included. Each test has certain advantages over the t-test and is included as a robustness check for the significance of the data. Please see Appendix A for detailed calculations and explanations of the tests statistics for the four other tests used.

Table 2 reports the $CAAR_{t2\text{-}t1}$ values for the Payment group for all event windows, the standard error, and the test statistics/ p-values for all three parametric and two non-parametric hypothesis tests. The test statistics in the table correspond to the null and alternative hypotheses from [14] adopted for the Payments sample:

H_0: $CAAR_{t2\text{-}t1, Payments} = 0$ [29]

H_1: $CAAR_{t2\text{-}t1, Payments} > 0$

For every event window, the $CAAR_{t2\text{-}t1}$ is significantly different from zero to at least the 10% significance level for both the Market Model and the Fama-French Model. I can therefore reject the null from [14] and conclude that there is a significant stock price hike for settlements with payments. This is consistent with my initial hypothesis that settlements with a reverse payment are anticompetitive because the payment distorts the normal negotiation of the entry date. This is also consistent with DMS's results.

However, a puzzling trend in my Payments sample is that the magnitude of the $CAAR_{t2\text{-}t1}$ values for windows (-3,0), (-2,0), and (-1,0) appear to be higher than the $CAAR_{t2\text{-}t1}$ values for windows (0,1), (0,2), and (0,3). On average between the Market Model and Fama-French Models, there is a 0.92% higher return in the window (-3,0) than the window (0,3), 0.49% higher return in (-2,0) than (0,2), and 0.33% higher return in (-1,0) than (1,0). A difference in magnitude between pre-event and post-event abnormal returns implies market anticipation prior to the announcement at t=0, as higher abnormal returns are appearing *before* the settlement is announced.

Table 3 displays the differences between $CAAR_{t2\text{-}t1}$ observations for pre-event and post-event windows. For example, "3 days pre- / post-event" is the difference in $CAAR_{t2\text{-}t1}$ between

Table 2. Event study results ($CAAR_{t2-t1}$) for settlements with an indication of payment and test statistics/p-values to test H_0: $CAAR_{t2-t1, Payment} = 0$

N=33			*Parametric*						*Non-Parametric*			
Event Window	$CAAR_{t2-t1}$	Standard Error	t-test statistic[1]	p-value	Patell Z statistic	p-value	BMP Test	p-value	Sign Test	p-value	Rank Test	p-value
Market Model												
(0,0)	0.45%	0.0033	1.37*	0.0855	1.77**	0.0373	1.87**	0.0308	1.10	0.1368	1.60*	0.0559
(-1,+1)	1.79%	0.0057	3.12***	0.0009	2.99***	0.0015	2.25**	0.0122	1.10	0.1368	1.94**	0.0270
(-2,+2)	2.15%	0.0074	2.91***	0.0018	2.93***	0.0017	2.23**	0.0129	1.79**	0.0366	1.80**	0.0366
(-3,+3)	2.71%	0.0088	3.09***	0.0010	2.79***	0.0030	2.27**	0.0115	2.14**	0.0162	1.89**	0.0301
(-3,0)	2.05%	0.0066	3.10***	0.0010	1.97**	0.0243	1.52*	0.0637	0.75	0.2278	1.75**	0.0412
(-2,0)	1.55%	0.0057	2.70***	0.0035	1.67**	0.0446	1.33*	0.0924	-0.30	0.3825	1.15	0.1261
(-1,0)	1.28%	0.0047	2.73***	0.0031	1.96**	0.0253	1.64*	0.0509	0.05	0.4803	1.47*	0.0713
(0,+1)	0.96%	0.0047	2.06**	0.0196	2.92***	0.0018	2.34***	0.0095	2.14**	0.0162	2.03**	0.0218
(0,+2)	1.06%	0.0057	1.85**	0.0321	3.15***	0.0008	2.26**	0.0120	0.75	0.2278	2.10**	0.0185
(0,+3)	1.11%	0.0066	1.68**	0.0470	2.61***	0.0046	2.19**	0.0143	1.44*	0.0745	1.56**	0.0608
Fama-French Model												
(0,0)	0.42%	0.0032	1.31*	0.0947	1.61*	0.0537	1.71**	0.0436	1.08	0.1394	1.47*	0.0718
(-1,+1)	1.78%	0.0056	3.20***	0.0007	2.81***	0.0025	2.15**	0.0157	1.43*	0.0762	1.79**	0.0379
(-2,+2)	2.08%	0.0072	2.90***	0.0019	2.75***	0.0030	2.02**	0.0219	1.08	0.1394	1.57*	0.0596
(-3,+3)	2.38%	0.0085	2.81***	0.0025	2.40***	0.0082	1.92**	0.0273	1.43*	0.0762	1.40*	0.0822
(-3,0)	1.85%	0.0064	2.89***	0.0019	1.61*	0.0537	1.22	0.1110	0.39	0.3497	1.35*	0.0892
(-2,0)	1.49%	0.0056	2.68***	0.0037	1.49*	0.0681	1.12	0.1317	0.04	0.4850	0.94	0.1742
(-1,0)	1.26%	0.0045	2.78***	0.0027	1.78**	0.0375	1.48*	0.0698	0.39	0.3497	1.39*	0.0829
(0,+1)	0.93%	0.0045	2.06**	0.0197	2.80***	0.0026	2.33***	0.0098	1.43*	0.0762	1.84**	0.0341
(0,+2)	1.01%	0.0056	1.82**	0.0345	2.99***	0.0014	2.12**	0.0172	2.13**	0.0167	1.93**	0.0276
(0,+3)	0.95%	0.0064	1.48*	0.0690	2.36***	0.0091	1.94**	0.0262	0.39	0.3497	1.23	0.1101

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

the windows (-3,0) and (0,3). In order to formally statistically test the differences between pre-event and post-event windows, I would not be able to use the standard error calculations from [22] because I cannot assume that the correlation between pre-event returns and post-event returns for the same sample of securities is zero. Therefore, to test whether the difference between pre- and post-event $CAAR_{t2\text{-}t1}$'s are significantly different from zero, the $\sigma(CAAR_{t2\text{-}t1,\ Sample\ 1} - CAAR_{t2\text{-}t1,\ Sample\ 2})$ from the test statistic in [23] would have to be calculated as:

$$\sigma(CAAR_{t2\text{-}t1,\ pre\text{-}event} - CAAR_{t2\text{-}t1,\ post\text{-}event}) = \qquad [30]$$

$$\sigma^2(CAAR_{t2\text{-}t1,\ pre\text{-}event}) + \sigma^2(CAAR_{t2\text{-}t1,\ post\text{-}event}) - 2cov(CAAR_{t2\text{-}t1,\ pre\text{-}event}, CAAR_{t2\text{-}t1,\ post\text{-}event})$$

Table 3. Difference between Pre- and Post-Event Date $CAAR_{t2\text{-}t1}$'s for settlements with indication of payment

Degrees of freedom (df) 64

Event Window	$CAAR_{t2\text{-}t1,\ Pre\text{-}Event}$	$CAAR_{t2\text{-}t1,\ Post\text{-}Event}$	Difference in CAARs
Market Model			
3 days pre- / post-event	2.05%	1.11%	0.94%
2 days pre- / post-event	1.55%	1.06%	0.49%
1 days pre- / post-event	1.28%	0.96%	0.32%
Fama-French Model			
3 days pre- / post-event	1.85%	0.95%	0.90%
2 days pre- / post-event	1.49%	1.01%	0.48%
1 days pre- / post-event	1.26%	0.93%	0.33%

To construct a test statistic for the difference between pre-and post-event CAAR's, I would need an estimate for the covariance in [25] that is very difficult to mathematically write out. However, the magnitudes between pre- and post-event windows are noticeably different up to 0.94% for the 3 days pre-/post-event windows. This asymmetry in the timing of returns is an interesting trend that is not present in the brand firm's stock return data from DSM's study.

The asymmetric timing of abnormal returns can also be seen in the difference between the Payments and No Payments groups. Table 4 displays the difference between the $CAAR_{t2\text{-}t1,\ Payments}$ and $CAAR_{t2\text{-}t1,\ No\ Payments}$ and test statistics to test the null hypothesis that the difference is equal to zero:

$$H_0: CAAR_{t2\text{-}t1,\ Payments} - CAAR_{t2\text{-}t1,\ No\ Payments} = 0 \qquad [31]$$

$$H_1: CAAR_{t2\text{-}t1,\ Payments} - CAAR_{t2\text{-}t1,\ No\ Payments} > 0$$

Table 4. Difference between $CAAR_{t2-t1}$'s for settlements with and without an indication of payment and test statistics/p-values to test H_0: $CAAR_{t2-t1,\ Payments} - CAAR_{t2-t1,\ No\ Payments} = 0$

df = 79

Event Window	$CAAR_{t2-t1,\ Payments}$	$CAAR_{t2-t1,\ No\ Payments}$	Difference in CAARs	$Var(CAAR_{t2-t1,\ Payments})$	$Var(CAAR_{t2-t1,\ No\ Payments})$	$SE(CAAR_{t2-t1,\ Payments} - CAAR_{t2-t1,\ No\ Payments})$	$t\text{-statistic}_2$	p-value
Market Model								
(0,0)	0.45%	0.58%	-0.13%	0.0004	0.0007	0.0051	-0.26	0.6022
(-1,+1)	1.79%	0.32%	1.47%	0.0011	0.0024	0.0090	1.63*	0.0535
(-2,+2)	2.15%	-0.05%	2.20%	0.0018	0.0032	0.0109	2.01**	0.0239
(-3,+3)	2.71%	0.05%	2.66%	0.0025	0.0026	0.0114	2.34**	0.0109
(-3,0)	2.05%	-0.08%	2.13%	0.0014	0.0020	0.0092	2.31**	0.0117
(-2,0)	1.55%	-0.11%	1.66%	0.0011	0.0014	0.0079	2.11**	0.0190
(-1,0)	1.28%	-0.02%	1.30%	0.0007	0.0002	0.0051	2.54***	0.0065
(0,+1)	0.96%	0.93%	0.03%	0.0007	0.0014	0.0071	0.04	0.4841
(0,+2)	1.06%	0.64%	0.42%	0.0011	0.0020	0.0086	0.49	0.3127
(0,+3)	1.11%	0.71%	0.40%	0.0014	0.0026	0.0099	0.40	0.3451
Fama-French Model								
(0,0)	0.42%	0.60%	-0.18%	0.0003	0.0004	0.0043	-0.42	0.6622
(-1,+1)	1.78%	0.34%	1.44%	0.0010	0.0012	0.0074	1.94**	0.0280
(-2,+2)	2.08%	0.04%	2.04%	0.0017	0.0023	0.0099	2.06**	0.0213
(-3,+3)	2.38%	0.15%	2.23%	0.0024	0.0029	0.0114	1.95**	0.0274
(-3,0)	1.85%	0.01%	1.84%	0.0014	0.0024	0.0095	1.94**	0.0280
(-2,0)	1.49%	-0.06%	1.55%	0.0010	0.0010	0.0072	2.16**	0.0169
(-1,0)	1.26%	0.04%	1.22%	0.0007	0.0009	0.0062	1.97**	0.0262
(0,+1)	0.93%	0.90%	0.03%	0.0007	0.0008	0.0060	0.05	0.4801
(0,+2)	1.01%	0.70%	0.31%	0.0010	0.0012	0.0074	0.42	0.3378
(0,+3)	0.95%	0.74%	0.21%	0.0014	0.0016	0.0085	0.25	0.4016

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

The difference between the Payments and No Payments sample is significant only in the windows prior to the event date, (-3,0), (-2,0), and (-1,0). These results suggest that the effect of a payment on the stock returns surrounding a settlement announcement is only significant *prior* to the actual settlement announcement date. This result is unexpected, because if Payments had a positive impact on $CAAR_{t2-t1}$, it should be distributed through all event windows – a result that DSM found for the brand firm. Therefore, it seems that there is another factor that must be influencing investors' reactions to the settlements before the terms are announced.

Reputation could be another factor influencing positive pre-event date abnormal returns surrounding settlements. One main difference between brand firms and generic firms involved in Paragraph IV settlements is the frequency at which the firms settle: over 50 brand firms settled the 81 settlements but only 12 generic firms settled the 81 settlements in total. This difference is significant in terms of the behavior of stock returns, because an important factor for how the stock market responds to a settlement is the reputation of the firm in terms of its propensity to settle. The Frequent and Infrequent characteristic of each settling firm serves as a proxy for this reputation/propensity to settle. As I describe in my Data – Sample Categorization section, I selected the firms that each settle more than 10% of the total dataset. Frequent settlers are TEVA, ACT/WPI, MYL, and BRL, which collectively settle 54 out of 81 settlements. I separated my dataset into four subgroups (shown in Figure 2), Payments/Frequent (N=27), Payments/Infrequent (N=6), No Payments/Frequent (N=27), and No Payments/Infrequent (N=21), and repeated the calculations from the Event Study Methodology section for each subsample. I then tested the same hypotheses in [14] to see if the $CAAR_{t2-t1}$ observations for each sample are significantly different from zero.

Tables 5 and 6 show the $CAAR_{t2-t1}$ observations for settlements with and without payments settled by frequent settlers. In both tables, the test statistics and p-values correspond to the null and alternative hypotheses from [14] for the samples Payment/Frequent settlers and No Payment/Frequent settlers. Similar to Table 2, Tables 5 and 6 also include test statistics for the five different hypothesis tests that I use. The results in Table 5 suggest that I can reject the null that $CAAR_{t2-t1,\ Payments/Frequent} = 0$ in the Payments sample with frequent settlers for all windows. The results in Table 5 seem to mirror the results for the Payments sample as a whole, with $CAAR_{t2-t1}$ observations that are slightly higher in magnitude. Table 6 shows some significant returns (-2,2), (-3,3), and (-1,1), at different levels of significant depending on whether the

Table 5. Event study results ($CAAR_{t2-t1}$) for settlements with an indication of payment settled by frequent settlers (TEVA, WPI/ACT, MYL, BRL) and test statistics/p-values to test H_0: $CAAR_{t2-t1,\ Payments/Frequent} = 0$

