Current Draft: March 2026

Health Care Reform and Firm Dynamics: Evidence from Medicare Part D and the Retail Pharmacy Industry

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The authors do not have any outside research support,
financial interests, or conflicts of interest to disclose.

Brandyn Churchill and Kelli Marquardt would split the presentation time (if permitted).

Abstract

Retail pharmacies fill over 4 billion prescriptions each year and are the most frequent healthcare touchpoint in the U.S. Yet relatively little is known about the economic factors driving pharmacy access. We provide new evidence on how Medicare Part D shaped the retail pharmacy industry using 2000-2009 National Establishment Time-Series data and a difference-in-differences strategy leveraging pre-period variation in the share of the customers likely enrolled in Medicare. The two-year period between Part D's passage and implementation was marked by substantial uncertainty about its financial implications for pharmacies. Though Part D ultimately increased prescription utilization, it also reduced drug prices and raised administrative costs. We find that Part D was associated with a 5-percent reduction in the number of pharmacies, driven entirely by a reduction in the number of openings rather than an increase in closures. Finally, we find suggestive evidence that the mortality reduction attributable to Part D was smaller in counties that experienced a reduction in pharmacy access.

JEL Codes: I18; M20
Key words: Medicare Part D; pharmacy; openings; closures

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1. Introduction

Retail pharmacies are an integral part of the U.S. health care system. Pharmacies fill over 4 billion prescriptions each year (Kaiser Family Foundation 2019) and are the most frequent service delivery touchpoint in the health care system (Trygstad 2020). Patients with commercial insurance (Valliant et al. 2022) and Medicare (Berenbrok et al. 2020) visit a pharmacy almost twice as often as they visit a physician, and pharmacists are among the most trusted members of the health care community (McHugh et al. 2022). Recognizing the potential for pharmacists to relieve a shortage of primary care physicians (Manolakis and Skelton 2010), states have passed scope-of-practice expansions allowing pharmacists to prescribe and administer a growing list of medicines, including vaccines (Trogdon et al. 2016; McConeghy and Wing 2016; Poudel et al. 2019), rescue inhalers and insulin pens (Shakya et al. 2024), and medications to prevent opioid overdoses (Abouk et al. 2019; Smart et al. 2024). Indeed, pharmacies' expanded role in delivering health care was highlighted during the COVID-19 pandemic (Viscari et al. 2021), and pharmacists played a central role in the nationwide COVID-19 vaccination campaign (Brownstein et al. 2022).

Despite pharmacies' ever-growing role in health care delivery, the industry has experienced significant challenges (Guadamuz et al. 2019). Between 2003 and 2018, one in six independent (i.e., non-chain) rural pharmacies closed (Salako et al. 2018). While the closure rate has generally been lower for chain pharmacies, many of these establishments have also struggled. From 2018 to 2020, CVS Health closed 244 stores and announced plans to close an additional 900 stores by the end of 2024 (CNN 2024). Likewise, Rite Aid announced the closure of approximately 25 percent of their stores when it filed for bankruptcy in 2023 (Bloomberg 2024); less than two years later, the company closed all remaining stores as part of a second bankruptcy (CBS 2025). Pharmacy closures have disproportionately occurred in

areas serving low-income patients and members of racial and ethnic minority communities (Guadamuz et al. 2024), potentially exacerbating existing health disparities (Essien et al. 2021). While these location decisions have important implications for health care access, relatively little is known about the determinants of retail pharmacy formation, performance, and dissolution.[1]

In this paper, we provide novel evidence on the role of government policy in shaping the retail pharmacy industry by studying the passage and implementation of Medicare Part D. Established by the Medicare Prescription Drug, Improvement, and Modernization Act of 2003, Medicare Part D provides prescription drug coverage to over 53 million enrollees (Sayed et al. 2023). At the time of its passage, it was the largest public health insurance expansion in the United States in over forty years (Oliver et al. 2004). Because the program took several years to be fully implemented and included several unprecedented components, there was substantial uncertainty about the potential effects of the program (Altman 2004). Indeed, as the legislation was being debated, the administrator for the Centers for Medicare and Medicaid Services was skeptical that insurers would want to offer Part D plans (Pear 2003). Even if they did, it was unknown whether beneficiaries would choose to enroll in the program and how the program would affect drug prices (Neuman and Cubanski 2009).

Ultimately, researchers have shown that Part D was associated with increased prescription drug utilization (Lichtenberg and Sun 2007; Ketcham and Simon 2008; Yin et al. 2008; Kaestner and Khan 2012), significantly reduced drug prices (Duggan and Scott Morton 2010; Duggan and Scott Morton 2011;

[1] Prior evidence showed has linked the entry of larger chain pharmacies into a market to price reductions (Bennett and Yin 2019; Moura and Barros 2020). Several recent papers have also connected retail pharmacy market pressure and incentives to the opioid epidemic (Janssen and Zhang 2023; Burton and Churchill 2025; Diaz-Campo and Bradford 2025; Kim et al. 2025; Mizushima et al. 2025). Finally, Atal et al. (2024) found that public pharmacy entry in Chile induced market segmentation and price increases in the private sector.

Lakdawalla and Yin 2015), and increased administrative costs (Radford et al. 2007; Bono and Crawford 2010; Zhang et al. 2010). As a result, the net effect of Medicare Part D on retail pharmacies is theoretically ambiguous. Prior to Part D, retail pharmacies were able to earn high margins on underinsured and insured cash customers (Berndt and Newhouse 2010), and gross margins on prescriptions covered by Medicare Part D were lower than those covered by Medicaid, commercial insurance, or cash customers (Spooner 2008).[2] As a result, prescription drug expenditures fell among the sizable group of Medicare Part D enrollees who previously had more generous coverage (Zhang et al. 2009; Lakdawalla and Yin 2015).[3]

To explore how Medicare Part D affected the retail pharmacy industry, we first adopt a framework where Medicare Part D generates uncertainty about the value of entering/exiting a market (Dixit 1989; Dixit and Pindyck 1994; Carlton 2005). We show that the uncertainty between Medicare Part D's passage and full implementation increased the value waiting to enter, particularly in areas where a greater share of the pharmacy customer base was comprised of Medicare beneficiaries. After the uncertainty was resolved with Part D's full implementation – and based on existing evidence documenting larger price reductions than utilization increases – the framework predicts that openings would remain suppressed and that closures may have increased. Next, we test these predictions using the 2000-2009 National Establishment Time-Series (NETS) data and a difference-in-differences identification strategy leveraging variation in the share of

[2] For example, CVS Caremark noted in its 2007 10-K that, "The Medicare Drug Benefit became effective on January 1, 2006. Since its inception the program has resulted in increased utilization and decreased pharmacy gross margin rates as higher margin business (such as cash and state Medicaid customers) migrated to the new Part D coverage" (CVS 2007).

[3] Engelhardt and Gruber (2011) estimated in survey data that Medicare Part D resulted in 75 percent crowd-out of prescription-drug insurance coverage and expenditures of those aged 65 or older. Likewise, Lichtenberg and Sun (2007) estimate a 72 percent crowd-out rate for prescriptions using claims data from a large pharmacy chain.

the local customer base that was presumably comprised of Medicare beneficiaries (Alpert et al. 2023).

We document several key empirical findings. First, we show that the introduction of Medicare Part D was associated with a 5-percent reduction in the number of pharmacies located in counties where elderly adults comprised a larger share of the population. This finding is robust to a variety of specification choices, sample restrictions, and methods for conducting statistical inference. Additionally, we show that this reduction was more pronounced for racial and ethnic minority communities and low-income areas, suggesting that Medicare Part D may have widened existing disparities in pharmacy access. Event study analyses indicate that the change was not driven by a differential pre-trend, and the magnitude of post-period estimates is consistent with the timing of Medicare Part D's implementation (Alpert 2016; Huh and Reif 2017). While we find evidence of reductions in both the number of standalone (i.e., non-chain) pharmacies and non-standalone pharmacies, the estimated reduction in the number of standalone pharmacies is 75 percent larger in magnitude.

Second, consistent with our theoretical framework, we show that the reduction in the number of pharmacies following the passage of Medicare Part D was driven by a reduction in the number of pharmacy openings. In contrast, we do not find any evidence that Medicare Part D was associated with increases in the number of pharmacy closures. Together, these patterns suggest that while Medicare Part D did not systematically put existing pharmacies out of business, it discouraged business formation. As a result, we show that counties where a higher share of the population was comprised of elderly adults subsequently had a less dynamic pharmacy market serviced by older pharmacies than counties where elderly individuals comprised a smaller share of the population.

Finally, we provide evidence on the relationship between pharmacy access and mortality. Consistent with prior evidence (Huh and Reif 2017), we show that

Medicare Part D was associated with an approximate 2-percent reduction in mortality for 66-year-olds relative to 64-year-olds. We then show that this reduction was driven by counties where elderly adults comprised a smaller share of the population. Within counties with an above-median share of the population comprised of elderly adults – where we uncovered a 5-percent reduction in the number of pharmacies – the mortality reduction is over 90 percent smaller in magnitude and statistically insignificant. These patterns provide suggestive evidence that reduced pharmacy access dampened the mortality reductions attributable to Medicare Part D.

The rest of the paper proceeds as follows: Section 2 describes the policy history of Medicare Part D, as well as the existing literature examining the effects of Medicare Part D on the health care industry and public health. Section 4 discusses the National Establishment Time-Series data that we use to study changes in business formation and firm performance, the National Vital Statistics data that we use to study changes in mortality, and our difference-in-differences identification strategy. Section 5 presents our results examining changes in the number of pharmacies in a county, pharmacy openings and closures, various performance metrics for existing establishments, and health outcomes. Finally, Section 5 discusses the policy implications and limitations of our results.

2. Policy Background and Existing Literature

2.1 Policy Background

When Medicare was signed into law by President Lyndon B. Johnson in 1965, it was intended to protect senior citizens from financial devastation associated with hospital stays and certain medical procedures. Beneficiaries were automatically enrolled in hospital coverage (Medicare Part A), and coverage for physician services (Medicare Part B) was offered as optional, supplementary insurance. At that time, prescription benefits were not covered, though over the next forty years

they became both more medically important and expensive (Duggan et al. 2008). By 2003, Medicare beneficiaries were spending an average of $2,500 per year on prescription drugs, or twice what the average American spent on health care in 1965 when adjusting for inflation (Engelhardt and Gruber 2011).

On December 8, 2003, President George W. Bush signed the Medicare Prescription Drug, Improvement, and Modernization Act of 2003, which created Medicare Part D. The legislation authorized the creation of a new stand-alone government-subsidized program offered by private insurers and pharmacy benefit managers for beneficiaries enrolled in traditional fee-for-service Medicare, in addition to authorizing Medicare Advantage plans to offer the Part D benefit (Neuman and Cubanski 2009). As such, it was the first time that a Medicare benefit was entirely privately managed, and Part D plans were permitted to negotiate independently with drug manufacturers (Frank and Newhouse 2006). Though prescription drug benefits were not available until Part D was fully launched in 2006, the law established a transitional discount card program that became widely available in mid-2004. Medicare beneficiaries were free to sign up for Medicare Part D coverage until May 15, 2006, and those enrolling afterwards were initially subject to a financial penalty to mitigate adverse selection. Beneficiaries eligible for both Medicare and Medicaid (i.e., "duals") were required to receive prescription benefits through Medicare (Basu et al. 2010; Abaluck and Gruber 2011). The law also included a low-income subsidy to help beneficiaries who could not otherwise afford the prescription drug benefit (Megellas 2006; Decarolis 2015).

Around the time of Part D's passage and implementation, retail pharmacy industry leaders predicted that the program would be somewhat dilutive to their performance as high-margin customers, including cash customers and individuals dual eligible for both Medicaid and Medicare, shifted to Part D plans (CVS 2006a;

Walgreens 2006; Rite Aid 2007a).[4] Although increased prescription drug utilization was projected to eventually offset the lower margin rates, industry leaders reported that the initial increases were not large enough to fully offset the reduced margin rate (CVS 2006b; Rite Aid 2007b). However, because pharmacy sales made up only 60-70 percent of total sales at these larger chain pharmacies (CVS 2006a; Walgreens 2006; Rite Aid 2007a), their firmwide performance was less sensitive to the margin reduction than independent pharmacies who received over 90 percent of their revenue from prescriptions (NCPA Digest 2008).[5]

2.2 Existing Literature on Medicare Part D

We build on prior work studying the effects of Medicare Part D on the pharmaceutical industry. This work has shown that Part D increased prescription drug utilization among those who previously lacked prescription drug coverage (Zhang et al. 2009; Kaestner and Khan 2012), as well as those who previously had less generous coverage (Yin et al. 2008; Engelhardt and Gruber 2011). Yet there is mixed evidence on the size of the utilization increase. For example, Lichtenberg and Sun (2007) used data from a large retail pharmacy chain and estimated that Medicare Part D increased prescription drug utilization by nearly 13 percent. In contrast, Yin et al. (2008) estimated a 1.1-5.9-percent increase using these same data. Similarly, Ketcham and Simon (2008) estimated a 4.7-percent increase in utilization using data from a larger collection of pharmacies. Finally, Levy and

[4] Prior work has shown that Medicaid reimbursement rates at this time were upwardly distorted (Duggan and Scott Morton 2006).

[5] Another difference between CVS and independent pharmacies is that CVS includes both a retail pharmacy business and a pharmacy benefit manager (PBM) business. David Rickard concluded on the 2006 Q1 earnings call that Medicare Part D "was slightly dilutive to the retail business, slightly accretive to the PBM business, and slightly dilutive to the corporation overall" (CVS 2006c). Relatedly, a recent working paper indicates that vertically integrated insurers increase internal prices for prescriptions and "tunnel" excess profits to pharmacies to avoid regulatory caps on insurer profits (Yde 2025).

Weir (2010) found little evidence of a change in prescription drug utilization using data from the Health and Retirement Study (2010).

