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Pharmaceutical Stock Prices around Medicare Part D Expansion

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By

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Abstract:

On January 1, 2006 Medicare part D expanded, giving prescription coverage to many Americans. This event offers an interesting question regarding market efficiency, specifically because Medicare expansion was introduced into congress as far back as 1999. Because Medicare part D affected pharmaceutical drug coverage, this study focuses specifically on securities in the pharmaceutical industry. Following an efficient market hypothesis, we would expect to see significant abnormal returns in the post event window, anticipating the legislations effect on demand within the industry. Results showed significant abnormal returns in post-event window, but not in the pre-event window. The returns in the post-event window were both statically and economically significant. This suggests that most of the abnormal returns stemmed from a reaction after the implementation instead of anticipating the implementation.

Keywords: Pharmaceutical; Medicare Part D; Cumulative Abnormal Returns

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1. Introduction

Medicare part D is a section of coverage that pays for self-administered prescription drugs for Medicare beneficiaries, controlled by the Center for Medicare and Medicaid Services (CMS). Other sections of Medicare have covered some prescription medications, though not completely. For example, Medicare part B covers professionally administered prescription medications. Some part C plans also included coverage of prescription drugs; however, this plan was required to be bundled with parts A and B. Part D was drafted as a comprehensive solution to the rapidly rising costs of prescription drugs. Over the period between 1980-2005, prescription drug costs rose at an annual rate of 11.9%, making them the third fastest growing cost of health care. Between 2000 and 2005 prescription drug costs rose at an annual rate of 10.7%, the fastest growing cost of healthcare.[2] The pharmaceutical industry is massive, the Department of Health and Human Services has estimated that Americans spent more than $460 billion on drugs, accounting for 16.7 percent of total health-care spending. Medicare part D is available to all consumers that have Medicare coverage under part A & B, allowing many users to have reasonable access to coverage. Medicare beneficiaries are also one of the largest users of prescription medication in the United States, with "almost 60 percent of all prescriptions … filled for beneficiaries of Medicare, Medicaid, and other government programs" (Duggand, 2010). Part D would fill the gap that part C created by allowing standalone plans that covered prescription drugs. Part D was able to fill the gap due to a change in the coverage payments made to medical service providers. In parts A&B, CMS had the ability to set prices for each covered service and then reimbursed providers for each service performed. Part D, however, CMS pays a lump sum into a plan for each enrolled customer and then has no control over the prices paid to the pharmaceutical companies. This, in some ways, allows pharmaceutical prices to continue to inflate because the insurance has minimal influence on the price of the prescription medication.

The legislation to enact part D was in the process of being implemented for many years before it was ratified. Originally proposed in 1999 by President Clinton, the bill was subsequently proposed in 2002

[2] See the Center for Medicare and Medicaid Services, 2007.

and 2003 by both Republicans and Democrats in the U.S. House and the Senate as well as by President George W. Bush. The bill was formally enacted in 2003 as part of the Medicare modernization act of 2003, eventually going into effect on January 1, 2006. The ratification of Medicare part D poses an interesting question regarding the efficiency of markets surrounding policy changes that impact large segments of the overall market. The change to this legislation allows a unique glimpse into the efficiency of the market because the information regarding this change, in some form or another, was known by the public. The market should have expected increased profits from the pharmaceutical industry because transforming cash paying customers into insured customers has been shown to create inelastic demand for healthcare products, therefore lifting prices (Duggand, 2006; Pavcnik, 2002). Because of the size of the healthcare industry, this inelastic demand expectation should have had a positive impact on the prices of these securities when the change was announced and was put into the process of being implemented.

The Medicare part D expansion should have also changed physicians' attitudes towards prescribing brand name medication. Reichert (2000) looked at attitudes towards prescribing medication compared to their knowledge of the costs of the medication, and found that

> "*88% of physicians felt the cost of medicines was an important consideration in the prescribing decision, and 71% were willing to sacrifice some degree of efficacy to make drugs more affordable for their patients… 94% of physicians gave strong consideration to the cost of medication when patents were self-paying, [only] 68% [gave cost consideration] when patients had Medicare, and 30% when patients had Medicaid or were participants in a health maintenance organization with a prescription plan.*"

This known behavior should have signaled to the market that once this change was implemented, many doctors would be more willing to prescribe name brand medications to their patients.