N=27			*Parametric*						*Non-Parametric*			
Event Window	$CAAR_{t2-t1}$	Standard Error	t-test statistic[1]	p-value	Patell Z statistic	p-value	BMP Test Z	p-value	Sign Test Z	p-value	Rank Test Z	p-value
Market Model												
(0,0)	0.58%	0.0034	1.73**	0.0417	1.97**	0.0244	1.96**	0.0252	1.20	0.1143	1.72**	0.0434
(-1,+1)	2.55%	0.0058	4.38***	<.0001	3.80***	<.0001	2.83***	0.0023	1.98**	0.0242	2.76***	0.0032
(-2,+2)	2.93%	0.0075	3.90***	<.0001	3.70***	0.0001	2.75***	0.0030	2.75***	0.0030	2.62***	0.0048
(-3,+3)	3.38%	0.0089	3.80***	<.0001	3.34***	0.0004	2.69***	0.0036	2.75***	0.0030	2.43***	0.0081
(-3,0)	2.51%	0.0067	3.73***	0.0001	2.30**	0.0106	1.69**	0.0458	1.20	0.1143	2.12**	0.0178
(-2,0)	2.13%	0.0058	3.66***	0.0001	2.35*	0.0930	1.80**	0.0360	0.43	0.3323	1.97**	0.0253
(-1,0)	1.85%	0.0048	3.88***	<.0001	2.68***	0.0037	2.17**	0.0152	0.82	0.2065	2.14**	0.0170
(0,+1)	1.29%	0.0048	2.71***	0.0034	3.36***	0.0004	2.53***	0.0057	2.75***	0.0030	2.46***	0.0075
(0,+2)	1.39%	0.0058	2.38***	0.0086	3.56***	0.0002	2.38***	0.0086	1.20	0.1143	2.40***	0.0087
(0,+3)	1.45%	0.0067	2.16**	0.0154	3.10***	0.0010	2.48***	0.0066	1.59*	0.0560	1.96**	0.0259
Fama-French Model												
(0,0)	0.56%	0.0032	1.74**	0.0413	1.93**	0.0268	1.97**	0.0244	1.17	0.1207	1.77**	0.0389
(-1,+1)	2.54%	0.0056	4.52***	<.0001	3.65***	0.0001	2.73***	0.0032	2.33***	0.0100	2.58***	0.0054
(-2,+2)	2.88%	0.0072	3.97***	<.0001	3.58***	0.0002	2.57***	0.0051	2.33***	0.0100	2.52***	0.0064
(-3,+3)	3.09%	0.0086	3.60***	0.0002	3.05***	0.0011	2.39***	0.0083	2.33***	0.0100	2.10**	0.0187
(-3,0)	2.29%	0.0065	3.53***	0.0002	1.95**	0.0256	1.40*	0.0816	1.17	0.1207	1.75**	0.0414
(-2,0)	2.05%	0.0056	3.66***	0.0001	2.15**	0.0158	1.55*	0.0604	0.79	0.2158	1.79**	0.0374
(-1,0)	1.80%	0.0046	3.92***	<.0001	2.45***	0.0071	1.93**	0.0266	0.79	0.2158	1.96**	0.0256
(0,+1)	1.30%	0.0046	2.84***	0.0023	3.39***	0.0003	2.68***	0.0037	1.94**	0.0261	2.45***	0.0077
(0,+2)	1.39%	0.0056	2.48***	0.0066	3.59***	0.0002	2.39***	0.0084	2.71***	0.0033	2.48***	0.0071
(0,+3)	1.37%	0.0065	2.11**	0.0176	3.04***	0.0012	2.41***	0.0081	1.17	0.1207	1.92**	0.0284

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Table 6. Event study results ($CAAR_{t2\text{-}t1}$) for settlements without an indication of payment settled by frequent settlers (TEVA, WPI/ACT, MYL, BRL) and test statistics/p-values to test H_0: $CAAR_{t2\text{-}t1,\ No\ Payment/Frequent} = 0$

N=27			*Parametric*						*Non-Parametric*			
Event Window	$CAAR_{t2\text{-}t1}$	Standard Error	t-test statistic[1]	p-value	Patell Z statistic	p-value	BMP Test Z	p-value	Sign Test Z	p-value	Rank Test Z	p-value
Market Model												
(0,0)	-0.02%	0.0037	-0.05	0.4786	-0.10	0.4590	-0.12	0.4505	-0.25	0.3998	-0.37	0.3567
(-1,+1)	0.50%	0.0049	1.02	0.1551	0.87	0.1931	0.90	0.1854	1.29**	0.0988	1.18*	0.1192
(-2,+2)	0.88%	0.0064	1.38*	0.0832	1.39*	0.0818	1.22*	0.1111	0.90	0.1833	1.26**	0.1052
(-3,+3)	0.92%	0.0075	1.22	0.1111	1.37*	0.0855	1.23*	0.1093	0.90	0.1833	0.75	0.2278
(-3,0)	0.59%	0.0057	1.04	0.1482	1.11	0.1340	1.13*	0.1289	0.52	0.3024	0.49	0.3113
(-2,0)	0.33%	0.0049	0.67	0.2519	0.49	0.3118	0.58	0.2805	0.13	0.4476	0.47	0.3213
(-1,0)	0.06%	0.0038	0.16	0.4378	-0.07	0.4714	-0.05	0.4809	0.52	0.3024	-0.11	0.4580
(0,+1)	0.42%	0.0040	1.05*	0.1473	1.06	0.1445	1.26**	0.1032	1.67***	0.0470	1.29**	0.0986
(0,+2)	0.53%	0.0049	1.09*	0.1385	1.25*	0.1059	1.01*	0.1558	0.52	0.3024	0.95*	0.1728
(0,+3)	0.31%	0.0057	0.54	0.2934	0.65	0.2573	0.56	0.2893	-0.25	0.3998	0.31	0.3777
Fama-French Model												
(0,0)	0.09%	0.0027	0.33	0.3693	0.22	0.4129	0.26	0.3958	0.85	0.1982	0.16	0.4364
(-1,+1)	0.61%	0.0048	1.27**	0.1026	1.15	0.1251	1.12*	0.1313	1.23**	0.1087	1.44**	0.0762
(-2,+2)	1.15%	0.0062	1.85**	0.0325	1.86**	0.0314	1.62**	0.0532	0.85*	0.1982	1.68**	0.0478
(-3,+3)	1.16%	0.0073	1.58**	0.0570	1.70**	0.0446	1.50**	0.0675	0.85	0.1982	1.04*	0.1492
(-3,0)	0.86%	0.0056	1.55*	0.0608	1.62*	0.0526	1.61**	0.0537	1.23**	0.1087	0.99	0.1614
(-2,0)	0.53%	0.0049	1.09	0.1382	0.92	0.1788	1.04*	0.1491	0.85*	0.1982	0.88*	0.1896
(-1,0)	0.23%	0.0039	0.59	0.2785	0.39	0.3483	0.41	0.3427	0.46	0.3219	0.37	0.3551
(0,+1)	0.47%	0.0039	1.20**	0.1150	1.18	0.1190	1.45**	0.0740	2.00***	0.0225	1.50**	0.0675
(0,+2)	0.72%	0.0048	1.49**	0.0685	1.61*	0.0537	1.34**	0.0909	0.46	0.3219	1.38**	0.0855
(0,+3)	0.40%	0.0056	0.71	0.2391	0.74	0.2297	0.64	0.2615	0.08	0.4693	0.47	0.3199

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Market Model or Fama-French Model was used. These significant returns seem to be driven by returns in the windows, (0,1) and (0,2), after the event date. While settlements with payments settled by frequent settlers seem to generate very high abnormal returns in every window, settlements without payments seem to generate abnormal returns only in the windows following the event.

To examine whether the effect of Payments were similar for settlements settled by frequent settlers and settlements settled by infrequent settles, I tested whether the difference between Payment and No Payment is significant conditional on Frequent or Infrequent. Beginning with the frequent settlers, I tested the difference between $CAAR_{t2\text{-}t1,\ Payment/Frequent}$ and $CAAR_{t2\text{-}t1,\ No\ Payment/Frequent}$:

$$H_0: CAAR_{t2\text{-}t1,\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ No\ Payments/Frequent} = 0 \quad [32]$$

$$H_1: CAAR_{t2\text{-}t1,\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ No\ Payments/Frequent} > 0$$

The results of the hypothesis test above can be seen in Table 7. I can reject the null hypothesis in [32] for windows (-3,3), (-2,2), (-1,1), (-3,0), (-2,0), (-1,0) and (0,1). It seems that the abnormal returns in the former three windows are driven by the latter four. Therefore, the effect of Payments within the Frequent group is significantly positive in the windows pre-event date. To check if this effect is present within the Infrequent group, I conducted a similar series of tests as in equations [14] and [21] to check if $CAAR_{t2\text{-}t1,\ Payments/Infrequent}$, $CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent}$, and the difference between them were statistically significant. The Payments/Infrequent group results not included in the text of this paper, but can be found in Appendix B. While there were some positive returns in windows (0,0) of the No Payments/Infrequent group (which will be discussed later in this section), there weren't any positive returns in the Payments/Infrequent group. There were no statistically significant differences between Payments and No Payments settlements when settled by infrequent settlers, suggesting that both the effect of having a payment and the pre-event date timing of this effect are driven by settlements by the frequent settlers rather than the infrequent ones. Therefore, it seems that reputation of having a higher propensity to settle – tested by the variable, Frequent – influences (i) the positive abnormal returns of settlements with indications of payments and (ii) the asymmetric timing of abnormal returns occurring prior to the event date 0.

Table 7. Difference between $CAAR_{t2-t1}$'s for settlements with and without an indication of payment settled by frequent settlers and test statistics/p-values to test H_0: $CAAR_{t2-t1, Payments/Frequent} – CAAR_{t2-t1, No Payments /Frequent} = 0$

df=52

Event Window	$CAAR_{t2 - t1, Payments/Frequent}$	$CAAR_{t2-t1, No Payments/ Frequent}$	Difference in CAARs	Var($CAAR_{t2-t1, Payments/ Frequent}$)	Var($CAAR_{t2-t1, No Payments/ Frequent}$)	SE ($CAAR_{t2-t1, Payments/Frequent}$ - $CAAR_{t2-t1, No Payments/ Frequent}$)	t-statistic2	p-value
Market Model								
(0,0)	0.58%	-0.02%	0.60%	0.0003	0.0004	0.0050	1.20	0.1178
(-1,+1)	2.55%	0.50%	2.05%	0.0009	0.0007	0.0076	2.69***	0.0048
(-2,+2)	2.93%	0.88%	2.05%	0.0015	0.0011	0.0098	2.08**	0.0212
(-3,+3)	3.38%	0.92%	2.46%	0.0021	0.0015	0.0117	2.11**	0.0198
(-3,0)	2.51%	0.59%	1.92%	0.0012	0.0009	0.0088	2.18**	0.0169
(-2,0)	2.13%	0.33%	1.80%	0.0009	0.0007	0.0076	2.36**	0.0110
(-1,0)	1.85%	0.06%	1.79%	0.0006	0.0004	0.0061	2.93***	0.0025
(0,+1)	1.29%	0.42%	0.87%	0.0006	0.0004	0.0062	1.40*	0.0837
(0,+2)	1.39%	0.53%	0.86%	0.0009	0.0006	0.0076	1.13	0.1318
(0,+3)	1.45%	0.31%	1.14%	0.0012	0.0009	0.0088	1.29	0.1014
Fama-French Model								
(0,0)	0.56%	0.09%	0.47%	0.0003	0.0002	0.0042	1.12	0.1339
(-1,+1)	2.54%	0.61%	1.93%	0.0009	0.0006	0.0074	2.61***	0.0059
(-2,+2)	2.88%	1.15%	1.73%	0.0014	0.0010	0.0096	1.81**	0.0380
(-3,+3)	3.09%	1.16%	1.93%	0.0020	0.0015	0.0113	1.71**	0.0466
(-3,0)	2.29%	0.86%	1.43%	0.0011	0.0008	0.0085	1.67*	0.0505
(-2,0)	2.05%	0.53%	1.52%	0.0008	0.0006	0.0074	2.05**	0.0227
(-1,0)	1.80%	0.23%	1.57%	0.0006	0.0004	0.0060	2.60***	0.0061
(0,+1)	1.30%	0.47%	0.83%	0.0006	0.0004	0.0060	1.38*	0.0867
(0,+2)	1.39%	0.72%	0.67%	0.0009	0.0006	0.0074	0.90	0.1861
(0,+3)	1.37%	0.40%	0.97%	0.0011	0.0009	0.0086	1.13	0.1318

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Section VII.2 Results – Positive Returns in No Payment Group:

For the sample of 48 settlements without an indication of reverse payment, I conducted a similar series of hypothesis tests to determine whether there is a significantly positive $CAAR_{t2-t1}$ in any of the event windows. The null and alternative hypotheses format again follows [14], and I specifically test:

H_0: $CAAR_{t2-t1,\ No\ Payments} = 0$ [33]

H_1: $CAAR_{t2-t1,\ No\ Payments} > 0$

I use the same five hypothesis tests for both the Market Model and Fama-French Model abnormal returns. The results of the event study for the No Payments sample as well as relevant test statistics/p-values are displayed in Table 8. After conducting the event study and hypothesis tests, I determined that I can reject the null hypothesis that $CAAR_{t2-t1,\ No\ Payments} = 0$ for every window except the event date itself, (0,0), and (0,1). While I can reject the null hypothesis for window (0,1) using every statistical test for both the Market Model and Fama-French Model, I can only reject the null hypothesis for (0,0) using the t-test for both $E(r_{it})$ models. This result suggests that there may be some abnormal stock return effect due to the event, because the windows (0,0) and (0,1) are the closest windows to the settlement announcement and capture any immediate positive returns due to trading.[29] This is an unexpected result, because I did not expect settlements without payments to generate any positive stock price jumps. In contrast, DSM's event studies do not show any significant positive return in brand firm's stock for any windows following the announcement of a settlement without payment. They therefore concluded that settlements without payments are not anticompetitive, because investors don't respond in a way that suggests belief of higher-than-expected profits. In addition, DSM assumes that settlements without payments are not anticompetitive because they represent the same negotiation that would occur inside a courtroom, without the distortion of a reverse payment.

[29] Panattoni (2009) uses only event windows (0,0) and (0,1) to capture abnormal return effects of patent litigation decisions, and stresses the importance in using both to account for time-of-day differences of news announcements.

Table 8. Event study results ($CAAR_{t2\text{-}t1}$) for settlements without an indication of payment and test statistics/p-values to test H_0: $CAAR_{t2\text{-}t1,\ No\ Payment} = 0$

N=48			*Parametric*						*Non-Parametric*			
Event Window	$CAAR_{t2\text{-}t1}$	Standard Error	t-test statistic$_1$	p-value	Patell Z statistic	p-value	BMP Test Z	p-value	Sign Test Z	p-value	Rank Test Z	p-value
Market Model												
(0,0)	0.58%	0.0038	1.51*	0.0659	0.75	0.2279	0.85	0.1988	0.96	0.1682	0.89	0.1880
(-1,+1)	0.32%	0.0070	0.46	0.3235	0.75	0.2256	0.79	0.2155	2.70***	0.0035	1.09	0.1386
(-2,+2)	-0.05%	0.0081	-0.06	0.4752	0.77	0.2212	0.71	0.2386	-0.20	0.4226	0.41	0.3414
(-3,+3)	0.05%	0.0072	0.07	0.4724	0.83	0.2044	0.71	0.2398	0.09	0.4626	-0.13	0.4489
(-3,0)	-0.08%	0.0065	-0.12	0.4508	0.37	0.3559	0.39	0.3495	0.09	0.4626	-0.45	0.3256
(-2,0)	-0.11%	0.0054	-0.21	0.4188	0.21	0.4189	0.24	0.4051	0.09	0.4626	-0.03	0.4884
(-1,0)	-0.02%	0.0021	-0.10	0.4619	0.04	0.4858	0.07	0.4739	1.54*	0.0618	0.17	0.4320
(0,+1)	0.93%	0.0054	1.72**	0.0425	1.42*	0.0786	1.62*	0.0527	2.70***	0.0035	1.79**	0.0375
(0,+2)	0.64%	0.0064	0.99	0.1600	1.22	0.1117	1.18	0.1198	0.09	0.4626	1.07	0.1430
(0,+3)	0.71%	0.0073	0.97	0.1664	1.10	0.1365	0.97	0.1656	-0.20	0.4226	0.73	0.2343
Fama-French Model												
(0,0)	0.60%	0.0037	1.64*	0.0504	0.98	0.1635	1.09	0.1379	1.22	0.1105	1.18	0.1209
(-1,+1)	0.34%	0.0064	0.53	0.2969	1.04	0.1490	1.02	0.1539	1.51*	0.0652	1.24	0.1088
(-2,+2)	0.04%	0.0089	0.05	0.4821	1.15	0.1251	1.04	0.1503	0.36	0.3607	0.73	0.2319
(-3,+3)	0.15%	0.0100	0.15	0.4402	1.25	0.1056	1.04	0.1493	0.07	0.4731	0.26	0.3966
(-3,0)	0.01%	0.0091	0.01	0.4956	0.77	0.2206	0.78	0.2176	0.36	0.3607	-0.07	0.4706
(-2,0)	-0.06%	0.0059	-0.10	0.4593	0.46	0.3228	0.50	0.3101	0.65	0.2593	0.23	0.4101
(-1,0)	0.04%	0.0055	0.07	0.4707	0.43	0.3336	0.46	0.3229	0.94	0.1750	0.50	0.3097
(0,+1)	0.90%	0.0052	1.74**	0.0409	1.53*	0.0630	1.78**	0.0374	2.67***	0.0038	1.85**	0.0331
(0,+2)	0.70%	0.0063	1.11	0.1340	1.60*	0.0548	1.57*	0.0581	0.36	0.3607	1.40*	0.0818
(0,+3)	0.74%	0.0073	1.01	0.1566	1.37*	0.0853	1.21	0.1135	-0.22	0.4123	1.01	0.1573

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

However, I want to further investigate the assumption that settlements without payments are not anticompetitive. As I stated in Section III, there are two assumptions present in DSM's paper:

(1) Settlements without payments are not anticompetitive because they represent a fair negotiation of the settlement terms between the brand and generic firms and serve as a proxy for the expected patent length from a trial

(2) A positive abnormal stock return indicates that an anticompetitive settlement has taken place

DSM's results support both of these assumptions, as they found significant positive abnormal returns for settlements with payments but not for settlements without payments. Assumption (1) is that settlements without payments are never anticompetitive because they represent the same negotiation process that would have occurred in a trial. However, using the EHHS theoretical framework in *Activating Actavis* and *The Actavis Inference: Theory and Practice*, I work out the threshold of entry date E at which the generic is willing to settle.