In contrast, there is stronger evidence that Medicare Part D lowered the price of prescription drugs. Leveraging variation across branded drugs in their pre-existing Medicare market share, Duggan and Scott Morton (2010) found that Medicare Part D increased drug utilization and reduced the growth in branded drug prices by approximately 12-14 percent. Among those who were previously uninsured, prices were estimated to have fallen by more than 20 percent. In contrast, the estimate for those who previously had prescription drug plans was over 70 percent smaller in magnitude, opposite signed, and statistically insignificant. Likewise, Duggan and Scott Morton (2010) estimated an 18 percent price reduction for dual-eligible individuals, though the estimate was not statistically significant. In related work, Lakdawalla and Yin (2015) used variation in insurers' potential Part D enrollment and data from a national retail pharmacy chain to show that Part D enrollment increases lowered drug prices and reduced profits from individuals enrolled in commercial insurance plans external to Medicare Part D.[6]

We also build on work which has explored the relationship between Medicare Part D and patient outcomes. Using administrative Medicare data, Kaestner et al. (2019) found that gaining prescription drug coverage through Medicare Part D reduced hospital admissions by approximately 4 percent. Comparing changes in mortality among those eligible for Medicare Part D (i.e., those aged 66) to the concurrent changes among those whose age made them ineligible (i.e., those aged 64), Huh and Reif (2017) found that Medicare Part D reduced mortality by approximately 2 percent. Using a complementary research design leveraging pre-existing county-level differences in prescription drug

[6] Several studies have also explored the ways in which Medicare Part D may have altered pharmaceutical manufacturers' strategic firm behaviors, such as innovation (Blume-Kohout and Sood 2013) and advertising (Lakdawalla et al. 2013; Alpert et al. 2023).

coverage rates, Dunn and Shapiro (2019) similarly found that Medicare Part D reduced mortality.

Finally, we add to an interdisciplinary literature exploring the implications of Medicare Part D for retail pharmacies. Much of this work has used surveys and structured interviews to discern pharmacists' satisfaction with the program (Radford et al. 2007; Radford et al. 2009; Bono and Crawford 2010; Zhang et al. 2010; Khan 2012). In their responses, pharmacists regularly cited low reimbursement rates and increased administrative burdens as challenges, particularly for independent pharmacies; early projections indicated that net income would fall by approximately 22 percent due to a 0.7 percent decline in the gross margin for prescriptions (Carroll 2008). Examining descriptive trends in the number of pharmacies over time, Klepser et al. (2011) noted a nationwide increase in the number of independent pharmacy closures beginning in late 2007 through 2008, though they were unable to disentangle whether these changes were due to Medicare Part D or the start of the Great Recession.

We make several important contributions. While prior evidence suggests that Medicare Part D increased the profitability of prescription drugs for pharmaceutical companies (Friedman 2009), its effect on the retail pharmacy industry is unclear. Moreover, much of the existing evidence is based on samples from a single large national pharmacy chain (Lichtenberg and Sun 2007; Yin et al. 2008; Lakdawalla and Yin 2015), though these data may not generalize to the entire industry (Ketcham and Simon 2008). As such, our ability to explore whether Medicare Part D was differentially related to changes in outcomes for the broader retail pharmacy industry is an important contribution. Additionally, adopting an industry-wide analysis allows us to study whether and how Medicare Part D has contributed to racial and ethnic health disparities in pharmacy access. Finally, we provide the first evidence on the connection between Medicare Part D-induced changes in the retail pharmacy industry and changes in patient outcomes.

3. Theoretic Framework

To understand how Medicare Part D affected retail pharmacies, we first consider Part D's effect on pharmacy profit. We show that though this relationship is ambiguous, the effect is likely higher in terms of both upside and downside risk in areas where Medicare beneficiaries comprised a larger share of the customer base. Based on this intuition, we formalize a model of pharmacy entry and exit decisions with uncertainty that yields testable predictions about entry timing and exit.

3.1 Medicare Part D and Pharmacy Profit

We begin by considering two representative markets: market A where a high share of the population is comprised of elderly adults ($s_e^A = H$) and market B where a low share of the population is comprised of elderly adults ($s_e^B = L$). Prior to Medicare Part D, elderly adults were more likely than their younger counterparts to lack prescription drug coverage and face the full out-of-pocket price of prescription drugs. In contrast, the younger population faced only a copayment, making their demand for prescription drugs relatively more price inelastic. Figure 1 shows that the difference in demand for the non-elderly and elderly populations produces a kink in the inverse demand curve. For quantities up to $1 - s_e$, the non-elderly share of the population, demand is relatively inelastic because consumers are insulated from paying the full price. Beyond this threshold, demand becomes relatively more elastic, due to the elderly adults who lacked prescription drug coverage prior to Part D. Because market A has a higher elder share, the kink occurs earlier in market A (light grey line) than in market B (dark grey line). As a result, the relatively more elastic segment accounts for a larger share of total demand in market A.

When the previously uninsured elderly population gains prescription drug coverage because of Medicare Part D, the full population becomes insured and faces a fraction of the list price. This results in the kink disappearing and demand becoming relatively more price inelastic. At any given price, quantity demanded

increases because of Part D as the elderly population who were previously priced out of the market can now participate more fully. Importantly, the size of the demand shift is larger in market *A* where the increase in coverage is relatively larger.

Although Medicare Part D increased prescription drug utilization, the effect on retail pharmacy profits is ambiguous for two reasons. First, there is no clear effect on prescription drug prices. On one hand, the outward shift in demand reflects increased willingness to pay among newly insured elderly patients. On the other hand, Part D introduced insurers as intermediaries for the elderly population, and these insurers possess bargaining power that puts downward pressure on reimbursement rates. The net effect on price depends on which of these two forces dominates. However, both the upward and downward pressure on price scale with the size of the demand shift, so the total effect on price will be more pronounced in market *A* than in market *B*. Second, even if price and quantity both increased, profits may not rise. Pharmacy profit depends on the margin between price and the average total cost at the realized quantity. If average total cost is increasing in quantity (e.g., due to capacity constraints, labor costs, inventory) or shifts in response to the policy (e.g., due to increased administrative burden), then a sufficiently large quantity increase could push costs above any price increase and reduce profit.

In Figure 2, we illustrate the combined effects of these two channels. For each market (low-elderly share and high-elderly share) and level of average total cost (low, medium, and high), the figure plots the change in profit as a function of price where the change in profit is defined as $(p - ATC) \times (Q^{Post}(p) - Q^{Pre}(p))$. There are two important things to highlight in this figure. First, the sign of the change in profit is sensitive to the realized price and cost level in both markets, confirming that the effect on profit is genuinely ambiguous. Second, the spread of the change in profit – both upside and downside risk – is significantly wider in market *A* than in market *B*. As a result, potential entrants into market *A* will face greater

uncertainty about the profitability of entering the market in the time between Medicare Part D's passage and its full implementation. This feature is a key motivating observation for our formal model.

3.2 Entry and Exit Decisions with Uncertainty

Set up. As above, consider two markets $m \in \{A,B\}$ where market A has a higher elderly share ($s_e^A = H$) and market B has a lower elderly share ($s_e^B = L$). Each market has one incumbent pharmacy and one potential entrant. Time is discrete with periods $t = 0, 1, 2,\ldots$ and firms are risk neutral with a discount rate $\delta \in (0,1)$. We will define $t = 0$ as the period prior to Part D's passage, $t = 1$ as the period where Part D is passed but not yet implemented, and $t = 2$ as the period where Part D is implemented.

Profits. Prior to Medicare Part D, per-period profit flow in both markets is denoted as $\pi_0 > 0$. At $t = 1$, Part D is passed and scheduled to be fully implemented at $t = 2$. At announcement, the per-period profit from implementation onwards is uncertain, with $\sigma_m > 0$ denoting the mean-preserving spread of uncertainty in market m:[7]

$$\pi_m = \begin{cases} \pi_0+\sigma_m, & \text{with prob. } 1/2 \\ \pi_0-\sigma_m, & \text{with prob. } 1/2 \end{cases} \quad (1)$$

Because the three channels through which Part D affects pharmacy profit (quantity, price, and cost) are likely to be more pronounced in market A than market B, the spread in profit outcomes is larger in market A, such that $\sigma_A > \sigma_B$. Thus, profits are expected to change after the implementation of Part D, and both the upside and downside risk to profits are relatively larger in the market where a higher share of the population was comprised of elderly adults. This state is realized at $t = 2$ and persists forever.

[7] The mean-preserving spread is a simplifying assumption for analytical tractability that isolates the role of the spread of uncertainty rather than its level. As such, we assume that the post-Part D profits are equal to the pre-Part D profits in expectation but allow for symmetric upside and downside risk. The spreads are allowed to differ across markets.

Entry Decision. A potential entrant must pay a fixed sunk cost, $K > 0$, to enter and begin earning profit in the same period. The cost is irrevocable once paid. At $t = 1$, the entrant chooses between entering immediately or waiting until $t = 2$ when the policy uncertainty has been resolved (Dixit 1989; Dixit and Pindyck 1994; Carlton 2005). If the firm enters at $t = 1$, it will pay the sunk cost, K, and earn profit π_0. From $t = 2$ onward, the entrant earns the realized (uncertain) per-period profit, so the present value obtained by entering at $t = 1$ is given by:

$$V_m^{Enter} = -K + \pi_0 + \frac{\delta}{1-\delta} \times \mathbb{E}[\pi_m] \tag{2}$$

where a potential pharmacy that opts not to enter at $t = 1$ forgoes paying K and does not earn π_0. Meanwhile, the present value from waiting is given by:

$$V_m^{Wait} = \delta \times \mathbb{E}\left[\max\left(0, \frac{\pi_m}{1-\delta} - \mathrm{K}\right)\right] \tag{3}$$

where after observing π_m, the pharmacy will enter at $t = 2$ only if the profits justify paying the sunk cost K. Thus, the option value of waiting is the difference between the present valued obtained when waiting and the present value obtain when entering at $t = 1$, $OV_m = V_m^{Wait} - V_m^{Enter}$. The potential entrant will wait if $OV_m > 0$ and will enter otherwise.

When there are sunk costs and uncertainty, delaying entry provides the firm with the option but not the obligation to enter (Dixit 1989; Dixit and Pindyck 1994). For all $K \geq 0$, it is the case that $\max\{\$0, \frac{1}{1-\delta} \times \pi_m - K\} \geq \frac{1}{1-\delta} \times \pi_m - K$, which implies that $V_m^{Wait} \geq V_m^{Enter} - \pi_0$. This latter expression highlights the choice facing the firm which will choose to enter at $t = 1$ if the value of current profit, π_0, is large enough to compensate for the lost flexibility associated with irreversible investment under uncertainty. Even if $\mathbb{E}[\pi_m] = \pi_0$, waiting allows the firm to avoid entry in low-π_m, states, at the cost of forgoing π_0. Moreover, although V_m^{Enter} is the same for both markets, the value of waiting differs, such that the option value of waiting in the

high-elder-share market is higher than in the low-elder-share market.[8] To see this, note that $g(\pi_m) = \max(0, \frac{\pi_m}{1-\delta} - K)$ is convex in π_m. Using equation (1) and the fact that $\sigma_A > \sigma_B$, convexity tells us that $g(\pi_0 + \sigma_A) + g(\pi_0 - \sigma_A) \geq g(\pi_0 + \sigma_B) + g(\pi_0 - \sigma_B)$. Dividing this expression by two and multiplying it by δ gives us $V_A^{Wait}(\sigma_A) \geq V_B^{Wait}(\sigma_B)$. In other words, V_m^{Wait} is increasing in the spread risk, σ_m. Because $\sigma_A > \sigma_B$ the value of waiting is weakly greater in market *A* than in market *B*. Intuitively, the convexity of V_m^{Wait} reflects the asymmetric payoff from waiting: by not entering, the pharmacy captures the upside in the high-state but avoids the downside in the low-state. A wider spready amplifies the upside without worsening the downside, so waiting becomes weakly more valuable as σ_m increases.

Exit Decision. Incumbent pharmacies have already paid the sunk cost, *K*. Because this cost is irrecoverable, the exit decision only depends on the profit flow. The incumbent pharmacy will exit if the profit flow is strictly negative (i.e., $\pi_{\{t,\, m\}} < 0$). Because Medicare Part D does not mechanically change the realized profits at $t = 0$ or $t = 1$, we do not predict observing a discrete change in closures. Moreover, the post-implementation change in profitability may deter entry (because entrants must justify *K*) without pushing incumbents below their shutdown thresholds (which only depend on the cost of covering net operating costs). As such, we would expect to see a relatively smaller change in closures relative to openings.

3.3 Numeric Example

We consider the case of two pharmacies deciding to enter areas that have the same pre-Part D profits and the same expected profits after Part D's implementation. However, one area has a higher share of the customer base comprised of Medicare beneficiaries than the other. Prior to the implementation of Part D, let $\pi_m = 10$ in

[8] When $\mathbb{E}[\pi_m] = \pi_0$, the value to entering is $-K + \pi_0 + \frac{\delta}{1-\delta} \times \pi_0$, which does not depend on σ_m and is therefore equal for both markets.

both markets. We set $K = 50$ and $\delta = 0.95$. Because $\pi_0 \geq 0$, there is no exit at $t = 0$ or $t = 1$.