Alternatively, Hellerstein (1998) investigated data showing that in 1989 fewer than 30% of prescriptions with generic and name brand options prescribed the former. The study found that physicians' knowledge of patients' insurance coverage had no impact on the prescriber's choice between generic and name brand medication. Ultimately, the only physicians at the time using price in the decision to prescribe were HMO-affiliated physicians and clinics. Mainly coming from cost management restrictions placed on physicians and clinics.

To determine if the implementation of Medicare Part D had any impact on the performance of pharmaceutical stocks, we collected price and volume information from the Center for Research in Securities Prices (CRSP). Our analysis shows that pharmaceutical securities had statistically and economically significant returns in multiple event windows surrounding and directly after the January 3, 2006 event date. Our analysis shows that industry had minimal abnormal returns in the pre-event period.

2. Hypothesis Development

Government programs and monetary policy changes have been shown to influence the returns of stocks. Specifically, monetary policy has been shown to significantly affect stock returns in 13 OECD countries between 1972-2002 (Ioannidis 2003). In other segments of the economy government spending has also been shown to increase the output, hours, and consumption of defense products (Fisher 2010). This shows that the government has significant ability to influence demand and prices through spending. Another study looking at the effect of government spending on consumption showed that government spending increases aggregate consumption for over a year after a spending shock, further showing the ability of the U.S. government to affect supply and demand (Laumer, 2020). Showing that government intervention has a significant impact on the behavior of consumers, especially in financial markets. Studies also point to increased price inelasticity between insured consumers and prescription drugs. Mendoza (2020) points to an incentive for price-substitution to risky and illegal drugs among people losing dependent coverage for medication. Mendoza also found that pharmaceutical innovation and advancement can cause product-hopping and may result in sharp price increases. This favors a broad range of pharmaceutical companies, DiMasi (2000) found that between 1963 and 1999 “Innovation in the pharmaceutical industry is widely dispersed and has become less concentrated over time”. The paper also showed while there has been high turnover in innovation contributing firms over time, some firms have consistently maintained high levels of innovation over long periods. This shows that price spikes and increased demand due to product hopping could benefit any firm in the industry and is not reserved for larger companies.

At the time of the Medicare expansion, literature pointed to increasing inelastic demand, with prices increasing 7-10 percent for every 10 percent increase in consumers of the medication being covered by Medicare (Duggand, 2006). In a study involving diabetics before and after the 2006 part D expansion, they found that treatment of symptoms crowded out prevention of diabetes. The study showed that before the part D expansion, roughly 13% - 25% of female diabetics who used insulin stopped using insulin to manage their condition when they turned 65, thus becoming eligible for Medicare insurance. Because Medicare would cover the treatment of the symptoms from diabetes for a lower cost compared to preventing the symptoms with the more expensive insulin. After the implementation of Medicare part D this was effectively reduced to zero because the means to prevention were economically available to diabetics (Kaliski 2020). This, combined with cost conscious prescription writers discussed in Reichert (2000), shows that increased coverage should directly influence the volume of prescription drugs prescribed to and used by patients. The arguments above lead to the following two hypotheses:

H0: The prices of pharmaceutical securities have no significant abnormal returns compared to the overall market in any CARs event window.

H1: The prices of pharmaceutical stocks have positive returns around the event date in anticipation of increased profitability for pharmaceutical companies.

3. Data Description

3.1. Data Description

To determine if the implementation of Medicare Part D had any impact on the performance of pharmaceutical stocks, we collected price and volume information from the Center for Research in Securities Prices (CRSP). In particular, we gathered information from securities within the pharmaceutical industry, four-digit SIC codes 2830 to 2836, because the legislation had direct implication on the profitability of the industry. Table 1 reports summary statistics for the 335 publicly traded pharmaceutical companies with positive trading volume on January 3, 2006, the first trading day after the implementation of part D on January 1, 2006. The descriptive variables are the total for the single event date.