Brand Firm (A) will settle if the following holds true (from *Activating Actavis)*:

$$EM_A + (T - E)D_A - X > T[PM_A + (1 - P)D_A] - C_A \qquad [34]$$

Simplifying Equation [34], we get the same equation as [1] from the Literature Review section:

$$E > PT + \frac{X - C_A}{M_A - D_A} \qquad \text{[15], same as [1]}$$

Generic Firm (B) will settle if the following holds true:

$$(T - E)D_B + X > T[(1 - P)D_B] - C_B \qquad [36]$$

Simplifying Equation [36], Equation [37] represents the maximum E at which the generic firm is willing to settle:

$$E < PT + \frac{C_B + X}{D_B} \qquad [37]$$

where (using the same definitions as EHHS in *Activating Actavis*):

P = Probability that brand firm A will win litigation

T = Remaining patent lifetime

PT = Expected patent length that would prevail in court

E = Settlement Entry Date

M_A = Monopoly profits for Firm A

D_A = Duopoly profits for Firm A

D_B = Duopoly profits for Firm B

$C_{A/B}$ = Litigation Costs for Firm A/B

X = Settlement payment size

The left sides of equations [34] and [36] above represent the expected firm profits under a settlement with entry date, E. The right sides of the equations represent the expected firm profits under litigation. The brand (Firm A) and generic (Firm B) will both opt for a settlement if the expected profits of a settlement exceeds the expected profits of litigation. The resulting E values in equations [35] and [37] therefore represent the thresholds of the entry date, E, under which both firms are willing to settle.

Figure 4. Timeline for EHHS Theoretical Framework

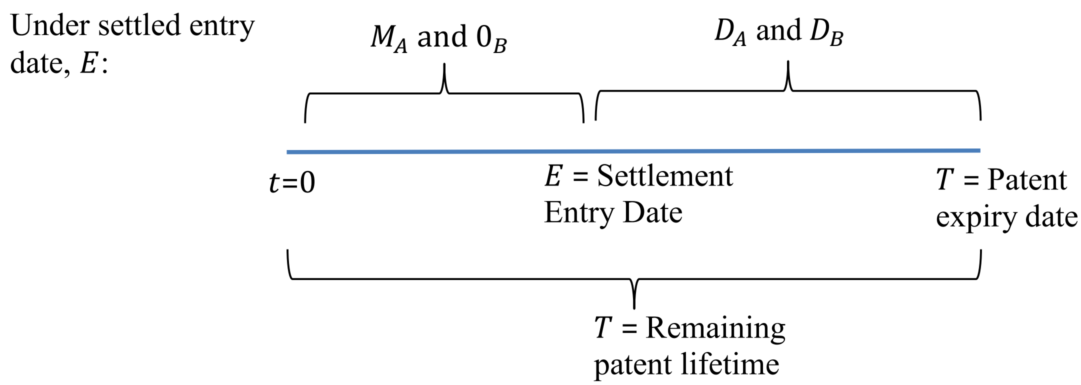


Figure 4 above shows a timeline of the dates in the model and the resulting monopoly/duopoly profits under the settled entry date, E. An assumption of the model is that after the generic enters, both the brand and generic firms compete in duopoly until the patent expiry date. In other words, there are no generic entrants that enter. As EHHS have described, this assumption is not always the case with reverse payment settlements. However, the only difference this makes for the model is the size of D_A and D_B. If we relax the assumption that duopoly results after entry and allow for multiple generic firms to enter, D_A and D_B decrease in size and the threshold E value for the brand firm gets closer to PT (as seen in [35]) while the threshold E value for the generic firm gets even further away from PT (seen in [37]).

The generic will only settle if equation [37] holds true, and this settlement is anticompetitive if the entry date is greater than the expected patent length from a trial:

$$E > PT \qquad [38], \text{same as } [2]$$

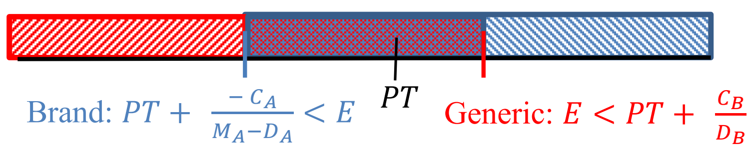
Combining [37] and [38], we can obtain the range of E for which the generic will settle and the settlement obtained is anticompetitive:

$$PT < E < PT + \frac{C_B + X}{D_B} \quad [39]$$

However, because $\frac{C_B+X}{D_B}$ is always positive, the generic is always willing to settle at a threshold of E greater than PT. Even when there is no reverse payment ($X = 0$), $\mathrm{E} < \mathrm{PT} + \frac{\mathrm{C_B}}{\mathrm{D_B}}$ and the threshold E is greater than PT. Therefore, it is possible for some settlements without payments to be anticompetitive because the generic firm is always willing to settle with values of E that are above PT.

Figure 5 below shows the ranges of possible E that the generic firm (depicted in red) and the brand firm (depicted in blue) are willing to settle when there is no payment.

Figure 5. Thresholds of entry date *E* for the Generic (red) and Brand (blue) firms for Settlements without Payments ($X = 0$)



We can see in the above figure that there is a range of settlements without payments that are anticompetitive, represented by the region shaded both red and blue to the right of PT, that the generic and the brand firm are willing to settle. While in the case of the brand firm, it is possible to obtain a threshold of settlements that are not anticompetitive and actually have a range of E below PT, the threshold at which generic firms are willing to settle is never below PT even when there is no payment.

In addition, if we combine the generic firm [37] and brand firm [35] decisions, we obtain a range of E for which they are both willing to settle:

$$PT + \frac{X - C_A}{M_A - D_A} < E < PT + \frac{C_B + X}{D_B} \quad [40]$$

Subtracting PT from all sides, the time difference between the settled entry date E and the expected entry date from a trail falls in a range of:

$$\frac{X - C_A}{M_A - D_A} < E - PT < \frac{C_B + X}{D_B} \quad [41]$$

$E - PT$ in equation [41] represents the additional delay from settlement rather than going to trial. It is therefore a measurement of how much more anticompetitive the settlement is than going to trial. As EHHS have explained, when the payment size, X, is lower than the brand firm's litigation costs, C_A, settlements may even result in a negative $E - PT$ and be less anticompetitive than the expected outcome of a trial. However, there is no scenario when the upper bound of the additional delay from settling, $E - PT$, is not positive. Therefore, even when $X = 0$, there is always a range of $E - PT$ that is positive, which means that there is always a range of possible values for E that are higher than PT. Therefore, the assumption that settlements without payments never have anticompetitive effects may not be reasonable. This could be a theoretical argument as to why there are positive abnormal returns even in settlements without payments in the dataset of generic firm stock returns.

An alternative explanation to the theoretical argument presented above for the presence of positive abnormal results in windows (0,0) and (0,1) in the No Payments sample could also be firm reputation and market underestimation of settlement results. To formally test the effect of firm reputation in the No Payments sample, I examined the differences in CAAR's of Frequent and Infrequent settlers conditional on No Payments. Out of the 48 No Payment settlements, 27 were settled by frequent settlers and 18 were settled by infrequent settlers. I conducted a similar series of statistical tests on the null hypothesis in [14] regarding whether $CAAR_{t2\text{-}t1,\ No\ Payments/Frequent}$ and $CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent}$ were significantly greater than 0 (Table 6 and Table 9). The effect of Frequency in the No Payments group was not immediately clear, since there are some significant abnormal returns in windows near (0,0) and (0,1) for both groups: in windows (-3,0), (0,1), (0,2) for frequent settlers and in windows (0,0) and (0,1) for infrequent settlers. Many of these results also depended on which statistical test was used. Therefore, to test the effect of being a frequent settler on settlements without payments, I test the hypotheses:

H_0: $CAAR_{t2\text{-}t1,\ No\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent} = 0$ [42]

H_1: $CAAR_{t2\text{-}t1,\ No\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent} > 0$

Table 10 displays the difference between $CAAR_{t2\text{-}t1,\ No\ Payments/Frequent}$ and

Table 9. Event study results ($CAAR_{t2-t1}$) for settlements without an indication of payment settled by infrequent settlers and test statistics/p-values to test H_0: $CAAR_{t2-t1,\ No\ Payment/Infrequent} = 0$

N=21			*Parametric*						*Non-Parametric*			
Event Window	$CAAR_{t2-t1}$	Standard Error	t-test statistic$_1$	p-value	Patell Z statistic	p-value	BMP Test Z	p-value	Sign Test Z	p-value	Rank Test Z	p-value
Market Model												
(0,0)	1.35%	0.0073	1.85**	0.0324	1.24	0.1067	1.32*	0.0931	1.74**	0.0409	1.66**	0.0493
(-1,+1)	0.10%	0.0130	0.08	0.4694	0.16	0.4378	0.17	0.4334	2.61***	0.0045	0.27	0.3923
(-2,+2)	-1.23%	0.0163	-0.76	0.2252	-0.42	0.3378	-0.39	0.3473	-1.32*	0.0938	-0.77	0.2202
(-3,+3)	-1.08%	0.0194	-0.56	0.2892	-0.30	0.3809	-0.22	0.4142	-0.88	0.1891	-0.99	0.1623
(-3,0)	-0.95%	0.0146	-0.65	0.2579	-0.70	0.2428	-0.74	0.2299	-0.44	0.3285	-1.17	0.1209
(-2,0)	-0.67%	0.0127	-0.53	0.2987	-0.25	0.4025	-0.24	0.4056	-0.01	0.4971	-0.54	0.2943
(-1,0)	-0.14%	0.0105	-0.13	0.4471	0.14	0.4462	0.15	0.4388	1.74	0.0409	0.36	0.3598
(0,+1)	1.59%	0.0104	1.53*	0.0626	0.94	0.1745	1.00	0.1585	2.18**	0.0147	1.15	0.1258
(0,+2)	0.79%	0.0127	0.62	0.2676	0.43	0.3355	0.58	0.2798	-0.44	0.3285	0.50	0.3081
(0,+3)	1.23%	0.0147	0.84	0.2009	0.92	0.1792	0.83	0.2024	-0.01	0.4971	0.70	0.2430
Fama-French Model												
(0,0)	1.25%	0.0072	1.74**	0.0412	1.23	0.1093	1.25	0.1061	0.89	0.1871	1.56*	0.0606
(-1,+1)	-0.01%	0.0100	-0.01	0.4959	0.27	0.3936	0.27	0.3945	0.89	0.1871	0.22	0.4130
(-2,+2)	-1.39%	0.0161	-0.86	0.1938	-0.37	0.6443	-0.33	0.3704	-0.42	0.3364	-0.79	0.2151
(-3,+3)	-1.16%	0.0190	-0.61	0.2710	-0.05	0.5199	-0.02	0.4915	-0.86	0.1951	-0.78	0.2187
(-3,0)	-1.09%	0.0144	-0.76	0.2250	-0.67	0.7486	-0.68	0.2472	-0.86	0.1951	-1.22	0.1124
(-2,0)	-0.82%	0.0124	-0.66	0.2550	-0.35	0.6368	-0.32	0.3759	0.02	0.4942	-0.65	0.2583
(-1,0)	-0.21%	0.0102	-0.21	0.4183	0.22	0.5871	0.23	0.4091	0.89	0.1871	0.32	0.3748
(0,+1)	1.45%	0.0102	1.42*	0.0775	0.98	0.1635	1.05	0.1470	1.76**	0.0390	1.05	0.1473
(0,+2)	0.68%	0.0125	0.55	0.2925	0.59	0.2776	0.81	0.2077	0.02	0.4942	0.53	0.2991
(0,+3)	1.18%	0.0144	0.82	0.2070	1.23	0.1093	1.09	0.1390	-0.42	0.3364	0.97	0.1674

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Table 10. Difference between $CAAR_{t2\text{-}t1}$'s for frequent and infrequent settlers for settlements without an indication of payment and test statistics/p-values to test H_0: $CAAR_{t2\text{-}t1,\ No\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent} = 0$

