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

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Abstract

Health care reforms are often enacted before implementation, creating uncertainty that can shape firms' decisions. We examine how Medicare Part D affected the retail pharmacy industry using 2000-2009 National Establishment Time-Series data, leveraging the fact that Part D disproportionately affected counties with larger elderly populations. Consistent with predictions from a conceptual model in which pre-implementation uncertainty discourages entry and lower post-implementation margins prevent full recovery, we find that Part D was associated with a 5-percent reduction in pharmacies, driven by fewer openings rather than more closures. We also find suggestive evidence that reduced pharmacy access dampened Part D's mortality benefits.

JEL Codes: I18; I13; D22; D81
Key words: Medicare Part D; pharmacy; openings; closures

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1. Introduction

Major reforms of regulated industries are typically legislated well in advance of when they take effect, generating prolonged windows of uncertainty during which firms must make strategic decisions. Policy uncertainty has been shown to depress investment and employment (Bernanke 1983; Baker et al. 2016), and prior work has studied how firms respond to anticipated policy changes related to fiscal policy (Fernández-Villaverde et al. 2015), monetary policy (Husted et al. 2020), trade policy (Handley and Limão 2017), and environmental regulation (Gowrisankaran et al. 2025). The health care industry, which accounts for nearly one-fifth of the U.S. economy, is recurrently the target of major federal reforms that are enacted with multi-year implementation lags and combine countervailing effects on the prices and quantities faced by providers. Yet how health care providers respond to this uncertainty is an important determinant of whether the intended beneficiaries can actually obtain care.[1]

In this paper, we examine the role of government policy in shaping a particularly important, yet understudied, health care supplier – the retail pharmacy industry. Specifically, we study how the entry and exit decisions of retail pharmacies responded to the passage and implementation of Medicare Part D. Established by the Medicare Prescription Drug, Improvement, and Modernization Act of 2003, Part D currently 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

[1] As we discuss later, there is a large body of evidence studying supply-side responses to major health insurance expansions (Finkelstein 2007; Kondo and Shigeoka 2013; Freedman et al. 2015; Dillender 2022; Geddes and Schnell 2025). However, much less is known about how firms respond to expansions that have an ambiguous ex ante effect on profitability and are preceded by a multi-year window of policy uncertainty.

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 even want to offer Part D plans (Pear 2003). Moreover, if they did, it was unknown whether beneficiaries would choose to enroll in the program and how the program would affect drug prices, and in turn, the pharmacy market structure (Neuman and Cubanski 2009).

Existing research has shown that Part D ultimately 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; 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 from cash-paying customers, including both the uninsured and those who opted to pay out of pocket despite having coverage (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] Indeed, total 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]

[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.

To organize the forces that govern how Medicare Part D affected the retail pharmacy industry, we first develop a model of pharmacy entry and exit under uncertainty (Dixit 1989; Dixit and Pindyck 1994; Carlton 2005). Though recent work has shown that supply-side responses to insurance expansions can depend on the level of expected reimbursement that providers receive (Geddes and Schnell 2025), we focus on a complementary mechanism in this paper: the uncertainty around expected profit, and the multi-year window between passage and implementation that gave firms the opportunity to delay entry. We show that this uncertainty increased the value of waiting to enter between Medicare Part D's passage and full implementation, particularly in areas where Medicare beneficiaries comprised a greater share of the pharmacy customer base. 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 not rebound and any change in closures would be expected to be smaller in magnitude than the change in openings, leaving the stock of pharmacies persistently lower. 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 the local customer base that was presumably made up 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 made up a larger share of the population. This finding is robust to a variety of specification choices, sample restrictions, and methods for conducting statistical inference. Importantly, 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 percentage reduction in the number of standalone pharmacies is almost twice as large as that of non-standalone pharmacies.

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 an increase in the number of pharmacy closures. Together, these patterns suggest that though Medicare Part D did not systematically put existing pharmacies out of business, it discouraged new entry. As a result, we show that counties where a higher share of the population was made up of elderly adults subsequently had a less dynamic pharmacy market served by older pharmacies than counties where elderly adults made up 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 made up a smaller share of the population. Within counties with an above-median elderly population share – 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.

Our findings contribute to several literatures. First, we add to growing evidence on how insurance expansions influence whether and how firms deliver care.[4] For example, Finkelstein (2007) found that the introduction of Medicare in 1965 induced sizable hospital entry and may have spurred technology adoption. Yet Freedman et al. (2015) concluded that Medicaid expansion for pregnant women did not increase technology adoption in the form of new neonatal intensive care units, and possibly slowed it in areas where the newly insured had previously held private coverage. In contrast to the mixed evidence on technology adoption, the effect of insurance expansions on firm hiring is more consistent, showing increases in hiring and employment in the health care sector (Dillender 2022; Hackmann et al. 2025).

Considerably less is known about firm-level entry decisions in retail health care delivery, where patient access depends on whether a business chooses to operate in a given market. Closest to our work, Geddes and Schnell (2025) examined how retail clinics responded to changes in insurance coverage induced by the Affordable Care Act.[5] They found that areas experiencing growth in private insurance coverage saw more clinic entry while those experiencing growth in Medicaid coverage saw more exits, demonstrating that supply-side responses to insurance expansions depend on both the type of insurance being expanded and the level of reimbursement that providers receive. Our work complements theirs in two important ways. First, although Part D was expected to increase prescription drug utilization, it was also expected to increase insurers' bargaining power.[6] As such,

[4] Parallel literature studies the effects of insurance expansions and reimbursement changes on individual provider decisions rather than firms. See, for example, Garthwaite (2012), Alexander and Schnell (2024), and Agniel et al. (2026).

[5] Related work has examined retail pharmacy responses to other policy and market shocks. Prior evidence has linked the entry of larger chain pharmacies into a market to price reductions (Bennett and Yin 2019; Moura and Barros 2020) and public pharmacy entry to market segmentation and price increases (Atal et al. 2024). Several recent papers have connected pharmacy market structure and incentives to the opioid epidemic (Janssen and Zhang 2023; Burton and Churchill 2025; Mizushima et al. 2025). Finally, a recent paper found no relationship between state Medicaid expansion as part of the Affordable Care Act and retail pharmacy access, though there was heterogeneity by local uninsurance rates (Kakani et al. 2026).