Table 1. Cross-Sectional Summary Statistics

This table reports summary statistics that describe the sample of pharmaceutical stocks on January 3, 2006. *Price* is the closing share price. *MCAP* is the market capitalization, or price times shares outstanding. *Rvolt* is the range-based volatility, or the log of the high ask price minus the log of the low bid price. %*Spread* is the closing relative spread, or the difference between the closing ask and bid prices, scaled by the quote midpoint. *Illiq* is Amihud's (2002) illiquidity, or absolute return divided by dollar volume (scaled by 10^6). *Turn* is share turnover, or volume divided by shares outstanding. *Nasdaq* is an indicator variable equal to one if the stock is listed on the NASDAQ and zero otherwise.

Variable	N	Mean	Std. Dev.	p25	Median	p75
Price	335	15.6021	19.1243	3.1900	8.0600	20.0000
MCAP	335	4.0784	18.1850	0.0721	0.2293	0.7752
Rvolt	335	0.0504	0.0386	0.0284	0.0408	0.0607
Spread	335	0.0088	0.0168	0.0007	0.0036	0.0087
Illiq	335	1.2393	11.6869	0.0009	0.0099	0.1013
Turn	335	0.0095	0.0128	0.0021	0.0054	0.0120
Nasdaq	335	0.7463	0.4358	0.0000	1.0000	1.0000

The observed companies have an average price of $15.60, with a standard deviation of $19.12. The lower quartile of companies had a price of $3.19, with the upper quartile having a price of $20.00. The securities in the sample had market capitalizations from $72.1 million in the lower quartile to $775.2 million in the upper quartile. The standard deviation for MCAP is $18.185 billion, showing that while most of the data has a value of less than $1 billion, there are major outliers that pull the average of $4.078 billion away from the median value of $229.3 million. Volatility, measured as the log difference in daily high and low prices (Alizadeh, Brandt, and Diebold, 2002), is recorded as an average of 5.04% on the day the sample was taken. With a standard deviation of 3.86%, there are significant differences in the volatility of the securities we observed. The lower quartile of observations had a volatility of 2.84% while the upper quartile had a volatility of 6.07%, the median value was 4.08%. This shows that the data is positively skewed regarding volatility. A measure of the average transaction cost per trade for securities in the sample was obtained from the difference in the daily closing bid and ask prices, divided by the midpoint price. This is denoted as the spread (see Chung and Zhang, 2014). The average closing spread is 8 basis points. The spread has a standard deviation of 16.8 basis points, this shows considerable change in the closing spread within the data. The lower quartile has a spread of 0.7 basis points while the upper quartile has a spread of 8.7 basis points. Again, we see positive skewness in the data. Liquidity, measured with Amihud's (2002) illiquidity, shows a rating of liquidity for a security. Low Amihud scores are associated with liquid securities. The average score is 1.2393, comparing this with the lower quartile, with a score of 0.0009, the median 0.0099, and the upper quartile 0.1013 we see that most securities are liquid with only a handful of observations bringing the average and standard deviation upwards. The average share turnover is 0.95% for stocks in the sample, turnover ranges from 0.21% in the bottom quartile to 1.20% in the upper quartile of the distribution. With a standard deviation of 1.28%, the distribution is positively skewed. We also find that 74.63% of the securities are listed on the NASDAQ, this listing would increase analyst coverage and awareness of the security.

Table 2. Cross-Sectional Correlation Matrix

This table reports correlation coefficients for the variables used in the cross-sectional analysis for the sample of 335 pharmaceutical stocks on January 3, 2006. *Price* is the closing share price. *MCAP* is the market capitalization, or price times shares outstanding. *Rvolt* is the range-based volatility, or the log of the high ask price minus the log of the low bid price. %*Spread* is the closing relative spread, or the difference between the closing ask and bid prices, scaled by the quote midpoint. *Illiq* is Amihud's (2002) illiquidity, or absolute return divided by dollar volume (scaled by 10^6). *Turn* is share turnover, or volume divided by shares outstanding. *Nasdaq* is an indicator variable equal to one if the stock is listed on the NASDAQ and zero otherwise. We report p-values in brackets.