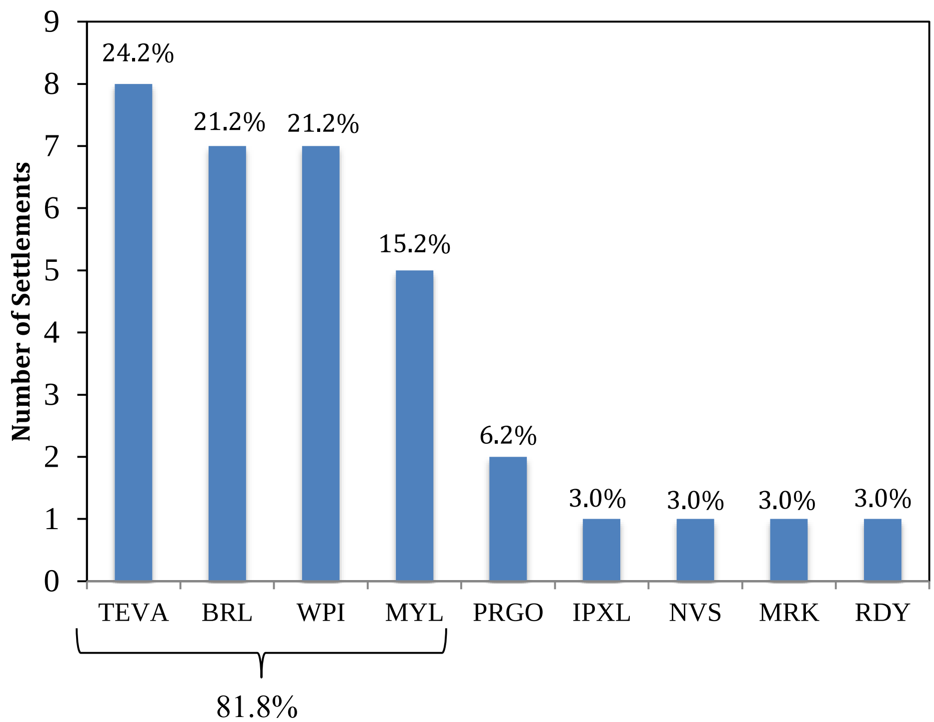
df = 46

Event Window	$CAAR_{t2\text{ - }t1,\ No\ Payments/\ Frequent}$	$CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent}$	Difference in CAARs	Var($CAAR_{t2\text{-}t1,\ No\ Payments/\ Frequent}$)	Var($CAAR_{t2\text{-}t,\ No\ Payments/\ Infrequent}$)	SE ($CAAR_{t2\text{-}t1,\ No\ Payments/Frequent}$ - $CAAR_{t2\text{-}t1\ No\ Payments/\ Infrequent}$)	t-statistic$_2$	p-value
Market Model								
(0,0)	-0.02%	1.35%	-1.37%	0.0004	0.0011	0.0082	-1.6720^*	0.0510
(-1,+1)	0.50%	0.10%	0.40%	0.0007	0.0035	0.0139	0.29	0.3866
(-2,+2)	0.88%	-1.23%	2.11%	0.0011	0.0056	0.0175	1.21	0.1162
(-3,+3)	0.92%	-1.08%	2.00%	0.0015	0.0079	0.0208	0.96	0.1710
(-3,0)	0.59%	-0.95%	1.54%	0.0009	0.0045	0.0157	0.98	0.1661
(-2,0)	0.33%	-0.67%	1.00%	0.0007	0.0034	0.0136	0.73	0.2345
(-1,0)	0.06%	-0.14%	0.20%	0.0004	0.0023	0.0112	0.18	0.4290
(0,+1)	0.42%	1.59%	-1.17%	0.0004	0.0023	0.0111	-1.05	0.8504
(0,+2)	0.53%	0.79%	-0.26%	0.0006	0.0034	0.0136	-0.19	0.5749
(0,+3)	0.31%	1.23%	-0.92%	0.0009	0.0045	0.0157	-0.58	0.7176
Fama-French Model								
(0,0)	0.09%	1.25%	-1.16%	0.0002	0.0011	0.0077	-1.5096^*	0.0689
(-1,+1)	0.61%	-0.01%	0.62%	0.0006	0.0021	0.0111	0.56	0.2891
(-2,+2)	1.15%	-1.39%	2.54%	0.0010	0.0054	0.0173	1.47*	0.0742
(-3,+3)	1.16%	-1.16%	2.32%	0.0015	0.0076	0.0204	1.14	0.1301
(-3,0)	0.86%	-1.09%	1.95%	0.0008	0.0044	0.0155	1.26	0.1070
(-2,0)	0.53%	-0.82%	1.35%	0.0006	0.0033	0.0134	1.01	0.1589
(-1,0)	0.23%	-0.21%	0.44%	0.0004	0.0022	0.0109	0.40	0.3455
(0,+1)	0.47%	1.45%	-0.98%	0.0004	0.0022	0.0109	-0.90	0.8135
(0,+2)	0.72%	0.68%	0.04%	0.0006	0.0033	0.0134	0.03	0.4881
(0,+3)	0.40%	1.18%	-0.78%	0.0009	0.0044	0.0155	-0.50	0.6903

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, ^ denotes a left-tailed p-value

$CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent}$, as well as the results of the testing the null hypothesis above. From the results in Table 10, I cannot reject the null in [42] for every window except (0,0) for both the Market and Fama-French Models. On the event date, (0,0), the $CAAR_{t2\text{-}t1}$ of the Infrequent group is actually higher than the $CAAR_{t2\text{-}t1}$ of the Frequent group, so the p-value displayed is calculated from conducting a left-tailed test (denoted with the symbol, ^). This suggests that on the event date itself, there is a significantly negative effect of Frequent on abnormal returns of the No Payment group. This is an unexpected result, because I would expect that the settlements that are negotiated by firms that frequently settle would garner more confidence from investors. However, if we examine the settlement rates of frequent and infrequent settlers, we see that most of the settlements with payments are settled by frequent settlers:

Figure 6. Frequencies of Firms that Settle with Payment



Since frequent settlers often seem to be involved with settlements with payments, perhaps the jump in stock prices for infrequent settlers of settlements without payments is due to a systematic underestimation of the Infrequent Settlers of settlements without payments before the official settlement announcement. The firm's reputations as infrequent settlers coupled with the fact that these settlements don't involve payments could cause the market to underestimate the terms of the settlement on the firm's profits. On date (0,0), this market underestimation corrects when the actual terms of the settlements without payments are released. This explanation implies that the stock price jump is not necessarily a result of anticompetitive settlements without payments, but rather the correction of market underestimation due to the negative reputation of the firm in terms of its propensity to settle. The positive (0,0) returns of No Payment/Infrequent settlements due to underestimation could be an alternative explanation to the theoretical argument presented above for the presence of positive abnormal returns in the No Payments sample.

VII.3 Results – Effect of being a Frequent Settler

While the impact of firm reputation as a Frequent or Infrequent settler has been discussed in the context of the effect of Payments, I also examine the two Frequent and Infrequent groups and the difference between them as a whole. Tables 11 and 12 display the $CAAR_{t2\text{-}t1}$ observations for the Frequent and Infrequent groups respectively, along with the test statistics to test the null from [14] that $CAAR_{t2\text{-}t1,\ Frequent}$ and $CAAR_{t2\text{-}t1,\ Infrequent}$ are not statistically significant. The results in Table 10 suggest that we can reject the null hypothesis that $CAAR_{t2\text{-}t1,\ Frequent}$ is not statistically significant for every window under almost every test. The results in Table 11 only permit the rejection of the null that $CAAR_{t2\text{-}t1,\ Infrequent}$ is not statistically significant for the windows (0,0) and (0,1). Interestingly, the positive abnormal returns present in the Frequent group resemble those in the Payment group from Section VII.1 (Table 2). There are also pre-event date returns in windows (-3,0), (-2,0), and (-1,0) that seem slightly higher in magnitude than post-event date returns in windows (0,3), (0,2) and (0,1). At the same time, the Infrequent group observations are similar to the No Payment group observations from section VII.2 (Table 8), with significant abnormal returns only occurring in the windows (0,0) and (0,1), depending on which $E(r_{it})$ model is used. These similarities will be explored further in detail later in this section in the context of possible correlation between Payment and Frequent, and No Payment and Infrequent.

Table 11. Event study results ($CAAR_{t2-t1}$) for settlements by frequent settlers (TEVA, ACT/WPI, MYL, BRL) and test statistics/p-values to test H_0: $CAAR_{t2-t1,\ Frequent} = 0$

N=54			*Parametric*						*Non-Parametric*			
Event Window	$CAAR_{t2-t1}$	Standard Error	t-test statistic$_1$	p-value	Patell Z statistic	p-value	BMP Test Z	p-value	Sign Test Z	p-value	Rank Test Z	p-value
Market Model												
(0,0)	0.28%	0.0022	1.30*	0.0967	1.32*	0.0933	1.41*	0.0789	0.67	0.2507	0.99	0.1615
(-1,+1)	1.53%	0.0038	4.04***	<.0001	3.30***	0.0005	2.76***	0.0029	2.31**	0.0105	2.83***	0.0026
(-2,+2)	1.91%	0.0049	3.92***	<.0001	3.60***	0.0002	2.87***	0.0021	2.58***	0.0049	2.78***	0.0030
(-3,+3)	2.15%	0.0058	3.73***	0.0001	3.33***	0.0004	2.82***	0.0024	2.58***	0.0049	2.29**	0.0116
(-3,0)	1.55%	0.0044	3.56***	0.0002	2.41***	0.0079	2.04**	0.0207	1.22	0.1117	1.88**	0.0307
(-2,0)	1.23%	0.0038	3.26***	0.0006	2.01**	0.0222	1.82**	0.0346	0.40	0.3447	1.76**	0.0405
(-1,0)	0.95%	0.0031	3.10***	0.0010	1.85**	0.0325	1.67**	0.0479	0.95	0.1724	1.48*	0.0709
(0,+1)	0.85%	0.0031	2.77***	0.0028	3.13***	0.0009	2.79***	0.0027	3.13***	0.0009	2.69***	0.0039
(0,+2)	0.96%	0.0038	2.55***	0.0054	3.40***	0.0003	2.48***	0.0067	1.22	0.1117	2.41***	0.0085
(0,+3)	0.88%	0.0044	2.02**	0.0216	2.66**	0.0040	2.18**	0.0148	0.95	0.1724	1.64*	0.0514
Fama-French Model												
(0,0)	0.33%	0.0021	1.56*	0.0594	1.47*	0.0708	1.66**	0.0484	1.43*	0.0766	1.36*	0.0871
(-1,+1)	1.58%	0.0037	4.33***	<.0001	3.33***	0.0004	2.81***	0.0025	2.52***	0.0059	2.87***	0.0023
(-2,+2)	2.02%	0.0047	4.29***	<.0001	3.90***	0.0000	3.01***	0.0013	2.25**	0.0124	3.01***	0.0015
(-3,+3)	2.13%	0.0056	3.83***	<.0001	3.49***	0.0002	2.79***	0.0026	2.25**	0.0124	2.25**	0.0130
(-3,0)	1.58%	0.0042	3.75***	<.0001	2.67***	0.0038	2.09**	0.0182	1.70**	0.0445	1.96**	0.0259
(-2,0)	1.29%	0.0036	3.54***	0.0002	2.28**	0.0113	1.88**	0.0303	1.16	0.1239	1.91**	0.0288
(-1,0)	1.01%	0.0030	3.42***	0.0003	1.98**	0.0239	1.76**	0.0389	0.88	0.1886	1.66**	0.0499
(0,+1)	0.89%	0.0030	2.99***	0.0014	3.13***	0.0009	3.01***	0.0013	2.79***	0.0026	2.83***	0.0026
(0,+2)	1.05%	0.0036	2.90***	0.0019	3.61***	0.0002	2.70***	0.0035	2.25**	0.0124	2.76***	0.0032
(0,+3)	0.88%	0.0042	2.10**	0.0181	2.69**	0.0036	2.19**	0.0144	0.88	0.1886	1.69**	0.0461

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level

Table 12. Event study results ($CAAR_{t2-t1}$) for settlements by infrequent settlers and test statistics/p-values to test H_0: $CAAR_{t2-t1,\ Infrequent} = 0$

N=27			*Parametric*						*Non-Parametric*			
Event Window	$CAAR_{t2-t1}$	Standard Error	t-test statistic[1]	p-value	Patell Z statistic	p-value	BMP Test Z	p-value	Sign Test Z	p-value	Rank Test Z	p-value
Market Model												
(0,0)	1.02%	0.0060	1.69**	0.0453	1.08	0.1397	1.25	0.1065	1.54*	0.0617	1.49*	0.0696
(-1,+1)	-0.29%	0.0105	-0.28	0.3918	-0.39	0.3476	-0.42	0.3362	1.54*	0.0617	-0.34	0.3679
(-2,+2)	-1.26%	0.0135	-0.93	0.1753	-0.83	0.2042	-0.86	0.1939	-1.93**	0.0271	-1.25	0.1065
(-3,+3)	-0.91%	0.0160	-0.57	0.2851	-0.53	0.2991	-0.44	0.3310	-1.16	0.1239	-1.16	0.1238
(-3,0)	-0.74%	0.0121	-0.61	0.2698	-0.74	0.2298	-0.84	0.2018	-0.77	0.2206	-1.18	0.1206
(-2,0)	-0.76%	0.0105	-0.72	0.2345	-0.72	0.2356	-0.75	0.2268	-0.77	0.2206	-1.13	0.1304
(-1,0)	-0.39%	0.0085	-0.46	0.3240	-0.41	0.3414	-0.48	0.3171	0.77	0.2206	-0.17	0.4338
(0,+1)	1.13%	0.0086	1.32*	0.0939	0.69	0.2440	0.81	0.2082	1.54*	0.0617	0.80	0.2114
(0,+2)	0.52%	0.0105	0.50	0.3097	0.28	0.3905	0.42	0.3371	-0.77	0.2206	0.37	0.3551
(0,+3)	0.86%	0.0121	0.71	0.2392	0.58	0.2799	0.58	0.2815	0.00	0.5000	0.38	0.3507
Fama-French Model												
(0,0)	0.93%	0.0060	1.54*	0.0614	0.94	0.1736	1.01	0.1557	0.81	0.2092	1.21	0.1142
(-1,+1)	-0.38%	0.0104	-0.36	0.3579	-0.31	0.6217	-0.31	0.3794	0.04	0.4846	-0.35	0.3646
(-2,+2)	-1.43%	0.0134	-1.06	0.1437	-0.87	0.8078	-0.88	0.1883	-1.50*	0.0665	-1.38*	0.0848
(-3,+3)	-1.08%	0.0158	-0.68	0.2474	-0.44	0.6700	-0.36	0.3583	-1.50*	0.0665	-1.16	0.1237
(-3,0)	-0.87%	0.0120	-0.73	0.2342	-0.76	0.7764	-0.84	0.1993	-1.50*	0.0665	-1.26	0.1045
(-2,0)	-0.88%	0.0104	-0.84	0.1997	-0.82	0.7939	-0.82	0.2070	-0.73	0.2321	-1.24	0.1092
(-1,0)	-0.42%	0.0085	-0.49	0.3106	-0.29	0.6141	-0.30	0.3841	0.42	0.3359	-0.10	0.4591
(0,+1)	0.97%	0.0085	1.14	0.1273	0.58	0.2810	0.67	0.2505	1.19	0.1162	0.53	0.2973
(0,+2)	0.37%	0.0103	0.36	0.3593	0.24	0.4052	0.36	0.3599	-0.35	0.3644	0.15	0.4394
(0,+3)	0.71%	0.0120	0.59	0.2764	0.66	0.2546	0.63	0.2642	-1.12	0.1319	0.33	0.3708

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level

To examine the significance of the effect of Frequent on abnormal returns, I take the difference between Frequent and Infrequent settlers conditional on settlements with payments and settlements without payments. Table 13 displays the difference between the Frequent and Infrequent groups conditional on Payments, as well as the test statistics to test the following hypotheses:

H_0: $CAAR_{t2\text{-}t1,\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ Payments/Infrequent} = 0$ [43]

H_1: $CAAR_{t2\text{-}t1,\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ Payments/Infrequent} > 0$

The null above can be rejected at all the pre-event windows, (-3,0), (-2,0), and (-1, 0). Therefore, it seems that among settlements with payments, the reputation of the firm has a significant effect of abnormal returns in the windows *prior* to the event date 0. This result is again very similar to the results found in Section VII.1 regarding the effect of Payment on abnormal returns, conditional on the settler being Frequent (Table 7).

In contrast, Table 10 exhibits the difference between the returns from settlements settled by frequent and infrequent settlers conditional on No Payments. As discussed in Section VII.2, Table 10 displays the difference in observations and the results from conducting the following hypothesis tests:

H_0: $CAAR_{t2\text{-}t1,\ No\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent} = 0$ [44]

H_1: $CAAR_{t2\text{-}t1,\ No\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent} > 0$

As discussed in Section VII.2, the reputation of the firm as a frequent settler seems to have no effect on most windows for settlements without payments except (0,0). On the event date, (0,0), Frequent actually seems to have a negative impact on abnormal stock returns. As discussed above in Section VII.2, this could be due to the systematic underestimation of settlement terms when an infrequent settler is involved in a settlement without payment, as the frequent settlers tend to target the settlements with payments.

Therefore, after testing the effects of Frequent, I found results that were very similar to the effects of Payments on abnormal stock returns. The results from Frequent – Infrequent|Payment (Table 13) and Payment – No Payment|Frequent (Table 7) showed similar significant effects of Frequent and Payment in pre-event windows, (-3,0), (-2,0), and (-1,0). Additionally, it seems that the presence of positive abnormal returns in (0,0) and (0,1) of the No Payments (Table 8) are driven by the infrequent settlers of these settlements (Table 10).