Medicare Part D will push prices in competing directions, creating uncertainty regarding the expected net profit per Medicare beneficiary at $t = 2$. Moreover, the upside and the downside risks will be larger in the area with more Medicare beneficiaries. To reflect this, let $\sigma_A = 9$ and $\sigma_B = 2$. At time $t = 1$, we have the following expect profit:

$$\pi_A = \begin{cases} 10 + 9 = 19, & \text{with prob. } 1/2 \\ 10 - 9 = 1, & \text{with prob. } 1/2 \end{cases}$$

$$\pi_B = \begin{cases} 10 + 2 = 12, & \text{with prob. } 1/2 \\ 10 - 2 = 8, & \text{with prob. } 1/2 \end{cases}$$

Using these figures, the respective probabilities of each state, and equation (2), we can calculate the value at $t = 1$ of entering the respective markets:

$$V_A^{Enter} = -50 + 10 + \frac{.95}{1 - .95} \times \left[\frac{1}{2} \times 19 + \frac{1}{2} \times 1\right] = 150$$

$$V_B^{Enter} = -50 + 10 + \frac{.95}{1 - .95} \times \left[\frac{1}{2} \times 12 + \frac{1}{2} \times 8\right] = 150$$

Similarly, we can use these figures, the respective probabilities of each state, and equation (3) to calculate the value at $t = 1$ of waiting to enter the markets:

$$V_A^{Enter} = .95 \times \left[\frac{1}{2} \times \max\left(0, \frac{19}{1 - .95} - 50\right) + \frac{1}{2} \times \max\left(0, \frac{1}{1 - .95} - 50\right)\right]$$

$$= .95 \times \left[\frac{330}{2} + \frac{0}{2}\right] = 156.75$$

$$V_B^{Enter} = .95 \times \left[\frac{1}{2}\max\left(0, \frac{12}{1 - .95} - 50\right) + \frac{1}{2}\max\left(0, \frac{8}{1 - .95} - 50\right)\right]$$

$$= .95 \times \left[\frac{190}{2} + \frac{110}{2}\right] = 142.5$$

which shows that the value of waiting is greater in the market where Medicare beneficiaries made up a greater share of the customer person.

Recall that a firm will enter if the value to doing so outweighs the value to waiting. In this setting with $\pi_0 > 0$ in both markets, the entrant will enter in market B at time $t = 1$ as $V_B^{Enter} = 150 > V_B^{Wait} = 142.5$. However, because $V_A^{Enter} = 150 < V_B^{Wait} = 156.75$, the entrant will not enter market A. Once π_m is revealed at $t = 2$, the entry and exit decisions will depend on the realized state. Based on the existing literature, the price reduction will dominate (Duggan and Scott Morton 2010, 2011) resulting in the low- π_m state where $\pi_A = 1$ and $\pi_B = 8$. Since $\pi_A = 1 < K = 50$, the prospective entrant that waited to enter market A will decide it is not worth the sunk cost to enter. Thus, there will be no rebound in potential entrants after $t = 2$. Furthermore, the profit for the incumbent pharmacies remains non-negative in both markets, resulting in no differential exit across markets.

4. Data and Methodology

4.1 National Establishment Time-Series Data

To test our theoretic predictions, we use 2000-2009 National Establishment Time-Series (NETS) data. The NETS is a longitudinal dataset sourced from the Dun & Bradstreet Duns Marketing Information file tracking outcomes and characteristics of over 60 million business establishments in the United States. The data include information on when each establishment opened, when the establishment exited the data due to closure, as well as each establishment's annual sales, number of employees, and location. Importantly, the NETS also contains Standard Industrial Classification (SIC) codes, which allow us to identify retail pharmacies (SIC 5912). The NETS data have previously been used by researchers to explore a variety of topics related to business performance (e.g., Currie et al. 2010; Neumark and Kolko 2010; Neumark et al. 2011; Kolko 2012; Orrenius et al. 2020; Carpenter et al. 2023).

Table 1 provides summary statistics for the outcomes of interest.[9] To ensure that our results are not driven by changes in the composition of counties contributing to identification, we restrict our analyses to a balanced county-year panel. Column 1 reports summary statistics for the full sample. Column 2 reports statistics for counties that had a below-median elderly population in the year 2000 (i.e., counties where elderly adults presumably comprised a smaller share of the customer base). Likewise, column 3 reports statistics for establishments located in counties that had an above-median elderly population in the year 2000 (i.e., counties where elderly adults presumably comprised a larger share of the customer base). On average, we see that counties that had a below-median elderly population in the year 2000 had considerably more pharmacies than counties where a higher share of the population was comprised of elderly adults (26.47 vs. 9.36). One explanation for this is that these younger counties were also considerably larger. When we examine the number of pharmacies per 100,000 individuals within each county, we find that counties where an above-median share of the population was comprised of elderly adults in the year 2000 had more pharmacies per 100,000 people than the below-median counties (18.84 vs. 27.19).

To examine the relationship between Medicare Part D and changes in the number of retail pharmacies, we leverage variation in the share of the county population comprised of elderly individuals through a difference-in-differences identification strategy (Alpert et al. 2023). The intuition behind this empirical decision is that Medicare beneficiaries were more likely to make up a greater share of the customer base in counties with relatively older populations. Specifically, we estimate:

[9] We report summary statistics for the covariates in Appendix Table 1. We obtain data on county-level unemployment rates from the U.S. Bureau of Labor Statistics and county-level population from the National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) Program.

$$Y_{cst} = \alpha + \beta \cdot \mathbf{1}\{\text{ABOVE-MEDIAN SHARE}\}_c \times \mathbf{1}\{\text{Year} \geq 2004\}_t + \mathbf{X}'_{cst}\lambda + \theta_c + \tau_{st} + \varepsilon_{cst} \quad (1)$$

where the dependent variable, Y_{cst}, is the number of pharmacies in county *c* located in state *s* in year *t*. We also examine changes in the number of pharmacy openings and closings. To model the count nature of these data, we estimate equation (1) using a Poisson regression. As such, β measures the change in the natural log of our outcomes of interest.

Our coefficient of interest, β, measures how Medicare Part D differentially affected pharmacy outcomes based on whether the customer base was likely comprised of elderly adults by interacting a variable indicating that the county had an above-median share of the population comprised of adults aged 65 or older in the year 2000, $\mathbf{1}\{\text{ABOVE-MEDIAN SHARE}\}_c$, with a post-period indicator, $\mathbf{1}\{\text{Year} \geq 2004\}_t$. We begin our post-period in 2004 to account for the passage of the Medicare Prescription Drug, Improvement, and Modernization Act in December 2003. Although Part D was not fully implemented until January 2006, beginning our post-period in 2004 accounts for the anticipatory changes in business decisions and drug utilization (Alpert 2016) and interim programs intended to bridge the gap between passage and implementation (Huh and Reif 2017).[10]

We include a vector of county-level economic and demographic characteristics, $\mathbf{X}_{cst}$, to account for time-varying factors that may affect pharmacy outcomes independent of Medicare Part D. These include the county-level unemployment rate, the natural log of the prime-age county population, the share of the prime-age county-level population comprised of Black individuals, and the share of the prime-age county-level population comprised of Hispanic individuals.

[10] Alpert (2016) showed that patients reduced drug utilization for chronic but not acute conditions between Medicare Part D's passage and implementation. Additionally, the Medicare Drug Discount Card and Transitional Assistance Programs began offering prescription discount cards in mid-2004 and provided $1.5 billion on prescription drug subsidies for low-income elderly adults (Huh and Reif 2017).

We account for time-invariant county-level characteristics through the inclusion of county fixed effects, θ_c. Finally, we account for state-level time-varying policies and economic trends through the inclusion of state-by-year fixed effects, τ_{st}. Standard errors are clustered at the county level (Bertrand et al. 2004).

In the presence of our covariates and fixed effects, our identification assumption is that the number of pharmacies in counties with an above-median share of elderly individuals in the year 2000 would have evolved similarly to the number of pharmacies in counties with a below-median share. While fundamentally untestable, we assess the validity of this assumption with the following event study specification:

$$Y_{cst} = \alpha + \sum_{t=2000,\, t\neq 2003}^{2009} \beta^t \cdot \mathbf{1}\{\text{ABOVE-MEDIAN SHARE}\}_c \times \mathbf{1}\{\text{Year} = t\}_t + \mathbf{X}'_{cst}\lambda + \theta_c + \tau_{st} + \varepsilon_{cst} \quad (2)$$

where the coefficients of interest, β^t, measure the evolution of pharmacy outcomes in counties with an above-median concentration of elderly individuals in the year 2000 relative to those counties with a lower concentration. In addition to allowing us to examine differential trends in the pre-period, this specification allows us to model potential dynamic treatment effects.

4.2 National Vital Statistics Mortality Files

Prior work found that Medicare Part D was associated with a reduction in deaths for 66-year-old adults relative to 64-year-old adults (Huh and Reif 2017). To study whether this relationship varied by changes in pharmacy access, we use mortality data from the 2000-2009 National Vital Statistics System of the National Center for Health Statistics.[11] The Vital Statistics data provide us with information on the number of county-level deaths in a given year for each age. Using these data, we estimate the following equation:

[11] We report summary statistics in Appendix Table 2.

$$Y_{acst} = \alpha + \beta \cdot \mathbf{1}\{\text{AGE} = 66\}_a \times \mathbf{1}\{\text{Year} \geq 2004\}_t + \mathbf{X}'_{cst}\lambda + \theta_{ac} + \tau_{st} + \varepsilon_{acst} \quad (3)$$

where the dependent variable, Y_{cat}, is the number of deaths for age *a* in county *c* in state *s* in year *t*. Our coefficient of interest, β, measures whether 66-year-olds experienced a differential mortality reduction relative to their 64-year-old counterparts following the passage of Medicare Part D. There are a few differences relative to our prior specifications. First, the vector $\mathbf{X}_{cst}$ includes the natural log of the county-level population of interest (i.e., the number of 66-year-olds or the number of 64-year-olds) rather than the natural log of the prime-age population. Additionally, we weight the regression by the square root of the size of the relevant population. These modifications align our specification with Huh and Reif (2017). Finally, we include age-by-county fixed effects, θ_{ac}, to capture time-invariant county-level differences in mortality for 66-year-olds relative to 64-year-olds.

5. Results

5.1 Change in the Number of Pharmacies

We begin by examining the relationship between the introduction of Medicare Part D and changes in the size of the retail pharmacy industry. The dependent variable in Table 2 is the number of pharmacies in a county, and we estimate equation (1) as a Poisson model. Column 1 reports the results from a sparse specification including only the natural log of the prime-age population, county fixed effects, and year fixed effects. Column 2 augments this specification with the shares of the prime-age county population comprised of Black and Hispanic individuals. Column 3 accounts for local economic conditions by further including the county-level unemployment rate. Finally, column 4 accounts for state-level time-varying policies and conditions through the inclusion of state-by-year fixed effects. Across all columns, we find that Medicare Part D was associated with a statistically

significant 5.0–5.7-percent reduction in the number of pharmacies ($100 \times (\exp\{-0.059\} - 1) = -5.7$).

Our static difference-in-differences estimate indicates that Medicare Part D reduced the number of retail pharmacies in areas where the customer base was presumably more likely to be comprised of elderly adults. Reassuringly, the dynamic event study estimates in Figure 3 suggest that this reduction was not driven by an existing difference in pharmacy availability. The pre-period estimates are small in magnitude, do not display any downward trend, and are statistically insignificant. Instead, we estimate that the number of pharmacies initially fell by 1.1 to 4.2 percent in the years following Part D's passage but prior to its full implementation.[12] This reduction increased in magnitude following full implementation, such that counties that had a higher share of the population comprised of elderly adults in the year 2000 experienced a 5.7 to 7.3 percent reduction in the number of pharmacies relative to the relatively younger comparison counties ($100 \times (\exp\{-0.076\} - 1) = -7.3$).

To further increase confidence that we are detecting a meaningful relationship between Medicare Part D and a reduction in the number of pharmacies, we adopt a variant of Fisher's (1935) permutation test. First, we match each county to another random county's elderly population share in the year 2000. We then re-estimate equation (1) and save the resulting coefficient. After repeating this process 100 times, we compare the actual estimate to the distribution of these placebo coefficients (Buchmueller et al. 2011; Cunningham and Shah 2018; Churchill 2021). Figure 4 shows that the reduction in the number of pharmacies we estimate as being attributable to the passage of Medicare Part D is well outside of the placebo distribution, indicating that we are unlikely to have obtained this value by chance.[13]

[12] We report these estimates and tests of joint significance in Appendix Table 3.

[13] Appendix Figure 1 plots the coefficient and corresponding confidence intervals for the actual result (dark grey triangle) and the 100 placebo results (light grey circles).

In Appendix Table 4 we show that these results are robust to alternative ways of defining the treatment group, including separating counties into quartiles based on the share of the population comprised of elderly adults in the year 2000 (column 2) and using the continuous population share (column 3). Meanwhile, we show in Appendix Figure 2 that the results are robust to excluding the smallest and largest pharmacies from the data.[14] Likewise, Appendix Figure 3 shows that the results are robust to iteratively excluding observations from each state, alleviating concerns that our results are driven by states with largest shares of older adults, such as Arizona and Florida.

As previously discussed, patients who are dual eligible for both Medicaid and Medicare are required to obtain prescription drug coverage through a Part D plan. Shortly after Medicare Part D's implementation, industry leaders at large chain pharmacies indicated that this shift was adversely affecting their margins (CVS 2006a; Walgreens 2006; Rite Aid 2007a). Likewise, the gross margin for claims dispensed at independent pharmacies was 20–30 percent smaller under Part D plans (Reisetter et al. 2006; Carroll 2008; Winegar et al. 2009). One explanation for this reduction is that patients were shifting from a relatively inelastic purchaser (i.e., the state) where prices were upwardly distorted (Duggan and Scott Morton 2006) to relatively more elastic Part D plans, and Duggan and Scott Morton (2010) showed this shift reduced drug prices for these patients by nearly 20 percent.