	Price	MCAP	Rvolt	Spread	Illiq	Turn	Nasdaq
Price	1						
MCAP	0.4349	1					
	(<.0001)						
Rvolt	-0.2869	-0.1416	1				
	(<.0001)	(0.0095)					
Spread	-0.2941	-0.1107	0.3785	1			
	(<.0001)	(0.0429)	(<.0001)				
Illiq	-0.0587	-0.0238	-0.0589	0.2575	1		
	(0.2843)	(0.6647)	(0.2820)	(<.0001)			
Turn	0.1444	-0.0567	0.1009	-0.0460	-0.0396	1	
	(0.0081)	(0.3011)	(0.0650)	(0.4016)	(0.4701)		
Nasdaq	-0.1982	-0.2616	0.1420	-0.0156	0.0083	0.18388	1
	(0.0003)	(<.0001)	(0.0092)	(0.7755)	(0.8798)	(0.0007)	

Table 2 shows the correlation coefficients for each variable used in the cross-sectional analysis. Each variable is compared to one another independently, displaying the percent of one variable that explains the outcomes of another. This aids in the avoidance of perfect multicollinearity in the OLS regression performed later on in the analysis. Price is heavily correlated with MCAP, Rvolt, Spread, Turn, and Nasdaq with values of 43.49%, -28.69%, -29.41%, 14.44%, and -19.82% respectively. MCAP, Rvolt, spread, and Nasdaq are each significant to the 99.99% level. Turn is also highly statistically significant at a 99% level. Illiq is the only variable that is not statistically significant with a value of -5.87% and a significance of 71.57%. MCAP is highly correlated with Nasdaq with a value of 26.16% at a significance of 99.99%. It is correlated with Rvolt at a -14.16% level with a significance of 99%. Spread is also correlated with a value of -11.07% at a significance of 95%. Every other variable is neither statistically nor economically significant when compared to MCAP. The correlation between Rvolt and Spread is highly statistically significant, with a coefficient of 37.85% and a significance of 99.99%. Nasdaq is also highly significant with a value of 14.20% at a significance of 99%. Turnover is correlated with a value of 10.09% at a significance of 90%. Illiq is neither statistically nor economically significant to this variable. Spread is highly statistically significant on Illiq, with a value of 25.75% and a significance of 99.99%. Turn and Nasdaq are neither statistically nor economically significant. Illiq is also not highly significant compared to Turn and Nasdaq. Finally, Turn and Nasdaq are highly statistically significant. With a value of 18.39% and a significance level of 99%.

4. Empirical Analysis and Results

4.1. CARs surrounding Medicare Part D Expansion

Our empirical analysis begins by looking at both raw returns and CARs for the sample of 335 pharmaceutical stocks surrounding the January 3, 2006 implementation of the Medicare Part D. We note that the actual implementation date for Medicare part D was January 1, 2006, however, the markets were closed on that date making January 3 the first trading day following the event.

Table 3. Cumulative Abnormal Returns Surrounding Medicare Part D Expansion

This table reports cumulative abnormal returns for 335 pharmaceutical stocks surrounding the expansion of Medicare Part D on January 3, 2006. The market adjusted return (MAR) on day *t* is determined as follows:

$$MAR_{i,t} = R_{i,t} - R_{m,t} \text{ ,}$$

where $R_{i,t}$ is the return on stock *i* on day *t* and $R_{m,t}$ is the market return either equal-weighted (E-W) or value weighted (V-W) across CRSP securities on day *t*. We also obtain parameter estimates from restricted (market model) an unrestricted (4-factor model) specifications of the following model that is estimated in the period ending 46 days before the event date (maximum of 255 days and minimum of 3 days):

$$E\left[R_{i,t}\right] = \beta_0 + \beta_1 EXMKT_t + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 UMD_t$$

where $EXMKT_t$ is the market risk premium, the return on the market, either E-W or V-W across CRSP securities on day *t* minus the risk-free return. HML_t is the high minus low book-to-market risk factor. SMB is the small minus large market capitalization risk factor. UMD is the winners minus losers momentum risk factor. The first two risk factors are discussed in Fama and French (1993), while the last is outlined in Carhart (1997). We then estimate the abnormal returns for each stock day during the event window (AR) as follows:

$$FF4\ AR_{i,t} = R_{i,t} - E\left[R_{i,t}\right].$$

The raw returns and abnormal returns are cumulated (CARs) over various event windows. T-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Event Range	Raw	E-W MAR	V-W MAR	E-W MM	V-W MM	E-W FF4	V-W FF4
[-2, +2]	3.08%***	0.91%**	1.59%***	0.82%*	1.76%***	1.15%**	2.15%***
	(7.992)	(2.352)	(4.139)	(2.085)	(4.496)	(2.928)	(5.513)
[-5, +5]	6.37%***	2.26%***	3.98%***	2.16%***	4.26%***	2.40%***	3.99%***
	(10.246)	(3.641)	(6.399)	(3.384)	(6.730)	(3.752)	(6.236)
[-10, +10]	7.81%***	3.74%***	6.46%***	3.95%***	6.71%***	4.11%***	6.09%***
	(8.533)	(4.093)	(7.056)	(4.068)	(6.958)	(4.233)	(6.266)
[-15, +15]	7.85%***	2.20%*	5.98%***	2.55%*	6.34%***	2.78%*	5.10%***
	(6.733)	(1.888)	(5.128)	(2.046)	(5.125)	(2.222)	(4.072)
[-20, +20]	12.02%***	4.04%**	8.86%***	4.45%**	9.40%***	4.64%***	7.61%***
	(9.039)	(3.044)	(6.664)	(3.079)	(6.606)	(3.204)	(5.260)

Column [1] of Table 3 shows cumulative raw returns. We find that the average cumulative return from day *t*-2 to *t+2* is 3.08%, which is significantly different from zero at the 0.01 level. When the event window was expanded to *t*-5 to *t*+5 the return more than doubled to 6.37% and remained statistically significant at the 0.01 level. Another expansion of the event window between *t*-10 and *t*+10 increased our raw return to 7.81% at a significance level of 0.01. The event window of *t*-15 to t+15 stays close to the previous window with a return of 7.85% at a significance level of 0.01. The final observed window of *t*-20 to *t*+20 shows a return of 12.02% at a significance of 0.01. This shows that investors were optimistic about the impact Medicare expansion would have on pharmaceutical securities.

Although the raw returns look both statistically and economically significant, the raw return does nothing to control for the momentum of the overall market. Other factors driving the market upwards may have little to do with expectations of increased profits for pharmaceutical companies. In columns [2] through [7] of Table 3, we report results for CARs that are adjusted using a variety of benchmarks. Columns [2], [4], and [6] use an equal-weighted market portfolio as the benchmark. Column [2] subtracts the equal-weighted market return from the event return. Column [4] takes the residual return from a market model regression where the event return is regressed on the equal-weighted market return. Column [6] reports additional robust results from a four-factor model, where CARs are estimated using the residuals from these multifactor models. Columns [3], [5], and [7] are analogous to columns [2], [4], and [6] but use a value-weighted market return instead of an equal-weighted return. Overall, the results tell a similar story to the raw returns. As the event window widened from the smallest window, *t*-2 to *t*+2, towards the largest window, *t*-20 to *t*+20, the abnormal return tended to increase by more than 2x. Even the smallest abnormal return, found in column [4] during the event window *t*-2 to *t*+2, returned 0.82% and was statistically significant at the 90% level. Following the same column to the event window of t-20 to *t*+20 we find an abnormal return of 4.45% with a statistical significance of 95%. Because this trend is followed in every column for each event window, regularly with a significance of 99%, we can conclude that there is a positive abnormal return for pharmaceutical stocks in the time period that is not attributed to movements in the overall market.

4.2. CARs after Medicare Part D Expansion

Table 4. Cumulative Abnormal Returns After Medicare Part D Expansion

This table reports cumulative abnormal returns for 335 pharmaceutical stocks after the expansion of Medicare Part D on January 3, 2006. The market adjusted return (MAR) on day t is determined as follows:

$$MAR_{i,t} = R_{i,t} - R_{m,t} \ ,$$

where $R_{i,t}$ is the return on stock *i* on day t and $R_{m,t}$ is the market return either equal-weighted (E-W) or value weighted (V-W) across CRSP securities on day *t*. We also obtain parameter estimates from restricted (market model) an unrestricted (4-factor model) specifications of the following model that is estimated in the period ending 46 days before the event date (maximum of 255 days and minimum of 3 days):

$$E[R_{i,t}] = \beta_0 + \beta_1 EXMKT_t + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 UMD_t$$

where $EXMKT_t$ is the market risk premium, the return on the market, either E-W or V-W across CRSP securities on day *t* minus the risk-free return. HML_t is the high minus low book-to-market risk factor. SMB is the small minus large market capitalization risk factor. UMD is the winners minus losers momentum risk factor. The first two risk factors are discussed in Fama and French (1993), while the last is outlined in Carhart (1997). We then estimate the abnormal returns for each stock day during the event window (AR) as follows:

$$FF4 \ AR_{i,t} = R_{i,t} - E[R_{i,t}].$$

The raw returns and abnormal returns are cumulated (CARs) over various event windows. T-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Event Range	Raw	E-W MAR	V-W MAR	E-W MM	V-W MM	E-W FF4	V-W FF4
[0, +2]	2.86%***	0.70%**	0.70%**	0.56%*	0.91%***	0.58%*	1.07%***
	(7.975)	(1.963)	(1.961)	(1.571)	(2.562)	(1.642)	(2.996)
[0, +5]	6.64%***	2.46%***	2.98%***	2.19%***	3.34%***	1.99%***	2.95%***
	(11.853)	(4.383)	(5.310)	(3.922)	(5.979)	(3.582)	(5.289)
[0, +10]	8.00%***	3.95%***	5.26%***	3.85%***	5.57%***	3.84%***	5.10%***
	(10.143)	(5.014)	(6.670)	(4.762)	(6.935)	(4.759)	(6.331)
[0, +15]	7.88%***	2.59%***	5.46%***	2.51%***	5.77%***	3.25%***	4.60%***
	(8.494)	(2.796)	(5.886)	(2.625)	(6.112)	(3.370)	(4.771)
[0, +20]	11.53%***	3.96%***	7.42%***	3.79%***	7.91%***	4.60%***	6.47%***
	(10.705)	(3.682)	(6.889)	(3.360)	(7.151)	(4.044)	(5.710)

In order to determine the market sentiment towards pharmaceutical stocks with the expansion of Medicare part D, it is necessary to view CARs event windows during and after the event. We should expect to see somewhat positive returns once the plan is implemented. This is what we find when looking at CAR event windows taking place during and after the event, shown in Table 4. In column [1], for event windows *t* 0 to *t* + 2 we report raw returns of 2.86%. In event windows t 0 to *t* + 5, t 0 to *t* + 10, *t* 0 to *t* + 15, and *t* 0 to *t* + 20 we report raw returns of 6.64%, 8.00%, 7.88%, and 11.53% respectively. Each raw return is also statistically significant at the 0.01 level.

This trend continues throughout columns [2] to [7], with the lowest abnormal return being column [4] during the event window t 0 to *t* + 2, which reported an equal weighted market model abnormal return of 0.56% with a 90% significance level. Every value in event windows t 0 to *t* + 5, as well as every larger event window, are both economically significant as well as statistically significant to the 0.01 level. Value weighting the models caused larger abnormal returns because the largest pharmaceutical companies often own the patents to many different drugs that would benefit from increased inelastic demand after the Part D expansion. In essence, these companies have more to gain from the increased coverage of the American people. Value weighted models, columns [3], [5], and [7], in the time period t 0 to *t* + 20 had abnormal returns of 7.42%, 7.91%, and 6.47%, respectively, while each value was statistically significant to 99%. Equal weight markets, columns [2], [4], and [6], in the same period of t 0 to *t* + 20 had reduced abnormal returns, though still economically significant. This outcome is expected as the market adjusted to the increased potential for profitability within the industry.

4.3. *CARs <u>before</u> Medicare Part D Expansion*

Table 5. Cumulative Abnormal Returns Before Medicare Part D Expansion

This table reports cumulative abnormal returns for 335 pharmaceutical stocks before the expansion of Medicare Part D on January 3, 2006. The market adjusted return (MAR) on day *t* is determined as follows:

$$MAR_{i,t} = R_{i,t} - R_{m,t} \text{ ,}$$

where $R_{i,t}$ is the return on stock *i* on day *t* and $R_{m,t}$ is the market return either equal-weighted (E-W) or value weighted (V-W) across CRSP securities on day *t*. We also obtain parameter estimates from restricted (market model) an unrestricted (4-factor model) specifications of the following model that is estimated in the period ending 46 days before the event date (maximum of 255 days and minimum of 3 days):

$$E[R_{i,t}] = \beta_0 + \beta_1 EXMKT_t + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 UMD_t$$

