Drug Prices under the Medicare Discount Drug Card Program

Information Policy and Drug Prices: Evidence from the Medicare Discount Drug Card Program*

Emin M. Dinlersoz† — University of Houston
Ruben Hernandez-Murillo‡ — Federal Reserve Bank of St. Louis
Han Li§ — Southwestern University of Finance and Economics
Roger Sherman¶ — University of Houston

December 2006

Abstract

In early 2004, the U.S. Government initiated the Medicare Discount Drug Card Program (MDDCP), which created a market for drug cards that allowed elderly and handicapped subscribers to obtain discounts on their prescription drug purchases. Pharmacy-level prices for many drugs were posted on the program website weekly from May 29, 2004 to December 31, 2005, as the largest undertaking in the history of government-sponsored information release began with the hope of promoting competition by facilitating access to prices. A large panel of pharmacy-level drug price data collected from the Medicare website indicates that there was significant and persistent dispersion in prices across cards throughout the program. Moreover, the time-path of prices was non-monotonic; the prices declined initially when consumers were choosing cards but rose later when subscribers were unable to switch from one card to another. In contrast, contemporaneous control prices from on-line drug retailers, which were unrelated to the program, rose steadily over time, indicating that MDDCP prices evolved in a way different from the general evolution of prices outside the program. In view of the fact that the program rules prevented consumers from changing their cards at will, the evolution of MDDCP prices is consistent with certain models of dynamic price competition with consumer switching costs, such as Klemperer's (1987a,b). Estimates of potential savings from purchasing at program prices are also provided.

JEL Classification: L11, L13, L50, D43, D83, I11, I18.
Keywords: Price dispersion, retail drug prices, price dynamics, government regulation, Medicare Discount Drug Card Program, Medicare Part D.

*We thank Austan Goolsbee and Ethan Lewis for comments. The views expressed in this article are those of the authors and do not necessarily reflect the official position of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

†Corresponding author. Department of Economics, 204 McElhinney Hall, Houston, TX 77204-5019. Email: edinlers@mail.uh.edu.

‡Research Division, 411 Locust Street, St. Louis, MO 63102. E-mail: Ruben.Hernandez@stls.frb.org.

§Research Institute of Economics and Management, ChengDu, SiChuan 610074, P.R.China. E-mail: hli@swufe.edu.cn

¶Department of Economics, 204 McElhinney Hall, Houston, TX 77204-5019. Email: rsherman@uh.edu.

1 Introduction

On May 29, 2004, in conjunction with the Medicare Discount Drug Card Program (MDDCP), the U.S. Government activated a website to publicize prices for over 800 prescription drugs posted by a large number of retail and mail-order pharmacies across all zip code areas in the United States. The MDDCP was initiated as a transition to the broader Medicare Part D prescription drug assistance program that went into effect in January 2006, aiming to lower the cost of drugs and therapy for elderly and handicapped individuals covered by Medicare. The website for the MDDCP contained price information from individual pharmacies across the nation for prescription drugs used mostly by Medicare eligible individuals, and it was updated continuously on a weekly basis. This mandatory release of prices on the Internet continues under the Medicare Part D program and it is unmatched in scale in the history of government policy on information transparency.

The MDDCP and its successor program, Medicare Part D, were supposed to induce competition among drug companies, largely through the extensive price information that intermediary drug card sponsors were required to post on the Medicare website. As a source of pressure to lower prices, intense competition among drug cards was to replace the bargaining power that Medicare had previously used directly with the drug companies. Under terms of the MDDCP and its Part D successor, Medicare is no longer allowed to exercise its bargaining power in this way. But at the same time the MDDCP generated price information to support competition among drug cards, the program design also required that subscribers commit to a single drug card once they subscribed, rather than switch cards at will. This institutional constraint on consumer switching could in principle act to inhibit competition by introducing prohibitively high switching costs. Thus, a major question is whether MDDCP competition among the drug-card sponsors was indeed effective in lowering drug prices as intended.

Using a large sample of prices collected from the MDDCP website during several weeks of the program, this paper studies the effects of the release of price information on the functioning of the prescription drug market that was created under the program. In particular, we focus on the effect of the release of on-line information about physical market prices on the evolution of prices in physical markets. Our approach is to analyze the change in level and dispersion of prices after the MDDCP price information became available to consumers on the Medicare website, and to compare price levels with non-MDDCP drug prices for identification of program effects. We use the data to understand the extent and determinants of price dispersion within the program and to investigate the dynamics of prices over the course of the program.

The empirical analysis indicates that the program did not bring convergent prices for drugs, but instead resulted in significant dispersion in prices across drug cards. There was no obvious trend of convergence in prices across drug cards. More importantly, the evidence also points to a non-monotonic time-path for prices. The prices tended to decline initially in the early phases of the program when card subscription was still diffusing across consumers, and they rose later when card subscription was mostly complete and consumers could no longer switch cards, although the magnitudes of these trends in prices were not exceptionally large relative to the average of prices at the beginning of the program. Control prices unrelated to the program were collected contemporaneously from on-line drug retailers,

and these control prices exhibited a steady upward trend throughout the MDDCP. In particular, when MDDCP prices declined, on-line prices rose, and when both sets of prices rose, the rise in MDDCP prices was actually greater than the rise in on-line prices. Thus, MDDCP prices evolved differently from the general evolution of prices outside the MDDCP. The time-path of prices within the MDDCP cannot be simply explained away by general trends in drug prices. Program-specific effects were important.

We also use non-program nationwide average prices that were typically used to reimburse patients to provide estimates of savings card users could obtain, excluding the enrollment fee. The estimates suggest that there were some savings to naïve consumers, i.e. those consumers who do not engage in vigorous search and simply buy randomly from a seller both under the regular prices and under the program. The savings were almost twice as large for searching consumers who can locate the card with the minimum price using the program's search engine, but otherwise buy randomly from a seller in the regular market. Naïve consumers, however, could actually save more by purchasing from on-line retailers at non-program prices instead of purchasing using cards in the MDDCP.

Certain models of consumer search and access to price information, such as that of Stahl (1994), predict that prices decline monotonically as the fraction of consumers informed about prices increases. Such a monotonic decline does not emerge in our sample. While prices declined early in the program, they tended to rise later on. The observed time-path of prices appears to be consistent with an environment where the switching costs are high. Some dynamic models of price competition with consumer switching costs, such as that of Klemperer (1987a,b), can account for the type of price dynamics observed here. Anticipation of the fact that consumers would be stuck with their choices escalates competition earlier on to attract and lock-in consumers, leading to lower prices initially but higher prices later on. We elaborate further on the relevance of dynamic price competition models with consumer switching costs below.

It is important to emphasize that the analysis in this paper is not a "before-and-after" comparison of the evolution of prices, simply because no "before" is available; the cards did not exist before prices were released on the Medicare website. Therefore, the analysis here cannot be classified under the general class of studies comparing the behavior of data with and without treatment, where identification comes from the presence of the treatment. Rather, the strategy followed here is to monitor the changes in prices over time starting with the initial on-line release of prices and to compare the evolution with that of a contemporaneous control group. Several reasons, discussed below, suggest that prices were likely to change gradually over time, and the important question is how any change in prices can be attributed to the program's environment. As mentioned earlier, we rely on non-program drug prices posted by on-line drug retailers as controls for general movements in drug prices, to identify and isolate changes in program prices due to program-specific effects. On-line prices are unlikely to be affected by the price choices made by cards within the MDDCP, because the program is applicable to a relatively small fraction of the overall population of prescription drug users.[1]

This paper is related to a growing literature that analyzes the role of better consumer price in-

[1] The estimated target population by this program was about 7.5 million people under Medicare.

formation on the functioning of markets (see, e.g., Milyo and Waldfogel (1999), Brown and Goolsbee (2000), Brynjolfsson and Smith (2000), and Baye, Morgan, and Scholten (2005)). The paper, however, differs from the rest of this literature in a number of important ways. First, the availability of a large amount of high-frequency (weekly) price data both across geography and over time allows us to make a more comprehensive analysis than previous studies. Second, most studies – with the exception of Brown and Goolsbee (2000) – only document the effect of search on the Internet on on-line prices. Instead, we are able to focus on the response of prices in the traditional market to the release of price information on the Internet. In addition, under the MDDCP the release of price information is mandatory, not voluntary, and it is exhaustive and covers all prices, rather than being limited to a selected subset of all prices as is the case with most price search engines on the Internet.[2] Third, institutional aspects of the program, discussed in detail below, open the way for non-monotonic evolution of prices, which is evident in the data. Such non-monotonicity is not expected when only the improved price information for consumers is the primary driver of prices. Additional constraints of the program seem to matter. In particular, the switching costs erected by the program are very likely to be responsible for the type of dynamics observed, as predicted by models in the spirit of Klemperer (1987a,b). Finally, this study has a policy relevance with potentially large welfare consequences. The design of a viable prescription drug program for elderly is still a major policy issue and the success of Medicare Part D remains to be seen. The analysis here provides evidence about the effectiveness of a government-sponsored program by analyzing the role of government-initiated release of information on the functioning of the resulting prescription drug market. The results are therefore valuable for understanding the effects of public information policy and for assessing the future of Medicare Drug policy.

The rest of the paper is organized as follows. Section 2 gives some background for the MDDCP. Section 3 presents our theoretical motivation, based on literature for markets with imperfect information and switching costs. Section 4 describes the data. Empirical analysis and results are in Section 5. Section 6 concludes.

2 The MDDCP Background

The design and the institutional environment of the MDDCP are crucial for understanding the functioning of the retail drug markets that were created by the program. The MDDCP allowed qualified drug-card sponsors to make arrangements with drug manufacturers to obtain discounts and pass the discounts on to Medicare recipients. Eligible consumers could then strictly voluntarily subscribe to a card of their choice and obtain their prescriptions at a discount specified by the card sponsor, either from retail pharmacies or by mail from mail-order pharmacies that have arrangements with the card sponsor. To subscribe to a card, a consumer had to pay a fixed annual fee (for at most two years), ranging between $0 and at most $30, and thereafter was entitled to receive that drug-card sponsor's discounts on all the drugs that sponsor covered. A consumer's problem was thus to choose both the

[2] Internet search engines have their own practices and some charge firms to be included in the results of a price search by consumers. See, e.g., Baye, Morgan and Scholten (2005) for more on the economics of price search engines.

drug card and the retail (or mail-order) pharmacy that provided the best discount on the bundle of drugs used by the consumer. The price information released on the Medicare website was designed to facilitate the process of searching for cards and pharmacies, so consumers could find the best deals on their bundles of drugs.

Institutional aspects of the program were critical in shaping the dynamics of program prices. First, a card sponsor was not required to commit to a given level of discount on drugs over time, but instead could change its prices at any time without notice. This flexibility in card prices left the door open for price fluctuations that could result from competition among cards, above and beyond general fluctuations in drug prices, such as those due to changes in manufacturers' costs or changes in demand due to the introduction of a generic version of a drug. Similar flexibility was applicable to individual pharmacies. For a given card, there was also no prior commitment for the prices to be the same across all pharmacies that offered discounts under the card. Thus, prices could potentially have evolved differently in different pharmacies and locations.

Second, in addition to the usual consumer search and switching costs that contribute to price dispersion in drug retail markets (see, e.g., Sorensen (2000, 2001), Scott-Morton (1997)), prohibitive consumer switching costs were erected by the very design of the program.[3] Once enrolled in a card program, a consumer was not allowed to switch to another card, except in certain special cases, such as when a consumer moves to a new location or if a card sponsor exited from the market. This restriction on switching introduced additional friction and inertia into the market, which may have impeded reallocation of consumers to low price card sponsors over time. The MDDCP had a nationally coordinated switching period between November 15 and December 31, 2004, during which consumers were allowed to review their card choices and change them if they wished to do so. After this period, which covered a window before a full year of the program, a consumer who is already enrolled in a card was not allowed to switch to another card until the program terminated at the end of 2005, subject to the exceptions mentioned. The prevention of switching after the switching period expired and the timing of the switching period, could potentially lead to price dynamics driven by card sponsors' incentives to charge lower prices in the early stages of the program in order to attract subscribers, and then to increase their prices once consumers were locked in to their card choices.

Third, the diffusion of card enrollment among eligible consumers was expected to be gradual over time, not instantaneously. Related is the rate of the diffusion of price search by consumers on the program's website. The enrollment was strictly voluntary and consumers had to evaluate card choices before making a decision. One of the main criticisms of the MDDCP was the complexity of the card-choice process, due to an abundance of alternative plans whose benefits were hard to assess. This criticism applies equally to Medicare Part D, which began in January, 2006. Adding to this complexity concern is the fact that most consumers eligible for cards were 65 years or older, not a group of particularly Internet-savvy consumers, although their general Internet usage rate has been rising over time.

[3] Usual switching costs in the context of prescription drugs include consumer learning costs about the side effects of a new drug that can substitute for the consumer's existing drug and physicians' inertia in changing a prescription due to rewards and loyalty programs offered by the manufacturer or the wholesaler of that drug.