If the estimated reduction in the number of pharmacies is due to Part D's relatively lower reimbursement rates, we would expect to detect a larger reduction in areas with a greater concentration of dual-eligible beneficiaries. To test this

[14] Prior work suggests that the sales and employment information in the NETS data may be less reliable for the largest and smallest establishments (Neumark et al. 2005; Barnatchez et al. 2017), particularly establishments with fewer than five employees. While this measurement issue is less of a concern when examining whether the firm exists – relative to studying changes in sales and the number of employees – we follow Barnatchez et al.'s (2017) recommendation and set the lower bounds at 5 and 10 employees. We set the upper bound at 34 employees to exclude pharmacies in the top 5 percent of the employment distribution.

possibility, in Table 3 we fully interact our right-hand side variables with an indicator for whether the county had an above-median county-level poverty rate in the year 2000 (column 1). We find that Medicare Part D was associated with a 2.9-percent reduction in the number of pharmacies in counties that had an above-median share of the population comprised of elderly adults in the year 2000 compared to below-median counties. However, in counties that also had an above-median share of the population living in poverty, we estimate a larger 5.8-percent reduction ($100 \times (\exp\{-0.029 - 0.031\} - 1) = -5.8$).

Prior work has shown that racial and ethnic minority communities have limited access to retail pharmacies compared to non-minoritized communities (Essien et al. 2021; Guadamuz et al. 2021; Guadamuz et al. 2024). In Table 3, we explore whether Medicare Part D inadvertently widened this disparity by fully interacting the right-hand side variables with an indicator for whether the county had an above-median share of the population comprised of Asian, Black, Hispanic, and Other Race/Ethnicity individuals in the year 2000 (column 2). We find that Medicare Part D was associated with a larger reduction in the number of pharmacies in more racially diverse counties. Specifically, we estimate a 3.8-percent reduction in the less racially diverse counties ($100 \times (\exp\{-0.039\} - 1) = -5.8$) and a 7.6-percent reduction in the most racially diverse counties ($100 \times (\exp\{-0.039 - 0.04\} - 1) = -7.6$). Finally, despite concerns that Medicare Part D would disproportionately harm pharmacies located within rural communities (Radford et al. 2007; Radford et al. 2009; Klepser et al. 2011), we do not detect any evidence that Medicare Part D was associated with a larger reduction in the number of pharmacies in rural counties relative to non-rural counties (column 3).

At the time of Medicare Part D's passage, there were also concerns that independent pharmacies would be put at a disadvantage relative to chain establishments. Independent pharmacies tend to operate on smaller margins than their chain counterparts (Berndt and Newhouse 2010), and the average independent

pharmacy receives a higher share of its revenue from prescription drug sales than chain pharmacies (Spooner 2008; Weigel et al. 2013). As a result, independent pharmacies were thought to be particularly vulnerable to reimbursement changes, including patients shifting from being high-margin cash customers to those with insurance and dual-eligible patients shifting from Medicaid to Part D plans. In Table 4, we leverage the fact that the NETS includes information about whether the observation is a standalone (i.e., non-chain) establishment or a non-standalone establishment. Column 1 shows that Medicare Part D was associated with a 7.5-percent reduction in the number of standalone pharmacies and a 3.8-percent reduction in the number of non-standalone pharmacies. These results suggest that the concerns that Medicare Part D would be particularly detrimental to independent pharmacies were justified.

5.2 Change in Openings, Closures, and Pharmacy Age

We have found clear evidence that Medicare Part D was associated with a reduction in the number of pharmacies in counties where elderly individuals were more likely to comprise a larger share of the customer base. In Table 5, we now explore whether these changes were attributable to a reduction in the number of new pharmacy openings and/or an increase in the number of pharmacy closures. We find that Medicare Part D was associated with a statistically significant 8.3-percent reduction ($100 \times (\exp\{-0.087\} - 1) = -8.3$) in the number of new pharmacy openings (column 1). In contrast, the relationship between Medicare Part D and closures is nearly 90 percent smaller in magnitude and statistically insignificant. Together, these results indicate that though Medicare Part D shrank the pharmacy industry in counties where elderly adults were more likely to comprise a larger share of the customer base, it did so primarily by discouraging the formation of new businesses, rather than by closing existing pharmacies.

Our theoretic framework predicted that the uncertainty attributable to the delay between Part D's passage and implementation would increase the value of waiting to open without affecting the likelihood of closure. After Part D was fully implemented, our framework – in conjunction with existing estimates documenting larger reductions in price than increases in utilization – predicts that openings would remain suppressed and that closures could increase. We test these predictions in Figure 5 using our event-study specification to explore the dynamic changes in pharmacy openings (Panel A) and pharmacy closures (Panel B).[15] Prior to the passage of Medicare Part D, there is no evidence that either pharmacy openings or closures were differentially trending in counties where elderly individuals comprised an above-median share of the population relative to counties where they comprised a below-median share. Consistent with the predicted effects of the uncertainty generated by the gap between Part D's passage and implementation, we estimate sizable reductions in the number of pharmacy openings without any change in closures during this period. We do not see a subsequent increase in the number of openings after the uncertainty was resolved and Part D was fully implemented, suggesting that, though uncertainty increased the value of waiting, the subsequent reduction in profitability ultimately discouraged pharmacies from entering the market.[16]

As with our results examining changes in the number of pharmacies, we show in Appendix Table 5 that the reduction in the number of openings is robust to alternative ways of defining treatment status, including using the quartile of the elder share population and using a continuous measure. Similarly, we show in Appendix Table 6 that patterns are robust to excluding the openings and closures

[15] These estimates are also reported in Appendix Table 3.
[16] Because of the reduction in the number of earnings, Appendix Figure 4 shows that the retail pharmacy market in these counties was increasingly dominated by older establishments.

of the smallest and largest establishments, while Appendix Figure 5 shows that the results are robust to the randomization placebo test.[17]

5.3 Change in Mortality

Huh and Reif (2017) found that Medicare Part D was associated with an approximate 2-percent reduction in mortality for 66-year-olds relative to 64-year-olds. Moreover, in a recent working paper, Battles (2026) showed that pharmacy access is an important predictor of medication adherence. Given our findings that Medicare Part D was associated with a reduction in the number of pharmacies in counties where Medicare beneficiaries made up a larger share of the customer base, it is possible that the Part D-driven health benefits identified by Huh and Reif (2017) were at least partially dampened by changes in pharmacy access in these areas. To test this possibility, we use National Vital Statistics data and the difference-in-differences strategy shown in equation (3). However, we do note that changes in the number of pharmacies may have affected mortality for both 66-year-old individuals and their 64-year-old counterparts.

In line with the prior evidence, Table 6 shows that Medicare Part D was associated with a 1.7-percent reduction in mortality for 66-year-old adults relative to their 64-year-old counterparts (column 1). We also find suggestive evidence that this health improvement was smaller in the same counties where we detected a reduction in the number of pharmacies. In counties where elderly adults comprised a below-median share of the population, we estimate a statistically significant 2.1-percent reduction in the number of 66-year-old deaths compared to their 64-year-old counterparts (column 2). In contrast, in counties where elderly adults comprised

[17] Appendix Table 7 shows that the reduction in the number of openings was most pronounced for standalone (i.e., non-chain) pharmacies. In Appendix Table 8, we explore whether Part D affected other aspects of pharmacy performance. We find reductions in county-level pharmacy sales and employment (Panel A). However, we do not find any change when using establishment-level data and with establishment fixed effects (i.e., conditioning on being open). These patterns indicate that the county-level reductions were entirely due to a reduction in the number of pharmacies.

an above-median share of the population, the estimate is over 90 percent smaller in absolute magnitude and statistically insignificant (column 3). Finally, we return to the entire sample but fully interact the right-hand side variables with an indicator for whether elderly individuals made up an above-median share of the county population in the year 2000. We find suggestive evidence that 66-year-olds in the above-median counties did not experience meaningful improvements in mortality, though the estimate is not statistically significant (column 4).[18]

6. Conclusion

Retail pharmacies play a key role in the U.S. health care system. In addition to dispensing prescription medication, pharmacies serve as sources of broader types of patient care, particularly for members of rural, low-income, and racial and ethnic minority communities (McConeghy and Wing 2016; Brownstein et al. 2022; Shakya et al. 2024; Smart et al. 2024). Yet the retail pharmacy industry has experienced significant challenges (Salako et al. 2018; Guadamuz et al. 2019), limiting access for groups vulnerable to health disparities (Essien et al. 2021; Guadamuz et al. 2024). Despite these industry-wide trends and their implications for patient welfare, relatively little is known about the factors driving retail pharmacy business performance.

In this paper, we study the relationship between Medicare Part D and retail pharmacy outcomes. At the time, Part D was the largest healthcare reform in over forty years with several unprecedented program components. These factors, in addition to the multi-year gap between Part D's passage and implementation, resulted in substantial uncertainty about how the legislation would affect the retail

[18] In Appendix Table 9 we examine changes in mortality for men (column 1), women (column 2), white individuals (column 3), and Asian, Black, Hispanic, and all other race/ethnicity individuals (column 4). We find no evidence of mortality improvements in the counties that we showed also experienced a reduction in the number of pharmacies relative to the counterfactual (Panel B). Instead, the public health improvements are concentrated entirely in counties where Medicare beneficiaries comprised a smaller share of the customer base (Panel C).

pharmacy industry. Ultimately, Part D led to modest increases in prescription drug utilization (Lichtenberg and Sun 2007; Ketcham and Simon 2008; Yin et al. 2008; Kaestner and Khan 2012) and sizable reductions in pharmaceutical prices (Duggan and Scott Morton 2010; Duggan and Scott Morton 2011; Lakdawalla and Yin 2015). Our simple theoretic framework indicates that these factors will have reduced the size of the retail pharmacy industry by discouraging firm formation.

Using 2000-2009 National Establishment Time-Series data and a difference-in-difference identification strategy, we show Medicare Part D was associated with a 5-percent reduction in the number of pharmacies located in counties where elderly adults comprised a larger share of the population. The reduction was most pronounced in lower-income areas and in racial and ethnic minority communities, implying that Medicare Part D may have widened disparities in pharmacy access. We then show that this change was driven by a reduction in the number of pharmacy openings; estimates for pharmacy closures are smaller in magnitude and statistically insignificant. Finally, we offer suggestive evidence that the mortality reductions previously attributed to Medicare Part D (Huh and Reif 2017) were dampened by changes in retail pharmacy access. While we find that Medicare Part D was associated with a 2 percent reduction in 66-year-old deaths compared to 64-year-old deaths in counties where elderly adults comprised a smaller share of the population, the estimate for above-median counties is over 50 percent smaller in absolute magnitude and statistically insignificant.

This study is subject to some limitations. First, although the timing of the reduction in the number of pharmacies is consistent with our theoretic predictions regarding the roles of increased uncertainty and lower profitability, we are unable to directly identify the pathway through which Medicare Part D discouraged business formation (e.g., lower reimbursement rates, additional administrative burdens, etc.). Although prior work has largely focused on demonstrating the

degree to which Medicare Part D reduced pharmaceutical prices (Zhang et al. 2009; Lakdawalla and Yin 2015), identifying the relative importance of alternative channels remains an important area for future research. Second, because our sample period includes the years immediately following the introduction of Medicare Part D, we are unable to determine whether the estimated relationships have been affected by more recent health care reform efforts. The Inflation Reduction Act of 2022 included several provisions intended to lower prescription drug prices (Cubanski et al. 2023), and it will be important to study whether this reform similarly discourages growth in the retail pharmacy industry. Despite these limitations, this study provides important new evidence that Medicare Part D has stunted growth of the retail pharmacy industry at a time when patients are more frequently turning to pharmacies as a source of preventive care.