where $EXMKT_t$ is the market risk premium, the return on the market, either E-W or V-W across CRSP securities on day *t* minus the risk-free return. HML_t is the high minus low book-to-market risk factor. SMB is the small minus large market capitalization risk factor. UMD is the winners minus losers momentum risk factor. The first two risk factors are discussed in Fama and French (1993), while the last is outlined in Carhart (1997). We then estimate the abnormal returns for each stock day during the event window (AR) as follows:

$$FF4\ AR_{i,t} = R_{i,t} - E[R_{i,t}].$$

The raw returns and abnormal returns are cumulated (CARs) over various event windows. T-statistics are reported in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Event Range	Raw	E-W MAR	V-W MAR	E-W MM	V-W MM	E-W FF4	V-W FF4
[-20, -1]	0.49%	0.08%	1.44%**	0.66%	1.49%**	0.04%	1.14%*
	(0.584)	(0.096)	(1.731)	(0.760)	(1.701)	(0.048)	(1.303)
[-15, -1]	-0.04%	-0.39%	0.51%	0.04%	0.57%	-0.47%	0.51%
	(-0.047)	(-0.521)	(0.680)	(0.048)	(0.711)	(-0.590)	(0.636)
[-10, -1]	-0.19%	-0.21%	1.20%**	0.10%	1.14%**	0.28%	0.98%*
	(-0.322)	(-0.358)	(2.067)	(0.173)	(1.880)	(0.455)	(1.610)
[-5, -1]	-0.27%	-0.19%	1.00%***	-0.03%	0.92%***	0.41%	1.03%***
	(-0.753)	(-0.537)	(2.798)	(-0.072)	(2.528)	(1.100)	(2.785)
[-2, -1]	0.21%	0.20%	0.89%***	0.26%	0.84%***	0.56%***	1.08%***
	(0.917)	(0.862)	(3.816)	(1.118)	(3.617)	(2.408)	(4.640)

The pre-event window is expected to be relatively uneventful so long as there is minimal data leakage regarding the expansion of Medicare part D. Table 5 displays the results of the event windows preceding the Medicare expansion. Column [1] displays the raw returns for the pre-event windows. The raw return periods of *t*-20 to *t*-1, *t*-15 to *t*-1, *t*-10 to *t*-1, *t*-5 to *t*-1, and *t*-2 to *t*-1 all show returns lower than 0.5%. Furthermore, none of these returns are statistically different from zero. The same story is shown for most returns in the pre-event windows. There are, however, a few instances of returns that are marginally economically significant as well as statistically significant. In column [3], the event window *t*-5 to *t*-1 and *t*-2 to *t*-1 have returns of 1.00% and 0.89% respectively while also having a significance of 99%. In the same column the event windows *t*-20 to *t*-1 and *t*-10 to *t*-1 have returns of 1.44% and 1.20% respectively while also having a significance of 95%. In column [5], within the event windows of t-5 to *t*-1 and *t*-2 to *t*-1 there is a return of 0.92% and 0.84% respectively. Both windows have a statistical significance of 99%. Within this same column but in the event windows of *t*-20 to *t*-1 and *t*-10 to *t*-1 there was a return of 1.49% and 1.14% respectively with a significance of 95%. Column [6] has only one statistically significant value, in the *t*-2 to *t*-1 event window we recorded an abnormal return of 0.56%. While this is arguably economically insignificant, it has a statistical significance of 99%. Column [6] follows a similar significance pattern found in columns [3] and [5]. Event windows *t*-5 to *t*-1 and *t*-2 to *t*-1 had an abnormal return of 1.03% and 1.08% respectively while having a significance of 99%. Windows *t*-20 to *t*-1 and *t*-10 each returned 1.14% and 0.98% with a significance of 90%. These results follow the pattern formed in Table 4, where Value-Weighted models had larger returns compared to Equal-Weighted models. This, again, might be since larger pharmaceutical stocks received a premium in anticipation for the Medicare expansion.

4.4. Cross-Sectional Regressions

Table 6 reports the cross-sectional regressions for the post event windows, allowing a closer look at the characteristics of pharmaceutical stocks that lead to large abnormal returns. Over most of the regression event windows the factors contributing the most to abnormal returns are low priced, high volume, NYSE listed securities, with other factors held constant.