Table 13. Difference between $CAAR_{t2\text{-}t1}$'s for frequent and infrequent settlers for settlements with an indication of payment and test statistics/p-values to test H_0: $CAAR_{t2\text{-}t1,\ No\ Payments/Frequent} - CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent} = 0$

df = 31

Event Window	$CAAR_{t2-t1,\ Payments/\ Frequent}$	$CAAR_{t2-t1,\ Payments/Infrequent}$	Difference in CAARs	$Var(CAAR_{t2-t1,\ Payments/Frequent})$	$Var(CAAR_{t2-t1,\ Payments/Infrequent})$	$SE(CAAR_{t2-t1,\ Payments/Frequent} - CAAR_{t2-t1,\ Payments/\ Infrequent})$	$t\text{-statistic}_2$	p-value
Market Model								
(0,0)	0.58%	-0.13%	0.71%	0.00030	0.00050	0.00969	0.73	0.2354
(-1,+1)	2.55%	-1.63%	4.18%	0.00091	0.00141	0.01640	2.55***	0.0080
(-2,+2)	2.93%	-1.35%	4.28%	0.00152	0.00235	0.02117	2.02**	0.0260
(-3,+3)	3.38%	-0.32%	3.70%	0.00214	0.00332	0.02516	1.47*	0.0758
(-3,0)	2.51%	-0.01%	2.52%	0.00122	0.00240	0.02110	1.19	0.1215
(-2,0)	2.13%	-1.07%	3.20%	0.00092	0.00142	0.01646	1.94**	0.0308
(-1,0)	1.85%	-1.27%	3.12%	0.00061	0.00094	0.01339	2.33**	0.0132
(0,+1)	1.29%	-0.49%	1.78%	0.00061	0.00096	0.01350	1.32*	0.0982
(0,+2)	1.39%	-0.41%	1.80%	0.00092	0.00141	0.01643	1.10	0.1399
(0,+3)	1.45%	-0.44%	1.89%	0.00122	0.00190	0.01904	0.99	0.1649
Fama-French Model								
(0,0)	0.56%	-0.22%	0.78%	0.00028	0.00048	0.00954	0.82	0.2092
(-1,+1)	2.54%	-1.66%	4.20%	0.00085	0.00142	0.01639	2.56***	0.0078
(-2,+2)	2.88%	-1.55%	4.43%	0.00142	0.00238	0.02118	2.09**	0.0225
(-3,+3)	3.09%	-0.81%	3.90%	0.00198	0.00337	0.02519	1.55*	0.0656
(-3,0)	2.29%	-0.10%	2.39%	0.00114	0.00178	0.01842	1.30	0.1016
(-2,0)	2.05%	-1.06%	3.11%	0.00085	0.00142	0.01635	1.90**	0.0334
(-1,0)	1.80%	-1.15%	2.95%	0.00057	0.00095	0.01337	2.21**	0.0173
(0,+1)	1.30%	-0.73%	2.03%	0.00057	0.00096	0.01345	1.51*	0.0706
(0,+2)	1.39%	-0.70%	2.09%	0.00085	0.00141	0.01631	1.28	0.1050
(0,+3)	1.37%	-0.92%	2.29%	0.00114	0.00190	0.01895	1.21	0.1177

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

From these similarities in terms of both the presence of abnormal returns and the effects on abnormal returns between Payments and Frequent, it seems that the two variables may be correlated. To further investigate this idea, I tested the correlation between Payment and Frequent for all observations in my dataset. Figure 7 displays the correlation matrix between the variables Payment and Frequent, where correlation between Frequent and Payments, $\rho_{Freq,Pay}$ is calculated as:

$$\rho_{Freq,Pay} = \frac{Cov(Freq, Pay)}{\sigma_{Freq}\sigma_{Pay}} \qquad [45]$$

Figure 7. Pearson Correlation Matrix between Payment, Frequent, and their Interaction Term (N=81, df = 79)

ρ	Freq	Pay	Pay*Freq
Freq	1.0000	0.2562	0.4953
Pay	0.2562	1.0000	0.8518
Pay*Freq	0.4953	0.8518	1.0000

The correlation between Frequent and Payment, $\rho_{Freq,Pay}$, is 0.2562. This is a moderate correlation coefficient that suggests there is some positive relationship between Payment and Frequent. To evaluate the significance of the positive relationship between Payment and Frequent, I tested the null hypothesis that this correlation coefficient is not significantly different from zero:

H_0: $\rho_{Freq,Pay} = 0$ [46]

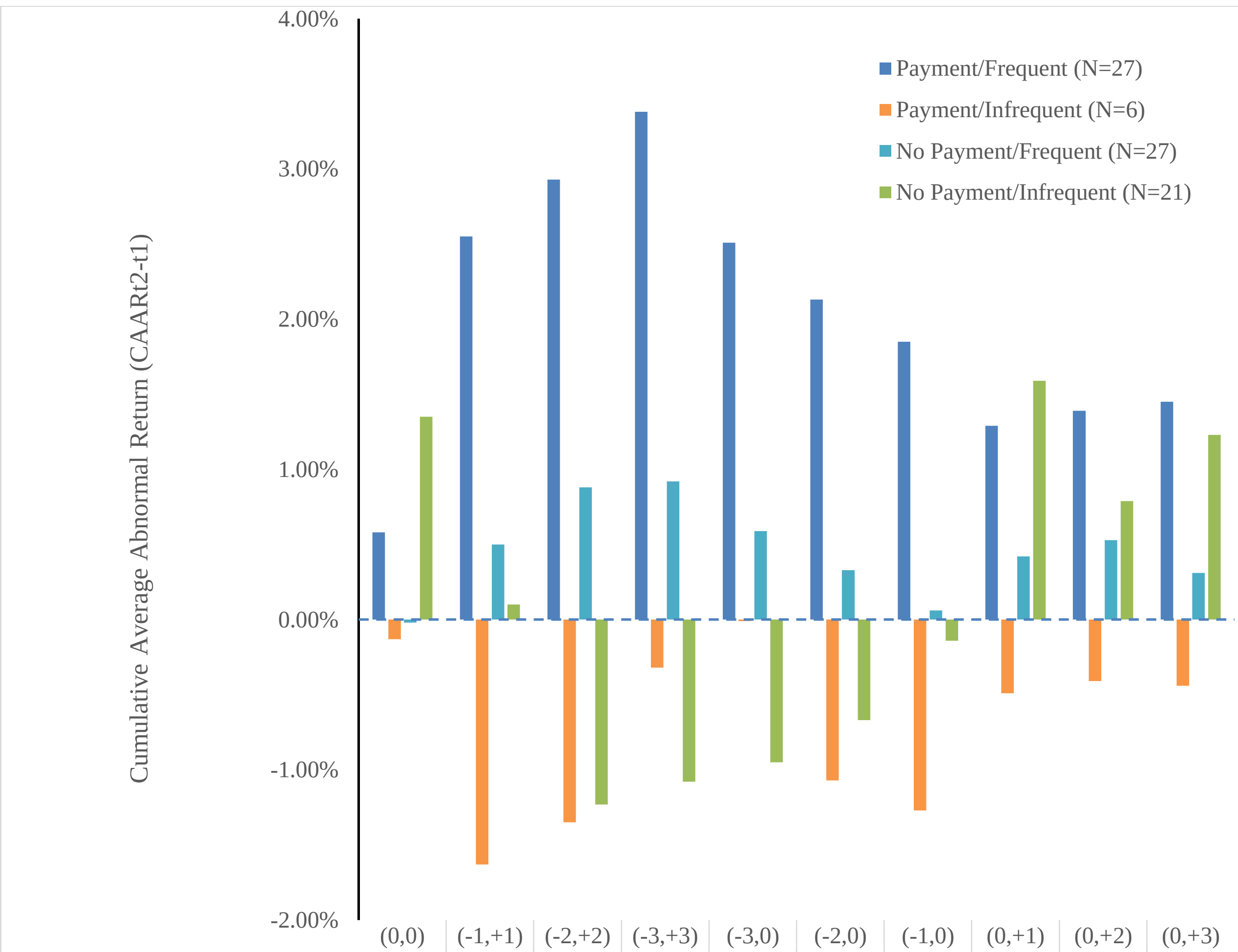
H_1: $\rho_{Freq,Pay} > 0$

After conducting a one-tailed t-test for the null hypothesis above, I found that I can reject the null to the 1.05%. These results imply that the variables Frequent and Payment are significantly correlated. The correlation between Payments and Frequent is also expected in the context of Figure 6, as more than 80% of all settlements with payments are settled by frequent settlers. Therefore, while I do not test the effects of the two variables in a multiple regression model, the effect of multicollinearity is present within my difference in means tests to examine the effects of

Payments and Frequent. The significant correlation between the two variables suggest that I cannot determine the isolated effects of either one separately.

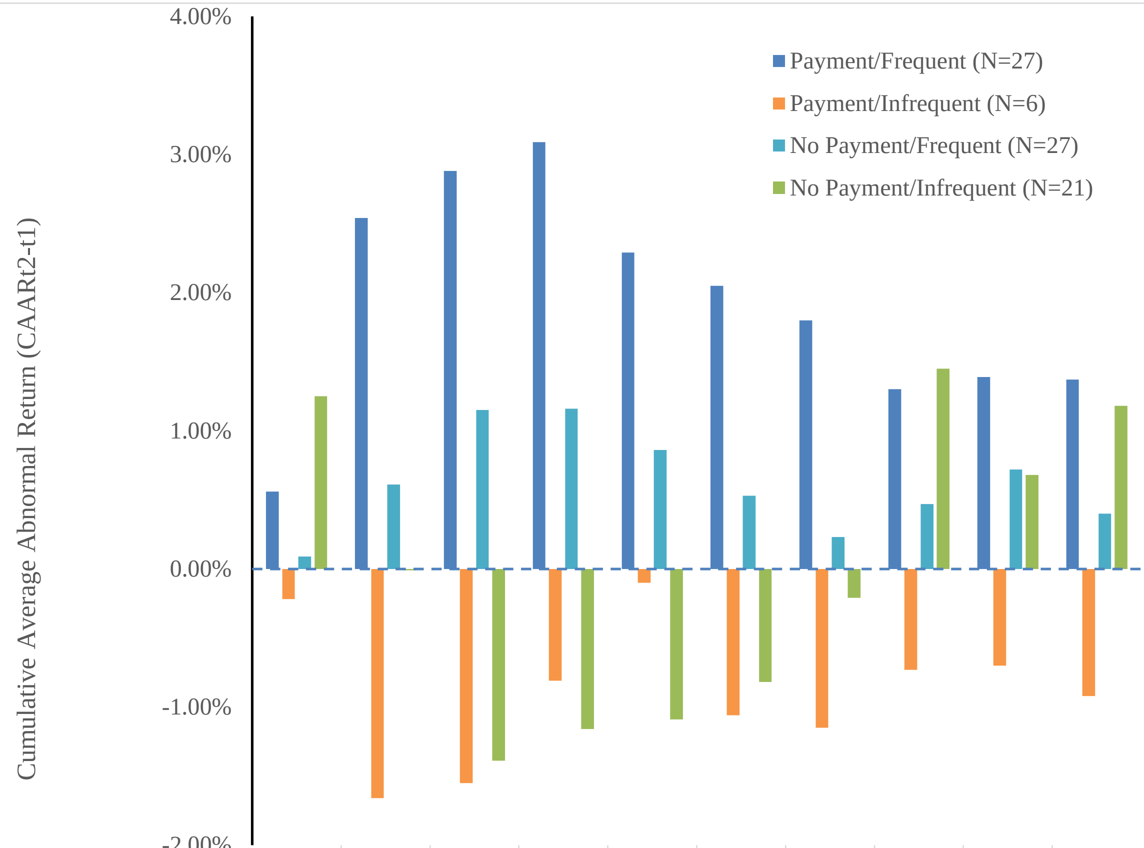
Figures 8 and 9 below summarize the $CAAR_{t2\text{-}t1}$ observations of the four data subgroups (Payment/Frequent, Payment/Infrequent, No Payment/Frequent, and No Payment/Infrequent) for each event window. Figure 8 shows the abnormal returns when the Market Model is used while Figure 9 shows the abnormal returns when the Fama-French Model is used to calculate the expected return.

Figure 8. Market Model $CAAR_{t2\text{-}t1}$ Observations for All Event Windows



	(0,0)	(-1,+1)	(-2,+2)	(-3,+3)	(-3,0)	(-2,0)	(-1,0)	(0,+1)	(0,+2)	(0,+3)
Payment/Frequent (N=27)	0.58%	2.55%	2.93%	3.38%	2.51%	2.13%	1.85%	1.29%	1.39%	1.45%
Payment/Infrequent (N=6)	-0.13%	-1.63%	-1.35%	-0.32%	-0.01%	-1.07%	-1.27%	-0.49%	-0.41%	-0.44%
No Payment/Frequent (N=27)	-0.02%	0.50%	0.88%	0.92%	0.59%	0.33%	0.06%	0.42%	0.53%	0.31%
No Payment/Infrequent (N=21)	1.35%	0.10%	-1.23%	-1.08%	-0.95%	-0.67%	-0.14%	1.59%	0.79%	1.23%

Figure 9. Fama-French Model CAAR$_{t2-t1}$ Observations for All Event Windows



	(0,0)	(-1,+1)	(-2,+2)	(-3,+3)	(-3,0)	(-2,0)	(-1,0)	(0,+1)	(0,+2)	(0,+3)
Payment/Frequent (N=27)	0.56%	2.54%	2.88%	3.09%	2.29%	2.05%	1.80%	1.30%	1.39%	1.37%
Payment/Infrequent (N=6)	-0.22%	-1.66%	-1.55%	-0.81%	-0.10%	-1.06%	-1.15%	-0.73%	-0.70%	-0.92%
No Payment/Frequent (N=27)	0.09%	0.61%	1.15%	1.16%	0.86%	0.53%	0.23%	0.47%	0.72%	0.40%
No Payment/Infrequent (N=21)	1.25%	-0.01%	-1.39%	-1.16%	-1.09%	-0.82%	-0.21%	1.45%	0.68%	1.18%

As discussed above, it seems that that settlements with firms that are Frequent settlers almost always trigger positive stock returns, especially in the days right before the settlement announcement (t=0). While it seems that the Payment/Infrequent group has negative abnormal returns in the event windows, these negative values are not significant and the small sample size (N=6) could be affecting the precision of the estimation. The No Payment/Infrequent group shows negative returns pre-event date and positive returns post-event date, which forms the basis for the alternative explanation to the theoretical model in Section VII.2, suggesting that there may be a market underestimation of these settlements.

While the literature surrounding reverse payment settlements focus only on the presence of payments as an indication of anticompetitive activity, my study has shown that there may be an alternative explanation for the presence of abnormal stock returns surrounding settlements with payments. The reputation of the firm as having a high propensity to settle also seems to have a significant effect on the abnormal returns. Furthermore, the occurrence of significant stock returns only in the event windows *before* the actual event date suggests that reputation, and not the presence of payments alone, are influencing stock returns. This is due to the fact that while the terms of the settlement are theoretically not known until the event date itself, the reputation of the firm as a frequent settler is known as soon as patent litigation surrounding the drug is announced. At the same time, the two factors of the presence of a payment and the reputation of the settler as having a high propensity to settle seem to be significantly correlated and the effects from these two variables cannot be clearly distinguished. Therefore, these results challenge the conclusion that abnormal stock returns for settlements with payments prove that the settlements are anticompetitive, because these high stock returns could be due to the reputation of the firm itself. However, since payments and reputation are correlated, it is also difficult to reject the conclusion that high stock returns are caused by the presence of payments. Thus, in the case of the generic firm, high stock returns themselves are not enough to prove the presence of anticompetitive settlements.