7. References

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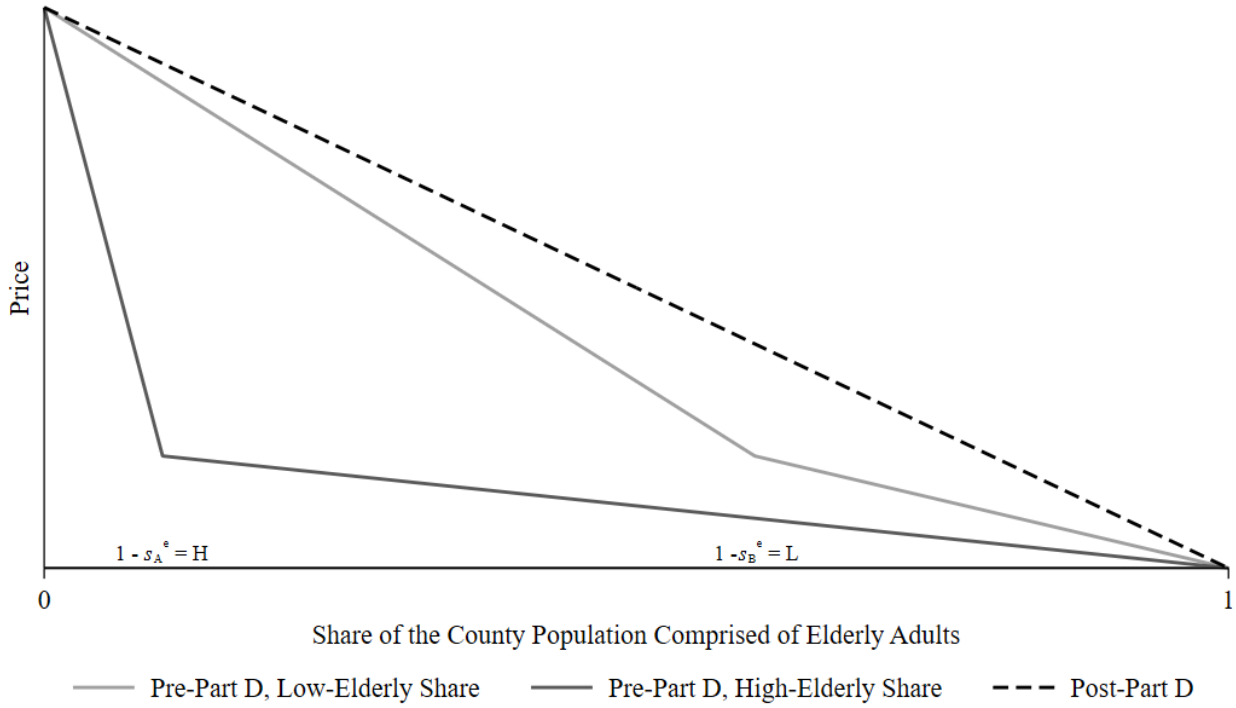
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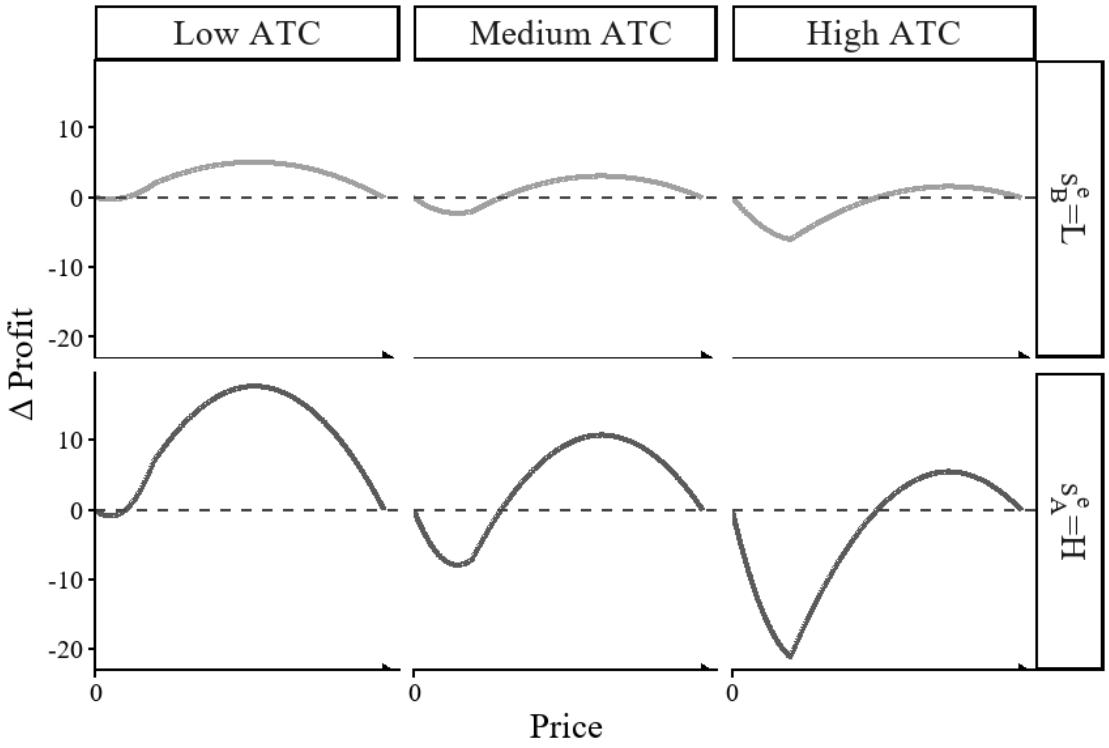
8. Figures

Figure 1: Prescription Drug Demand Before and After Medicare Part D



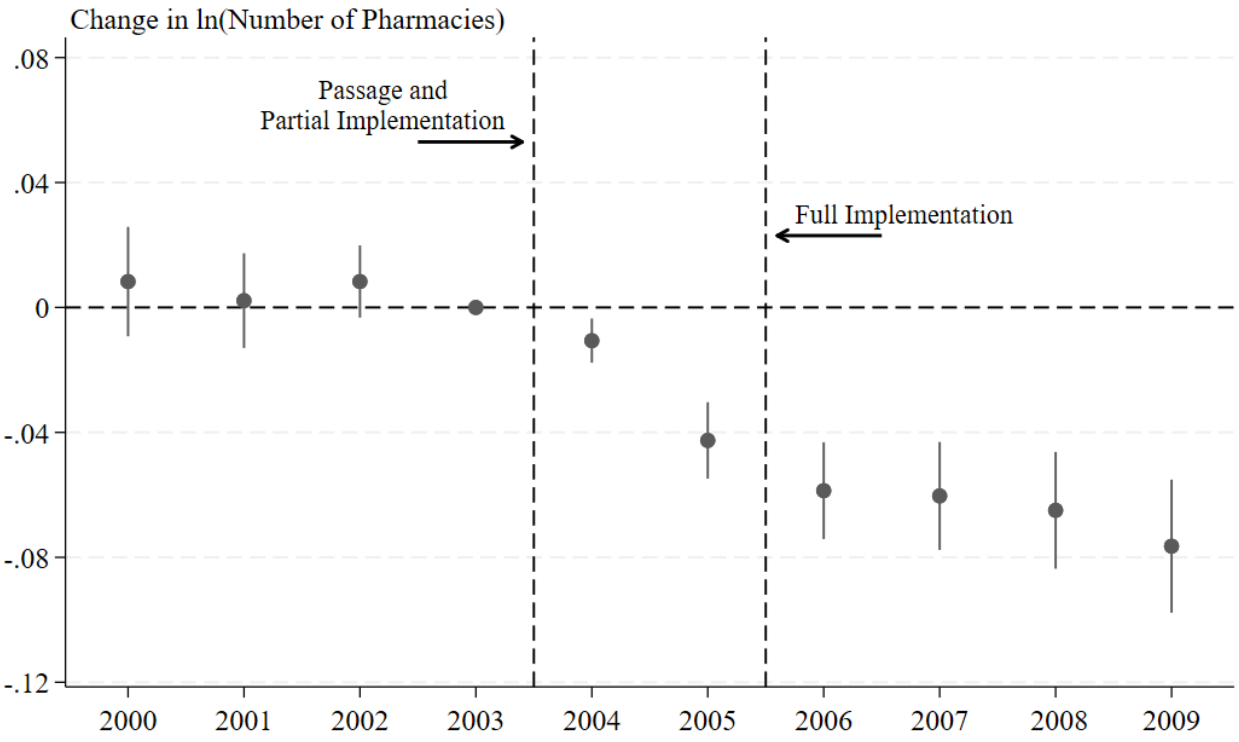
Note: The figure plots the pre-Part D inverse demand curves for market *A* (high-elderly share, solid dark grey) and market *B* (low-elderly share, solid light grey). The horizontal axis is the quantity share of the population served; the vertical axis is price, which can be thought of as either pharmaceutical list price or pharmacy reimbursement price. The kink occurs at quantity $(1 - s^e_m)$, reflecting the transition from the insured non-elderly population to the uninsured elderly population. The post-Part D curve is linear with no kink (dashed black), reflecting universal insurance coverage. The gap between the pre- and post-Part D curves is larger for market *A* at every price, reflecting its higher elder share.

Figure 2: Change in Profit Across Markets, Prices, and Average Total Cost



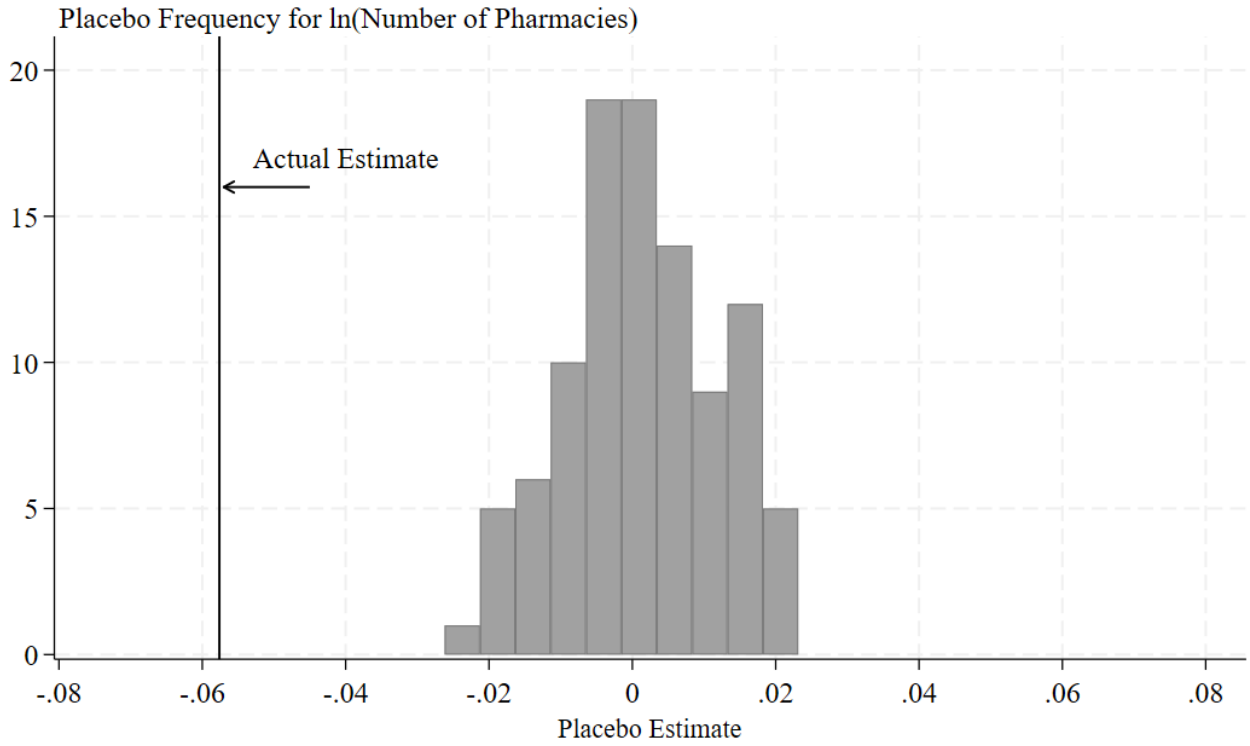
Note: Each panel plots the change in profit, calculated as the post-Part D profit less the pre-Part D profit, for a range of price values on the horizontal axis. Profit is defined as (P-ATC)*Q(p), where Q is the demand function. ATC values vary from low, medium, and high and correspond to the figure column. Pre-part D demand depends on the market and corresponds to the market *B* light grey line in Figure 1 for the top row of this figure, and to the market *A* dark grey line in Figure 1 for the bottom row of this figure.

Figure 3: Medicare Part D Was Associated with a Reduction in the Number of Pharmacies



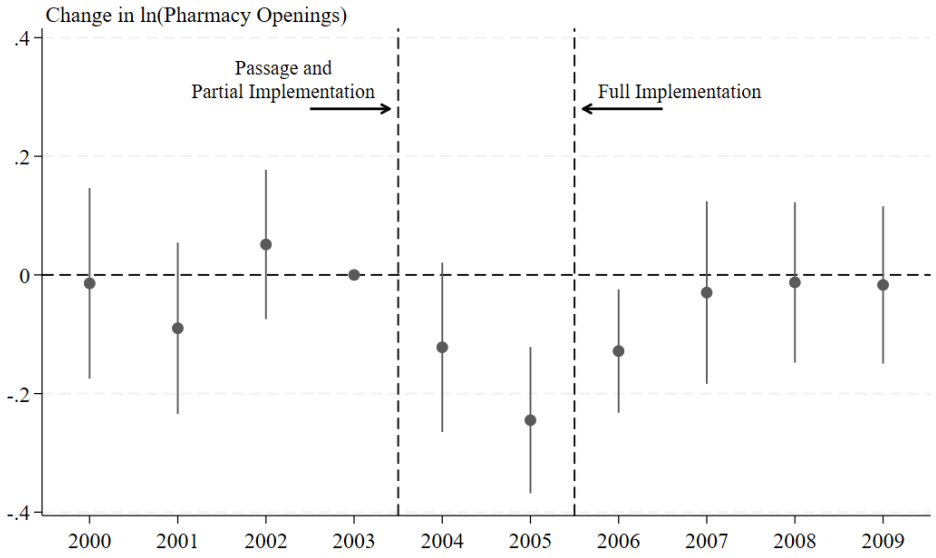
Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The grey circles indicate the coefficients and the vertical lines the 95 percent confidence intervals obtained from the event study specification shown in equation (2) comparing counties that had an above-median share of the population comprised of elderly adults in the year 2000 to counties that had a below-median share. The regression is estimated using a Poisson specification, so the results are interpreted as changes in natural log of the dependent variable. Standard errors are clustered at the county level.

Figure 4: The Relationship Between Medicare Part D and the Number of Pharmacies is Robust to Randomization Inference

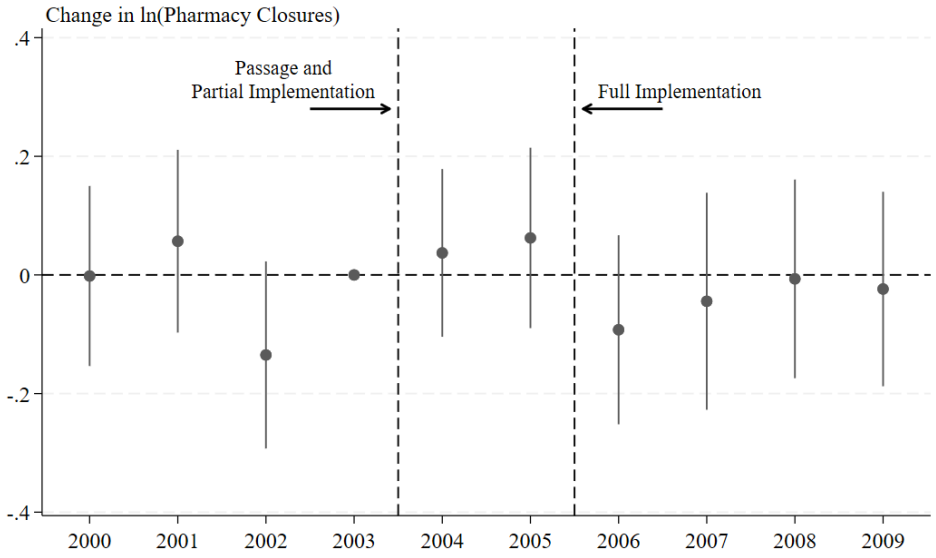


Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The independent variable of interest captures how the number of pharmacies changed following the passage of Medicare Part D in counties with an above-median share of the population comprised of elderly adults in the year 2000 relative to counties with a below-median share. The regressions include the full set of controls from equation (1). Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. The histogram plots the distribution of placebo coefficients obtained from 100 iterations randomly matching each county to a county population share in the year 2000. These placebo estimates and their confidence intervals are also plotted in Appendix Figure 2. The estimate we use from the correct match between counties and their population shares, shown in the vertical black line, are outside the placebo distribution, indicating that the result was unlikely to have been obtained by chance.