Before the program went into effect, Fox (2004) estimated that 22 percent of adults aged 65 and older had access to the Internet. Of this group, an estimated 66 percent used the Internet to locate health information, implying that about 14% of the relevant population used the Internet for health information search. While these rates are not very high, they cannot be taken as definitive figures for predicting the diffusion of price search under the MDDCP, because the program clearly gave incentives for price comparison by promising discounts, making it different from casual health information search or ordinary drug price search on the Internet. Therefore, the rate of diffusion could actually have been higher within the group of individuals eligible for the program. Some elderly, especially if cognitively handicapped, also relied on agents such as relatives or care-givers to guide them through the subscription process. Furthermore, some cards actually had subscription assistance programs, which helped elderly citizens choose the best options for them. From a theoretical standpoint, the critical mass of searching consumers needed to induce escalated competition among firms may correspond to very low actual fractions of consumers who search. While we do not have total enrollment data for the MDDCP, recent evidence on the diffusion of Medicare Part D suggests that about 90 percent coverage of the people 65 and older was achieved within the first 6 months from the start of the program in January 2006.[4]

Further evidence on consumers' enrollment and experience with the program comes from an October 2005 report on the progress of the MDDCP program prepared by Abt Associates, Inc. upon request from the Centers for Medicare and Medicaid Services.[5] Based on an extensive survey of card enrollees and non-enrollees, the report found that wide-spread awareness of the MDDCP was obtained within a few months of the program, mostly in the spring of 2004. Therefore, non-enrollment due to lack of information about the program can be ruled out. A majority of the respondents reported that they had more than enough information to make a choice among the cards, but about one quarter to half of them did not consider more than just one drug card. Some of these consumers were simply ignorant about card choice and took the first card that came their way, while others were auto-enrolled by their State Pharmacy Assistance Programs or had their enrollment facilitated by the Center for Medicaid Studies. Pharmacists played a key role in helping consumers choose a card in their best interests.

Of more importance are estimates of the intensity of search for program price information on the program website. The report reveals that about 13 percent of survey participants obtained information from the Medicare website, either directly or with the help of a family member, friend or counselor who accessed the website for them. Not too surprisingly, website usage rate was highest among people eligible for Medicare due to disability and those who were younger and may therefore be more comfortable with computer and Internet use. Many of those who accessed the website were enthusiastic about it and found the information they were looking for, while some found the website confusing due to the large number of card options listed. A major reason survey respondents gave for choosing a card was that the card could be used at their pharmacy of choice. Cost of card ownership was also an important consideration. About a third of the respondents said they paid less with the card they chose

[4] See Heiss, McFadden, and Winter (2006).

[5] See Hassol, Jureidini, Doksum, and Hadden (2005).

compared with other cards, and that the annual enrollment fee for their chosen card was acceptable to them. Some consumers simply opted for a free card, i.e. one with no annual fee, reasoning that they had nothing to lose.

Overall, the available evidence suggests that the Medicare website and the price information posted on the website were indeed utilized to some extent in making decisions, either directly by consumers or indirectly through the assistance of others. However, given that the search rates were not impressively large, whether the diffusion of enrollment and access to price information was enough to make any changes in prices is an empirical issue. We also note that card sponsors had to set their prices without perfect information on the extent of consumer search for lower prices. Therefore, even though the consumer search rates were not too high, card sponsors might have lowered their prices to attract consumers in the absence of perfect information on the extent of price search. Next, we consider the theoretical arguments that can shed light on what to expect in terms of the evolution of prices.

3 Theoretical considerations

Consumer search is an important source of price dispersion in retail drug markets (e.g. Sorensen (2000, 2001)). Our focus is on the implications of models of consumer search and better access to price information on firms' pricing behavior, subject to the institutional aspects of the program. While essentially static models of search are abundant in the literature (see, e.g., Salop and Stiglitz (1977), Reinganum (1979), Burdett and Judd (1983), Stahl (1989)), a dynamic approach is most relevant for our purposes, because we are not only interested in the static price dispersion in the market created by the discount drug card program, but also in how prices evolve over time as switching costs change.

The central question is what happens as card subscription diffuses over time and as subscribers use price information on the program website to search for lower prices for their prescriptions, subject to the institutional constraints of the program. In a static model of oligopolistic competition, where a consumer is either completely uninformed of prices or fully informed, Stahl (1989) shows that as the fraction of consumers who are informed increases, average price falls monotonically. However, price dispersion exhibits non-monotonic behavior with respect to that fraction, initially increasing for low values of the informed fraction, but decreasing for higher values. While comparative statics from this static model can be used, as in Brown and Goolsbee (2000), to draw some conclusions for an essentially dynamic framework, the MDDCP's institutional environment introduces further considerations for firms' and consumer's dynamic behavior.

As discussed in the previous section, a major constraint of the program is that it prevents consumers from using more than one card, or from changing their card choices after they subscribe, with few exceptions. After the initial enrollment period, there was a period of no switching and then the November-December 2004 switching period, which fell roughly into the middle of the MDDCP and allowed consumers to change their cards if they wished to do so. After the switching period, consumers could not change their card choices till the termination of the program. As long as consumer search for lower prices was effective, the prohibitive switching cost could have induced card sponsors to compete intensely in the early stages of the program to attract consumers who had not yet chosen a card.

Such competition could bring lower prices. But as more and more consumers got locked in to their choices, card sponsors would have incentive to raise prices. So after the switching period, prices may be expected to rise as sponsors take advantage of consumers' inability to change cards. Overall, then, the environment of the program could result in prices falling first during the early stages where enrollment continued, possibly rising later until the switching period, falling again during the switching period, and once again rising thereafter.

The conjectured time-path of prices can indeed arise in certain models of dynamic price competition with consumer switching costs, such as those of Klemperer (1987a,b) and Farrell and Shapiro (1989) in a two-period framework and that of Beggs and Klemperer (1992) in a multi-period framework.[6] Because the MDDCP had a life-time of less than two years, finite-horizon versions of these models are more appropriate. Furthermore, cards are differentiated in many dimensions, so a differentiated-products approach is reasonable. Klemperer (1987a) offers exactly this type of framework, which features a two-period differentiated-products duopoly in which consumers are partially "locked in" by switching costs that they face in the second period. These switching costs make demand more inelastic in the second period. Perhaps less obviously, they also do so in the first period, because consumers recognize that a firm with a higher market share in the first period charges a higher price in the second period, and hence they are less inclined to purchase from that firm in the first period. Prices are lower in the first period as firms compete to build a customer base that is valuable later. However, prices may be higher in both periods than they would be in a market without switching costs. Klemperer (1987b) has similar findings, but in a homogeneous product case. Theoretically, the MDDCP erected infinitely large switching costs, so we expect the price effects outlined above to be pronounced.

There are two main considerations under MDDCP that can make the price dynamics different than in Klemperer (1987b). First, Klemperer (1987b) assumes perfect consumer information about prices, whereas some card enrollees under MDDCP chose their drugs under imperfect information about prices, according to the available evidence. Lack of perfect information about prices would not change the competition in the second period of these models, because the constraints on switching would prevent consumers from abandoning their firms even if they were informed of a lower price at some point. However, the intensity of competition in the first period could change. Firms could take advantage of consumers' imperfect information and not lower their prices as much as they would in the case of perfect information in Klemperer (1987b). Nevertheless, if a critical mass of consumers searches, even with imperfect information we would still expect to see lower prices in the first period.

Second, there is no artificially introduced "switching period" in Klemperer (1987b). The MDDCP's allowance for a round of card-switching in the middle of the program creates incentives for a price war by card sponsors. An implication is that, in addition to lower prices at the early phases of the program, we expect to see lower prices during the switching period, compared to non-switching periods.

Certain considerations, however, may have prevented the predicted non-monotonic path for prices. Given the continuing nature of the prescription drug program with Part D, card sponsors who use bait-and-switch strategies could suffer harm to their reputations. While the MDDCP itself lasted only

[6] For more references to the literature on dynamic competition with switching costs, see Beggs and Klemperer (1992).

two years, many of the card sponsors continued on to participate in Medicare Part D when it started in January 2006, so sponsors had to also consider the possibility of alienating consumers because of bait-and-switch price strategies. One of the program's goals, as stated in the Medicare's program-related website, was to monitor prices and prevent bait-and-switch behavior. However, the program did not spell out any strict guidelines as to what exactly constitutes bait-and-switch and there appeared to be little enforcement to prevent such behavior. In addition, the nationally co-ordinated switching period gave all card sponsors a clear incentive to reduce their prices and raise them thereafter. If many sponsors engage in a price reduction during that period and raise their prices later, it is hard to single out a sponsor's pricing behavior and label it "deviant".

The discussion so far suggests that the level of program prices may not have declined steadily over time but instead could fall in switching periods and rise in non-switching periods. What about the dispersion of prices? As mentioned earlier, we expect a decline in the dispersion of prices under many models of consumer search with homogenous products. One reason such convergence in prices might not occur here is the heterogeneity of the drug cards. While all cards promised discounts, their geographic coverage, drug coverage (formulary), and eligibility criteria differed to some extent. As a result, it is possible that different cards ended up serving distinct or at least partially overlapping consumer segments, effectively resulting in a market with differentiated products. In addition, the complexity of the card choice process and the abundance of alternatives, coupled with some evidence that price search was not very intense, may also prevent a strong convergence in prices. Switching costs can also prevent prices from converging over time. When consumers get locked in to their choices, each card could charge its own preferred price for a drug, which is not likely to be identical across cards due to product differentiation.

In summary, in view of the institutional environment of the program and the predictions arising from models of dynamic competition with switching costs, we expect to observe a non-monotonic path for prices. However, the degree of initial decline and subsequent rise in prices, the exact timing and duration of each episode, and the change in the dispersion of prices all depend on the underlying fundamentals, and the pattern the program prices will follow is ultimately an empirical issue.

4 Data

In this section we describe the drugs for which data were collected, the geographic areas covered, the timing of data collection, and the other prices that were obtained for control purposes.

4.1 Drugs

Prices were collected for 28 prescription drugs, which were chosen based on the following three criteria. First, all the drugs were in the top 100 drugs in claims filed by the elderly in 2001, and in the top 200 highest selling drugs for the elderly in 2003. This selection of relatively popular drugs ensures that each drug had sufficiently large demand and also was supplied by many cards. In fact, all cards supplied all 28 drugs in our sample. The relatively high demand for these drugs implies that the price

dynamics we look for are likely to have been apparent and economically important for these drugs, compared to obscure drugs that are demanded less. Second, half of the drugs are short-term drugs, such as antibiotics and pain killers, and the other half are long-term, maintenance drugs, such as those used for diabetes and cardiovascular diseases. The evolution of short-term drug prices is expected to be different from that of maintenance drugs, for which consumers are likely to search more intensely for a bargain. Finally, drug dosages were selected to reflect the most frequently prescribed dosages for the drugs, so that the demand is large relative to what would be in the cases with unusually high or low dosages.[7] Each drug price pertains to a 30-day supply of the drug. The drugs and some of their attributes are presented in Table 1.

4.2 Geographic areas

The price data from the Medicare website come in clusters of zip codes. Ninety zip codes were chosen by using a random stratified sampling, stratified to oversample zip codes that have a greater fraction of the population made up of elderly residents (individuals who are 65 years of age or older). To see if there were any demand-side effects on prices, we needed to ensure a sufficient variation in market size and other demand shifters, such as income, for discount drugs. The population of residents who are 65 or older in a zip code is a proxy for the local market size for cards, and the variation in this variable will allow us to understand the role of market size in assessing geographic differences in prices, if such differences are indeed there. The fraction of elderly people in a zip code population varies in our sample from a low of 3 percent to a high of 92.6 percent, with an average of 28 percent and a standard deviation of 25 percent. To analyze the effect of possible demand shifters, such as income and race composition, on price dispersion across zip codes, we have also gathered zip code level demographic data from the U.S. Census Bureau's 2000 Zip Code Statistics, as shown in Table 2.

The program's price search engine listed prices for all pharmacies within a circle of a certain radius whose center coincides with the center of the selected zip code area. Depending on the radius of choice, this circle contains the pharmacies not only inside the chosen zip code area, but also ones in neighboring zip codes. The search engine allowed for a choice of 4 different radii for any given zip code, and these radii varied by zip code. For densely populated urban areas, radii tended to be much smaller, whereas for less densely populated suburban and rural areas, the radii were larger, so that card holders in these areas could obtain price information for a sufficient number of pharmacies within a broader driving distance. However, the program website did not provide any information on exactly how these radii were determined for a given zip code. We chose to collect price data for all pharmacies within the smallest and the second smallest radii around a given zip code. This selection of radii enables us to assess the sensitivity of our results on the average and the dispersion of prices to the choice of radius.

[7] Drug-specific information was obtained from Mosby's Drug Consult (2004, 2005), which features information on the typical usage and dosages of drugs.

4.3 Timing of data collection

The price data were updated weekly on the Medicare website between May 29, 2004 and December 31, 2005. As shown in Figure 1, the sample in this paper was collected for several weeks in order to cover important periods of time during which the MDDCP was in effect.[8] Prices were first made available on-line on May 29, 2004 and enrollment actually began even earlier, on May 3, 2004. Data collection was initiated on June 21, 2004, three weeks after subscribers were first allowed to use their cards under the program.[9]

The first wave of data was collected each week for a period of 7 weeks during the summer of 2004. We refer to this period as the pre-switching period. The second wave was collected during the last week of December 2004. This week falls into the period between November 15 and December 31, which was the nationally coordinated switching period. Price observations from this period enable us to test whether card sponsors lowered their prices in an effort to induce switches. Finally, the third wave was collected after the switching period was over, to assess the behavior of prices during the period when switching cards was not allowed. This period consists of 9 weeks of data. We label this period the post-switching period.