[6] Chen (2019) found lower pharmacy drug prices in areas with more concentrated insurance markets.

there was uncertainty about how it would affect prices and, as a result, pharmacy profits.[7] Second, we focus on the dynamic nature of the policy and the uncertainty surrounding its implementation. Though Part D was passed in late 2003, it did not take effect until January 2006, leaving over two years during which firms could anticipate the program but remained uncertain about many of its operational and financial details. We show that this transitional uncertainty suppressed firm entry, and that the effects persisted after the uncertainty was resolved, consistent with the documented downward price effect (Duggan and Scott Morton 2010, 2011; Lakdawalla and Yin 2015).

More broadly, we contribute to a literature on the effects of implementation lags, uncertainty, and anticipation. A long-standing theoretical literature has shown that, when entry costs are sunk and the post-policy environment is uncertain, the option value of waiting can be substantial, leading firms to delay entry even when the policy is beneficial in expectation (Dixit 1989; Dixit and Pindyck 1994; Carlton 2005). Empirical work has documented the importance of these dynamics for firm strategic decisions across a variety of settings (Goolsbee and Syverson 2008; Rittenhouse and Zaragoza-Watkins 2018; Caldara et al. 2020; Dickson et al. 2025). Within health care, Finkelstein (2004) showed that anticipated changes in demand for existing vaccines influenced subsequent innovation. In addition to firm decisions, individual agents also respond with anticipation to uncertainty. Alpert (2016) showed that Medicare beneficiaries reduced drug utilization in anticipation of Part D, and Malani and Reif (2015) documented anticipatory effects of medical malpractice reforms on physician supply. We contribute to this literature by providing what is, to our knowledge, the first establishment-level evidence that policy uncertainty during a federally legislated implementation window suppressed firm entry in a major retail health care industry. We further show that the openings

[7] This contrasts with the setting in Geddes and Schnell (2025) in which it was known that prices under private insurance exceeded those under Medicaid.

did not rebound after the uncertainty was resolved, leaving the stock of pharmacies persistently lower.

Finally, we contribute to the literature on the effects of Medicare Part D specifically. This work has shown that Part D increased prescription drug utilization among those who previously lacked drug coverage (Zhang et al. 2009; Kaestner and Khan 2012) as well as among those who previously had less generous coverage (Yin et al. 2008; Engelhardt and Gruber 2011), though estimates of the size of the utilization response have varied.[8] There is stronger consensus that Part D reduced the price of prescription drugs and pharmacy profits (Duggan and Scott Morton 2010; Lakdawalla and Yin 2015). 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). Complementary literature has examined the consequences of Part D for patient outcomes, showing that Part D reduced hospital admissions (Kaestner et al. 2019) and mortality among the newly eligible (Huh and Reif 2017; Dunn and Shapiro 2019).

We contribute to the Part D literature by examining a previously unexplored channel through which the policy shaped patient welfare: its effect on the supply of retail pharmacies. 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).[9] As such, our ability to explore whether

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

[9] Klepser et al. (2011) conducted a descriptive trend analysis in the number of pharmacies over time, finding a nationwide increase in the number of independent pharmacy closures beginning in late

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. Moreover, our finding that the mortality reductions attributable to Part D were dampened in counties that experienced reductions in pharmacy access is, to our knowledge, the first evidence that the program's health benefits depended on the supply-side response of the retail pharmacy industry.

The rest of the paper proceeds as follows: Section 2 describes the role of retail pharmacies in the U.S. health care system followed by the policy history of Medicare Part D. Section 3 introduces the theoretical framework, emphasizing both the role of Part D on pharmacy profit and the related timing of pharmacy entry and exit decisions. Section 4 discusses the National Establishment Time-Series database 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 6 discusses the policy implications and limitations of our results.

2. Industry and Policy Background

2.1 Retail Pharmacies in U.S. Health Care

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

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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.

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). Recent causal evidence indicates that pharmacies themselves substantively shape patients' prescription drug consumption (Battles 2026). 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.[10] 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 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

[10] These medicines include 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).

disparities (Essien et al. 2021). Although these location decisions have important implications for health care access, relatively little is known about the determinants of retail pharmacy formation, performance, and dissolution.

2.2 Medicare Part D 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 adjusted 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).[11] Part D 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

[11] The legislation also affected Parts B and C. It shifted Part B reimbursement for physician-administered drugs from 95 percent of average wholesale price to 106 percent of average sale price (Nguyen 2006; Hung and Dickson 2025). Meanwhile, it rebranded Medicare Part C as Medicare Advantage and included enhanced payments to make these plans more attractive through reduced cost sharing and expanded benefits (Megellas 2006).

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 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 harmful their performance as high-margin customers, including cash customers and dual-eligible individuals, shifted to Part D plans (CVS 2006a; Walgreens 2006; Rite Aid 2007a).[12] Although increased prescription drug utilization was projected to eventually offset the lower margin rates, the initial increases were projected to be too small 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 that received over 90 percent of their revenue from prescriptions (NCPA Digest 2008).[13]

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

[13] Another difference between CVS and independent pharmacies is that CVS includes both a retail pharmacy business and a pharmacy benefit manager (PBM) business. Executives 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).

Pharmacists' own perspectives largely mirrored these executive predictions. Several research teams used surveys and structured interviews of practicing pharmacists to assess 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).

3. Theoretical Framework

To organize our empirical analysis, we develop a simple framework that clarifies both the expected direction of the response and the locations most likely to be affected. To understand how Medicare Part D affected retail pharmacies, we first consider Part D's effect on pharmacy profit in Section 3.1. 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 made up a larger share of the customer base. Based on this intuition, in Section 3.2 we formalize a model of pharmacy entry and exit decisions with uncertainty that yields the predictions about the timing of entry and exit that we test empirically in Section 5.