Figure 5: Medicare Part D Was Associated with a Reduction in the Number of Pharmacy Openings



(A)



(B)

Source: National Establishment Time-Series, 2000-2009.

Note: The dependent variable in Panel A is the number of pharmacy openings in a county. The dependent variable in Panel B is the number of pharmacy closures in a county. The grey circles indicate the coefficients and the vertical lines the 95 percent confidence intervals obtained from the event study specification shown in equation (2) comparing counties that had an above-median share of the population comprised of elderly adults in the year 2000 to counties that had a below-median share. The regression is estimated using a Poisson specification, so the results are interpreted as changes in natural log of the dependent variable. Standard errors are clustered at the county level.

9. Tables

Table 1: Summary Statistics

	(1)	(2)	(3)
Sample →	Overall	Below-Median Share	Above-Median Share
Pharmacies	17.98	26.47	9.36
	(58.05)	(76.87)	(25.48)
Openings	1.32	2.06	0.56
	(5.85)	(7.77)	(2.57)
Closures	0.74	1.12	0.36
	(2.68)	(3.48)	(1.38)
Pharmacies per 100K	22.99	18.84	27.19
	(13.78)	(9.17)	(16.19)
Openings per 100K	1.05	1.08	1.02
	(2.68)	(1.98)	(3.24)
Closures per 100K	0.74	0.70	0.79
	(2.24)	(1.60)	(2.74)
Observations	29,340	14,770	14,570

Source: National Establishment Time-Series, 2000-2009.
Note: The table reports the sample mean and standard deviations (in parentheses).

Table 2: Medicare Part D was Associated with a Reduction in the Number of Retail Pharmacies in Counties with an Above-Median Elderly Population in the Year 2000

	(1)	(2)	(3)	(4)
1{Year ≥ 2004} ×	-0.059***	-0.051***	-0.051***	-0.058***
1{High Share 65+ in 2000}	(0.016)	(0.014)	(0.014)	(0.009)
Psuedo-R^2	0.919	0.919	0.919	0.919
Observations	29,340	29,340	29,340	29,340
County and Year FE?	Y	Y	Y	Y
ln(Prime-Age County Population)?	Y	Y	Y	Y
Prime-Age County Demographics?		Y	Y	Y
County Unemployment Rate?			Y	Y
State-by-Year FE?				Y

Source: National Establishment Time-Series, 2000-2009.

Note: The estimates are obtained via the Poisson specification shown in equation (1). The dependent variable is the number of pharmacies in a county. The independent variable of interest is an indicator for the passage of Medicare Part D interacted with an indicator for whether the county had an above-median share of elderly adults in the year 2000. All columns include county and year fixed effects. Column 1 also includes the natural log of the county-level prime-age population. County 2 further includes county-level demographic characteristics, including the share of the prime-age county population comprised of Black individuals and the share of the prime-age county population comprised of Hispanic individuals. Column 3 further includes the county-level unemployment rate. Finally, column 4 includes state-by-year fixed effects. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 3: Medicare Part D was Associated with a Larger Reduction in the Number of Pharmacies in Racial and Ethnic Minority Communities and in Poorer Communities

	(1)	(2)	(3)
1{Year ≥ 2004} ×	-0.029***	-0.039***	-0.046***
1{High Share 65+ in 2000}	(0.011)	(0.012)	(0.011)
1{Year ≥ 2004} ×	-0.031*		
1{High Share 65+ in 2000} ×	(0.017)		
1{High Share Poverty in 2000}			
1{Year ≥ 2004} ×		-0.040**	
1{High Share 65+ in 2000} ×		(0.018)	
1{High Share Non-White in 2000}			
1{Year ≥ 2004} ×			0.026
1{High Share 65+ in 2000} ×			(0.019)
1{Rural Counties}			
Psuedo-R^2	0.919	0.919	0.919
Observations	29,340	29,340	29,340

Source: National Establishment Time-Series, 2000-2009.
Note: The estimates are obtained via a modified version of Poisson specification shown in equation (1) that fully interacts all the right-hand side variables with an indicator for being in a particular group of interest. In column 1 the indicator denotes whether the county had an above-median share of the population living in poverty in the year 2000, in column 2 the indicators denotes whether the county had an above-median share of the population comprised of Asian, Black, Hispanic, and all other non-white individuals in the year 2000, and in column 3 the indicator denotes whether the county is rural (i.e., "noncore"). The dependent variable is the number of pharmacies in a county. All columns include county and year fixed effects, county-level demographic and economic controls, and state-by-year fixed effects that are interacted with the indicator of interest. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 4: Medicare Part D was Associated with a Reduction in Both Standalone and Non-Standalone Pharmacies

	(1)	(2)
Sample →	Standalone Pharmacies	Non-Standalone Pharmacies
1{Year ≥ 2004} ×	-0.078***	-0.039***
1{High Share 65+ in 2000}	(0.013)	(0.012)
Psuedo-R^2	0.877	0.877
Observations	29,340	29,340

Source: National Establishment Time-Series, 2000-2009.
Note: The estimates are obtained via the Poisson specification shown in equation (1). The dependent variable is the number of pharmacies in a county. The independent variable of interest is an indicator for the passage of Medicare Part D interacted with an indicator for whether the county had an above-median share of elderly adults in the year 2000. All columns include county and year fixed effects, county-level demographic and economic controls, and state-by-year fixed effects. Column 1 explores changes among standalone (i.e., non-chain) pharmacies, while column 2 explores changes among non-standalone pharmacies. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 5: Medicare Part D was Associated with a Reduction in the Number of Pharmacy Openings

	(1)	(2)
Outcome →	Openings	Closures
1{Year ≥ 2004} ×	-0.087**	0.010
1{High Share 65+ in 2000}	(0.037)	(0.041)
Psuedo-R^2	0.718	0.581
Observations	29,340	29,340

Source: National Establishment Time-Series, 2000-2009.
Note: The estimates are obtained via the Poisson specification shown in equation (1). The dependent variable in column 1 is the number of pharmacy openings in a county, and the dependent variable in column 2 is the number of pharmacy closures in a county. The independent variable of interest is an indicator for the passage of Medicare Part D interacted with an indicator for whether the county had an above-median share of elderly adults in the year 2000. All columns include county and year fixed effects, county-level demographic and economic controls, and state-by-year fixed effects. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 6: Suggestive Evidence That Medicare Part D Was Associated with a Smaller Mortality Reduction in Counties Experiencing a Reduction in the Number of Pharmacies

	(1)	(2)	(3)	(4)
Sample →	All Counties	Counties with a Low Share 65+ in 2000	Counties with a High Share 65+ in 2000	All Counties
1{Year ≥ 2004} × **1**{Age = 66}	-0.017***	-0.021***	-0.002	-0.021***
	(0.007)	(0.007)	(0.013)	(0.007)
1{Year ≥ 2004} × **1**{Age = 66} × **1**{High Share 65+ in 2000}				0.019
				(0.015)
Pseudo-R^2	0.846	0.867	0.747	0.846
Observations	58,660	29,520	29,140	58,660

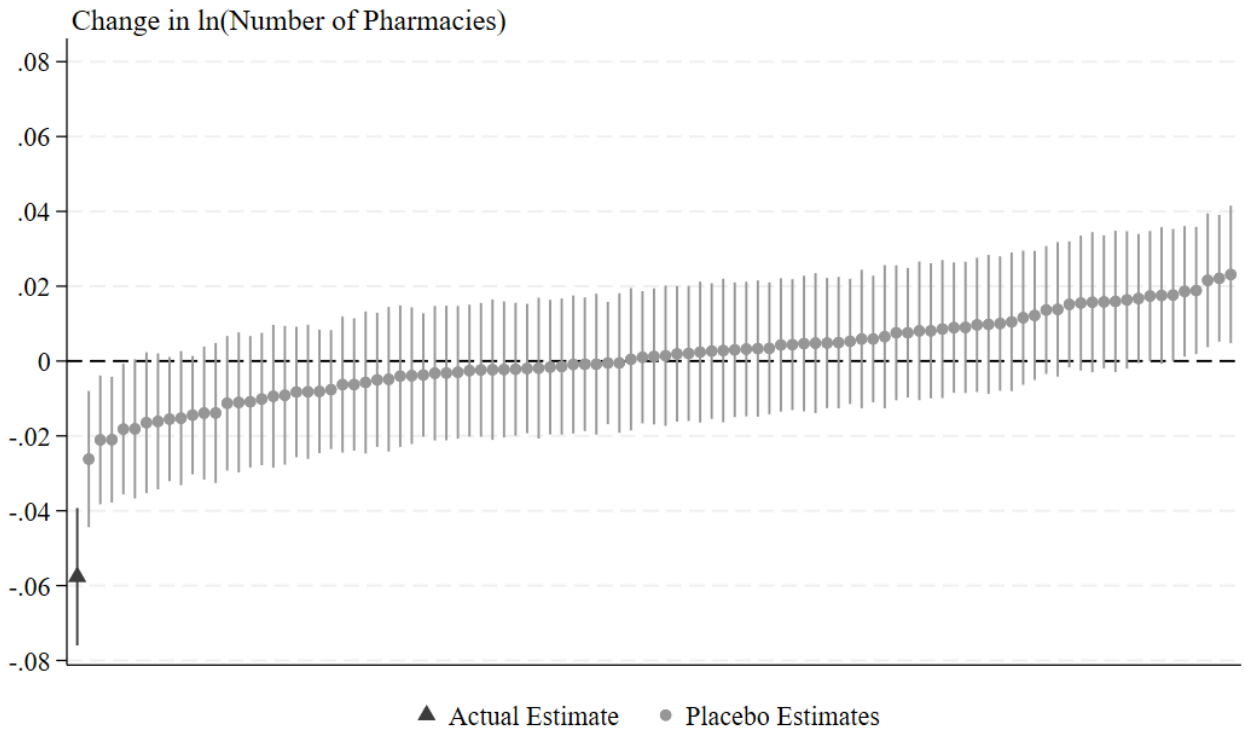
Source: Vital Statistics Mortality Files, 2000-2009.

Note: The dependent variable is the number of county-level deaths in a given year. The independent variable of interest is an indicator for the passage of Medicare Part D interacted with an indicator for being aged 66. The estimates are obtained from equation (4) comparing changes for those aged 66 to the changes for those aged 64. All columns include county fixed effects, county-level demographic and economic controls, and state-by-year fixed effects. Following Huh and Reif (2017), the regressions are weighted by the square root of the population. Column 1 examines all counties, column 2 examines counties that had an above-median share of the population comprised of adults aged 65 or older in the year 2000, and column 3 examines counties that had a below-median share of the population comprised of elderly adults in the year 2000. Column 4 examines all counties but modifies equation (5) by interacting all of the right-hand side variables with an indicator for whether the county had a above-median share of the population comprise of elderly adults in the year 2000. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