Each price observation pertains to a drug sold by a pharmacy at a given location under the discount offered by a given card at a point in time. All retail prices pertain to a one-month (30-day) supply of a drug. The prices are posted prices, not necessarily transaction prices. Transactions may have taken place only at a subset of the posted prices, and some cards may have had no sales for some drugs. Lacking sales data, we are unable to make any statements on these issues. No card sponsor imposed any explicit restrictions on the geographic variation in prices. The information that many national card sponsors provided on their web-sites (and in their brochures) allowed for price variation across pharmacies and over time.[10] Geographic variation may have occurred for several reasons, including the changing demand and cost conditions individual pharmacies face across locations or simply the changing composition of cards across locations.

4.4 Other price data

Part of our analysis aims to assess the magnitude of savings offered through the cards by controlling for changes in the general level of drug prices unrelated to the MDDCP. Ideal control data for this purpose would be comparable pharmacy-level non-program retail price data collected at a weekly frequency to match the sample of MDDCP prices. Unfortunately, such detailed data are difficult to

[8] The data collection process was automated using a web-crawler software (IOpus Internet Macros) that allowed periodical recording of the data from the Medicare website.

[9] The price data during the initial weeks of the program contained certain glitches, as noted by others (see, e.g., Antos and Pinell (2004)). Some prices reported by pharmacies were found to be inaccurate and incorrect. However, these problems were fixed to a large extent within the first couple of weeks of the program. To ensure reliable data, we started collection in the 4th week of the program.

[10] A brochure offered by a Walgreens store in Houston, Texas specifically stated that prices are subject to change from one store to the other and over time.

find, and data available are very expensive.[11] Instead, we collected nation-wide wholesale prices for the drugs in our sample. These prices come from Mosby's Drug Consult (2004, 2005), which lists prices for major drug wholesalers by dosage and duration. They are a representative sample of the wholesale prices typically used to reimburse patients on their prescriptions.[12] Unlike the card prices, however, these prices are not available by geographic units; rather, a single nationwide price is reported by each supplier (usually a manufacturer). In addition, the price quotes are not available at a weekly frequency. Instead, they are representative of the price levels that prevailed for the year the database was formed. Despite their shortcomings, these prices are the best readily available benchmarks and can be used as good approximations to compare discount drug card prices to regular prices consumers pay.

Another important issue is the identification of program effects. To attribute the evolution of prices to program-specifics, one needs to weed out the general trends exhibited by drug prices over the course of the program. For this purpose, we collected concurrent weekly prices posted by Internet drug retailers for the same drugs and dosages as in the program data. We used a major Internet prescription drug search engine provided by *Destinationrx.com*, which quotes prices from several Internet drug retailers.[13] There are eight on-line retailers in our sample. These are on-line stores of some major discount retailers (*Costco.com* and *Walmart.com*), on-line stores of some large drug retail chains (*CVS.com* and *Walgreens.com*), some specialized on-line drug retailers (*RxUSA.com*, *Drugstore.com*, and *Homemed.com*), and the pharmacy branch of a major health care service provider (*AARPharmacy.com*).

Unlike program prices, on-line prices exhibit no geographic variation. Because they are subject to general nationwide trends in drug prices, they can serve as a good comparison group for the prices posted by card sponsors. The purpose of this comparison is two-fold: First, it allows us to assess whether consumers would be able to obtain lower prices simply by purchasing on-line, rather than going through the process of choosing a card and hunting for lower prices. Shopping from on-line retailers is arguably a much simpler and more flexible way of obtaining drugs compared to the whole process of choosing a drug card that provides the best deal. Second, and more importantly, on-line prices can be used to control for general changes in drug prices unrelated to the program. Drug prices can change over time due to changes in manufacturers' costs, general inflation, or other common factors. All such general trends would apply equally to MDDCP prices and on-line prices. Therefore, if different time patterns are observed for program versus other on-line prices, it is likely that program

[11] For the entire set of zip codes, we were quoted a price of about $50,000 by IMS, Inc., a firm that gathers zip-code-level price data from pharmacies. The firm was unwilling to release any partial data at a lower cost for the smaller set of zip codes we use.

[12] The nature of these prices are described in Mosby's as follows: "Prices are AWP (average wholesale price), a benchmark price used for reimbursement. AWP represents what a retail pharmacist or a dispensing physician might pay for a product, without any special discounts. There are, however, many discounts already in place, so the AWP can often approximate the price that a consumer might pay. The prices listed here are not intended to serve as an up-to-date substitute for supplier price lists. The price listings give the reader a good idea of the range between the high and low prices." For further information on the nature of these prices, visit *http://www.mosbydrugs.com.*

[13] Once again, the data collection process was automated using IOpus Internet Macros that allowed periodical recording of the data from the website *DestinationRX.com.*

effects are an important cause.

5 Analysis

We begin with an analysis of differences in price levels in Section 5.1. These differences result primarily from price differences across cards, but a host of card characteristics and geographic area characteristics help to explain the differences. Section 5.2 estimates the extent of savings that may be possible through the MDDCP. Section 5.3 focuses on dynamics, to see whether prices fell initially when consumers first chose their cards and during the switching period, and then rose in periods when consumers were unable to switch cards. The entire analysis of this section uses the second smallest radius for each zip code. The results turned out to be very similar when the smallest radius was used instead.

5.1 Analysis of price differences

The starting point is to understand whether there was significant price dispersion in the market for discount drug cards and, if so, what drove that dispersion. Figure 2 illustrates the dispersion of prices for one of the drugs, Lipitor, for the week of June 28-July 3, 2004. The upper left panel is the histogram of the entire set of Lipitor prices observed across cards, zip codes and pharmacies. The upper right panel is the distribution of average price of a drug within a card. The average for a card is calculated using all price observations pertaining to the card. The average price varies between about \$65 and \$74. However, as shown in the lower two panels, the dispersion of price within a card is usually very small, amounting to an economically negligible variation within a card across pharmacies. This finding points to almost uniform pricing by cards across pharmacies and locations even though such uniformity was not explicitly guaranteed by any card.

To see whether the pattern in Figure 2 is typical of all drugs, we consider a general expression for the price p_{drcz} of drug d offered by card c at pharmacy r in zipcode z at time t

$$p_{drczt} = \mu + f_d + f_r + f_c + f_z + f_t + e_{drczt}, \tag{1}$$

where μ is a constant, f_i is a fixed effect for $i \in \{d, r, c, z, t\}$ and e_{drczt} is a zero mean error term that accounts for remaining unobserved factors. The contribution of each of the three main factors to the overall variation in price can be analyzed by using analysis of variance (ANOVA) to understand the components of variation in prices. Since pharmacies are "nested" within zipcodes, a nested ANOVA was performed to decompose the total variation in prices for each drug.

Results of ANOVA for the first week of data (June 21 to June 26, 2004) are shown in Table 3. The variation in price of any drug across cards is the major component of the total variation in drug prices. On average, about 87 percent of the total variation in price is explained by cards, and there is little variation in price within cards. The variations across zipcodes and pharmacies are usually dwarfed by the substantial variation across cards. The hypothesis that the average price of a drug is equal across cards is rejected strongly for all drugs. We repeated ANOVA for other weeks and the findings supported the same conclusions.

We also performed ANOVA for mail order prices for cards that offer a mail-order option. We expected to see zero variation in mail-order prices across zipcodes, as these prices, by definition, should be independent of geographic location, excluding any shipping costs. Indeed, the results suggested that the entire variation in the case of mail-order prices excluding shipping charges is attributable to the cards.

5.2 Geographic variation in prices

The finding in the previous section that there is little variation in retail prices across zip codes opens the question of how much geography matters for pharmacies' pricing behavior, if it matters at all. By the effect of geography, we mean the location-specific factors that may affect prices, such as income level of residents, population, age composition in a location, which are particularly relevant as demand shifters.

It is important to be able to control for all other factors in investigating geographic variation in prices. The ideal experiment would look at the geographic variation in prices for a given drug-card combination, holding constant the pharmacy composition across zip codes. Such an experiment is impossible, however, because pharmacy composition changes across zip codes. Nevertheless, one comes close to this ideal experiment by looking at the prices charged by the stores of a given pharmacy chain across zip codes. The individual stores of a chain, such as Walgreens or CVS, tend to have very similar structures and practices, so a good first-order approximation can be obtained by assuming that the store-level features are roughly constant across zip codes for a given chain. Of course, in the context of the MDDCP there may have been other restrictions supporting uniform prices across stores of a chain. Certain cards may have required chain stores to have uniform prices across all zip codes as part of their arrangements with a pharmacy chain. However, such arrangements were rarely explicit and cannot be taken for granted. For instance, as mentioned earlier, the brochure describing the details of Walgreen's discount drug card stated that prices may vary by store location.

To obtain more insight, we documented the distribution of prices for major chains in our data. Each panel in Figure 3 contains the histogram of the coefficient of variation of prices across the stores of a chain for all drug-card combinations – approximately 1400 combinations – for the week of June 28-July 3, 2004. For each drug-card combination, we calculated the coefficient of variation of prices across all stores of a pharmacy chain and then arranged these coefficients in a histogram. The histograms and the related summary statistics indicate that for most, but not all, cases the coefficient of variation was exactly zero: there was little or no variation in prices across stores of a given chain. This means that the price variation across zip codes arose mainly because the composition of cards and pharmacies changed across zip codes. Different compositions by zip codes might have motivated consumers to search beyond their immediate neighborhoods for cards and pharmacies that offer good deals.

5.3 Sources of price variation

While the analysis of variance in prices clearly indicates that much of the cross-sectional variation was attributable to the variation across cards, it does not provide information about specific factors

responsible for this variation. Identifying key demand and supply factors that affect prices is important for understanding why prices differed across drugs, cards, pharmacies, or zip codes.

Consider the following version of (1) that includes explanatory variables explicitly for a given a time period t

$$p_{drcz} = \mu + \boldsymbol{\beta}_d' \mathbf{X}_d + \boldsymbol{\beta}_r' \mathbf{X}_r + \boldsymbol{\beta}_c' \mathbf{X}_c + \boldsymbol{\beta}_z' \mathbf{X}_z + \varepsilon_{drcz}, \tag{2}$$

where $\boldsymbol{\beta}_i$ is a $K_i \times 1$ vector of coefficients and $\mathbf{X}_i$ is a $K_i \times N$ matrix of observables, for $i = d, r, c, z$. Each $\mathbf{X}_i$ has the form

$$\left[\begin{array}{cccccc} \mathbf{x}_1 & \mathbf{x}_2 & . & . & . & \mathbf{x}_{K_i} \end{array} \right]',$$

where $\mathbf{x}_j$ is a $N \times 1$ vector that contains variables specific to cluster $j = 1, ..., K_i$ within group $i = d, r, c, z$.

The structure of the error term in (2) is assumed to be

$$\varepsilon_{drcz} = \varepsilon_d + \varepsilon_r + \varepsilon_c + \varepsilon_z + e_{drcz}, \tag{3}$$

where e_{drcz} is the error term in (2). The terms ε_i ($i \in \{r, d, c, z\}$) represent the remaining unobserved part of the fixed effect f_i after the observable $\mathbf{X}_i$ is added to the specification in (1) to obtain (2). Note that (3) implies that error terms are correlated within drugs, cards, pharmacies and zipcodes, due to the presence of cluster-specific errors ε_i ($i \in \{r, d, c, z\}$). Since the unobserved components ε_i are fixed over time, we can include dummy variables for drugs, cards, pharmacies, and zipcodes to account for these unobserved effects. Because these dummies absorb all the remaining fixed effects, the error term (3) reduces to e_{drcz} as in (1), and we can implement the regression in (2) without using any cluster effects.[14]

The results of the regression are shown in Table 4 for two specifications for the week of June 21 to 27, 2004. We used the same specification for other time periods and the results were robust. In evaluating the results, it should be kept in mind that the drugs in our sample form only a small subset of all drugs (28 drugs out of more than 800) covered by the MDDCP. Therefore, some of the characteristics that would in general apply to the drugs in the entire list of the MDDCP may not be fully represented in this relatively small sample.

The explanatory variables, including the dummies, account for 98 percent of the variation in prices. Given the large number of observations, all coefficients are precisely estimated. Some of the coefficient estimates are worth highlighting. Long-term, maintenance drugs in our sample are on average cheaper than the short-term drugs, based on the prices for 30-day supplies. This should not be taken as evidence of the cost-of-therapy being lower for long-term drugs in general, because long-term prescriptions are typically renewed for several months and some short-term prescriptions are prescribed for periods shorter than a month, such as some antibiotics (e.g., Zithromax) that are used for intense treatment for a week in certain cases. If the drug is used only 7 days, the cost of a therapy will be low.

[14] Because there is a very large number of dummy variables in this regression, in particular more than 1000 pharmacy dummies, we use the "de-meaned" regression approach (see, e.g. Greene (1993), pp. 468-469). By de-meaning the observations by pharmacy, we get rid of the pharmacy dummies and still obtain the usual OLS estimates for the coefficients of interest.