3.1 Medicare Part D and Pharmacy Profit

We begin by considering two representative markets: market A with a high elderly population share (s_e^A) and market B with a low elderly population share (s_e^B). These two markets are intended to capture the dimension along which exposure to Part D varied while holding other features of the local market fixed. 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 more price inelastic. Figure 1 shows that the difference in demand for the non-elderly and elderly populations produced a kink in the inverse demand curve. Intuitively, market demand was the horizontal sum of two groups: the insured non-elderly, who faced only a copayment, and the previously uninsured elderly, who faced the full out-of-pocket price. The kink appears where the insured non-elderly demand is saturated and only the more price-sensitive uninsured elderly remain.[14] For quantities up to the non-elderly share of the population $(1 - s_e)$, demand was relatively inelastic because consumers were insulated from paying the full price. Beyond this threshold, demand was relatively more elastic, due to the elderly adults who lacked prescription drug coverage prior to Part D facing the full out-of-pocket price. Because market *A* has a higher elderly population share, the kink occurred earlier in market *A* (dark grey line) than in market *B* (light grey line). As a result, the relatively more elastic segment accounted for a larger share of total demand in market *A*.[15]

In this setup, when the previously uninsured elderly population gained prescription drug coverage through Medicare Part D, the full population became insured and faced a fraction of the list price. This resulted in the kink disappearing and demand becoming relatively more price inelastic. At any given price, quantity demanded increased because of Part D as the elderly population who were

[14] There are various prices in the prescription drug market, including what manufacturers receive per unit from wholesalers, what wholesalers receive per unit from pharmacies, and what pharmacies receive per unit from insurers and patients. For our illustrative model, we abstract away from these distinctions and instead think of a single object called price, and we note that economic factors influencing any single component will likely be felt throughout the entire chain.

[15] This setup parallels the supply-side framework of Geddes and Schnell (2025), who similarly modeled a health care provider facing demand from two populations with different effective prices: a perfectly elastic segment at the administered reimbursement price and a downward-sloping segment from market-priced patients. In our setting the kink in the inverse demand curve arises from differences in pre-Part D drug coverage rates between elderly and non-elderly patients rather than from differences in administered versus market-based pricing.

previously priced out of the market could now participate more fully. Importantly, the size of the demand shift was larger in market *A*, given its higher elderly population share and correspondingly larger increase in coverage. Intuitively, Part D delivered a larger demand shock to high-elderly population share markets because a greater share of their customer base was newly insured.

Although Medicare Part D increased prescription drug utilization, the effect on retail pharmacy profits is ambiguous due to both the response of price and cost. 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 magnitude of the effect on price will be larger 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 (ATC= low, medium, high), the figure plots the change in profit as a function of price, p, defined as $(p - ATC) \times (Q^{Post}(p) - Q^{Pre}(p))$. That is, the change in profit per period equals the per-unit margin $(p - ATC)$ multiplied by the change in quantity dispensed at price p, where the change in quantity is based on the pre vs post Part D demand. There are two features worth noting. 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, capturing both upside and downside risk, is substantially 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

We now construct a dynamic model motivated by two institutional features. First, Part D was passed in late 2003 but did not take effect until January 2006, providing potential entrants more than two years to delay opening. Second, the magnitude of Part D's effect on local pharmacy profits was uncertain until the program was implemented. The standard machinery of irreversible investment under uncertainty (Dixit 1989; Dixit and Pindyck 1994) maps these features into a sharp prediction about the timing and location of market entry.

Set up. As above, consider two markets $m \in \{A,B\}$ where market A has a higher elderly population share ($s_e^A = H$) and market B has a lower elderly population 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 $\delta \in (0,1)$. Let $t = 0$ denote the period prior to Part D's passage, $t = 1$ denote the period in which Part D is passed but not yet implemented, and $t = 2$ denote the period in which Part D is implemented. Mapped to calendar years, t = 0 corresponds to the period prior to the MMA, t = 1 to the 2004–2005 announcement window, and t = 2 to 2006 onward.

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 $t = 1$, the per-period profit from implementation onwards is uncertain, with $\sigma_m > 0$ denoting the mean-preserving spread of uncertainty in market m:[16]

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

Intuitively, σ_m captures the width of the range of post-policy profit outcomes in market m. Equation (1) captures this by specifying that, conditional on market m, post-implementation profit takes one of two values, $\pi_0 + \sigma_m$ or $\pi_0 - \sigma_m$, each with equal probability, so that expected post-policy profit equals the pre-period flow π_0 in both markets, though the spread of outcomes differs.

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 (i.e., $\sigma_A > \sigma_B$). Thus, when profits change after the implementation of Part D, 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.

Entry Decision. A potential entrant must pay a fixed, irrevocable sunk cost, $K > 0$, to enter and begin earning profit in the same period. 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). The key tension is that entering at $t = 1$ locks in the irreversible cost K before the post-policy

[16] 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.

profit is known, while waiting until $t = 2$ forfeits one period of profit π_0 but allows the entrant to avoid entering in low-profit states.

If the firm enters at $t = 1$, it will pay the sunk cost, K, and earn profit π_0.[17] From $t = 2$ onward, the entrant earns the realized (uncertain) per-period profit, so the present value of entering at $t = 1$ is given by:

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

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:

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

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 value when waiting and 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. Put plainly, OV_m is the value to the firm of being able to defer the entry decision by one period, given the information it expects to receive in the interim. Further, waiting becomes weakly more valuable as σ_m grows, because the firm captures the upside when the realized state turns out high but avoids the downside when it turns out to be low. We now establish this formally.

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 $\max\{\$0, \frac{1}{1\text{-}\delta} \times \pi_\mathrm{m} - K\} \geq \frac{1}{1\text{-}\delta} \times \pi_\mathrm{m} - K$, which implies that $V_m^{Wait} \geq V_m^{Enter} - \pi_0$. This latter expression highlights the choice facing the firm,

[17] We are assuming that Medicare Part D's passage does not itself alter pharmacy profits. However, Alpert (2016) found that elderly individuals reduced their prescription drug utilization by approximately 6 percent following Part D's passage, though utilization rebounded following full implementation. A lower profit level between passage and implementation would raise the value of waiting to enter the market.