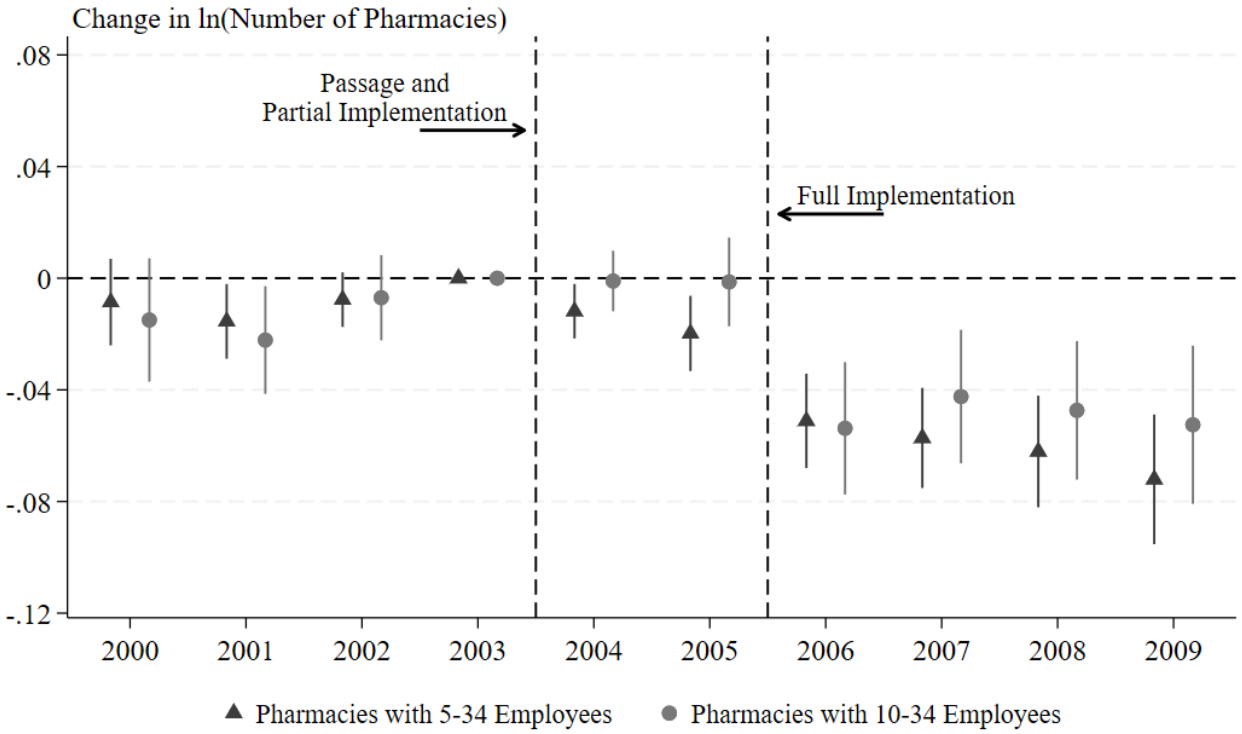
10. Appendix Figures

Appendix Figure 1: Comparison of the Actual Result to 100 Placebo Estimates



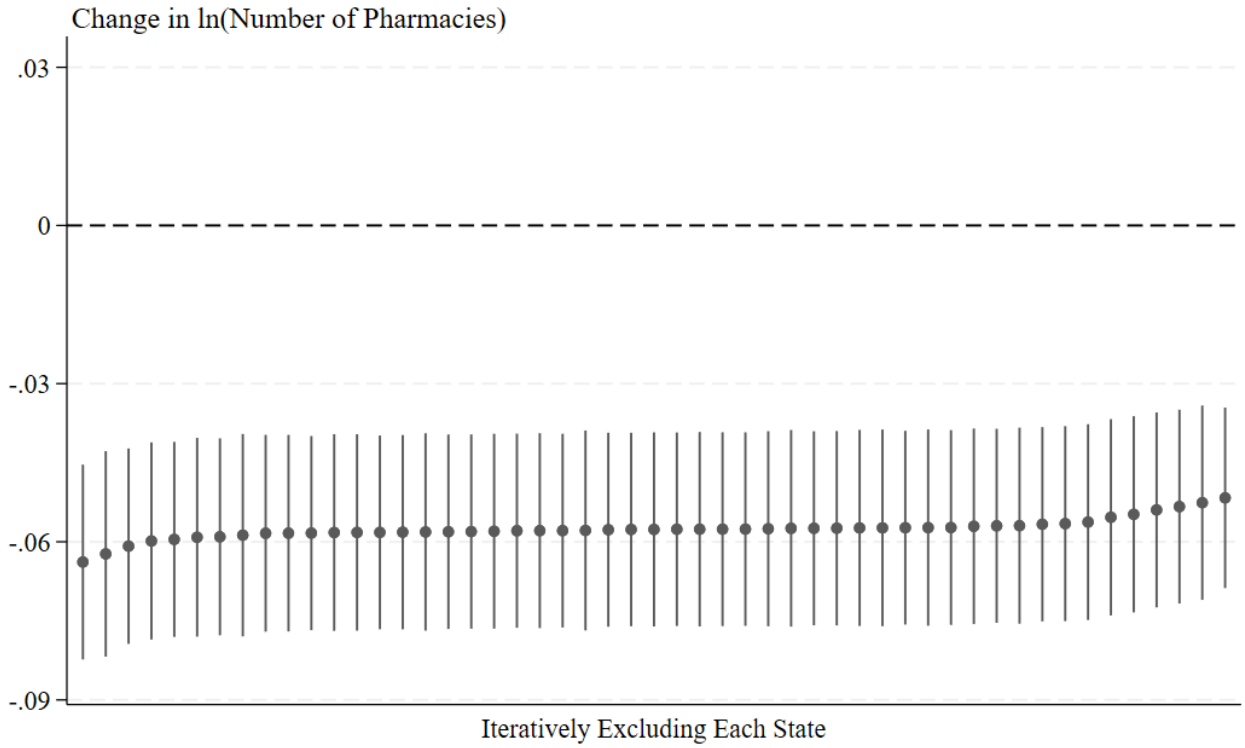
Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The independent variable of interest captures how the number of pharmacies changed following the passage of Medicare Part D in counties with an above-median share of the population comprised of elderly adults in the year 2000 relative to counties with a below-median share. The regressions include the full set of controls from equation (1). Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. The light grey circles denote the placebo coefficients obtained from 100 iterations randomly matching each county to a county population share in the year 2000, while the vertical lines denote the corresponding 95 percent confidence interval. The dark grey triangle indicates the estimate obtained when matching counties to their actual population shares.

Appendix Figure 2: The Relationship Between Medicare Part D and the Number of Pharmacies is Robust to Excluding the Smallest and Largest Establishments



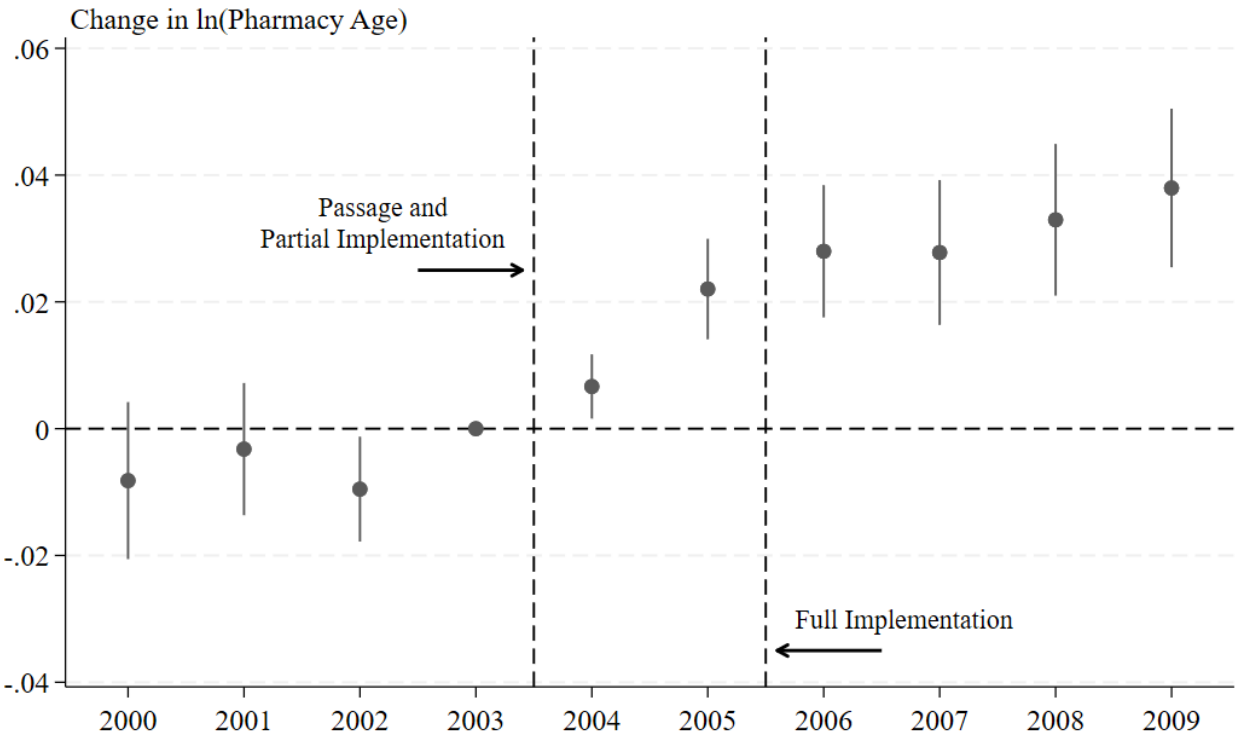
Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The markers indicate the coefficients and the vertical lines the 95 percent confidence intervals obtained from the event study specification shown in equation (2) comparing counties that had an above-median share of the population comprised of elderly adults in the year 2000 to counties that had a below-median share. The regression is estimated using a Poisson specification, so the results are interpreted as changes in natural log of the dependent variable. The dark grey triangles denote results where the sample is limited to pharmacies with 5-34 employees, while the light grey circles denote results where the sample is limited to pharmacies with 10-34 employees. Standard errors are clustered at the county level.

Appendix Figure 3: The Relationship Between Medicare Part D and the Number of Pharmacies is Robust to Iteratively Excluding Observations from Each State



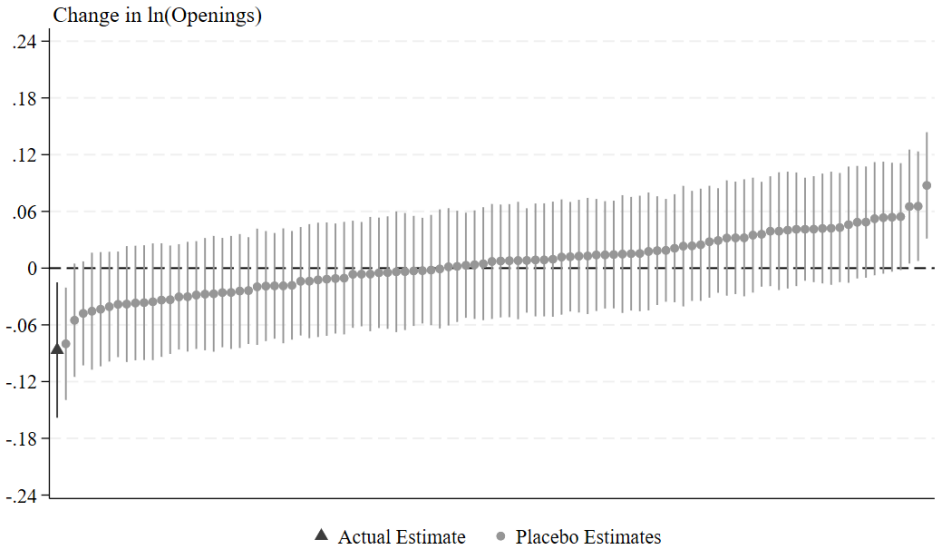
Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The independent variable of interest captures how the number of pharmacies changed following the passage of Medicare Part D in counties with an above-median share of the population comprised of elderly adults in the year 2000 relative to counties with a below-median share. The regressions include the full set of controls from equation (1). Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. The grey circles denote the point estimates and the vertical lines the corresponding 95 percent confidence interval. The figure plots the distribution estimates obtained from iteratively excluding observations from each state that are ordered from smallest to largest (in absolute magnitude). Standard errors are clustered at the county level.

Appendix Figure 4: Medicare Part D Was Associated with an Increase in Pharmacy Age

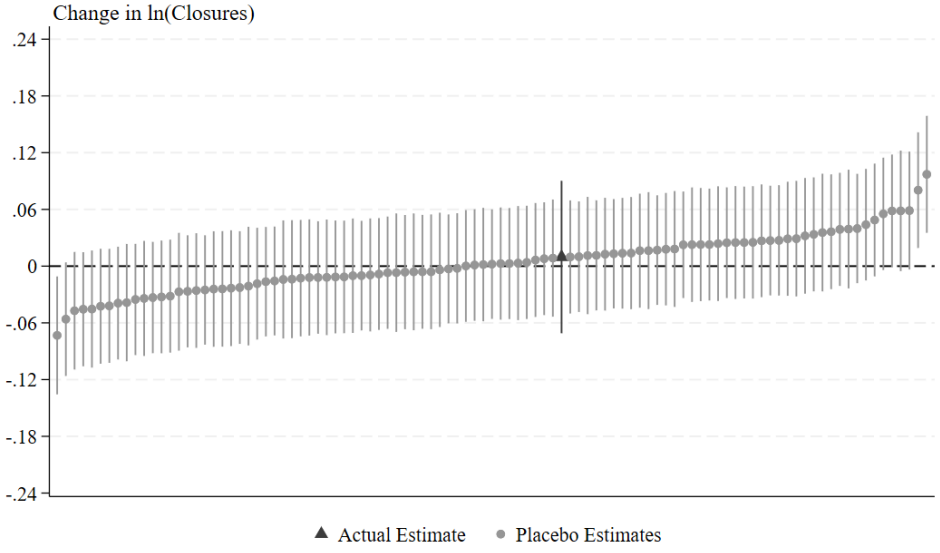


Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the age of the pharmacy. The grey circles indicate the coefficients and the vertical lines the 95 percent confidence intervals obtained from a modified version of the event study specification shown in equation (4) comparing counties that had an above-median share of the population comprised of elderly adults in the year 2000 to counties that had a below-median share. Rather than include establishment fixed effects, the regression utilizes county fixed effects and allows the composition of establishments contributing to identification to change over time capture changes in entry/exit. The regression is estimated using a Poisson specification, so the results are interpreted as changes in natural log of the dependent variable. Standard errors are clustered at the county level.

Appendix Figure 5: Comparisons of the Actual Relationship Between Medicare Part D and Changes in Pharmacy Openings and Closings to 100 Placebo Estimates



(A)



(B)

Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable in Panel A is the number of pharmacy openings in a county, and the dependent variable in Panel B is the number of pharmacy closures in a county. The independent variable of interest captures how the number of pharmacies changed following the passage of Medicare Part D in counties with an above-median share of the population comprised of elderly adults in the year 2000 relative to counties with a below-median share. The regressions include the full set of controls from equation (1). Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. The light grey circles denote the placebo coefficients obtained from 100 iterations randomly matching each county to a county population share in the year 2000, while the vertical lines denote the corresponding 95 percent confidence interval. The dark grey triangle indicates the estimate obtained when matching counties to their actual population shares.

11. Appendix Tables

Appendix Table 1: Summary Statistics of Control Variables for NETS Regressions

	(1)	(2)	(3)
Sample →	Overall	Below-Median Share	Above-Median Share
ln(Prime-Age Population)	10.39	10.94	9.83
	(1.33)	(1.30)	(1.12)
Share Black	0.093	0.127	0.059
	(0.146)	(0.166)	(0.113)
Share Hispanic	0.071	0.091	0.050
	(0.124)	(0.149)	(0.113)
Unemployment Rate	5.75	5.86	5.64
	(2.36)	(2.45)	(2.25)
Observations	29,340	14,770	14,570

Source: National Establishment Time-Series, 2000-2009.
Note: The table reports the sample mean and standard deviations (in parentheses).