Generic drugs and brand name drugs for which generic alternatives are available are cheaper, as might be expected. The prices are also lower for drugs that are prescribed more often. The drugs with expired patents appear to have higher prices, and those with an unexpired exclusive patent command even higher prices. In addition, newer drugs have higher prices, as indicated by the positive coefficient on the year of approval by the FDA.

The coefficients on selected pharmacy chains suggest that Wal-mart had slightly higher prices, by about 14 cents, than the omitted category of all remaining pharmacies, while CVS prices were lower by about a dollar. Eckerd, which merged with CVS in the spring of 2004 shortly before the MDDCP went into effect, had prices that were higher by about 70 cents.

Turning to the card characteristics, cards with national coverage, with higher subscription fees, with a mail-order service and with a broader formulary tended to have higher prices. Cards that had arrangements to provide discounts with a larger number of drug manufacturers and cards that provided enrollment assistance had lower prices. It appears that certain quality dimensions, such as formulary breadth, extensive geographic coverage, and cost-reducing features such as association with a larger number of manufacturers, were important for the variation of price across card sponsors.

Characteristics of geographical, or zip-code, areas also influenced prices to some extent. Zip codes with a higher fraction of elderly in the population had lower prices. Zip codes with a higher median household income also had lower prices, while zip codes with higher housing rents were associated with higher drug prices. However, the magnitudes of the estimated coefficients for these variables are very small. As discussed earlier, much of the effects of geographic control variables come from the changing composition of cards and pharmacies across locations. For instance, the observation that the zip codes with a higher fraction of elderly had lower prices implies that these high-elderly-fraction zipcodes attracted cards and pharmacies with lower prices, not because certain cards specifically charged lower prices in these zip codes compared to other zip codes they operate in.

5.4 Estimates of savings

The differences in prices across cards found in the previous section raises the following questions: Were the price differences large enough to reward searching for lower prices across the different cards? How big were the discounts offered by the cards compared to non-card prices? Several small-scale studies tried to assess the extent of the discounts in the early phases of the program with only a handful of drugs and a few zipcodes.[15] Such investigations generally found some savings accruing to card holders, but the very small scale of these investigations prevented any general conclusions on the magnitude and extent of savings.

In what follows, we ignore the sunk cost (the enrollment fee) of card ownership and only look at the savings a card owner could obtain from using his card to purchase at card prices versus purchasing at regular retail or on-line prices.[16] To obtain estimates of savings we used regular drug prices reported by Mosby's Drug Consult database. Define $\overline{p}_{dt}$ and $p_{dt}^{\min}$ as the average and the minimum of the

[15] See, e.g. Antos and Ximena (2004). Their approach is to first identify a few health conditions that are common in the elderly and then to calculate the total price of a bundle of drugs typically prescribed to remedy these conditions.

[16] The enrollment fee was zero for many cards and could not exceed $30 under the program.

average price of a drug across cards in a given week t

$$\begin{aligned} \overline{p}_{dt} &= \frac{1}{C_t}\sum_c \overline{p}_{dct} = \frac{1}{C_t}\sum_c \left(\frac{1}{n_{ct}}\sum_z\sum_r p_{rdczt}\right), \\ p_{dt}^{\min} &= \min_c \overline{p}_{dct}. \end{aligned} \tag{4}$$

Similarly, define the average and minimum regular prices obtained from Mosby's (2004) database as

$$\begin{aligned} \overline{p}_d^R &= \frac{1}{n_d}\sum_i p_{di}^R, \\ p_d^{R,\min} &= \min_i p_{di}, \end{aligned} \tag{5}$$

where i indexes the wholesalers listed in the Mosby's database for a given drug and dosage for a given year.

In addition to the prices in Mosby's database, a separate, independent source is the set of prices we collected from on-line pharmacies, as described earlier. Let p_{dit}^I be the price posted by an Internet retailer i for drug d at week t. Analogous to (5), define the average and minimum prices for on-line retailers as $\overline{p}_{dt}^I$ and $p_{dt}^{I,\min}$.

We now define several alternative measures of potential savings. The first measure is the savings a "naïve" (or non-searching, or uninformed) consumer could obtain. A naïve consumer is defined as one who purchases randomly from one of the firms with equal probabilities of sampling across available options in the market. For a single purchase of the drug at a given point in time, if this consumer uses a card instead of buying at the regular wholesale price, his saving is the percentage difference between the average regular price and the average card price. We report the average of this saving across all weeks in the data in percentage form as follows

$$S_d^{\text{naïve}} = \frac{100}{T}\sum_{t=1}^{T}\left(\frac{\overline{p}_d^R - \overline{p}_{dt}}{\overline{p}_d^R}\right). \tag{6}$$

The second measure is the savings that accrued to a consumer, called a "searcher", who used the program website to search for the lowest price card for a given drug, but otherwise would have purchased randomly in the regular market due either to high search costs in the geographic market or to the absence of any comprehensive price listings for all the pharmacies in the consumer's geographic neighborhood. The savings of such a consumer is defined as the percentage difference between the average price in the regular market and the minimum price in the discount card market averaged across weeks, and is obtained simply by replacing $\overline{p}_{dt}$ in (6) by $p_{dt}^{\min}$.

The third measure we consider is the savings an "expert" consumer could obtain. An expert consumer is defined as one who is fully informed of prices in both markets and thus is always able to purchase at the minimum price. The average savings across weeks for such a consumer is formally defined as the percentage difference between the minimum price in the regular market and the minimum price in the discount card market averaged across weeks, and is obtained by replacing $\overline{p}_d^R$ in (6) by $p_d^{R,\min}$ and $\overline{p}_{dt}$ by $p_{dt}^{\min}$.

Following Baye, Morgan, and Scholten (2003), we also define the "value of information" in the discount drug card market. This measure gives the saving of a consumer fully informed of all card prices with respect to that of a naïve consumer who purchases randomly from one of the cards:

$$V_d^{\text{card}} = \frac{100}{T} \sum_{t=1}^{T} \left(\frac{\overline{p}_d - p_d^{\min}}{\overline{p}_d} \right). \tag{7}$$

We can define analogous savings measures by using on-line prices as a benchmark, instead of the Mosby's prices. The definitions of savings for naïves, searchers and experts can be easily modified to obtain the savings compared to on-line prices by replacing the statistics pertaining to Mosby's prices with their on-line counterparts. In addition, we report for each drug the value of information for regular prices listed in Mosby's database and for the on-line prices.

The savings measures and the values of information defined above are reported by drug in Table 5. First, note that the average savings compared to Mosby's prices were positive and significantly different from zero. A naïve consumer could obtain an average savings of 11.2%. The average savings were even higher for a searcher, about 25%. An expert consumer, on the other hand, had little to gain from purchasing in the discount card market: an average savings of only 2.3% accrued to such a consumer. Because most of the drug card users were most likely non-experts in search, the estimates of savings to naïve consumers, or at best to searchers, is likely to be the most reasonable estimate.

When we consider the savings with respect to on-line prices, a somewhat different picture emerges. A searcher still could obtain an average savings of 16.3% by purchasing at the minimum card price instead of purchasing randomly from one of the on-line pharmacies. However, the benefit for a naïve consumer was negative (but statistically insignificant), and an expert consumer could obtain positive (again statistically insignificant) savings. Thus, compared with on-line prices, card prices did not appear to provide substantial savings. Also the average value of information was the highest for regular prices, indicating the biggest rewards to search, with an average savings for an informed consumer that amounted to around 20% of the average price. These savings were followed closely by card prices. Value of information in the on-line market was the lowest.

Overall, the results indicate that cards could in principle provide some savings even to consumers who were not sophisticated bargain hunters, but such savings were not substantial. The returns to vigorous search across different channels of sale appear to be higher. The users of medicare search tools could expect to obtain some savings especially if they had no other means of search for lower prices in the regular retail market.

We do not attempt to draw any conclusions regarding the competitiveness of the three markets solely based on the value of information because markets differ, among other dimensions, in terms of the number of firms and the degree of competition. The value of information depends on the number of firms serving the market under many models of competition.[17] In addition, any welfare consequences based on savings would be misleading because consumer welfare does not depend only on prices. Finally, drug cards were heterogeneous in many dimensions, so a consumer was not likely to choose a card based solely on price.

[17] See Baye, Morgan, and Scholten (2002) for more on the determinants of the value of information.

5.5 Dynamics of prices

We now turn to the evolution of prices through the MDDCP. Price changes within two balanced panels of pharmacies from the pre-switching period and the post-switching period are examined in Section 5.3.1. The behavior of prices around the switching period is investigated in Section 5.3.2. The evolution of on-line prices is examined for comparison with program prices in Section 5.3.3. Section 5.3.4 considers the evolution of price dispersion within the program.

5.5.1 Results from the balanced panels

Using a slight modification of (1), a price observation can be written as

$$p_{drczt} = \mu + f_t + f_{ct} + f_{dt} + f_d + f_c + f_r + f_z + \eta_{drczt}, \tag{8}$$

where we introduced the interaction terms f_{ct}, a card and time specific effect, and f_{dt}, a drug and time specific effect. The term f_{ct} captures potentially different behavior of cards over time. Different cards may have had different pricing policies that may have depended on time as the state of the competition between cards changed. Therefore, we allow for card effects to interact with time. In addition, the time and drug interaction effect, f_{dt}, captures the possibility of different drugs experiencing different price changes over time, e.g. cards may have competed more intensely in certain popular drug categories. The fixed effect f_t can be interpreted as the general time effect on prices, which is a blend of the program's effect on price and general fluctuations in drug prices outside the program, such as overall inflation or changes in manufacturers' costs.

The specification in (8) can be estimated using our unbalanced panel of observations. There are two drawbacks to this approach. First, there is a very large number of effects (both pure and interaction effects) to be estimated, which demands a large memory in any standard software. Second, and more importantly, the included effects are not guaranteed to exhaust the set of relevant effects which may lead to omitted variable bias, and the time-invariant fixed effects can potentially be correlated with the error term. One approach to alleviate these concerns is to use time-differencing, which gets rid of the time-invariant fixed effects. Taking the difference of the prices for two consecutive time periods t and t' we obtain

$$\Delta p_{drczt} = d_{ct} + d_{dt} + d_t + \epsilon_{drczt}, \tag{9}$$

where

$$\begin{aligned} d_{ct} &= (f_{ct'} - f_{ct}), \\ d_{dt} &= (f_{dt'} - f_{dt}), \\ d_t &= (f_{t'} - f_t), \\ \epsilon_{drczt} &= (\eta_{drczt'} - \eta_{drczt}). \end{aligned} \tag{10}$$

By first-differencing in time, we get rid of all the fixed effects that pertain to pharmacies, cards, drugs and zipcodes, and we are left with only the time effects that we want to focus on. Note that

differencing works only if we have the exact same pharmacies across the two time periods. Therefore, we need to restrict attention to a common set of pharmacies (a balanced panel) across time periods.

Now, consider the following regression based on (8):

$$\Delta p_{drczt} = \beta_{ct} D_{ct} + \beta_{dt} D_{dt} + \beta_t D_t + \epsilon_{drczt}, \tag{11}$$

where D_{ct}, D_{dt} and D_t are dummies for the differenced effects d_{ct}, d_{dt} and d_t. Starting with $t = 1$ and $t = 2$, we can take the pairwise differences of average prices for consecutive time periods, and then stack them up on the left hand side to run the regression (11) and obtain the estimated coefficients $\widehat{\beta}_{ct}$, $\widehat{\beta}_{dt}$ and $\widehat{\beta}_t$ which are the OLS estimates of d_{ct}, d_{dt}, and d_t, respectively. By the structure in (10), the error term ϵ_{drczt} has serial correlation, which we take into account in estimating the standard errors.

Estimation (11) can be implemented for a balanced panel of observations. One problem with this approach is that the resulting panel has a low cross-sectional dimension if we restrict attention only to observations common across all weeks of data in the sample period. Due to DNS (Domain Name Service) errors that occurred randomly over time during data collection in repeatedly accessing the website, there was some random attrition in our sample and the balanced panel that can be constructed across all weeks of observation is limited in its size.[18] Because the attrition was entirely random across observations, there is no concern about a systematic bias in the sample. As a solution, we implement (11) separately for the 7 weeks in the pre-switching period and then for the 9 weeks in the post-switching period. This approach allows us to have a large number of cross-sectional observations for both periods. However, the observation units in the balanced panel for the post-switching period are not exactly the same as those in the balanced panel for the pre-switching period, once again because of the random attrition in the sample. We handle the data for the switching period separately as discussed below.

We first consider the evolution of prices using a panel from weeks 4 to 10 of the program, the pre-switching period. The results of the difference regression for this period are shown in the left panel of Table 6. The estimated coefficients $\widehat{\beta}_t$ are all negative and statistically significant, except for week 5 of the program. Most of the drop in prices in this period took place between the 5th and 8th weeks, resulting in a decline in general level of prices of about \$4.77. By the end of the 10th week, the prices were lower by about \$4.63. However, this reduction represents a small portion ($\sim 5.5\%$) of the average (\$81.90) of all price observations during the 4th week of the program when data collection began.