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-elderly population share market is higher than in the low-elderly population share market.[18] 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 spread amplifies the upside without worsening the downside, so waiting becomes weakly more valuable as σ_m increases. This yields our first testable prediction: between Part D's passage and its implementation, entry should be delayed more in markets with a higher elderly population share than in markets with a lower elderly population share. Whether entry rebounds after implementation depends on the realized effect of Part D on prices; because prior work has documented net price declines under Part D (Duggan and Scott Morton 2010, 2011; Lakdawalla and Yin 2015), we expect openings to remain suppressed rather than recover post-implementation.

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

[18] 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.

incumbent pharmacy will exit the market 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 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 depend only on whether revenues cover per-period operating). As such, we would expect to see a smaller change in closures relative to openings.[19]

4. Data and Methods

4.1 National Establishment Time-Series Data

To test our theoretical 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 96 million business establishments in the United States. The data include information on when each establishment opened, when it exited the data due to closure, as well as its 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.[20] 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

[19] Appendix A includes a numeric example using our conceptual framework.

[20] We report summary statistics for the covariates in Appendix Table B1. 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.

panel. Column 1 reports summary statistics for the full sample. Column 2 reports statistics for counties with a below-median elderly population share in the year 2000 (i.e., counties where elderly adults presumably made up a smaller share of the customer base). Likewise, column 3 reports statistics for counties with an above-median elderly population share in the year 2000 (i.e., counties where elderly adults presumably made up a larger share of the customer base). On average, we find that counties that had a below-median elderly population share in the year 2000 had considerably more pharmacies than counties where elderly adults comprised a greater share of the population (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 elderly adults comprised a higher share of the population in the year 2000 had more pharmacies per 100,000 people than the below-median counties (27.19 vs. 18.84).

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 made up 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:

$$Y_{cst} = \mathrm{Exp}(\alpha + \beta \cdot \mathbf{1}\{\text{ABOVE-MEDIAN SHARE}\}_c \times \mathbf{1}\{\text{Year} \geq 2004\}_t + \mathbf{X}'_{cst}\lambda + \theta_c + \tau_{st} + \varepsilon_{cst}) \quad (4)$$

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 closures. 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 made up of elderly adults. We construct this measure by interacting a variable indicating that the county had an above-median share of the population made up 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).[21]

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 made up of Black individuals, and the share of the prime-age county-level population made up of Hispanic individuals. 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

[21] 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).

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:

$$Y_{cst} = \text{Exp}(\alpha + \textstyle\sum_{t=2000,\, t\neq 2003}^{2009} \beta^t \cdot \mathbf{1}\{\text{ABOVE-MEDIAN SHARE}\}_c \times \mathbf{1}\{\text{Year} = t\}_t + \mathbf{X}'_{cst}\lambda + \theta_c + \tau_{st} + \varepsilon_{cst}) \quad (5)$$

where the coefficients of interest, β^t, measure the evolution of pharmacy outcomes in counties with an above-median elderly population share in the year 2000 relative to those counties with a lower share. 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.[22] 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:

$$Y_{acst} = \text{Exp}(\alpha + \beta \cdot \mathbf{1}\{\text{AGE} = 66\}_a \times \mathbf{1}\{\text{Year} \geq 2004\}_t + \mathbf{X}'_{acst}\lambda + \theta_{ac} + \tau_{st} + \varepsilon_{acst}) \quad (6)$$

where the dependent variable, Y_{acst}, 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. We estimate this equation

[22] We report summary statistics in Appendix Table B2.

overall, as well as separately for counties with an above-median elderly population share and below-median elderly population share.

There are a few differences relative to our prior specifications. First, the vector $\mathbf{X}_{acst}$ 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 (4) 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 made up 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 made up 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.[23] This reduction increased in magnitude following full implementation, such that counties that had a higher share of the population made up 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 (4) 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.[24]

In Appendix Table B4 we show that these results are robust to alternative ways of defining the treatment group, including separating counties into quartiles

[23] We report these estimates and tests of joint significance in Appendix Table B3.
[24] Appendix Figure B1 plots the coefficient and corresponding confidence intervals for the actual result (dark grey triangle) and the 100 placebo results (light grey circles).

based on the share of the population made up of elderly adults in the year 2000 (column 2) and using the continuous population share (column 3). Meanwhile, we show in Appendix Figure B2 that the results are robust to excluding the smallest and largest pharmacies from the data.[25] Likewise, Appendix Figure B3 shows that the results are robust to iteratively excluding observations from each state, alleviating concerns that our results are driven by states with the largest shares of elderly 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 payer (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 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

[25] 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.

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 made up 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 ($100 \times (\exp\{-0.029 - 0.031\} - 1) = -5.8$).[26]

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 made up 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 ($100 \times (\exp\{-0.039\} - 1) = -3.8$) 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 (Fraher et al. 2005; 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).

[26] We also explored whether these high-poverty areas were otherwise experiencing a change in the number of pharmacies coincident with the timing of Part D. In Appendix Table B5, we replicate our baseline results from Table 2 but instead use the poverty rate in the year 2000 to assign treatment status. The point estimates are smaller in magnitude and statistically insignificant.

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, an increase in the number of pharmacy closures, or both. 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 theoretical 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 there would not be a subsequent increase in openings 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).[27] 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 made up an above-median share of the population relative to counties where they made up 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.[28] As with our static difference-in-differences estimate, the event-study estimates do not reveal any change in closures.

[27] These estimates are also reported in Appendix Table B3.

[28] Because of the reduction in the number of openings, Appendix Figure B4 shows that the retail pharmacy market in these counties was increasingly dominated by older establishments.