Appendix Table 2: Summary Statistics for Vital Statistics Mortality Data

	(1)	(2)	(3)
Sample →	Overall	Below-Median Share	Above-Median Share
Panel A: 66-Year-Old Deaths			
Overall	333,056	241,572	91,484
Male	192,374	138,873	53,501
Female	140,682	102,699	37,983
White	276,897	193,436	83,461
Non-White	56,159	48,136	8,023
Panel B: 64-Year-Old Deaths			
Overall	309,949	226,347	83,602
Male	181,373	131,543	49,830
Female	128,576	94,804	33,772
White	255,360	179,558	75,802
Non-White	54,589	46,789	7,800

Source: National Establishment Time-Series, 2000-2009.
Note: The table reports the sample mean and standard deviations (in parentheses).

Appendix Table 3: Event Study Estimates

	(1)	(2)	(3)
Outcome →	ln(Establishments)	ln(Openings)	ln(Closures)
Pre-Period			
1{Year = 2000} ×	0.008	-0.014	-0.002
1{Above-Median Share}	(0.009)	(0.082)	(0.077)
1{Year = 2001} ×	0.002	-0.090	0.057
1{Above-Median Share}	(0.008)	(0.074)	(0.079)
1{Year = 2002} ×	0.008	0.051	-0.135*
1{Above-Median Share}	(0.006)	(0.064)	(0.080)
Post-Period			
1{Year = 2004} ×	-0.011***	-0.122*	0.037
1{Above-Median Share}	(0.004)	(0.073)	(0.072)
1{Year = 2005} ×	-0.043***	-0.245***	0.062
1{Above-Median Share}	(0.006)	(0.063)	(0.078)
1{Year = 2006} ×	-0.059***	-0.128**	-0.092
1{Above-Median Share}	(0.008)	(0.053)	(0.081)
1{Year = 2007} ×	-0.060***	-0.030	-0.044
1{Above-Median Share}	(0.009)	(0.079)	(0.093)
1{Year = 2008} ×	-0.065***	-0.013	-0.007
1{Above-Median Share}	(0.010)	(0.069)	(0.085)
1{Year = 2009} ×	-0.076***	-0.017	-0.024
1{Above-Median Share}	(0.011)	(0.068)	(0.084)
Pre = 0?	F = 6.93	F = 2.69	F = 5.81
	p = 0.074	p = 0.442	p = 0.121
Post = 0?	F = 72.10	F = 28.61	F = 5.480
	p = 0.000	p = 0.000	p = 0.484
Pre = Post?	F = 78.30	F = 36.93	F = 10.52
	p = 0.000	p = 0.000	p = 0.310
Observations	29,340	29,340	29,340

Source: National Establishment Time-Series, 2000-2009.

Note: The dependent variable in column 1 is the number of pharmacies in a county, in column 2 the number of pharmacy openings, and in column 3 the number of pharmacy closures. The estimates are obtained from the event study specification shown in equation (2) comparing counties that had an above-median share of the population comprised of elderly adults in the year 2000 to counties that had a below-median share. The regression is estimated using a Poisson specification, so the results are interpreted as changes in natural log of the dependent variable. The F-tests for Pre = 0 evaluate whether pre-period coefficients are jointly zero, the tests for Post = 0 assess the joint significance of post-period effects, and Pre = Post evaluates for differences on average coefficient between pre and post period. Standard errors, shown in parentheses, are clustered at the county level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Appendix Table 4: The Relationship Between Medicare Part D and the Number of Pharmacies is Robust to Alternative Ways of Specifying the Independent Variable

	(1)	(2)	(3)
1{Year ≥ 2004} × **1**{High Share 65+ in 2000}	-0.058*** (0.009)		
1{Year ≥ 2004} × **1**{Q2 Share 65+ in 2000}		-0.048*** (0.011)	
1{Year ≥ 2004} × **1**{Q3 Share 65+ in 2000}		-0.080*** (0.012)	
1{Year ≥ 2004} × **1**{Q4 Share 65+ in 2000}		-0.085*** (0.013)	
1{Year ≥ 2004} × Share 65+ in 2000			-1.024*** (0.130)
Psuedo-R^2	0.919	0.919	0.919
Observations	29,340	29,340	29,340

Source: National Establishment Time-Series, 2000-2009.

Note: The estimates are obtained via the Poisson specification shown in equation (1). The dependent variable in column 1 is the number of pharmacies in a county, the dependent variable in column 2 is the number of pharmacy openings in a county, and the dependent variable in column 3 is the number of pharmacy closures in a county. The independent variable of interest in column 1 is an indicator for the passage of Medicare Part D interacted with an indicator for whether the county had an above-median share of elderly adults in the year 2000. The independent variables of interest in column 2 are the interaction of the post-period indicator with indicators for whether the share of the county population comprised of elderly individuals in the year 2000 was in the 2nd, 3rd, or 4th quartile. The independent variable of interest in column 3 is the post-period indicator interacted with the share of the county population in the year 2000 comprised of elderly individuals. All columns include county and year fixed effects, county-level demographic and economic controls, and state-by-year fixed effects. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Appendix Table 5: The Relationship Between Medicare Part D and the Number of Pharmacy Openings is Robust to Alternative Ways of Specifying the Independent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in ln(Openings)			Change in ln(Closures)		
1{Year ≥ 2004} ×	-0.087**			0.010		
1{High Share 65+ in 2000}	(0.037)			(0.041)		
1{Year ≥ 2004} ×		-0.056			-0.076**	
1{Q2 Share 65+ in 2000}		(0.037)			(0.036)	
1{Year ≥ 2004} ×		-0.137***			-0.055	
1{Q3 Share 65+ in 2000}		(0.045)			(0.053)	
1{Year ≥ 2004} ×		-0.071			0.020	
1{Q4 Share 65+ in 2000}		(0.063)			(0.057)	
1{Year ≥ 2004} ×			-0.805			-0.169
Share 65+ in 2000			(0.509)			(0.480)
Psuedo-R^2	0.718	0.718	0.718	0.581	0.581	0.581
Observations	29,340	29,340	29,340	29,340	29,340	29,340

Source: National Establishment Time-Series, 2000-2009.

Note: The estimates are obtained via the Poisson specification shown in equation (1). The dependent variable in columns 1-3 is the number of pharmacy openings in a county, and the dependent variable in columns 4-6 is the number of pharmacy closures in a county. The independent variable of interest in column 1 is an indicator for the passage of Medicare Part D interacted with an indicator for whether the county had an above-median share of elderly adults in the year 2000. The independent variables of interest in column 2 are the interaction of the post-period indicator with indicators for whether the share of the county population comprised of elderly individuals in the year 2000 was in the 2nd, 3rd, or 4th quartile. The independent variable of interest in column 3 is the post-period indicator interacted with the share of the county population in the year 2000 comprised of elderly individuals. All columns include county and year fixed effects, county-level demographic and economic controls, and state-by-year fixed effects. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level.

*** p < 0.01, ** p < 0.05, * p < 0.10

Appendix Table 6: The Relationship Between Medicare Part D and the Number of Pharmacy Openings is Robust to Excluding the Smallest and Largest Establishments

	(1)	(2)	(3)	
Outcome →	Change in ln(Openings)		Change in ln(Closures)	
Sample →	Pharmacies with 5-34 Employees	Pharmacies with 10-34 Employees	Pharmacies with 5-34 Employees	Pharmacies with 10-34 Employees
1{Year ≥ 2004} ×	-0.158**	-0.104	0.001	0.050
1{High Share 65+ in 2000}	(0.063)	(0.084)	(0.049)	(0.066)
Psuedo-R^2	0.556	0.550	0.467	0.431
Observations	29,340	29,340	29,340	29,340

Source: National Establishment Time-Series, 2000-2009.

Note: The estimates are obtained via the Poisson specification shown in equation (1). The dependent variable in columns 1 and 2 is the number of pharmacy openings in a county, and the dependent variable in columns 3 and 4 is the number of pharmacy closures in a county. The independent variable of interest is an indicator for the passage of Medicare Part D interacted with an indicator for whether the county had an above-median share of elderly adults in the year 2000. All columns include county and year fixed effects, county-level demographic and economic controls, and state-by-year fixed effects. Columns 1 and 3 only consider establishments with 5-34 employees, while columns 2 and 4 only consider establishments with 10-24 employees. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Appendix Table 7: Medicare Part D was Associated with a Reduction in Both Standalone and Non-Standalone Openings

	(1)	(2)
Sample →	Standalone Pharmacies	Non-Standalone Pharmacies
	Panel A: Change in ln(Openings)	
1{Year ≥ 2004} ×	-0.111**	-0.038
1{High Share 65+ in 2000}	(0.045)	(0.059)
Psuedo-R^2	0.680	0.590
Observations	29,340	29,340
	Panel B: Change in ln(Closures)	
1{Year ≥ 2004} ×	-0.119*	0.137**
1{High Share 65+ in 2000}	(0.064)	(0.060)
Psuedo-R^2	0.510	0.477
Observations	29,340	29,340

Source: National Establishment Time-Series, 2000-2009.
Note: The estimates are obtained via the Poisson specification shown in equation (1). The dependent variable in Panel A is the number of pharmacy openings in a county, and the dependent variable in Panel B is the number of pharmacy closures in a county. The independent variable of interest is an indicator for the passage of Medicare Part D interacted with an indicator for whether the county had an above-median share of elderly adults in the year 2000. All columns include county and year fixed effects, county-level demographic and economic controls, and state-by-year fixed effects. Column 1 explores changes among standalone (i.e., non-chain) pharmacies, while column 2 explores changes among non-standalone pharmacies. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level.
*** p < 0.01, ** p < 0.05, * p < 0.10

Appendix Table 8: Medicare Part D was Unrelated to Changes in Sales Conditional on Being Open

	(1)	(2)
Outcome →	ln(Sales)	ln(Number of Employees)
	Panel A: County-Level Analysis	
1{Year ≥ 2004} ×	-0.050***	-0.029**
1{High Share 65+ in 2000}	(0.014)	(0.012)
R^2	0.978	0.979
Observations	29,340	29,340
	Panel B: Establishment-Level Analysis	
1{Year ≥ 2004} ×	0.003	0.003
1{High Share 65+ in 2000}	(0.005)	(0.004)
R^2	0.943	0.947
Observations	527,401	527,401

Source: National Establishment Time-Series, 2000-2009.

Note: The estimates are obtained from equation (3) estimated via ordinary least squares. The dependent variable in column 1 is the natural log of pharmacy sales, while the dependent variable in column 2 is the natural log of the number of pharmacy employees. The independent variable of interest is an indicator for the passage of Medicare Part D interacted with an indicator for whether the county had an above-median share of elderly adults in the year 2000. Panel A examines all pharmacies, Panel B limits the sample to standalone (i.e., non-chain) pharmacies, and Panel C limits the sample to non-standalone pharmacies. All columns include establishment and year fixed effects, county-level demographic and economic controls, and state-by-year fixed effects. Standard errors, shown in parentheses, are clustered at the county level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Appendix Table 9: Medicare Part D and Mortality, by Demographic Characteristics

	(1)	(2)	(3)	(4)
Outcome →	Male	Female	White	Non-White
		Panel A: All Counties		
1{Year ≥ 2004} × **1**{Age = 66}	-0.014	-0.028**	-0.019***	-0.013
	(0.009)	(0.012)	(0.006)	(0.026)
Pseudo-R^2	0.894	0.874	0.902	0.907
Observations	58,660	58,660	58,660	58,660
	Panel B: Counties with a High Share 65+ in the Year 2000			
1{Year ≥ 2004} × **1**{Age = 66}	-0.013	0.007	-0.006	0.018
	(0.019)	(0.020)	(0.013)	(0.039)
Pseudo-R^2	0.811	0.781	0.843	0.792
Observations	29,140	29,140	29,140	29,140
	Panel C: Counties with a Low Share 65+ in the Year 2000			
1{Year ≥ 2004} × **1**{Age = 66}	-0.014	-0.036***	-0.023***	-0.014
	(0.011)	(0.013)	(0.006)	(0.027)
Pseudo-R^2	0.904	0.884	0.911	0.909
Observations	29,520	29,520	29,520	29,520
	Panel D: All Counties			
1{Year ≥ 2004} × **1**{Age = 66}	-0.014	-0.036***	-0.023***	-0.014
	(0.011)	(0.013)	(0.006)	(0.027)
1{Year ≥ 2004} × **1**{Age = 66}	0.002	0.043*	0.017	0.032
× **1**{High Share 65+ in 2000}	(0.022)	(0.024)	(0.014)	(0.047)
Pseudo-R^2	0.800	0.769	0.825	0.804
Observations	58,660	58,660	58,660	58,660

Source: Vital Statistics Mortality Files, 2000-2009.

Note: The dependent variable is the number of county-level deaths in a given year for men (column 1), women (column 2), white individuals (column 3), and Asian, Black, Hispanic, and all other race individuals (column 4). The independent variable of interest is an indicator for the passage of Medicare Part D interacted with an indicator for being aged 66. The estimates in Panels A-C are obtained from equation (4) comparing changes for those aged 66 to the changes for those aged 64. All columns include county fixed effects, county-level demographic and economic controls, and state-by-year fixed effects. Panel A examines all counties, Panel B examines counties that had an above-median share of the population comprised of adults aged 65 or older in the year 2000, and Panel C examines counties that had a below-median share of the population comprised of elderly adults in the year 2000. Panel D examines all counties and is estimated using equation (5) where we interact the independent variable of interest with an indicator for whether the county had a above-median share of the population comprise of elderly adults in the year 2000. This column includes age-by-year, county-by-age, and county-by-year fixed effects. Because they are estimated via a Poisson specification, the results are interpreted as changes in natural log of the dependent variable. Standard errors, shown in parentheses, are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$