We repeated the analysis for the post-switching period using a balanced panel. The evolution of the prices in the sample of weeks from the post-switching period shows a very different pattern compared to the pre-switching period, as seen in the right panel of Table 6. In fact, the estimated β_t's are all positive and statistically significant for this period, even though their magnitudes are different. Between the starting and ending weeks of the sample in the post-switching period, prices rose by

[18] DNS errors tended to occur when the website was repeatedly accessed. In general, there may be several reasons behind a DNS error, one of which is to prevent repeated accesses to the same website from an individual computer identified by an IP address. Such errors are issued to prevent "suspicious" access to the website. Certain websites can also "block" access from an IP address temporarily as a security measure.

about $8, controlling for drug and card effects. Much of this increase took place between the end of the switching period and the end of June 2005. Thereafter, prices somewhat stabilized and did not increase by much. Between the end of the switching period and the end of June, prices rose at a pace of about $2 a month. The total rise in prices represents about 9.5% of the average drug price in the 4th week of the program. While we are unable to make statements at this point on what exactly happened to prices during the period between the last week of the pre-switching period and the first week of the post-switching period, the initial decline in prices in the early phases of the program and the subsequent rise in the later phases appears to be consistent with the price dynamics one would expect when switching costs are important. Below, we also consider the pattern of prices for the single week of price observations we have from the switching period.

Figure 4 displays the discrepancy in the average evolution of prices for different cards and drugs. Specifically, the upper two histograms display the frequency distributions of the time-average of the card-time plus the pure-time effects

$$\overline{\widehat{\beta}}_c = \frac{1}{T}\sum_{t=1}^{T}\left(\widehat{\beta}_t + \widehat{\beta}_{ct}\right),$$

for the pre- and post-switching periods, on the left and on the right panels, respectively. The bottom two panels contain the frequency distributions of the time-average of the drug-time plus the pure-time effects

$$\overline{\widehat{\beta}}_d = \frac{1}{T}\sum_{t=1}^{T}\left(\widehat{\beta}_t + \widehat{\beta}_{dt}\right),$$

for the pre-switching period on the left and the post-switching period on the right. The time-averaging reveals the average tendency of the interaction effects within a given period. As evident from the histograms on the left hand sides of the upper and lower panels, most cards and drugs had lower prices on average during the pre-switching period. However, located in the right tails of these histograms, there were a few outlier cards and drugs that exhibited an average upward trend in prices even during this period. In contrast, for the post-switching period, all cards and drugs exhibited an average upward trend in price, as seen in the histograms on the right hand side of the upper and lower panels. Overall, these histograms suggest that prices of cards and drugs on average moved in the same direction within the pre- and post-switching periods with few exceptions.

We also repeated estimation (11) by adding a long-term drug dummy interacted with a time dummy to explore whether the long-term drugs exhibited any different behavior compared to the short-term drugs. In results not reported, we found that during the pre-switching period, the prices for the long term drugs actually fell less, and the post-switching period they rose less compared to the short term drugs. Overall, the long-term drug prices fell by an average of about $1 in the pre-switching period and rose by about $4 in the post-switching period. The fact that prices fell less for long-term drugs during the pre-switching period does not give support to the hypothesis that consumers searched more vigorously for bargains on these drugs. If this was the case, we would have expected to see a steeper decline for these prices compared to the prices of short-term drugs. One possible explanation for the observed pattern is that consumers with an existing prescription for a given long-term drug who have

purchased from their preferred pharmacy for a long time may not have found it worthwhile to search vigorously for a card and pharmacy – which illustrates another form of switching costs.

5.5.2 The switching period

For the nationally coordinated card switching period that ran between November 15 to December 31, 2004, we were able to collect only one week of price data, due to technical problems we experienced in accessing the website repeatedly during much of that period.[19] We were able to collect data for only 15 drugs and the generally smaller number of observations for that period precludes us including the switching period in the balanced panel analysis of the previous section. Instead, we compared the average price level for each drug using two paired t-tests. For each drug, we perform two paired t-tests across common cards and pharmacies: one for the difference between the week from the switching period and the last week of the pre-switching period, and the other for the difference between the first week of the post-switching period and the week from the switching period. The paired t-test approach gets rid of the fixed effects that are common across the two time periods and isolates the time effects, just like the balanced panel used earlier.

As shown in Table 7, both of these tests indicated a statistically significant decline in prices for most drugs (12 out of 15) between the last week of the pre-switching period and the week of the switching period, and a subsequent statistically significant rise for most drugs (11 out of 15) between the week of the switching period and the first week of the post-switching period. The magnitude of price drops and raises varied across drugs. Some drugs, such as Glucotrol and Lanoxin, did not experience a decline in price at all between the last week of the pre-switching period sample and our one week sample from the switching period. A few drugs, such as Cipro, Biaxin, and Levaquin, exhibited relatively large drops in their prices and a subsequent relatively large increase. In other drugs, prices declined little and rose little. Overall, prices declined on average by about $1.80 between the week of August 2, 2004 and the week of December 20, 2004, and rose on average by about $1.50 between the week of December 20, 2004 and March 7, 2005.

Given the nature of the timing of data collection, we cannot say precisely whether the decline in prices between the week of August 2, 2004 and the week of December 20, 2004 was confined to the switching period only. Because card enrollment continued during this period, card sponsors could have continued to reduce their prices to some extent to attract further consumers, as they did in the initial phases of the program. From a theoretical standpoint, during this period the card sponsors were presumably facing the tension between attracting further consumers versus charging higher prices to their already committed consumers. Some card sponsors, in anticipation of the switching period, may have also lowered prices in an effort to deter consumers from switching. Thus, some of the observed

[19] When the Medicare website was accessed repeatedly within a short period of time, a DNS (Domain Name Server) error prevented us from reaching the website. These errors were especially severe during the switching period because the format and the design of the website was changed, along with the location of the price data on the website (Overall, the website was redesigned 3 times after the initial release of the prices and we had to make the necessary adjustments to our web crawler software to accommodate these design changes). These changes made data collection more difficult, resulting in a need to access the website more frequently over a longer period of time within a week.

price decline in this period could have occurred even before the switching period. We are more comfortable attributing the rise in prices after the switching period to the existence of switching costs, because during that period card enrollment probably diffused to a large extent and enrolled consumers were committed until the end of the program. Even though we are unable to present evidence on the dynamics of prices either within or in the immediate time-neighborhood of the switching period, the pattern we observe for the periods at either end of the switching period suggests that prices generally fell during the switching portion of the program, especially in the initial phases, and rose later once the switching period was over.

In summary, the evidence from the balanced panel estimation and the paired t-tests point to initially declining but later rising prices, even though the magnitudes of change in price levels were not exceptionally large compared to the average price level across drugs. The pattern exhibited by prices lends more support to a model where prices move in a non-monotonic path, falling when consumers could switch cards and rising in periods when they are no longer able to switch cards. Models suggesting a monotonic decline in prices due to enhanced consumer price information receive no support. Even though prices declined initially, they tended to rise later during the post-switching period. The observed patterns are broadly consistent with what one might expect in the case of dynamic price competition in the presence consumer switching costs, which are a crucial feature in the design of the MDDCP.

5.5.3 Evolution of non-program on-line prices

We now consider the evolution of on-line drug prices as a benchmark for the evolution of program prices. The basic idea for this comparison is simple. If the time effects found in the evolution of program prices are specific to the program rather than being driven entirely by general trends in drug prices, the same time effects should not emerge in the evolution of on-line prices unrelated to the program. To explore this, we consider a regression of the form

$$p_{dit} = \alpha + \beta_t D_t + \beta_i D_i + \beta_d D_d + \epsilon_{dit}, \tag{12}$$

where D_t is a time dummy, D_i is a dummy for on-line retailer i, and D_d is a dummy for drug d. The focus is once again on the estimates $\widehat{\beta}_t$ of the coefficients of time dummies.

For on-line prices, we had few problems in data collection over time, so there is a larger number of weeks and the price changes can be observed with a higher frequency over a longer period of time, sometimes even more frequent than once a week. Table 8 presents the results of the estimation in (12). The time dummies have almost uniformly positive and significant coefficients and the coefficients are almost monotonically increasing over time. By the last week of data, prices were higher by about $3.39, controlling for vendor and drug fixed effects.

We repeated the estimation in (12) using the total price (base price plus shipping fee) as the dependent variable and the results were very similar. The total price increased over time by about $3.53 and the estimated coefficients were uniformly positive and statistically significant in almost all cases.

Finally, we also used a balanced panel approach as in (11) to estimate the time effects for on-line prices. The size of this panel was much smaller than that of the unbalanced panel used in (12), because we did not have prices for all sellers and for all drugs every week. The average growth rate of price between the first and the last periods of observation was %3.31 with a standard deviation of 0.11%. Only 4 drugs exhibited a decline in price. Cephalexin experienced the largest increase (%23) and Atenolol had the largest drop (39%). Overall, the results from the balanced panel were similar qualitatively to the estimates of time dummy coefficients in Table 8.

The observed pattern for on-line drug prices thus indicates that the evolution of program prices was indeed different from the evolution of prices outside the program. On-line prices tended to rise over time, as opposed to the program prices, which first declined and then increased. Since on-line prices are subject to general trends in drug prices, but not to the effects of the program, the patterns found suggest that the evolution of programs prices are indeed driven by program effects, rather than by general trends. Two trends were especially important. First, on-line prices rose during the pre-switching period during which the program prices exhibited a clear decline. The decline in program prices is consistent with the predictions of dynamic price competition models suggesting an escalated competition in the early stages of a market where sellers lower their prices to lure consumers. Second, the overall rise in on-line prices fell short of the rise in program prices during the post-switching period. Indeed, the program prices actually increased about $4 more than on-line prices by the end of this period. Therefore, the upward trend in program prices after the switching period cannot be explained simply by a general rise in drug prices due to non-program effects. This "extra" upward trend is also consistent with the dynamic price competition models with switching costs, which predict higher prices when consumers are already locked in to their earlier choices and can thus be exploited by sellers.

5.5.4 Evolution of price dispersion

The analysis of the dynamics of price dispersion is equally important from a theoretical point of view. Did the prices converge when the general level of prices was falling during the pre-switching period, or when it was rising during the post-switching period? We measure the dispersion of prices as follows. At any point in time, we first calculate the average of a drug's price within a card. Then, we compute the dispersion of that average around its mean across cards. In other words, for each drug d and time t the dispersion measure is

$$\sigma_{dt}^2 = \sum_c Var(\overline{p}_{dct}) + 2\sum_{i \neq j} Cov(\overline{p}_{dit}, \overline{p}_{djt}),$$

where $\overline{p}_{dct}$ is the average price within a card as also used earlier in (4). An estimate of σ_{dt}^2 can be readily obtained as

$$\widehat{\sigma}_{dt} = \left[\frac{1}{C_t - 1} \sum_{c=1}^{C_t} (\overline{p}_{dct} - \overline{\overline{p}}_{dt})^2 \right]^{1/2},$$

where

$$\overline{\overline{p}}_{dt} = \frac{1}{C_t} \sum_{c=1}^{C_t} \overline{p}_{dct}.$$

The stability of the variance over time for a given drug can then be tested using the hypotheses

$$\begin{aligned} H_o &: \sigma_{d1}^2 = \sigma_{d2}^2 = ... = \sigma_{dT}^2, \\ H_a &: \sigma_{dt}^2 \neq \sigma_{d\tau}^2, \text{ for at least one pair } (t, \tau), \tau \neq t. \end{aligned} \tag{13}$$

Under the assumption of the independence of observations across time periods, the set of hypotheses in (13) can be tested using either a Levene's test or a Bartlett's test. Below we discuss the results for both tests, as Levene's Test is robust to deviations from normality, while Bartlett's Test is not.

We used the balanced panel of observations for the first seven weeks to test the hypotheses in (13). Bartlett's Test resulted in a rejection (at 5% or lower levels) of the equality of variances over time in 9 of the 28 drugs. Levene's Test, on the other hand, rejected the null hypothesis only for 5 drugs. Thus, there appears to be no overwhelming evidence that the dispersion of average price across cards changed substantially during the pre-switching period.

We repeated the dispersion analysis for the post-switching period. Bartlett's test rejected the equality of variances over the 9 weeks for only 3 drugs. Levene's test rejected the null hypothesis for only 1 drug. Therefore, we found no strong evidence that the dispersion of prices was changing over the course of the program in a statistically significant way. Thus, competition did not force prices to converge thereby reducing price dispersion.

There may be several reasons why prices did not converge. First, differences across cards in their attributes certainly created some amount of product differentiation. Product differentiation may have led consumers to care not only about prices but other attributes of cards as well, allowing cards to charge prices different from each other. Because different card sponsors have arrangements with different drug manufacturers, cards' cost structures were also different – another source that can contribute to non-convergence of prices to a given level. Second, effective consumer search is needed for convergence to take place, especially during the early phases of the program when card sponsors were lowering their prices and consumers were making their card choices. While there is evidence of search by card enrollees, the fraction of searchers does not seem to be overwhelming according to the available estimates mentioned in Section 2. Third, switching costs, by preventing allocation of consumers to low-price cards especially later in the program, could also have prevented convergence. We also note that the initial decline in prices and the increase later on are not necessarily inconsistent with non-convergence of prices. Cards may have lowered their prices to attract consumers, but in the presence of product differentiation and differences in cost structure, cards' prices may have still differed from each other, leading to persistence in dispersion. Similarly, when prices rose, cards' prices need not have converged to the same level, because high prices targeted by cards need not be similar, given the differences across cards.