As with our results examining changes in the number of pharmacies, in Appendix Table B6 we explore the robustness of the results to alternative ways of defining treatment status, including using the quartile of the elderly population share and using a continuous measure; the results continue to indicate that there were fewer openings in counties where elderly individuals made up a larger share of the population. Similarly, we show in Appendix Table B7 that the patterns are robust to excluding openings and closures of the smallest and largest establishments, while Appendix Figure B5 shows that the results are robust to the randomization placebo test.[29]

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.[30] 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

[29] Appendix Table B8 shows that the reduction in the number of openings was most pronounced for standalone (i.e., non-chain) pharmacies. In Appendix Table B9, 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 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.

[30] A broader literature establishes that the supply of health care infrastructure can itself causally affect mortality. For example, Hollingsworth et al. (2024) show that early-twentieth-century investments by the Duke Endowment to expand and modernize hospitals reduced both infant and long-run mortality. This evidence motivates our examination of whether the mortality benefits of Part D varied with the supply-side response of the retail pharmacy industry.

difference-in-differences strategy shown in equation (6). 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 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).[31]

6. Conclusion

Major health care reforms are often legislated well in advance of when they take effect, generating prolonged windows of uncertainty that can shape how firms enter and exit markets. Retail pharmacies are a particularly consequential setting for

[31] In Appendix Table B10 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).

studying these dynamics: 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 how policy factors and uncertainty shape 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 health care 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 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 theoretical framework indicates that these factors would reduce the size of the retail pharmacy industry by discouraging firm formation.

Using 2000-2009 National Establishment Time-Series data and a difference-in-differences identification strategy, we show that 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 90 percent smaller in absolute magnitude and statistically insignificant.

Though the Medicare Prescription Drug, Improvement, and Modernization Act was signed into law over twenty years ago, our results provide important insights for today's retail pharmacy market. The Inflation Reduction Act of 2022 charges the Secretary of Health and Human Services to negotiate a "maximum fair price" with drug companies for drugs that have high Medicare spending, no generic or biosimilar equivalents, and are several years past FDA approval (Cubanski et al. 2023). Ten drugs were included in the first round of negotiation, and the Centers for Medicare and Medicaid Services (2026b) estimated that the negotiated prices would have saved Medicare $6 billion in net prescription drug costs, a 22 percent aggregate reduction, if the prices had been in effect in 2023; beneficiaries are projected to save $1.5 billion in 2026 when the negotiated prices go into effect. Though lower prices would likely lead to utilization increases and financial relief for those purchasing these drugs, our estimates suggest that uncertainty generated by the negotiating process and the eventual lower reimbursement rates may inadvertently discourage firm formation and reduce pharmacy access, particularly for those in lower-income areas and racial and ethnic minority communities.

This study is subject to some limitations. First, although the timing of the reduction in the number of pharmacies is consistent with our theoretical 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). 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. Despite these limitations, this study provides important new evidence that Medicare Part D slowed growth of the retail pharmacy industry at a time when patients are more frequently turning to pharmacies as a source of preventive care.

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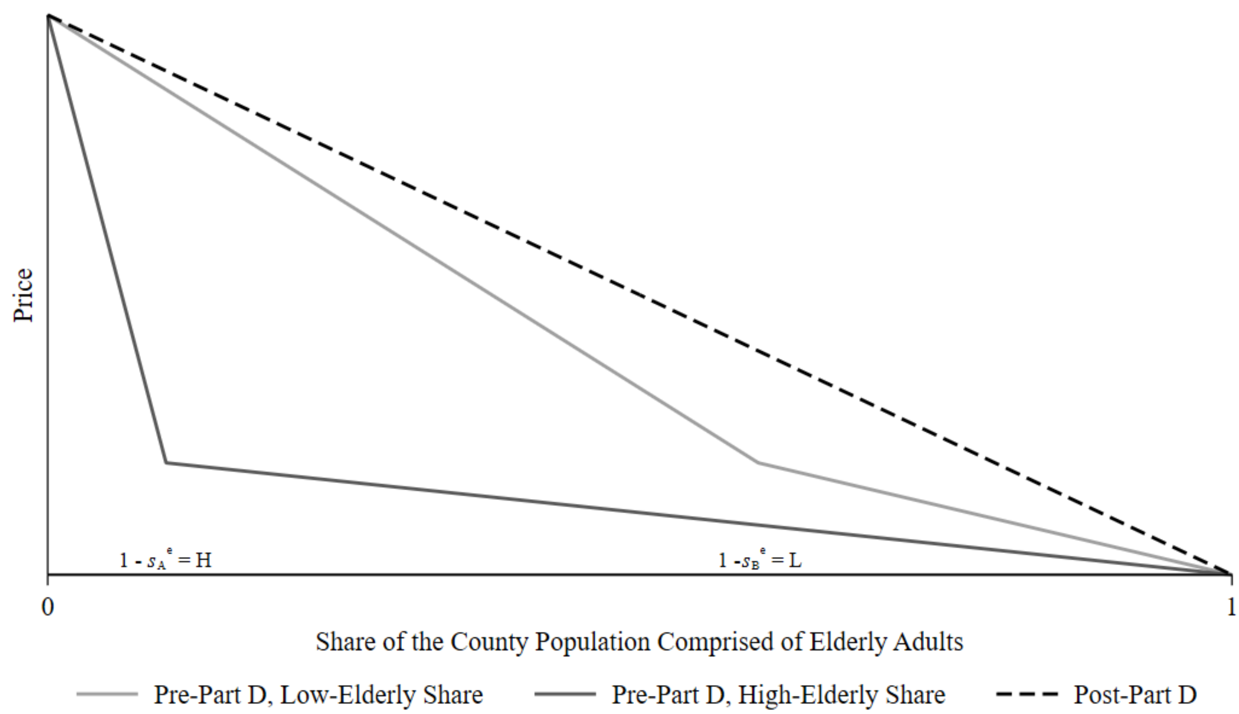
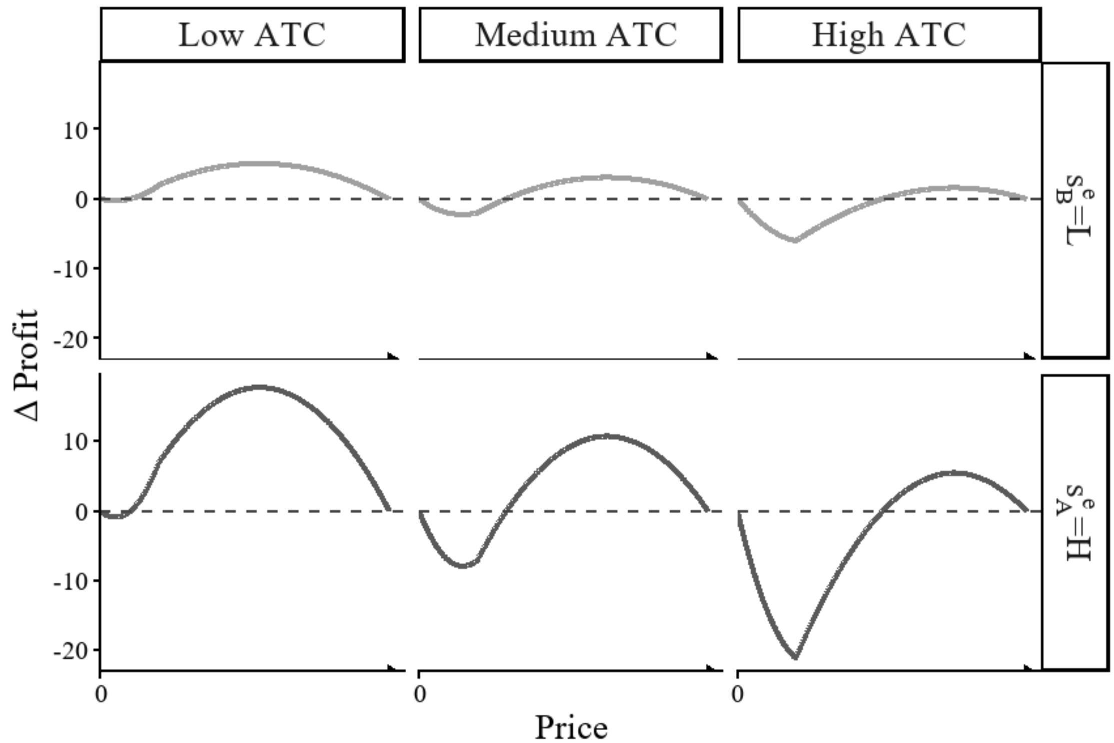
8. Figures