<u>VII.4 Results – Drug Percentage of Firm Sales</u>

In addition to the presence of a payment and the settling firm's reputation, to answer Question II, I also test whether or not the percentage of firm annual sales that a drug's annual sales comprises influences the abnormal return. Since the presence of a payment and whether the firm is a frequent settler are technically dummy variables, to avoid restricting my regression to have the same slope, I separated my data into the four subgroups mentioned in previous sections and then regressed the $CAR_{i,t2\text{-}t1}$, a firm-specific cumulative abnormal return, onto the percentage of total sales in year t that the annual sales of the drug in year t would comprise:

$$CAR_{i,t2\text{-}t1} = \beta_0 + \beta_1(Sales_t) + \epsilon_i \quad [24]$$

Details about the regression can also be found in Section VI. Hypothesis Testing – t-test. For each subgroup, I tested the null and alternative hypotheses regarding the coefficient, $\widehat{\beta_2}$:

H_0: $\widehat{\beta_2} = 0$ [26]

H_1: $\widehat{\beta_2} > 0$

Tables 14-17 display the results the OLS estimators of the coefficients β_1 and β_2, as well as the results of the hypothesis test above.

From the results in Tables 14 and 15, it seems that I can reject the null that $\widehat{\beta_2}$, the effect of drug sales percentage on abnormal returns, is zero for all windows prior to the event date for the Payment/Frequent group and only the windows (0,2) or (0,3) (depending on whether the Market Model or Fama-French are used) for the Payment/Infrequent group. Therefore, it seems that the relative sales of a drug also affects abnormal returns prior to the event date t=0 for settlements with payments that are settled by frequent settlers. The importance of the drug for the company's revenue is therefore another factor that influences the presence of positive returns *before* the event date. If investors see that firms with a reputation for settling often are involved in a payment settlement, most of the positive effects on stock returns occur early on because investors don't need to wait for the settlement to be officially published to begin trading at a higher price. The sales percentage of a drug playing a role in the pre-event date early stage therefore makes sense in this context, as most of the positive effects of settling have already occurred early on.

At the same time, from Table 15, it seems that the sales percentage of the drug does not play an important role in determining abnormal returns if the firm involved in the settlement does not have the reputation of being a frequent settler (the Payment/Infrequent group). This result is also expected, as there were no positive abnormal returns at all in the Payment/Infrequent sample. These results suggest that perhaps frequency is a more important determinant for abnormal returns, as neither the presence of a payment nor the percentage of drug sales seem to affect or induce positive stock returns for the infrequent group.

Tables 16 and 17 display the results of the regression and hypothesis test from [26] on the No Payment/Frequent and No Payment/Infrequent group. From Table 16, it seems that I can reject the null hypothesis that $\widehat{\beta_2}$ is equal to zero for almost every window. For settlements without payments settled by frequent settlers, the drug sales percentage influences the presence of abnormal returns for almost every window except the windows that include days further away from the event date, such as (-3,0), (0,2), and (0,3), depending on which expected returns model is used. While the actual returns for the No Payment/Frequent group are not statistically significant from zero except in the windows (0,0) and (0,1), the sales percentage has a significant effect on these abnormal returns for almost every window. This could be due to the fact that when a frequent settler enters into a settlement, whether this settlement involves a payment or not, investors will respond positively when the drug brings in a higher revenue. However, the

Table 14. Regression of $CAR_{i, t2-t1}$ observations on drug sales percentage of firm annual sales for settlements with payments settled by frequent settlers and test statistics/p-values to test H_0: $\widehat{\beta_1}= 0$

N=27

Event Window	$CAAR_{t2-t1}$	$\widehat{\beta_1}$	$\widehat{\beta_2}$	R Squared	Adjusted R Squared	SE ($\widehat{\beta_2}$)	t- test statistic$_3$	p-value	Standardized $\widehat{\beta_1}$
Market Model									
(0,0)	0.58%	0.0052	0.0015	0.0065	-0.0332	0.0037	0.41	0.3444	0.0808
(-1,+1)	2.55%	0.0049	0.0500	0.5224	0.5033	0.0096	5.23***	<.0001	0.7227
(-2,+2)	2.93%	0.0084	0.0507	0.4059	0.3822	0.0123	4.13***	0.0002	0.6371
(-3,+3)	3.38%	0.0141	0.0477	0.3176	0.2903	0.0140	3.41***	0.0011	0.5636
(-3,0)	2.51%	0.0080	0.0414	0.1616	0.1280	0.0189	2.19**	0.0189	0.4019
(-2,0)	2.13%	0.0012	0.0488	0.2459	0.2157	0.0171	2.85***	0.0043	0.4959
(-1,0)	1.85%	-0.0011	0.0473	0.3931	0.3689	0.0118	4.02***	0.0003	0.6270
(0,+1)	1.29%	0.0112	0.0042	0.0107	-0.0289	0.0081	0.52	0.3038	0.1035
(0,+2)	1.39%	0.0125	0.0035	0.0032	-0.0367	0.0123	0.28	0.3904	0.0562
(0,+3)	1.45%	0.0113	0.0078	0.0218	-0.0173	0.0105	0.75	0.2312	0.1477
Fama-French Model									
(0,0)	0.56%	0.0048	0.0020	0.0121	-0.0274	0.0035	0.55	0.2921	0.1102
(-1,+1)	2.54%	0.0036	0.0529	0.5232	0.5042	0.0101	5.24***	<.0001	0.7234
(-2,+2)	2.88%	0.0083	0.0499	0.3794	0.3546	0.0128	3.91***	0.0003	0.6160
(-3,+3)	3.09%	0.0119	0.0460	0.3055	0.2777	0.0139	3.32***	0.0014	0.5527
(-3,0)	2.29%	0.0049	0.0436	0.1656	0.1322	0.0196	2.23**	0.0176	0.4069
(-2,0)	2.05%	-0.0003	0.0505	0.2363	0.2057	0.0182	2.78***	0.0051	0.4861
(-1,0)	1.80%	-0.0031	0.0511	0.3904	0.3660	0.0128	4.00***	0.0003	0.6248
(0,+1)	1.30%	0.0115	0.0037	0.0094	-0.0302	0.0077	0.49	0.3148	0.0972
(0,+2)	1.39%	0.0134	0.0013	0.0004	-0.0395	0.0126	0.11	0.4584	0.0211
(0,+3)	1.37%	0.0118	0.0044	0.0061	-0.0337	0.0113	0.39	0.3493	0.0781

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Table 15. Regression of $CAR_{i,\ t2\text{-}t1}$ observations on drug sales percentage of firm annual sales for settlements with payments settled by infrequent settlers and test statistics/p-values to test H_0: $\widehat{\beta_1} = 0$

N=6

Event Window	$CAAR_{t2\text{-}t1}$	$\widehat{\beta_1}$	$\widehat{\beta_2}$	R Squared	Adjusted R Squared	SE($\widehat{\beta_2}$)	t-test statistic[3]	p-value	Standardized $\widehat{\beta_2}$
Market Model									
(0,0)	-0.13%	-0.0054	0.0272	0.0866	-0.1418	0.0441	0.62	0.2857	0.2943
(-1,+1)	-1.63%	-0.0196	0.0219	0.0367	-0.2041	0.0561	0.39	0.3581	0.1915
(-2,+2)	-1.35%	-0.0164	0.0192	0.0282	-0.2148	0.0563	0.34	0.3753	0.1678
(-3,+3)	-0.32%	-0.0129	0.0646	0.1000	-0.1250	0.0969	0.67	0.2708	0.3162
(-3,0)	-0.01%	-0.0065	0.0430	0.0442	-0.1948	0.0999	0.43	0.3447	0.2102
(-2,0)	-1.07%	-0.0113	0.0043	0.0006	-0.2492	0.0861	0.05	0.4813	0.0249
(-1,0)	-1.27%	-0.0131	0.0022	0.0009	-0.2489	0.0356	0.06	0.4774	0.0302
(0,+1)	-0.49%	-0.0119	0.0469	0.2202	0.0252	0.0442	1.06	0.1739	0.4692
(0,+2)	-0.41%	-0.0104	0.0421	0.3045	0.1307	0.0318	1.32	0.1282	0.5518
(0,+3)	-0.44%	-0.0117	0.0488	0.4462	0.3078	0.0272	1.80*	0.0735	0.6680
Fama-French Model									
(0,0)	-0.22%	-0.0087	0.0436	0.2020	0.0025	0.0434	1.01	0.1857	0.4494
(-1,+1)	-1.66%	-0.0209	0.0283	0.0565	-0.1794	0.0579	0.49	0.3252	0.2376
(-2,+2)	-1.55%	-0.0192	0.0248	0.0909	-0.1364	0.0392	0.63	0.2808	0.3015
(-3,+3)	-0.81%	-0.0161	0.0536	0.0931	-0.1337	0.0836	0.64	0.2783	0.3051
(-3,0)	-0.10%	-0.0093	0.0548	0.0737	-0.1579	0.0971	0.56	0.3014	0.2715
(-2,0)	-1.06%	-0.0132	0.0172	0.0121	-0.2349	0.0779	0.22	0.4179	0.1100
(-1,0)	-1.15%	-0.0153	0.0250	0.0776	-0.1530	0.0430	0.58	0.2965	0.2786
(0,+1)	-0.73%	-0.0143	0.0470	0.2731	0.0913	0.0384	1.23	0.1438	0.5226
(0,+2)	-0.70%	-0.0147	0.0512	0.3736	0.2170	0.0331	1.54*	0.0987	0.6112
(0,+3)	-0.92%	-0.0156	0.0424	0.3628	0.2034	0.0281	1.51	0.1029	0.6023

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Table 16. Regression of $CAR_{i,\ t2\text{-}t1}$ observations on drug sales percentage of firm annual sales for settlements without payments settled by frequent settlers and test statistics/p-values to test H_0: $\widehat{\beta_1} = 0$

N=27

Event Window	$CAAR_{t2\text{-}t1}$	$\widehat{\beta_1}$	$\widehat{\beta_2}$	R Squared	Adjusted R Squared	SE($\widehat{\beta_2}$)	t-test statistic[3]	p-value	Standardized $\widehat{\beta_2}$
Market Model									
(0,0)	-0.02%	-0.0042	0.0438	0.4395	0.4171	0.0099	4.43***	0.0001	0.6630
(-1,+1)	0.50%	0.0007	0.0460	0.1236	0.0885	0.0245	1.88**	0.0361	0.3515
(-2,+2)	0.88%	0.0025	0.0677	0.1473	0.1132	0.0326	2.08**	0.0241	0.3838
(-3,+3)	0.92%	0.0039	0.0574	0.0893	0.0528	0.0366	1.57*	0.0651	0.2988
(-3,0)	0.59%	0.0004	0.0597	0.1722	0.1390	2.2800	0.03	0.2075	0.4149
(-2,0)	0.33%	-0.0042	0.0809	0.4451	0.4229	0.0181	4.48***	0.0001	0.6672
(-1,0)	0.06%	-0.0039	0.0492	0.2197	0.1885	0.0185	2.65***	0.0069	0.4687
(0,+1)	0.42%	0.0005	0.0407	0.2121	0.1806	0.0157	2.59***	0.0078	0.4605
(0,+2)	0.53%	0.0025	0.0306	0.0491	0.0111	0.0269	1.14	0.1333	0.2216
(0,+3)	0.31%	-0.0007	0.0415	0.0767	0.0397	0.0288	1.44*	0.0811	0.2769
Fama-French Model									
(0,0)	0.09%	-0.0032	0.0442	0.4441	0.4219	0.0099	4.47***	0.0001	0.6664
(-1,+1)	0.61%	0.0023	0.0414	0.0975	0.0614	0.0252	1.64*	0.0564	0.3123
(-2,+2)	1.15%	0.0061	0.0585	0.1116	0.0761	0.0330	1.77**	0.0443	0.3341
(-3,+3)	1.16%	0.0067	0.0537	0.0779	0.0410	0.0370	1.45*	0.0793	0.2791
(-3,0)	0.86%	0.0025	0.0660	0.1991	0.1670	0.0265	2.49***	0.0099	0.4462
(-2,0)	0.53%	-0.0023	0.0819	0.4316	0.4088	0.0188	4.36***	0.0001	0.6570
(-1,0)	0.23%	-0.0022	0.0488	0.2107	0.1791	0.0189	2.58***	0.0080	0.4590
(0,+1)	0.47%	0.0013	0.0367	0.1801	0.1473	0.0157	2.34**	0.0137	0.4244
(0,+2)	0.72%	0.0053	0.0207	0.0244	-0.0146	0.0262	0.79	0.2182	0.1563
(0,+3)	0.40%	0.0010	0.0319	0.0476	0.0095	0.0285	1.12	0.1372	0.2182

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Table 17. Regression of $CAR_{i,\, t2\text{-}t1}$ observations on drug sales percentage of firm annual sales for settlements without payments settled by infrequent settlers and test statistics/p-values to test H_0: $\widehat{\beta_1} = 0$

N=21

Event Window	$CAAR_{t2\text{-}t1}$	$\widehat{\beta_1}$	$\widehat{\beta_2}$	R Squared	Adjusted R Squared	SE($\widehat{\beta_2}$)	t-test statistic$_3$	p-value	Standardized $\widehat{\beta_2}$
Market Model									
(0,0)	1.35%	-0.0020	0.0151	0.7785	0.7662	0.0019	7.95***	<.0001	0.8823
(-1,+1)	0.10%	0.0007	0.0002	0.0003	-0.0552	0.0026	0.07	0.4708	0.0176
(-2,+2)	-1.23%	-0.0053	-0.0058	0.1941	0.1493	0.0028	-2.08**^	0.0260	-0.4406
(-3,+3)	-1.08%	-0.0098	0.0015	0.0097	-0.0453	0.0036	0.42	0.3396	0.0986
(-3,0)	-0.95%	-0.0064	-0.0023	0.0434	-0.0097	0.0026	-0.90	0.1891	-0.2083
(-2,0)	-0.67%	-0.0022	-0.0050	0.2266	0.1837	0.0022	-2.30**^	0.0170	-0.4761
(-1,0)	-0.14%	0.0020	-0.0047	0.2531	0.2116	0.0019	-2.47**^	0.0119	-0.5031
(0,+1)	1.59%	-0.0034	0.0200	0.7634	0.7503	0.0026	7.62***	<.0001	0.8738
(0,+2)	0.79%	-0.0052	0.0143	0.7571	0.7436	0.0019	7.49***	<.0001	0.8701
(0,+3)	1.23%	-0.0055	0.0189	0.7139	0.6980	0.0028	6.70***	<.0001	0.8449
Fama-French Model									
(0,0)	1.25%	-0.0013	0.0135	0.7204	0.7049	0.0020	6.81***	<.0001	0.8488
(-1,+1)	-0.01%	0.0018	-0.0019	0.0276	-0.0264	0.0027	-0.71	0.2420	-0.1662
(-2,+2)	-1.39%	-0.0039	-0.0087	0.3298	0.2925	0.0029	-2.98**^	0.0041	-0.5743
(-3,+3)	-1.16%	-0.0065	-0.0027	0.0264	-0.0277	0.0038	-0.70	0.2469	-0.1625
(-3,0)	-1.09%	-0.0059	-0.0042	0.1119	0.0626	0.0028	-1.51*^	0.0747	-0.3345
(-2,0)	-0.82%	-0.0028	-0.0059	0.2404	0.1982	0.0025	-2.39**^	0.0141	-0.4903
(-1,0)	-0.21%	0.0032	-0.0066	0.3441	0.3076	0.0021	-3.07***^	0.0033	-0.5866
(0,+1)	1.45%	-0.0028	0.0181	0.7382	0.7236	0.0025	7.12***	<.0001	0.8592
(0,+2)	0.68%	-0.0024	0.0106	0.6692	0.6508	0.0018	6.03***	<.0001	0.8180
(0,+3)	1.18%	-0.0019	0.0150	0.6252	0.6043	0.0027	5.48***	<.0001	0.7907

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, ^ denotes a left-tailed p-value

presence of the asymmetric timing of abnormal returns is not present here as it was in the Payment/Frequent group, because the positive returns are less “sure” or “expected” when the settlement does not involve a payment.