6 Conclusion and implications for Medicare Part D

This paper used a large panel of drug prices to assess the competitive effects of government sponsored release of price information over the Internet under the Medicare Discount Drug Card Program (MDDCP). The designers of the program claimed that access to price information by consumers would lower prices over time and reduce the dispersion of prices across drug card sponsors. In contrast, we found significant and persistent price dispersion across drug card sponsors for the set of drugs we analyzed. The overwhelming fraction of variation in drug prices is attributable to the variation of prices across card sponsors, the primary price-setters within the MDDCP. We also found that prices were essentially uniform across individual stores of most retail pharmacy chains for a given card. Most of the geographic variation in prices was attributable to the change in the composition of cards and pharmacies from one location to another.

Cards offered some savings to subscribers. During our sample period, a naïve consumer, who buys with equal probability from one of the sellers in a market, could in principle obtain an estimated average savings of 11.2 percent by using a card instead of buying at a regular price for our sample of drugs. However, naïve consumers were actually better off purchasing from on-line retailers at non-program prices instead of purchasing using cards. The average savings were even higher (about 25 percent) for a searcher, who was assumed to be able to locate the minimum price seller for a drug across cards, but otherwise bought randomly like a naïve consumer in the regular market.

The card prices did not steadily decline over time, as models of improved access to price information would suggest. Instead, prices declined during the initial phases of the program but then increase later when consumers were unable to switch cards. Control prices were used to see if the evolution of program prices exhibited any significant deviation from the general evolution of prices outside the program. On-line prices from Internet drug retailers unrelated to the program manifested an upward trend throughout the sample period, a pattern distinct from that exhibited by the downward and then upward movement of MDDCP prices.

The dynamics of program prices can be reconciled with the predictions of certain models of dynamic price competition with consumer switching costs, such as those of Klemperer (1987a,b). Such models appear to be relevant in the MDDCP context, because the program erected substantial switching costs by requiring consumers to stick with their card choices during most of the program's duration. The very design of the program left consumers vulnerable to price changes by card sponsors. The card sponsors appear to have reduced their prices initially to lure customers to subscribe, but then raised their prices in the later stages of the program to take advantage of consumers when they were locked in to their choices. It appears that the design of the program was more of an impediment to competition than a catalyst.

To what extent these results will carry over to the Medicare's Part D prescription drug assistance program currently in effect remains to be seen. While Part D has a much more complicated structure compared to the simple environment of the transitory MDDCP, main elements of the drivers of price dynamics under MDDCP are still applicable under Part D. For instance, as in the MDDCP, consumers

can switch plans only from November 15 through December 31 of every year, except for special cases.[20] Therefore, the substantial switching costs continue to be in place. There are certain differences between the two programs that may lead to differences in price dynamics. Consumer non-enrollment in Part D carries a financial penalty that becomes gradually more severe, unlike in the case of MDDCP, where enrollment was entirely voluntary. As a result, consumer participation is higher under Part D and the available market size for card sponsors is larger. Indeed, the enrollment in Part D has been strong: about 90 percent coverage of the people 65 and older was achieved within the first 6 months from the start of the program in January 2006, as mentioned earlier. Another difference is that the prescription drug benefit providers engage in a multi-period competition under Part D, instead of the two-period interaction under the MDDCP. This broader time horizon also introduces considerations of market growth, as the size of the population under Medicare increases over time. Prescription drug benefit providers will thus set prices for a broader horizon considering the trade-offs of charging lower prices to attract newcomers and higher prices to already committed consumers. Models of multi-period interaction between firms, such as Beggs and Klemperer (1992), suggest that such market growth puts downward pressure on prices, but prices are still higher than they would be without switching costs. Such considerations were not present in the MDDCP, which lasted only for two years during which market growth was not substantial. These differences between the two programs notwithstanding, in the light of the evidence from the MDDCP we certainly do not expect prices to decline secularly and the dispersion in prices to diminish over time. Rather we expect the Part D prices will follow a non-monotonic pattern, for similar reasons that MDDCP prices did.

References

[1] Antos, Joseph, and Pinell, Ximena (2004) *Private Discounts, Public Subsidies: How the Medicare Prescription Drug Discount Card Really Works.* AEI Press, Washington, D.C.

[2] Baye, Michael, Morgan, John and Scholten, Patrick (2005) "Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site", *Journal of Industrial Economics*, **52:** 463-96.

[3] Baye, Michael, Morgan, John and Scholten, Patrick (2003) "The Value of Information in Online Markets: Theory and Evidence", *Journal of Public Policy and Marketing,* **22:** 17-25.

[4] Beggs, Alan and Klemperer, Paul (1992) "Multi-period Competition with Switching Costs", *Econometrica*, **60:** 651-666.

[5] Brown and Goolsbee (2000) "Does the Internet Make Markets More Competitive? Evidence form the Life Insurance Industry", *Journal of Political Economy*, **110:** 481-507.

[20] These special cases are: The consumer permanently moves out of the plan's service area, the consumer qualifies for extra help paying for prescription drugs, the plan stops offering prescription drug coverage, or the consumers enters or leaves a nursing home.

[6] Burdett, Kenneth and Judd, Kenneth (1983) "Equilibrium Price Dispersion", *Econometrica,* **51**: 955-969.

[7] Farrell, Joseph and Shapiro, Carl (1988) "Dynamic Competition with Switching Costs", *Rand Journal of Economics*, **19:** 123-137.

[8] Fishman, Arthur and Rob, Rafael (2003) "Consumer Inertia, Firm Growth and Industry Dynamics", *Journal of Economic Theory*, **109:** 24-38.

[9] Hassol, Andrea, Jureidini, Susan, Doksum, Teresa, and Hadden, Louise (2005) "Evaluation of the Medicare-Approved Prescription Drug Discount Card and Transitional Assistance Program", Final Report, Abt Associates, Inc.

[10] Heiss, Florian, McFadden, Daniel, and Winter, Joachim (2006) "Who Failed to Enroll In Medicare Part D, and Why? Early Results", *Health Affairs*; **25:** w344-w354.

[11] Klemperer, Paul (1987a) "The Competitiveness of Markets with Switching Costs", *Rand Journal of Economics,* **18:** 138-150.

[12] Klemperer, Paul (1987b) "Markets with Consumer Switching Costs", *Quarterly Journal of Economics*, **102:** 375-94.

[13] Milyo, Jeffrey, and Waldfogel, Joel (1999) "The Effect of Price Advertising on Prices: Evidence in the Wake of 44 Liquormart", *American Economic Review,* **89**: 1081-1096.

[14] *Mosby's Drug Consult* (2004, 2005) 14th and 15th Editions, Elsevier Science Health Science Division.

[15] Reinganum, Jennifer (1979) "A Simple Model of Equilibrium Price Dispersion", *Journal of Political Economy*, **87:** 851-858.

[16] Salop, Steve and Stiglitz, Joseph (1977) "Bargains and Ripoffs: A Model of Monopolistically Competitive Prices", *Review of Economic Studies*, **44**: 493-510.

[17] Sorensen, Alan T. (2000) "Equilibrium Price Dispersion in Retail Markets for Prescription Drugs", *Journal of Political Economy*, **108:** 833-850.

[18] Sorensen, Alan T. (2001) "Price Dispersion and Heterogeneous Consumer Search for Retail Prescription Drugs", NBER Working Paper 8548.

[19] Stahl, Dale O. (1994) "Oligopolistic Pricing and Advertising", *Journal of Economic Theory*, **64:** 162-177.

[20] Winter, Joachim, Balza, Rowilma, Caro, Frank, Heiss, Florian, Jun, Byung-hill, Matzkin, Rosa and McFadden, Daniel (2006) "Medicare Prescription Drug Coverage: Consumer Information and Preferences", *Proceedings of the National Academy of the Sciences*, **103:** 7929-7934.

Drug name	Typical usage duration	Total sales rank (2003)	Rank in claims by elderly (2001)	Typical indications	Generic available?	Typical dosage	In top 50 drugs for elderly (2001)?	Wholesale cost (2001)
Lipitor	Long term	1	5	Cholesterol	N	10mg	Y	$742
Zocor	Long term	2	12	Cholesterol	N	20mg	Y	$1,520
Norvasc	Long term	13	2	Cardio	N	5mg	Y	$514
Zoloft	Long term	7	27	Depression	N	50mg	Y	$882
Lanoxin	Long term	NA	4	Cardio	Y	0.125mg	Y	$78
Plavix	Long term	12	10	Cardio	N	75mg	Y	$1,232
Isosorbide Mono.	Long term	NA	20	Cardio	Y	60mg	Y	$429
Pravachol	Long term	18	38	Cholesterol	N	20mg	Y	$931
Atenolol	Long term	175	45	Cardio	Y	25mg	Y	$256
Metoprolol	Long term	NA	28	Cardio	Y	50mg	Y	$337
Glucophage	Long term	99	9	Diabetes	Y	500mg	Y	$817
Detrol	Long term	86	32	Urinary	N	1mg	Y	$1,021
Glucotrol XL	Long term	127	40	Diabetes	N	10mg	Y	$265
Zestril	Long term	NA	33	Cardio	Y	10mg	Y	$352
Amoxicillin	Short term	NA	> 100	Antibiotics	Y	500mg	N	NA
Augmentin	Short term	177	> 100	Antibiotics	Y	500mg	N	NA
Zithromax	Short term	NA	> 100	Antibiotics	N	500mg	N	NA
Minocycline	Short term	NA	> 100	Antibiotics	Y	100mg	N	NA
Levaquin	Short term	25	> 100	Antibiotics	N	500mg	N	NA
Carisoprodol	Short term	NA	> 100	Pain	Y	350mg	N	NA
Cephalexin	Short term	171	> 100	Antibiotics	Y	250mg	N	NA
Ambien	Short term	31	> 100	Insomnia	N	10mg	N	NA
Cipro	Short term	48	> 100	Antibiotics	N	500mg	N	NA
Biaxin	Short term	138	> 100	Antibiotics	N	500mg	N	NA
Skelaxin	Short term	132	> 100	Pain	N	400mg	N	NA
Flexeril	Short term	NA	> 100	Pain	Y	10mg	N	NA
Cefzil	Short term	152	> 100	Antibiotics	N	500mg	N	NA
Doxycycline Hyc.	Short term	NA	> 100	Antibiotics	Y	50mg	N	NA

Table 1. Drugs used in the empirical analysis

Variable	Description
LONG_TERM	Dummy variable, 1 if the drug is a maintenance drug, 0 if the drug is primarily for short term use
GENERIC	Dummy variable, 1 if the drug has a generic equivalent or is itself generic, 0 if the drug is brand-name
PRES_2003	The total number of prescriptions for a drug in 2003
PAT_EXPIRE	Dummy variable, 1 if the drug's patent has expired by 2004, 0 otherwise
PAT_EXCLUSIVE	Dummy variable, 1 if the drug has an exclusive patent for a specific condition, 0 otherwise
FDA_YEAR	The year a drug was approved by the FDA
WALGREENS	Dummy variable, 1 if the pharmacy is a store of Walgreens, 0 otherwise
CVS	Dummy variable, 1 if the pharmacy is a store of CVS, 0 otherwise
ECKERD	Dummy variable, 1 if the pharmacy is a store of Eckerd, 0 otherwise
GEO	Dummy variable, 1 if the card offers national coverage, 0 otherwise
FEE	The fixed one-time enrollment fee to a given card in dollars
MFG	The number of manufacturers a card has a contract for discount prices
ASSIST	Dummy variable, 1 if the card offers enrollment assistance, 0 otherwise
MAIL	Dummy variable, 1 if the card has a mail-order option for drugs, 0 otherwise
FORMULARY	Dummy variable, 1 if the drug offers the entire formulary of Medicare-approved drugs, 0 otherwise
FRAC65+	Fraction of people in a zipcode who are 65 years or older
MEDHINC	Median household income in a zipcode
RENT	Median rent for renter occupied housing units in a zipcode
FRACWHITE65+	Fraction of people 65 years or older in a zipcode who are white
FRACFEM65+	Fraction of people 65 years or older in a zipcode who are female
POP65+	Population in a zipcode who are 65 years and older
POPWHITE65+	Population in a zipcode who are 65 years and older and white
POPFEM65+	Population in a zipcode who are 65 years and older and female

Table 2. Variables used in the empirical analysis

Drug	% of total variation in prices attributable to[1]		
	Cards	Zipcodes	Pharmacies
Ambien	96.2	0.003	0.008
Amoxicillin	89.3	0.044	0.430
Atenolol	86.1	0.025	0.319
Augmentin	96.9	0.002	0.017
Biaxin	75.2	0.200	2.805
Carisoprodol	97.5	0.001	0.003
Cefzil	56.8	0.750	9.028
Cephalexin	94.7	0.027	0.296
Cipro	96.4	0.001	0.015
Detrol	84.2	0.002	2.510
Doxycycline Hyclate	91.0	0.041	0.456
Flexeril	96.7	0.015	0.175
Glucophage	94.4	0.053	0.558
Glucotrol XL	74.8	0.338	3.371
Isosorbide Mononitrate	95.9	0.003	0.019
Lanoxin	82.1	0.199	2.234
Levaquin	95.1	0.035	0.418
Lipitor	86.0	0.175	1.932
Metoprolol	23.5	11.308	1.458
Minocycline	93.4	0.053	0.313
Norvasc	82.2	0.212	2.256
Plavix	92.2	0.054	0.617
Pravachol	94.7	0.039	0.411
Skelaxin	94.1	0.034	0.358
Zestril	85.1	0.202	2.164
Zithromax	83.3	0.160	2.127
Zocor	97.0	0.002	0.022
Zoloft	86.8	0.161	2.137
AVERAGE	**86.5**	**0.505**	**1.302**
SD	15.3	2.123	1.838
MEDIAN	**91.6**	**0.043**	**0.443**
INTERQ. RANGE	11.3	0.169	1.879

Notes:

[1]A nested analysis of variance (ANOVA) was performed for each drug, where pharmacies were nested in zipcodes. The reported percentages are the percentages of total sum of squares. The remaining percentage for each drug is accounted by the error terms.