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



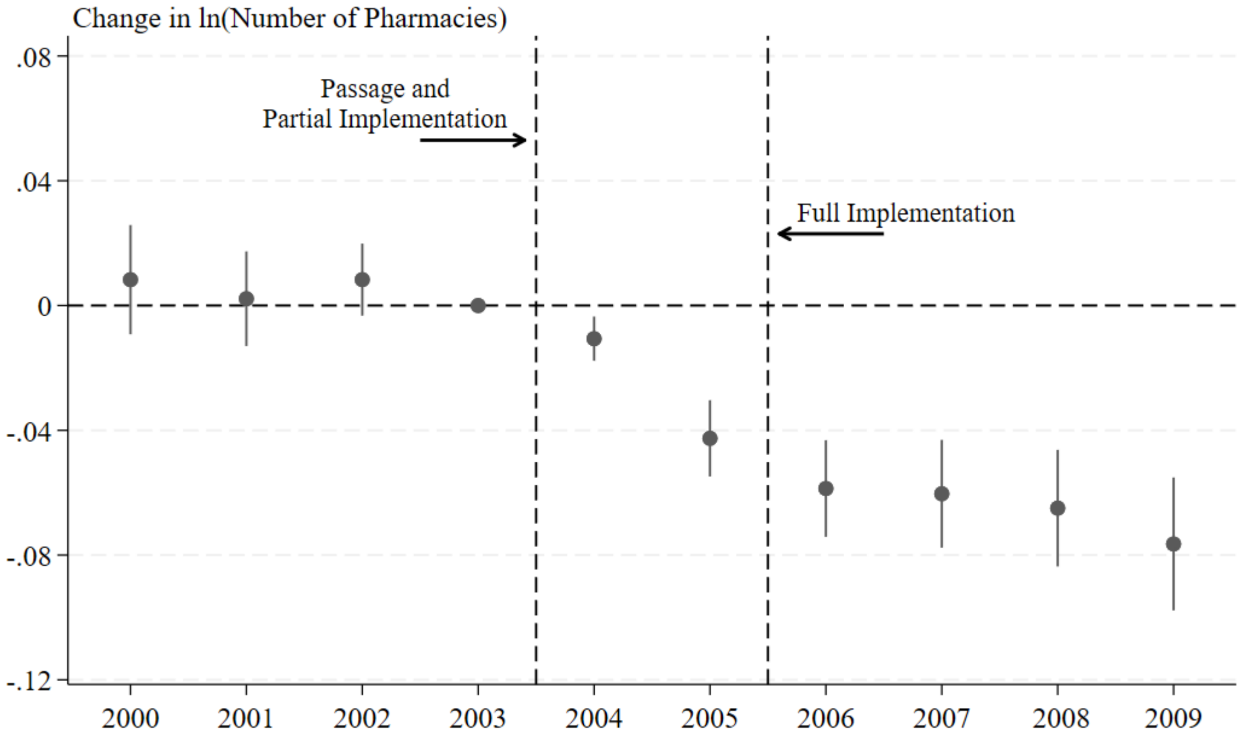
Note: The figure plots the pre-Part D inverse demand curves for market *A* (high-elderly share, solid dark grey) and market *B* (low-elderly share, solid light grey). The horizontal axis is the quantity share of the population served; the vertical axis is price, which can be thought of as either pharmaceutical 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