On the other hand, Table 17 shows that for the No Payment/Infrequent group, the sales percentage positively influences abnormal returns on and after the event date in the windows (0,0), (0,1), (0,2), and (0,3). However, sales percentage actually significantly negatively influences abnormal returns in the windows prior to the event date, (-3,0), (-2,0), and (-1,0). These results suggests that the greater the sales of a drug relative to the firm’s annual sales, the lower the abnormal returns are prior to the event date. Perhaps this result is due to the fact that when a drug has higher sales, and is therefore more important monetarily to a company, the market expects and wants the firm to enter into a settlement that involves a payment rather than one without a payment. This could be related to the possible market underestimation of the settlement seen in the alternative explanation to the presence of positive returns in the No Payments sample in Section VII.2. However, once the terms of the settlement are officially announced, this market underestimation corrects and sales once again positively influences the abnormal returns.

VIII. Comparison to DMS’s Brand Firm Returns

While DSM did not divide their data into subgroups depending on whether the settlement involved a payment or not, I will analyze the Payment and No Payment samples of the generic firms in my dataset and compare them to the Payment and No Payment brand firms of DSM’s dataset.[30] The first difference is that while it seems that the Payment groups of both the generic and brand firm involved significantly positive stock returns in all windows, the brand firm did not have the same pre-event date asymmetric pattern in their returns as the generics did.[31] In addition, while there were no positive abnormal returns for settlements without a reverse payment for the brand firm, there were significantly positive returns in windows (0,0) and (0,1) for the generic firms on the opposite side of those settlements. Finally, the third difference is that while DSM found significantly positive differences between the returns from settlements with

[30] Comparing to the data in tables on pages 41-44 of DMS’s paper.

[31] While DMS did not have event windows (-3,0), (-2,0), and (-1,0), they did have event windows (-3,3), (-2,2), (-1,1) and (0,3), (0,2), (0,1). Since the $CAAR_{t2\text{-}t1}$’s for event windows (-3,3), (-2,2), and (-1,1) are merely the sum of the $CAAR_{t2\text{-}t1}$’s for (-3,0), (-2,0), (-1,0) and (0,3), (0,2), (0,1), I extrapolated what the values for (-3,0), (-2,0), (-1,0) would be.

payments and settlements without payments for the event date (0,0) and windows after the event date, (0,1), (0,2), and (0,3), I did not find significantly positive differences for the generic firms in these windows. In fact, I only found significantly positive differences between the stock returns for settlements with payments and settlements without payments in the windows before the event date, (-3,0), (-2,0), and (-1,0).

The first and third difference regarding the asymmetric timing of abnormal returns could be related to the reputation factor of generic firms. As described in the previous section, there are much fewer generic firms than brand firms that settle and therefore the firm's reputation for having a high propensity to settle could be an important factor in the timing of abnormal returns. As described in Section VII.1 and VII.3, both the effect of Payment on frequent settlers and the effect of Frequency on settlements with payments present an asymmetric timing of abnormal returns earlier than the event date (Tables 7 and 12). Therefore, the effect of reputation combined with the presence of a payment could be the reason for this asymmetric timing in generic firms that is not present in brand firms.

The second difference, the presence of abnormal payments on dates (0,0) and (0,1) in no payment settlements, could be due to the generic entry date, E, threshold above the expected litigation entry date, PT, as discussed in Section VII.2. It is interesting to note that if generic firms are involved on the other side of these same settlements without payments, then this threshold E is similarly above PT for both the brand and generic firms and should represent higher-than-expected profits for both. Therefore, it is unexpected that the market doesn't react to these no payment settlements the same way for the brand and generic firm. This could be due to the fact that the market is more sensitive with the generic firm's stock returns since it is the generic firm that establishes this threshold of E greater than PT. An interesting study could result from the investigation of the correlations between generic and brand firms, and the implications for anticompetitive activity from these interactions.

IX. Conclusion

This paper examines publicly available security price information for publicly traded generic firms involved in Paragraph IV ANDA settlements to (I) test how the settlement announcement affects the stock price of the generic firm and (II) examine what other factors besides the involvement of a payment in the settlement affect the generic stock prices. I found that on average, settlements with payments produce significantly positive abnormal stock returns of approximately 1.6% in windows before and approximately 1% in windows after the event date, t=0. Settlements without payments produced positive abnormal returns only on the event date, t=0, of around 0.5% and in the window, (0,1), of 0.9%. Similarly, settlements that were settled by frequent settlers, Teva, Actavis/Watson, Mylan, and Barr Laboratories, had a significantly positive abnormal return of approximately 1.2% before the event date and 0.9% after the event date. Settlements that were settlement by infrequent settlers resulted in positive abnormal returns also only in the windows (0,0) and (0,1) of approximately 1% and 1.1% respectively. The difference between abnormal returns from settlements with and without payments were significant only in the windows prior to the event date, (-3,0), (-2,0), and (-1,0), of approximately 1.7%. Similarly, the difference between abnormal returns generated from frequent and infrequent settlers were also only significant in the same pre-event date windows above of approximately 1.9%. These results are in line with DSM's results that many settlements with payments produce significant abnormal stock returns and are therefore anticompetitive. However, my results question which factor, the presence of a payment or the reputation of the settling firm, is responsible for these positive abnormal returns.

Most of the previous literature on this topic has focused on the following explanations for a stock price hike after the announcement of a reverse payment settlement:

(i) The actual presence of an anticompetitive payment, X, that causes the settled entry date, E, to be greater than the expected entry date under litigation, PT

(ii) The firm's reputation that causes confidence in the terms of the settlement for the firm's profit

(iii) A systematic market underestimation prior to the announcement of the settlement and a subsequent correction once the settlement is announced

Only the first explanation, (i), implies that a positive stock price hike actually signals the presence of anticompetitive activity. While I found positive abnormal returns from settlements both with and without payments that support explanation (i) that there may be anticompetitive activity present, my study also shows that explanation (ii) is another possible cause for positive stock returns through the similar effects and high correlation of Payment and Frequent. At the same time, (iii) could also be a factor when looking at the negative impacts of Frequent on abnormal returns in the sample of settlements without payments. Therefore, while the presence of anticompetitive activity could be indicated through the presence of significant abnormal stock returns in my study, it is not the only possible cause of these positive returns.

Furthermore, in regards to settlements without payments, I introduce a theoretical model building upon the EHHS model that shows that there is a range of equilibrium settlement entry dates, E, that are anticompetitive even when there is no payment involved in the settlement. This is due to the fact that the maximum E threshold that the generic is willing to accept is higher than PT, the expected patent length/generic entry date under litigation. In a large portion of Hatch-Waxman settlement literature, including the *FTC v. Actavis* case and the Actavis Inference that emerged from the Supreme Court opinions on the case, the expected outcomes from settlements without payments are assumed to be equivalent to the expected outcome from litigations. While this may be the case for the brand firm, the Activating Inference theoretical model adapted for the generic firm tells a different story. Even when there are no payments ($X = 0$), the generic is still willing to settle below a maximum threshold of E that is above PT. Therefore, the theoretical model demonstrates that even settlements without payments can be anticompetitive. This idea is supported in the data, as there are significantly positive abnormal returns in windows (0,0) and (0,1) for generic firms involved in settlements without payments.

At the same time, the percentage of a firm's annual sales that the drug's sales comprises is also an important factor that significantly influences the abnormal returns for settlements that are settled by frequent settlers, for settlements both with and without payments. While sales percentage is often thought of as positively influencing the anticompetitive effects of settlements with payments, its effects actually influences settlements settled by frequent settlers more so than merely settlements with payments. This is another indication of the importance of the reputation of the settling firm that is often ignored by literature regarding the anticompetitive effects of reverse payment settlements.

Therefore, when evaluating the anticompetitive implications of reverse payment settlements through stock return analysis, it is important to keep in mind that there are multiple other factors besides the presence of a reverse payment that could cause the a stock price hike on announcement day. Some of these other factors, such as firm reputation and sales percentage of the drug, do not directly support the conclusion that these settlements are anticompetitive. However, since many of these predictors are correlated, it is often difficult to either reject or affirm that significant security returns reveals anticompetitive behavior. Finally, when examining the payments without settlements, the theoretical model that I propose adapted from EHHS suggest that we should not be looking at generic firms in the same way as brand firms, because generic firms are willing to accept an entirely different threshold of E. It is important to question the mere presence or lack of payment in these reverse-payment settlements as a direct indication of anticompetitive activity.

X. Potential Issues in the Data

While the sample sizes of the Payment/Frequent, No Payment/Frequent, and No Payment/Infrequent are larger, there are only six settlements in the Payment/Infrequent group. While I found no significant stock returns in most windows of this subsample, it could be due to the extremely small sample size. It is therefore difficult to make conclusions from the data of only this group.

In addition, 23 out of the 48 settlements without payments (approximately 48%) were announced as "confidential." While the actual presence of a payment is not known, these settlements are labeled as No Payments because there was no indication of a payment. DSM uses a similar procedure in accounting for confidential settlements. While the stock market would not be responding to the settlements in the same way as a settlement announcement that outlined that there are no payments involved, there were no other ways to categorize these settlements. This could be another explanation for why there are positive abnormal returns in No Payments sample in windows (0,0) and (0,1), but it requires the assumption that some investors know confidential information that the rest of the market does not know.

Appendix A. Calculations for the Patell, BMP, Sign, and Rank Test

Appendix A.1 Patell Test

The t-test statistics for the t-tests form the intuitive bases for the scaled/standardized abnormal returns used by Patell (1976) and Boehmer, Musumeci, and Poulsen (BMP) (1991). Scaled test statistics can better accommodate instances of heteroskedasticity in abnormal returns by standardizing each abnormal return by its own standard deviation before summing it into a test statistic. The Patell Standardized Abnormal Return , SAR_{it}, can be written as:

$$\mathrm{SAR_{it}} = \frac{AR_{it}}{S_{AR_{it}}} \quad [A.1]$$

where AR_{it} is the abnormal return for security i on date t and $S_{AR_{it}}$is the standard error calculated during the estimation period. Since AR_{it} is the difference between the actual stock return on date t, r_{it}, and the predicted stock return, $E(r_{it})$, the standard error of AR_{it} can be calculated as the error variance of predicting r_{it}:

$$\mathrm{s^2}_{\mathrm{AR_{it}}} = \mathrm{s^2}_{\mathrm{AR_{it_E}}}[1 + \frac{1}{(\mathrm{t_{E2}} - \mathrm{t_{E1}} + 1)} + \frac{\left(\mathrm{r_{mt}} - \overline{\mathrm{r_{mt_E}}}\right)^2}{\sum_{\mathrm{t_{E1}}}^{\mathrm{t_{E2}}}\left(\mathrm{r_{mt_E}} - \overline{\mathrm{r_{mt_E}}}\right)^2}] \quad [A.2]$$

where t_{E2} and t_{E2} are the beginning and ending dates of the estimation window and $\overline{r_{mt_E}}$ is the mean of the market return during the estimation period.[32] $s^2{}_{AR_{it_E}}$is the variance of the sample of stock returns over the estimation period:

$$s^2{}_{AR_{it_E}} = \frac{\sum_{t=t_{E1}}^{t_{E2}} AR_{it}^2}{(t_{E2} - t_{E1} - 2)} \quad [A.3]$$

By standardizing each statistic with its own standard deviation first, the test ensures that that each abnormal return will have the same variance.

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32 This calculation follows the general formula of calculating the error variance of predicting Y for a simple regression, $Y_i = \alpha + \beta X_i + \epsilon_i$:

$$Var\left(Y_0 - \widehat{Y_0}\right) = \sigma^2\left[1 + \frac{1}{n} + \frac{(X_0 - \bar{X})^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2}\right]$$

where $X_0$is the particular value of X_i for which we wish to predict Y_i, and $\widehat{Y_0}$is that prediction (DeSalvo, 1971). In this case, the independent variable, X_i, is the market return.
The standard error of the estimated value, σ is calculated as:

$$\hat{\sigma} = \left[\frac{\sum_{i=1}^{n}\left\{Y_i - \hat{\alpha} - \hat{\beta}X_i\right)^2}{n-2}\right]$$

To test the first set of null and alternative hypothesis in [14] regarding $CAAR_{t2\text{-}t1}$, the Patell test calculates the test statistic as:

$$test\ statistic_{Patell} = \frac{1}{\sqrt{N}} \frac{1}{\sqrt{Q_{t2-t1}}} \sum_{i=1}^{N} \sum_{t=t1}^{t2} SAR_{it} \qquad [A.4]$$

where Q_{t2-t1} is the variance of a single stock's return over the event window, (t1, t2):

$$Q_{t2-t1} = (t2 - t1 + 1)(\frac{118}{116}) \qquad [A.5]$$

Q_{t2-t1} is the same for all the standardized stock returns in the sample per window (since the estimation period length is the same when calculating abnormal returns for every stocks). The $test\ statistic_{Patell}$ is for an event window (t1,t2) and N events in the sample. The test statistic follows the standard normal distribution.

Appendix A.2 BMP Test

The BMP test (Boehmer, Muscumeci, Poulson, 1991) is a modified version of the Patell test that modifies the calculation of the standard deviation of $ASAR_t$ and $CSAR_{t2\text{-}t1}$ by estimating it during the event period itself instead of during the estimation period. Since there is often the possibility of event-induced volatility, the BMP test adds a control to the Patell test to account for increases in event-induced volatility to avoid the t test's tendency of underestimating of the standard error and Type I errors. Since the BMP Test is an extension of the Patell test in an attempt to correct the tendency to ignore event-induced volatility, it is included as a robustness check to the previous two statistical tests.

The BMP test uses the same standardized variables as the Patell test and adjusts for changes in the standard deviations during the event window itself. The standardized cumulative abnormal return can be calculated as:

$$SCAR_{i,t2-t1} = \frac{CAR_{i,t2\text{-}t1}}{S_{CAR_i,t2-t1}} \qquad [A.6]$$

where $CAR_{i,t2\text{-}t1}$ is calculated the same way as [13] and $S_{CAR_i,t2-t1}$ can be calculated as:

$$s^2_{CAR_{i,t2-t1}} = s_{AR_{it}}{}^2 \left\{ (1 + t2 - t1) \left[1 + \frac{(1 + t2 - t1)}{(1 + t_{E2} - t_{E1})} + \frac{\left(\sum_{t=t1}^{t2} r_{mt} - (1 + \mathrm{t2} - \mathrm{t1}) \overline{r_{mt_E}} \right)^2}{\sum_{t=t_{E1}}^{t_{E2}} (r_{mt} - \overline{r_{mt_E}})^2} \right] \right\} \quad [A.7]$$

where $s_{AR_{it}}$ is calculated the same way as above in the Patell test.

The standard deviation calculation for the test statistic to test $CAAR_{t2-t1}$ in [14] can be written as:

$$s_{SCAR_{i,t2-t1}}{}^2 = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (SCAR_{i,t2-t1} - \overline{SCAR})^2} \quad [A.8]$$

where:

$$\overline{SCAR} = \frac{1}{N} \sum_{i=1}^{N} SCAR_{i,t2-t1} \quad [A.9]$$

Therefore, the $CAAR_{t2-t1}$ test statistic to test the hypotheses in [14] is calculated as:

$$test\ statistic_{BMP} = \frac{\sum_{i=N}^{N} SCAR_{i,t2-t1}}{\sqrt{N} * S_{SCAR_{i,t2-t1}}} \quad [A.10]$$

The $test\ statistic_{BMP}$ follows a standard normal distribution. The above calculations for the Patell and BMP test follow Cowan (2007)'s *Eventus Guide* formats.