Table 3. The components of variation in drug prices (Week of June 21-26, 2004)

Independent Variables	Dependent variable: Price	
	I	II
LONG_TERM	-51.10	-51.10
	(0.04)	(0.04)
GENERIC	-11.58	-11.58
	(0.07)	(0.07)
PRES_2003	-0.0000027	-0.0000027
	0.0000001	0.0000001
PAT_EXPIRE	48.09	48.09
	(0.06)	(0.06)
PAT_EXCLUSIVE	192.93	192.93
	(0.09)	(0.09)
FDA_YEAR	1.89	1.89
	(0.02)	(0.02)
WALMART	0.14	0.16
	(0.05)	(0.06)
CVS	-0.94	-0.94
	(0.06)	(0.06)
ECKERD	0.69	0.68
	(0.03)	(0.04)
GEO	4.94	5.14
	(0.61)	(0.61)
FEE	0.07	0.08
	(0.01)	(0.01)
MFG	-0.44	-0.47
	(0.06)	(0.06)
ASSIST	-4.15	-4.17
	(0.70)	(0.70)
MAIL	2.04	2.13
	(0.48)	(0.48)
FORMULARY	1.82	1.73
	(0.15)	(0.17)
FRAC65+	-0.33	--
	(0.09)	
MEDHINC	-0.00037	-0.00022
	(0.000013)	(0.000097)
RENT	0.0064	0.0066
	(0.00037)	(0.00039)
FRACWHITE65+	-0.29	--
	(0.03)	
FRACFEM65+	-0.24	--
	(0.02)	
POP65+	--	-0.03
		(0.002)
POPWHITE65+	--	0.029
		(0.0017)
POPFEM65+	--	0.0024
		(0.0003)
Card dummies	Y	Y
Drug dummies	Y	Y
Zipcode dummies	Y	Y
Pharmacy dummies	Y	Y
N	1,230,215	1,230,215
R^2	0.98	0.98
Notes: Robust standard errors in parantheses		

Table 4. Static price regression

	Savings (in %)								
	Regular versus card prices			Online versus card prices (with shipping)[5]			Value of Information		
Drug	Naïve[1]	Searcher[2]	Expert[4]	Naïve[1]	Searcher[3]	Expert	On-line	Card	Regular
Ambien	5.2	17.5	14.2	12.0 (10.8)	13.6 (12.6)	0.7 (-0.4)	1.8 (2.0)	13.0	3.8
Amoxicillin	50.1	63.6	10.8	-42.0 (-66.3)	-16.9 (-27.0)	-54.4 (-70.5)	18.2 (22.4)	24.1	59.3
Atenolol	54.4	75.6	67.4	22.8 (9.7)	45.7 (45.7)	-1.7 (-1.7)	29.0 (39.0)	46.2	25.5
Augmentin	-1.6	8.3	-29.3	3.2 (2.6)	5.0 (3.8)	-5.1 (-6.5)	1.8 (1.2)	9.6	29.0
Biaxin	5.7	9.0	-22.0	-4.0 (-5.1)	3.4 (1.9)	-0.08 (-1.6)	7.2 (6.7)	3.5	25.4
Carisoprodol	38.7	89.4	43.5	48.6 (43.7)	57.3 (57.3)	-147.6 (-147.6)	16.8 (24.1)	82.6	81.2
Cefzil	14.3	16.5	-12.7	-19.1 (-19.4)	-17.3 (-17.8)	-20.2 (-20.7)	1.9 (1.6)	2.5	25.9
Cephalexin	NA	NA	NA	69.2 (66.2)	77.6 (73.2)	47.1 (36.7)	27.5 (20.8)	57.6	NA
Cipro	5.0	9.8	-12.2	5.2 (4.4)	8.8 (8.0)	4.0 (3.1)	3.8 (3.8)	5.0	19.6
Detrol	5.9	11.1	1.9	-1.39 (-3.2)	3.4 (-0.4)	-2.3 (-6.4)	4.7 (2.7)	5.6	9.4
Doxycycline Hyclate	63.4	79.2	79.3	NA	NA	NA	NA	43.1	0.0
Flexeril	6.8	21.9	3.7	-4.2 (-7.8)	5.9 (2.6)	-31.7 (-37.3)	9.8 (9.5)	16.3	19.0
Glucophage	-25.1	-11.0	-137.6	NA	NA	NA	7.6 (11.5)	11.3	39.5
Glucotrol XL	-12.2	-3.6	-71.4	-31.2 (-39.9)	-29.8 (-37.3)	-41.6 (-49.8)	1.3 (2.4)	7.9	53.3
Isosorbide Mononitrate	59.6	81.8	74.8	-19.2 (-27.2)	-19.2 (-27.2)	-222.3 (-244.2)	0 (0)	54.4	27.8
Lanoxin	-2.8	11.5	-38.9	4.0 (-9.4)	16.1 (16.1)	2.4 (2.4)	12.6 (23.2)	13.9	36.3
Levaquin	10.1	14.2	14.2	-1.4 (-1.8)	3.9 (3.2)	-0.8 (-1.5)	12.6 (23.2)	4.6	0.0
Lipitor	5.7	11.3	6.5	4.2 (2.1)	8.7 (7.1)	2.9 (1.2)	4.6 (5.0)	6.0	5.1
Metoprolol	NA	NA	NA	-23.6 (-48.8)	24.8 (24.8)	-23.9 (-23.9)	39.1 (49.5)	39.3	NA
Minocycline	-46.3	24.7	24.7	47.9 (46.6)	61.6 (61.6)	25.4 (25.4)	25.4 (27.2)	48.5	0.0
Norvasc	6.8	12.0	2.0	1.2 (-2.0)	6.5 (5.4)	1.1 (-0.09)	25.4 (27.2)	5.5	10.2
Plavix	-2.0	3.1	-17.0	2.1 (0.8)	5.5 (4.9)	0.5 (-0.02)	3.4 (4.2)	5.0	17.2
Pravachol	-9.5	-1.9	-1.9	-4.8 (-6.5)	1.2 (0.4)	-6.1 (-7.0)	5.6 (6.5)	6.9	0.0
Skelaxin	-16.4	-8.6	-30.9	-9.1 (-10.8)	-1.5 (-4.7)	-8.1 (-11.7)	8.3 (6.3)	6.6	17.1
Zestril	28.5	36.1	31.7	-31.6 (-35.8)	-25.5 (-29.2)	-44.4 (-48.7)	4.1 (4.3)	11.3	6.5
Zithromax	14.2	20.3	20.3	-2.6 (-2.9)	-2.6 (-2.9)	-10.4 (-10.8)	4.1 (4.3)	7.0	0.0
Zocor	24.4	42.9	34.1	-20.2 (-21.5)	-15.9 (-15.9)	-53.4 (-53.4)	0 (0)	24.4	13.4
Zoloft	8.0	14.0	5.3	3.0 (1.2)	6.9 (5.1)	0.5 (-1.6)	4.0 (3.9)	6.5	9.2
AVERAGE	**11.2***	**24.9***	**2.3**	**0.4 (-4.6*)**	**8.7* (-19.0*)**	**-22.6* (-26.0*)**	**9.1* (10.6*)**	**20.3***	**20.5***
SD	25.9	29.1	44.9	25.1 (28.1)	26.3 (20.6)	53.8 (57.0)	10.0 (12.4)	21.1	20.3
MEDIAN	**6.3**	**14.1**	**4.5**	**-1.4 (-3.0)**	**5.2 (-10.3)**	**-3.7 (-6.4)**	**5.0 (4.9)**	**10.5**	**17.1**
INTERQ. RANGE	23.7	24.1	39.5	20.8 (19.7)	14.7 (23.1)	32.4 (37.2)	7.7 (13.6)	22.2	22.7

Notes:

1"Naïve" is defined a consumer who is uninformed and purchases randomly in both markets.

[2] "Searcher" is defined as a consumer who is informed of the minimum card price but otherwise purchases randomly in the regular market.

[3] "Searcher" is defined as a consumer who is informed of the minimum on-line price but otherwise purchases randomly in the discount card market.

[4] "Expert" is defined as a consumer who is fully informed in both markets.

[5] The figures inside the parantheses include shipping fees. The figures outside the parantheses are based on the on-line base prices.

A (*) indicates difference from zero at 5% or lower levels.

Table 5. Estimates of savings from discount drug cards

	Dependent variable: First Difference in Price		
Independent variables: Dummy for the week of	**Estimates for Pre-switching period**	**Independent variables: Dummy for the week of**	**Estimates for Post-switching period**
6/28/2004	0.21	***4/4/2005***	2.85
	[0.27]		[0.11]
7/5/2004	-2.25	***5/16/2005***	4.53
	[0.38]		[0.16]
7/11/2004	-3.73	***6/6/2005***	6.54
	[0.47]		[0.20]
7/18/2004	-4.77	***6/20/2005***	7.74
	[0.54]		[0.23]
7/25/2004	-4.64	***7/11/2005***	7.74
	[0.61]		[0.26]
8/2/2004	-4.63	***7/18/2005***	7.70
	[0.66]		[0.28]
		8/1/2005	7.80
			[0.31]
		8/15/2005	7.83
			[0.33]
N	92,700	**N**	18,280
R^2	0.53	**R^2**	0.51

Notes: Robust standard errors in parantheses. Omitted time dummy is the first week for each regression: ***6/21/2004*** for the pre-switching period and ***3/7/2005*** for the post-switching period.

Table 6. Estimated coefficients of time dummies from the difference regressions

	(Switching period price) - (Pre-switching period price)			(Post-switching period price) - (Switching Peirod Price)		
Drug	**Average difference ($)**	**Paired t-stat**	**P-value**	**Average difference ($)**	**Paired t-stat**	**P-value**
Ambien	-1.99	**-6.91**	0.00	0.31	**5.42**	0.00
Amoxicillin	-2.28	**-26.56**	0.00	1.33	**11.38**	0.00
Atenolol	-0.77	**-9.62**	0.00	0.18	0.67	0.49
Augmentin	-3.07	**-2.46**	0.01	0.72	**2.88**	0.00
Biaxin	-2.65	**-10.55**	0.00	2.80	**22.66**	0.00
Carisoprodol	-0.63	**-1.29**	0.04	1.50	**3.29**	0.00
Cefzil	-2.93	**-17.94**	0.00	-0.10	-0.89	0.37
Cipro	-4.81	**-5.00**	0.00	3.69	**3.35**	0.00
Detrol	-2.09	**-4.18**	0.00	3.27	**12.47**	0.00
Doxycycline Hyclate	0.58	**8.73**	0.00	0.21	**4.25**	0.00
Flexeril	-0.70	**-3.18**	0.00	2.61	**16.08**	0.00
Glucotrol XL	0.34	**7.92**	0.00	1.03	**14.00**	0.00
Isosorbide Mononitrate	-3.36	**-14.22**	0.00	2.30	1.31	0.18
Lanoxin	1.32	**22.87**	0.00	0.05	0.60	0.54
Levaquin	-3.80	**-10.78**	0.00	2.48	**12.42**	0.00
Average	-1.79			1.49		
Standard error	0.45			0.33		

Notes: Bolded t-statistics indicate significance at 5% or lower levels. "Switching period price" is the price during the one week of data available from the switching period. "Pre-switching period price" is the price during the last week (week of ***8/2/2004***) of price observations in our pre-switching period sample. "Post-switching period price" is the price during the first week (week of ***4/4/2005***) of price observations in our post-switching period sample.