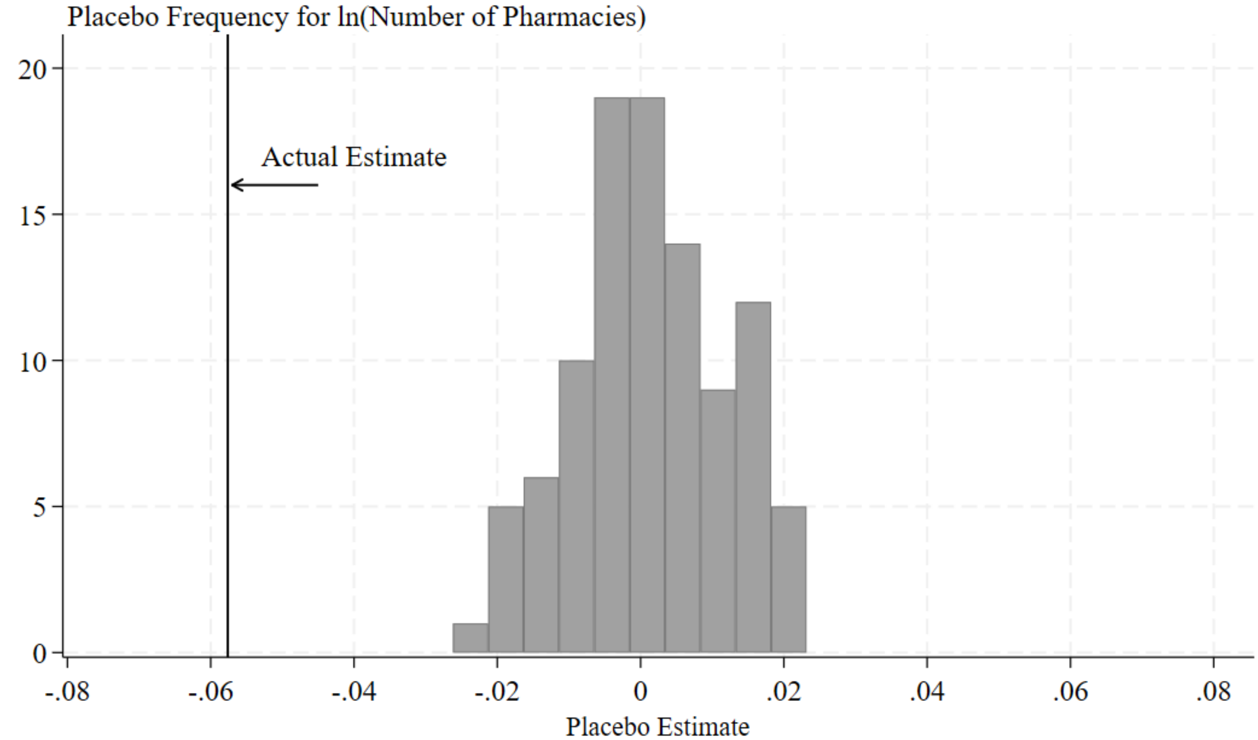
Note: Each panel plots the change in profit, calculated as the post-Part D profit less the pre-Part D profit, for a range of price values on the horizontal axis. Profit is defined as (P-ATC)*Q(p), where Q is the demand function. ATC values vary from low, medium, and high and correspond to the figure 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



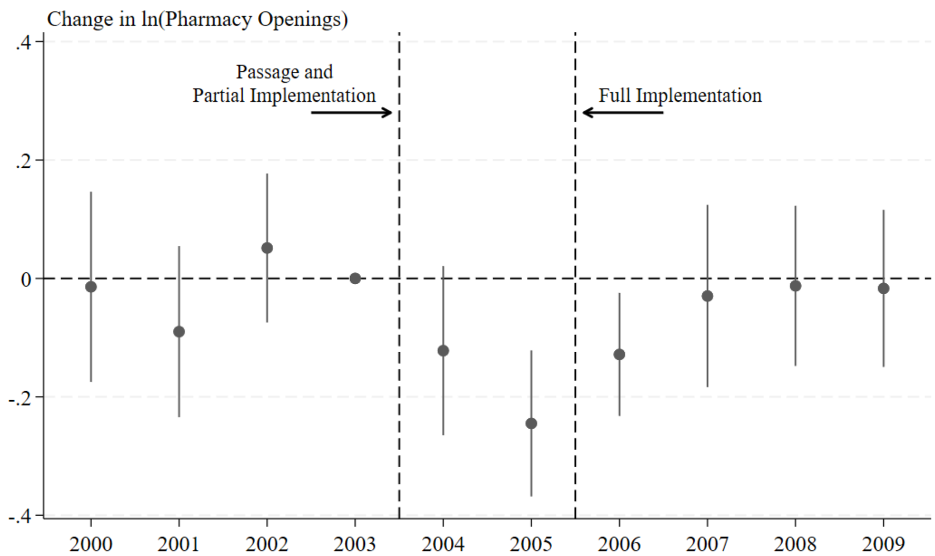
Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The grey circles indicate the coefficients and the vertical lines the 95 percent confidence intervals obtained from the event study specification shown in equation (5) comparing counties that had an above-median share of the population made up 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