Table 6. Cross-Sectional Regressions

This table reports the results from estimating specifications of the following cross-sectional regression equation on a sample of 335 pharmaceutical stocks:

$$CAR_i = \alpha + \beta_1 LN(Price_i) + \beta_2 LN(MCAP_i) + \beta_3 Rvolt_i + \beta_4 \%Spread_i + \beta_5 Illiq_i + \beta_6 Turn_i + \beta_7 Nasdaq_i + \varepsilon_i$$

where the dependent variable is the market model cumulative abnormal return around the expansion of Medicare Part D. *Price* is the closing share price. *MCAP* is the market capitalization, or price times shares outstanding. *Rvolt* is the range-based volatility, or the log of the high ask price minus the log of the low bid price. %*Spread* is the closing relative spread, or the difference between the closing ask and bid prices, scaled by the quote midpoint. *Illiq* is Amihud's (2002) illiquidity, or absolute return divided by dollar volume (scaled by 10^6). *Turn* is share turnover, or volume divided by shares outstanding. *Nasdaq* is an indicator variable equal to one if the stock is listed on the NASDAQ and zero otherwise T-statistics are reported in parentheses obtained from heteroscedastic corrected standard errors. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Event Window				
	[0, +2]	[0, +5]	[0, +10]	[0, +15]	[0, +20]
LN(Price)	-0.0041	-0.0236**	-0.0376***	-0.0378**	-0.0532***
	(-0.87)	(-3.34)	(-3.82)	(-3.27)	(-3.98)
LN(MCAP)	-0.0020	0.0020	0.0005	-0.0044	0.0040
	(-0.69)	(0.45)	(0.08)	(-0.61)	(-0.48)
Rvolt	0.0465	-0.0464	0.1460	0.1811	0.1603
	(0.43)	(-0.28)	(0.63)	(0.66)	(0.51)
Spread	-0.2562	-0.0466	0.2430	0.5447	0.4874
	(-0.94)	(-0.11)	(0.42)	(0.80)	(0.62)
Illiq	0.0006	-0.0004	-0.0004	-0.0007	-0.006
	(1.69)	(-0.72)	(0.53)	(-0.87)	(-0.66)
Turn	0.7604**	1.2946**	1.7579**	1.4640*	1.5844
	(2.53)	(2.83)	(2.75)	(1.95)	(1.83)
Nasdaq	-0.0160	-0.0398**	-0.0527**	-0.0621**	-0.0683
	(-1.86)	(-3.04)	(-2.88)	(-2.90)	(-2.76)
Constant	0.0607	0.0638	0.1369	0.2402	0.2903
	(1.13)	(0.78)	(1.20)	(1.79)	(1.87)
Adj. R^2	0.0234	0.0742	0.1262	0.1323	0.1556
N	335	335	335	335	335

In the event window t 0 to t+2 share turnover was the only significant variable, with a significance of 95%, showing that securities with hih volume lead to abnormal returns. In the period t 0 to t+5 low price, high turnover, and NYSE listed securities all had significant influence on the abnormal return with a 95% significance. The event window t=0 to t+10 low price, high turnover and NYSE listing follows a similar trend of significance, with values of 99%, 95%, and 95% respectively. In the period t 0 to t + 15, the trend of low price, high turnover and a NYSE listing continues, with those having the only statistically significant values with significance of 95%, 90%, and 95% respectively. Finally, the t 0 to t + 20 event window had low price as the only significant value, with a significance of 99%.

5. Concluding Remarks

On January 1, 2006 Medicare was expanded with part D to increase the availability of insurance coverage for consumers of prescription medication. With this expansion came the expectation that prices and demand for prescription medications would increase due to higher volumes of insured customers. Our findings lead us to reject H0 and accept H1 due to the highly significant, both economically and statistically, results of the CARs analysis. Our results found large abnormal returns in the post event window and minimal abnormal returns in the pre-event window, showing that implementing Medicare part D influenced the industry. Our analysis also showed that companies with low price, high volume, and a NYSE listing contributed significantly to the abnormal returns in the post event windows.

Further research is needed to discover if the Medicare expansion had the lasting effect that investors expected. Existing literature, specifically Duggand (2010), found that prices of pharmaceutical medication decreased after the expansion. It would be worthwhile to look at the maximum length of time these securities held their expansion premium to discover when the markets realized that no significant increased profits would be realized.

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