Table 7. Analysis of price changes around the switching period

Independent variables	Dependent variable		Independent variables	Dependent variable	
Dummy for the date:	**Base price**	**Total price**	**Dummy for the date:**	**Base price**	**Total price**
6/28/2004	0.00	0.00	***1/13/2005***	1.95	1.99
	[0.58]	[0.58]		[0.63]	[0.63]
7/8/2004	0.00	0.00	***5/6/2005***	2.62	2.66
	[0.58]	[0.58]		[0.62]	[0.62]
7/15/2004	0.00	0.00	***5/27/2005***	2.81	2.85
	[0.58]	[0.58]		[0.62]	[0.62]
7/26/2004	1.73	1.74	***6/10/2005***	2.81	2.85
	[0.60]	[0.60]		[0.62]	[0.62]
8/3/2004	1.73	1.74	***6/20/2005***	2.81	2.85
	[0.60]	[0.60]		[0.62]	[0.62]
8/10/2004	1.73	1.74	***7/11/2005***	3.25	3.31
	[0.60]	[0.60]		[0.62]	[0.62]
8/17/2004	1.73	1.74	***7/29/2005***	3.25	3.31
	[0.60]	[0.60]		[0.62]	[0.62]
8/24/2004	1.73	1.74	***8/1/2005***	3.30	3.36
	[0.60]	[0.60]		[0.62]	[0.62]
9/1/2004	1.81	1.87	***8/18/2005***	3.33	3.38
	[0.61]	[0.61]		[0.66]	[0.66]
9/13/2004	1.82	1.87	***9/16/2005***	3.39	3.53
	[0.62]	[0.62]		[0.66]	[0.66]
9/15/2004	1.83	1.85	***9/29/2005***	3.39	3.53
	[0.61]	[0.61]		[0.66]	[0.66]
9/21/2004	1.86	1.91	***10/4/2005***	3.39	3.53
	[0.60]	[0.61]		[0.66]	[0.66]
9/24/2004	1.86	1.91	***10/16/2005***	3.39	3.53
	[0.60]	[0.61]		[0.66]	[0.66]
9/28/2004	1.86	1.91	***10/17/2005***	3.39	3.53
	[0.60]	[0.61]		[0.66]	[0.66]
10/5/2004	1.81	1.85	***10/20/2005***	3.39	3.53
	[0.63]	[0.63]		[0.66]	[0.66]
10/15/2004	1.88	1.89			
	[0.63]	[0.64]			
10/20/2004	1.55	1.56			
	[0.64]	[0.64]			
12/10/2004	1.93	1.97			
	[0.62]	[0.62]			
12/29/2004	1.89	1.93			
	[0.62]	[0.62]			
N	2955				
R^2	0.98				

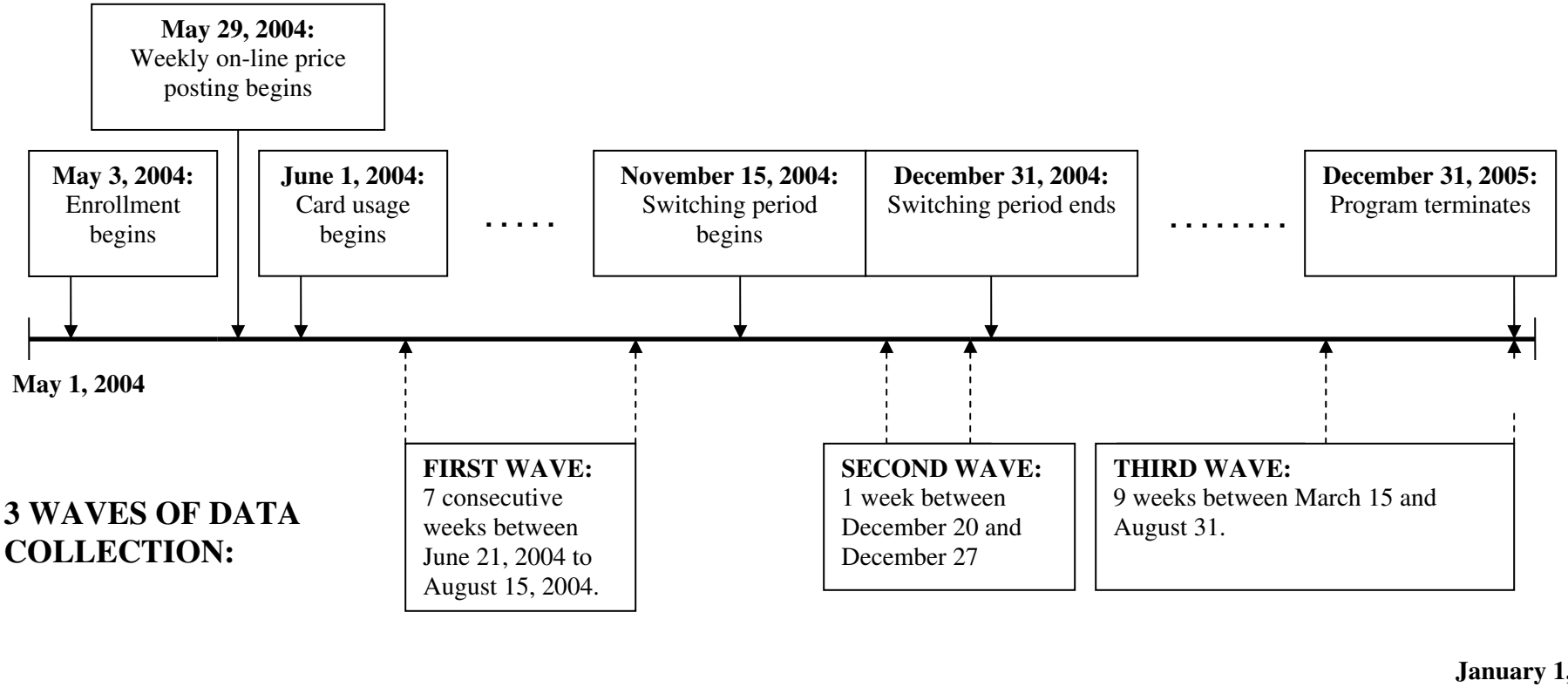
Notes: Robust standard errors in brackets. Total price includes shipping fee for standard delivery for each vendor. Dates in italics refer to the day the price data was collected.

Color legend:

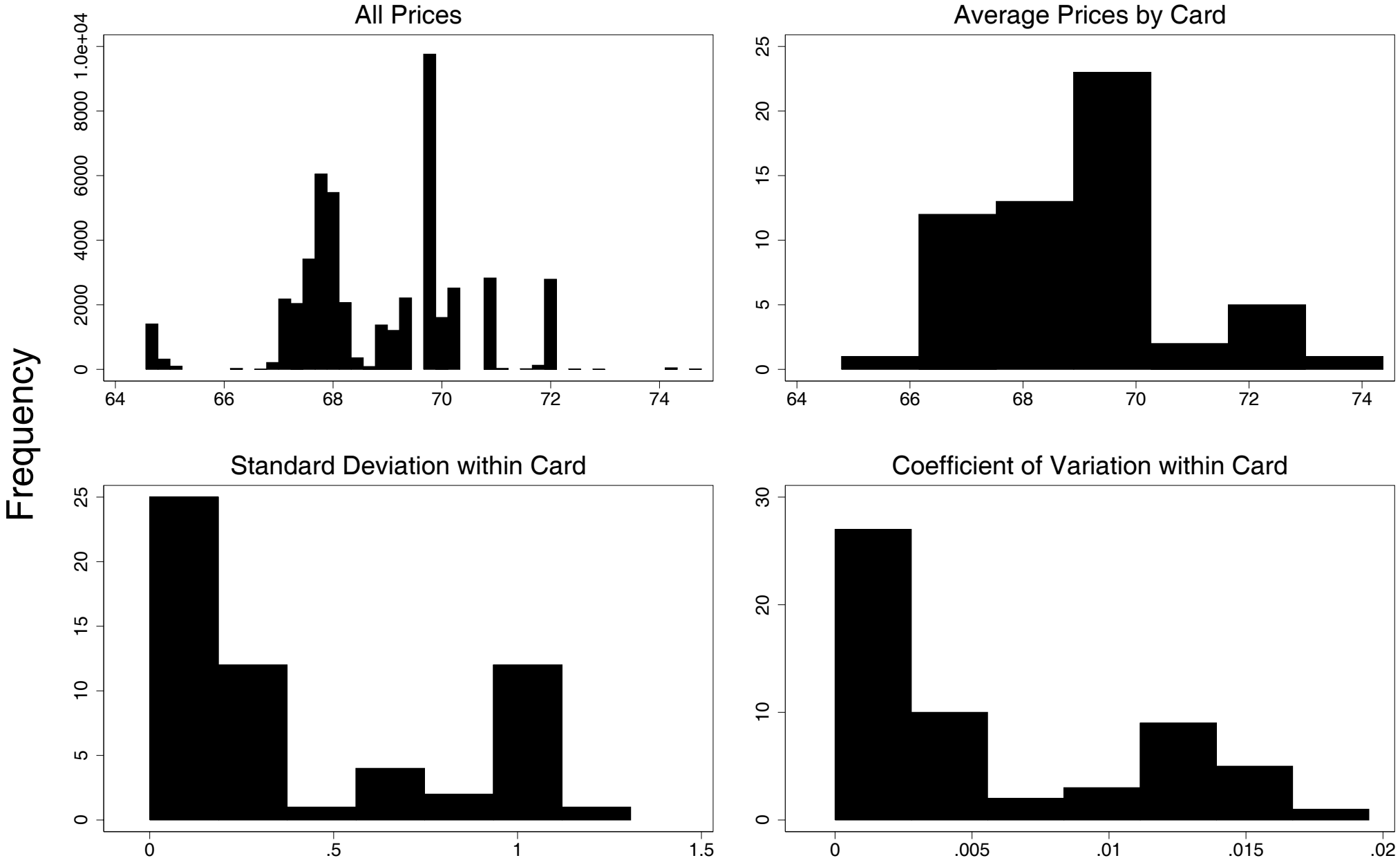
Pre-switching period
Switching period
Post-switching period

Table 8. Estimated time dummies for on-line price regression

Figure 1. The chronology of important events in MDDCP and the timing of data collection



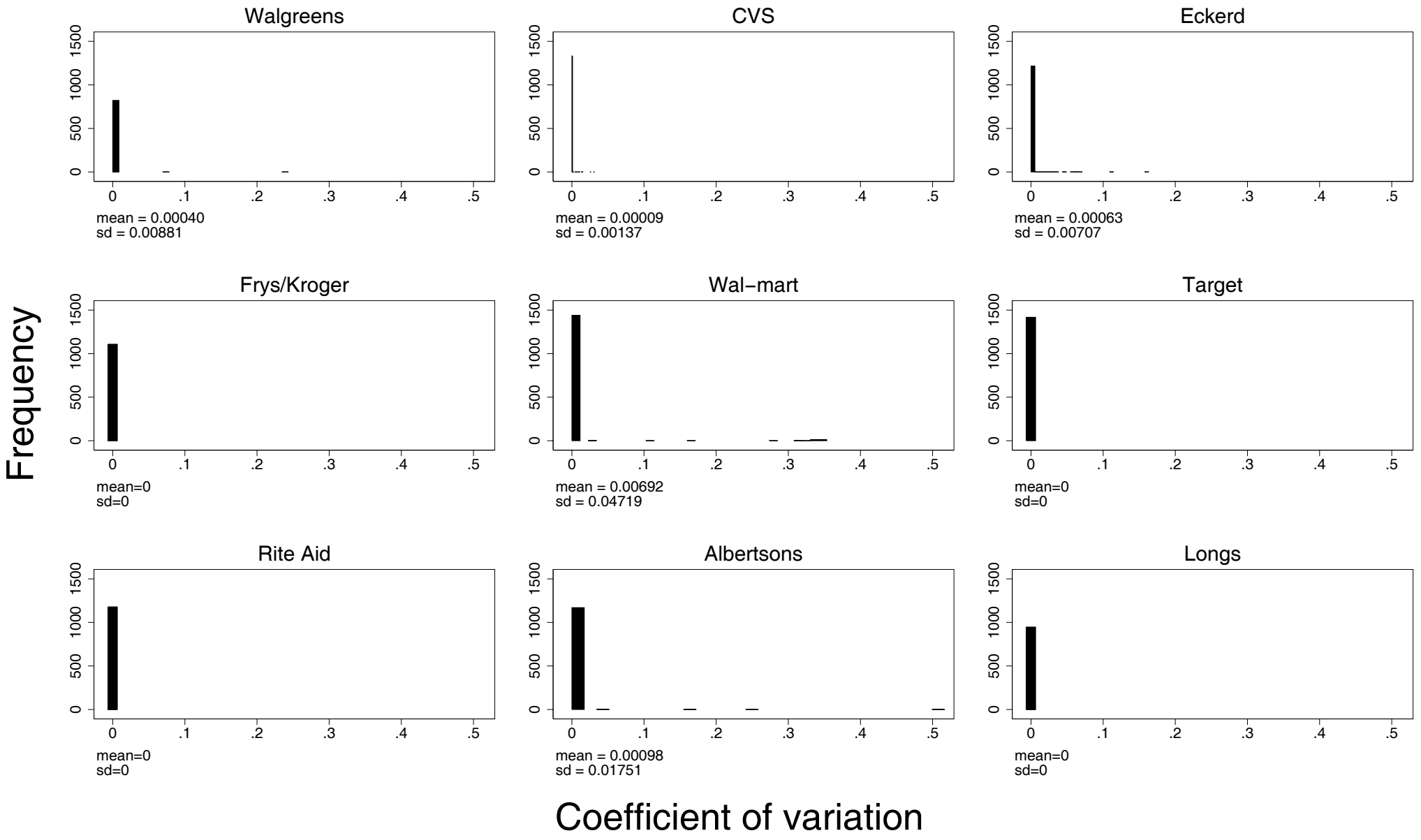
Lipitor Price Dispersion



Week of 6/28 to 7/03

Within–chain dispersion analysis

Coefficient of variation of price



Week of 6/28 to 7/03

Figure 4. The distribution of the time-average of price changes across cards and drugs