Appendix A.3 Sign Test

As a final robustness check to the assumption that AR_{it}'s are normally distributed, I also include two non-parametric tests in my study. The first is the generalized sign test (Cowan 1992), which tests whether $CAAR_{t2-t1}$ is significantly different based on its probability to be positive or negative when drawn from the sample. The assumptions needed for the test are that the abnormal returns and cumulative abnormal returns are independent across securities and are symmetrically distributed about zero under the null hypothesis. If we define p as Prob[$CAAR_{T2-T1} \geq 0.0$], then the null and alternative hypotheses are for both performance variables:

H_0: $p \leq \hat{p}$ [A.11]

H_1: $p > \hat{p}$

where $\hat{p}$ is the percentage of positive returns for the performance variables calculated during the event window (t_{E1}, t_{E2}):

$$\hat{p} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{120}\sum_{t_{E1}}^{t_{E2}} S_{it_E},\ where\ S_{it_E}\begin{cases}1\ if\ positive\ return\\ 0\ if\ negative\ return\end{cases} \quad [A.12]$$

Under the null hypothesis in [14], when we expect the average $CAAR_{t2-t1}$ to be zero, the probability that it is positive should equal the proportion of positive returns observed during the estimation period. The sign test statistic can be written as:

$$test\ statistic_{sign} = \frac{(w - N\hat{p})}{\sqrt{N\hat{p}(1-\hat{p})}} \quad [A.13]$$

where w is the number of stocks with positive $CAAR_{t_{E2}-t_{E1}}$ during the event period (t_{E1}, t_{E2}). N is the total number of securities in the sample and $\hat{p}$ is defined above. The distribution of the test statistic should follow a normal distribution, N(0,1). Since an important assumption required for the sign test is that it the variables must be symmetric about zero, a significantly skewed sample may reduce the specificity of the test (MacKinlay, 1997). Therefore, the following rank test that symmetrizes the data points by design serves as a useful sensitivity check to the sign test.

Appendix A.4 Rank Test

The second non-parametric test that I include in my study is the rank test proposed by Corrado (1989). Let K_{it} denote the rank of an abnormal return data point (AR_{it}) within security i's dataset of abnormal returns within the combined estimation and event window, from 1 to the number of days in the combined periods. For every security, the number of ranks will equal the number of days in the estimation window plus the number of days in the event window:

$$Number\ of\ ranks\ =\ 120\ + (t2 - t1\ + 1) \quad [A.14]$$

By construction, for a given security, the average rank of K_{it}, $\widetilde{K}$, is $\frac{120+(t_2-t_1+1)}{2}$, where 120 is the number of days in the estimation window and $(t2 - t1 + 1)$ is the number of days in the event window. The null hypothesis in [14] that $CAAR_{t2-t1}$ is zero can be converted to a null hypothesis based on the rank of the abnormal return for security i on date t:

H_0: $K_{it} = \widetilde{K}$ [A.15]

H_1: $K_{it} > \widetilde{K}$

Where $\widetilde{K}$ is the average rank of a given K_{it}:

$$\widetilde{K} = \frac{120 + (t_2 - t_1 + 1)}{2} \quad [A.16]$$

If there is on average no positive abnormal return, then the average $CAAR_{t2-t1}$ rank should equal the average rank, $\widetilde{K}$. Therefore, the rank test statistic can be written as (Cowan, 2007):

$$test\ statistic_{rank} = \sqrt{(t2 - t1 + 1)} * \frac{\overline{K_{t1,t2}} - \widetilde{K}}{S(K)} \quad \text{[A.17]}$$

where $\overline{K_{t1,t2}}$ is the average rank of K_{it} across the sample of N securities and across $(t2 - t1 + 1)$ days of the event window:

$$\overline{K_{t1,t2}} = \frac{1}{(t2 - t1 + 1)} \sum_{t=t1}^{t2} \frac{1}{N} \sum_{i=1}^{N} K_{it} \quad \text{[A.18]}$$

The standard deviation of $\overline{K_{t1,t2}}$, $S(K)$, can be calculated as:

$$S(K) = \sqrt{\frac{\sum_{t=1}^{120+(t2-t1+1)} (\overline{K_t} - \widetilde{K})^2}{120 + (t2 - t1 + 1)}} \quad \text{[A.19]}$$

Where $\overline{K_t}$ is the average rank across all stocks on date t of the combined estimation and event period:

$$\overline{K_t} = \frac{1}{N} \sum_{i=1}^{N} K_{it} \quad \text{[A.20]}$$

This procedure transforms the AR_{it} data into a symmetric, normal distribution.[33] Eventus software transforms the single-day test statistic into a CAAR test statistic simply by summing it across the event window similar to the way a scaled test statistic is summed across multiple days in the Patell test, assuming ranks of AR's across different days in the event window are independent.[34]

[33] Detailed calculations can also be found in Corrado (1989, 387-388).
[34] See Cowan (2007, 89) for full calculation details.

Appendix B. Additional Data Tables

Table 18. Event study results ($CAAR_{t2-t1}$) for settlements with payments settled by infrequent settlers and test statistics/p-values to test H_0: $CAAR_{t2-t1,\ Payments/Infrequent} = 0$

N=6			*Parametric*						*Non-Parametric*			
Event Window	$CAAR_{t2-t1}$	Standard Error	t-test statistic[1]	p-value	Patell Z statistic	p-value	BMP Test Z	p-value	Sign Test Z	p-value	Rank Test Z	p-value
Market Model												
(0,0)	-0.13%	0.0091	-0.14	0.4433	-0.03	0.4865	-0.06	0.4755	0.01	0.4946	0.12	0.4514
(-1,+1)	-1.63%	0.0153	-1.06	0.1439	-1.12	0.1306	-2.29**	0.0109	-1.62*	0.0527	-1.26	0.1042
(-2,+2)	-1.35%	0.0198	-0.68	0.2478	-0.97	0.1659	-1.55*	0.0605	-1.62*	0.0527	-1.29	0.1001
(-3,+3)	-0.32%	0.0235	-0.14	0.4458	-0.55	0.2909	-0.67	0.2520	-0.80	0.2110	-0.68	0.2481
(-3,0)	-0.01%	0.0200	-0.01	0.4982	-0.26	0.3959	-0.36	0.3592	-0.80	0.2110	-0.36	0.3585
(-2,0)	-1.07%	0.0154	-0.70	0.2435	-1.07	0.1430	-1.38*	0.0845	-1.62*	0.0527	-1.46*	0.0735
(-1,0)	-1.27%	0.0125	-1.02	0.1550	-1.12	0.1314	-2.99***	0.0014	-1.62*	0.0527	-1.05	0.1479
(0,+1)	-0.49%	0.0126	-0.39	0.3492	-0.28	0.3896	-0.69	0.2459	-0.80	0.2110	-0.41	0.3408
(0,+2)	-0.41%	0.0154	-0.27	0.3947	-0.21	0.4187	-0.63	0.2647	-0.80	0.2110	-0.13	0.4474
(0,+3)	-0.44%	0.0178	-0.25	0.4024	-0.48	0.3151	-1.02	0.1543	0.01	0.4946	-0.48	0.3167
Fama-French Model												
(0,0)	-0.22%	0.0090	-0.25	0.4033	-0.31	0.6217	-0.45	0.3272	0.05	0.4783	-0.27	0.3932
(-1,+1)	-1.66%	0.0154	-1.08	0.1406	-1.15	0.8749	-2.51***	0.0061	-1.58*	0.0572	-1.17	0.1225
(-2,+2)	-1.55%	0.0199	-0.78	0.2180	-1.16	0.8770	-2.15**	0.0157	-2.40***	0.0083	-1.53	0.0638
(-3,+3)	-0.81%	0.0237	-0.34	0.3661	-0.85	0.8023	-1.18	0.1200	-1.58*	0.0572	-1.08	0.1414
(-3,0)	-0.10%	0.0172	-0.06	0.4769	-0.36	0.6405	-0.53	0.2980	-1.58*	0.0572	-0.48	0.3177
(-2,0)	-1.06%	0.0154	-0.69	0.2450	-1.08	0.8599	-1.55*	0.0605	-1.58*	0.0572	-1.48*	0.0703
(-1,0)	-1.15%	0.0126	-0.92	0.1798	-1.01	0.8438	-2.25**	0.0121	-0.76*	0.2230	-0.82	0.2064
(0,+1)	-0.73%	0.0127	-0.58	0.2821	-0.61	0.7291	-1.87**	0.0310	-0.76	0.2230	-0.80	0.2125
(0,+2)	-0.70%	0.0153	-0.46	0.3239	-0.60	0.7257	-1.46*	0.0724	-0.76	0.2230	-0.65	0.2573
(0,+3)	-0.92%	0.0178	-0.52	0.3025	-0.91	0.8186	-1.83**	0.0340	-1.58*	0.0572	-1.09	0.1395

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Table 19. Difference between $CAAR_{t2\text{-}t1}$'s for settlements with and without an indication of payment settled by infrequent settlers and test statistics/p-values to test H_0: $CAAR_{t2\text{-}t1,\ Payments/Infrequent} - CAAR_{t2\text{-}t1,\ No\ Payments\ /Infrequent} = 0$

df = 25

Event Window	$CAAR_{t2\text{ - }t1,\ No\ Payments/Infrequent}$	$CAAR_{t2\text{ - }t1,\ Payments/Infrequent}$	Difference in CAARs	Var($CAAR_{t2\text{-}t1,\ Payments/\ Infrequent}$)	Var($CAAR_{t2\text{-}t1,\ No\ Payments/\ Infrequent}$)	SE ($CAAR_{t2\text{-}t1,\ No\ Payments/Infrequent}$ - $CAAR_{t2\text{-}t1,\ No\ Payments/\ Frequent}$)	$t\text{-statistic}_2$	p-value
Market Model								
(0,0)	1.35%	-0.13%	1.48%	0.0011	0.0005	0.0117	1.27	0.1079
(-1,+1)	0.10%	-1.63%	1.73%	0.0035	0.0014	0.0201	0.86	0.1990
(-2,+2)	-1.23%	-1.35%	0.12%	0.0056	0.0024	0.0256	0.05	0.4803
(-3,+3)	-1.08%	-0.32%	-0.76%	0.0079	0.0033	0.0305	-0.25	0.5977
(-3,0)	-0.95%	-0.01%	-0.94%	0.0045	0.0024	0.0248	-0.38	0.6464
(-2,0)	-0.67%	-1.07%	0.40%	0.0034	0.0014	0.0200	0.20	0.4215
(-1,0)	-0.14%	-1.27%	1.13%	0.0023	0.0009	0.0164	0.69	0.2483
(0,+1)	1.59%	-0.49%	2.08%	0.0023	0.0010	0.0163	1.27	0.1079
(0,+2)	0.79%	-0.41%	1.20%	0.0034	0.0014	0.0200	0.60	0.2770
(0,+3)	1.23%	-0.44%	1.67%	0.0045	0.0019	0.0231	0.72	0.2391
Fama-French Model								
(0,0)	1.25%	-0.22%	1.47%	0.0011	0.0005	0.0115	1.28	0.1061
(-1,+1)	-0.01%	-1.66%	1.65%	0.0021	0.0014	0.0184	0.90	0.1884
(-2,+2)	-1.39%	-1.55%	0.16%	0.0054	0.0024	0.0256	0.06	0.4736
(-3,+3)	-1.16%	-0.81%	-0.35%	0.0076	0.0034	0.0304	-0.12	0.5473
(-3,0)	-1.09%	-0.10%	-0.99%	0.0044	0.0018	0.0225	-0.44	0.6681
(-2,0)	-0.82%	-1.06%	0.24%	0.0033	0.0014	0.0198	0.12	0.4527
(-1,0)	-0.21%	-1.15%	0.94%	0.0022	0.0009	0.0162	0.58	0.2836
(0,+1)	1.45%	-0.73%	2.18%	0.0022	0.0010	0.0162	1.34*	0.0961
(0,+2)	0.68%	-0.70%	1.38%	0.0033	0.0014	0.0197	0.70	0.2452
(0,+3)	1.18%	-0.92%	2.10%	0.0044	0.0019	0.0229	0.92	0.1832

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Table 20. Difference between $CAAR_{t2\text{-}t1}$'s for settlements settled by infrequent settlers and test statistics/p-values to test H_0: $CAAR_{t2\text{-}t1, Frequent} - CAAR_{t2\text{-}t1, Infrequent} = 0$

df=79

Event Window	$CAAR_{t2 - t1, Frequent}$	$CAAR_{t2\text{-}t1, Infrequent}$	Difference in CAARs	$Var(CAAR_{t2\text{-}t1, Frequent})$	$Var(CAAR_{t2\text{-}t1, Infrequent})$	$SE(CAAR_{t2\text{-}t1, Frequent} - CAAR_{t2\text{-}t1, Infrequent})$	t-statistic$_2$	p-value
Market Model								
(0,0)	0.28%	1.02%	-0.74%	0.00025	0.00098	0.00640	-1.16	0.8752
(-1,+1)	1.53%	-0.29%	1.82%	0.00077	0.00300	0.01120	1.62*	0.0546
(-2,+2)	1.91%	-1.26%	3.17%	0.00129	0.00492	0.01436	2.21**	0.0150
(-3,+3)	2.15%	-0.91%	3.06%	0.00180	0.00693	0.01703	1.80**	0.0378
(-3,0)	1.55%	-0.74%	2.29%	0.00102	0.00392	0.01281	1.79**	0.0386
(-2,0)	1.23%	-0.76%	1.99%	0.00077	0.00298	0.01116	1.78**	0.0395
(-1,0)	0.95%	-0.39%	1.34%	0.00051	0.00197	0.00907	1.48*	0.0714
(0,+1)	0.85%	1.13%	-0.28%	0.00051	0.00199	0.00911	-0.31	0.6213
(0,+2)	0.96%	0.52%	0.44%	0.00077	0.00296	0.01112	0.40	0.3451
(0,+3)	0.88%	0.86%	0.02%	0.00102	0.00397	0.01289	0.02	0.4920
Fama-French Model								
(0,0)	0.33%	0.93%	-0.60%	0.00024	0.00098	0.00639	-0.94	0.8250
(-1,+1)	1.58%	-0.38%	1.96%	0.00072	0.00294	0.01106	1.77**	0.0403
(-2,+2)	2.02%	-1.43%	3.45%	0.00120	0.00488	0.01424	2.42***	0.0089
(-3,+3)	2.13%	-1.08%	3.21%	0.00167	0.00675	0.01676	1.91**	0.0299
(-3,0)	1.58%	-0.87%	2.45%	0.00096	0.00389	0.01272	1.93**	0.0286
(-2,0)	1.29%	-0.88%	2.17%	0.00072	0.00294	0.01106	1.96**	0.0268
(-1,0)	1.01%	-0.42%	1.43%	0.00047	0.00195	0.00900	1.59*	0.0579
(0,+1)	0.89%	0.97%	-0.08%	0.00048	0.00196	0.00902	-0.09	0.5357
(0,+2)	1.05%	0.37%	0.68%	0.00071	0.00285	0.01090	0.62	0.2685
(0,+3)	0.88%	0.71%	0.17%	0.00095	0.00386	0.01267	0.13	0.4484

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

Appendix C. Notations

- **(t1, t2):** an event window that beings on date t1 and ends on date t2
- $\boldsymbol{t = 0}$**:** the date of the settlement announcement
- **(t_{E1}, t_{E2}):** the estimation window that begins on date t_{E1} and ends on date t_{E2}. In this paper, I use the estimation window (-150, -30)
- $\boldsymbol{N}$**:** the number of firms in a given sample
- $\boldsymbol{i}$**:** a specific firm in a given sample
- $\boldsymbol{AR_{it}}$**:** the abnormal return of security i on date t, which is the difference between security i's return on date t, R_{it}, and security i's expected return on date t, $E(R_{it})$
- $\mathbf{CAR_{i,t2\text{-}t1}}$**:** the cumulative abnormal return of security i across the event window (t1,t2)
- $\mathbf{CAAR_{t2\text{-}t1}}$**:** the cumulative average abnormal return of all securities in a sample of N securities across the event window (t1,t2)

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