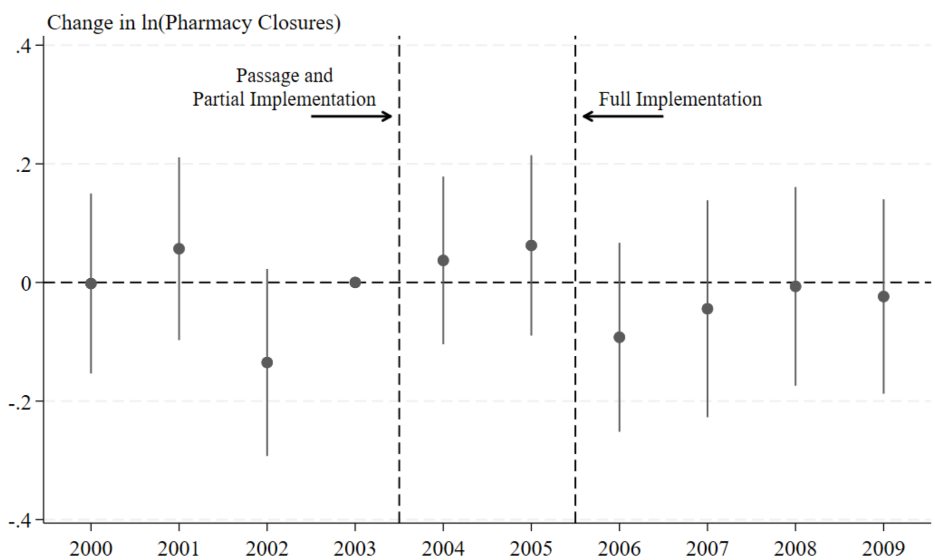


Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The independent variable of interest captures how the number of pharmacies changed following the passage of Medicare Part D in counties with an above-median share of the population made up 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 (4). 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 (5) comparing counties that had an above-median share of the population made up 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} × **1**{High Share 65+ in 2000}	-0.059***	-0.051***	-0.051***	-0.058***
	(0.016)	(0.014)	(0.014)	(0.009)
Pseudo-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 (4). 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 made up of Black individuals and the share of the prime-age county population made up 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} × **1**{High Share 65+ in 2000}	-0.029***	-0.039***	-0.046***
	(0.011)	(0.012)	(0.011)
1{Year ≥ 2004} × **1**{High Share 65+ in 2000} × **1**{High Share Poverty in 2000}	-0.031*		
	(0.017)		
1{Year ≥ 2004} × **1**{High Share 65+ in 2000} × **1**{High Share Non-White in 2000}		-0.040**	
		(0.018)	
1{Year ≥ 2004} × **1**{High Share 65+ in 2000} × **1**{Rural Counties}			0.026
			(0.019)
Pseudo-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 (4) 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 made up 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} × **1**{High Share 65+ in 2000}	-0.078***	-0.039***
	(0.013)	(0.012)
Pseudo-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 (4). 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} × **1**{High Share 65+ in 2000}	-0.087**	0.010
	(0.037)	(0.041)
Pseudo-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 (4). 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	0.929	0.937	0.867	0.929
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 (6) 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 a below-median share of the population made up of adults aged 65 or older in the year 2000, and column 3 examines counties that had an above-median share of the population made up of elderly adults in the year 2000. Column 4 examines all counties but modifies equation (6) by interacting all of the right-hand side variables with an indicator for whether the county had an above-median share of the population made up 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 A: 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 made up of Medicare beneficiaries than the other. Prior to the implementation of Part D, let $\pi_m = 10$ in 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 expected 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:

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

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

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

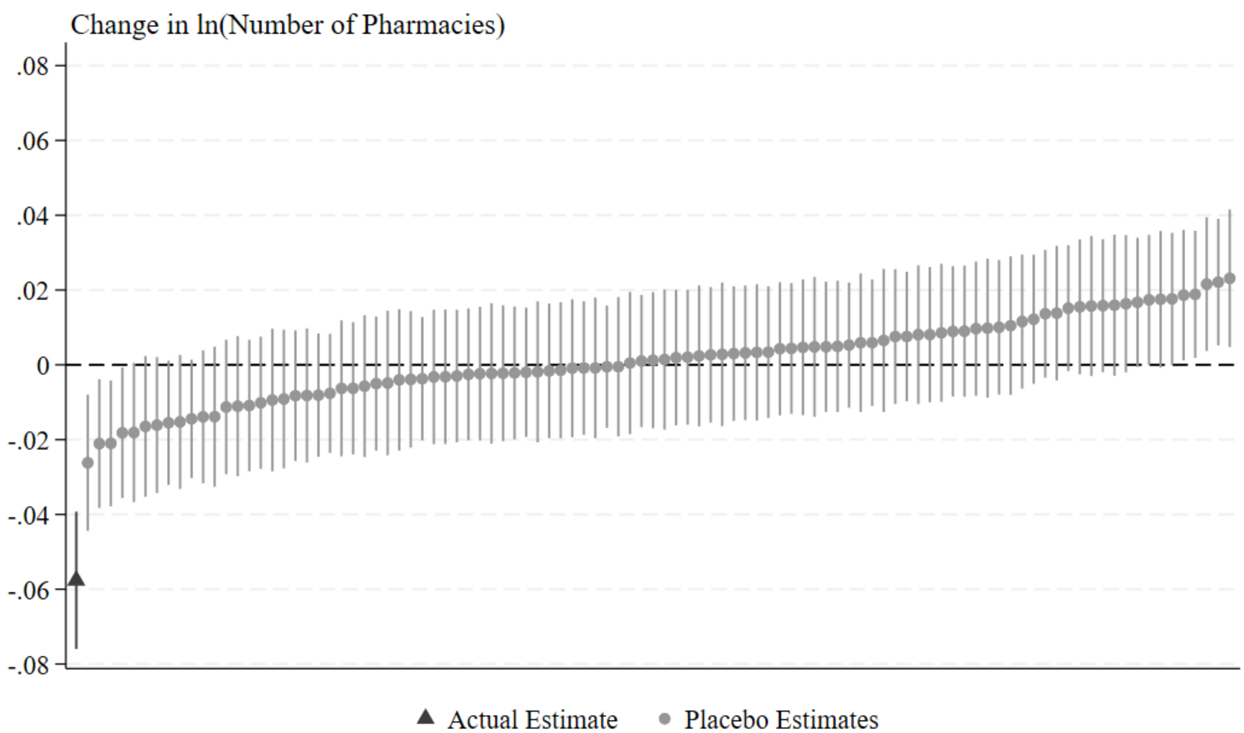
$$= .95 \times \left[\frac{190}{2} + \frac{110}{2}\right] = 142.5$$

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

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 $V_A^{Enter} = 150 < V_A^{Wait} = 156.75$, 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 the present discounted value of profit ($\pi_A / (1 - \delta) = 1 / (1 - 0.05) = 20$) is less than the sunk cost of entry ($K = 50$), 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.

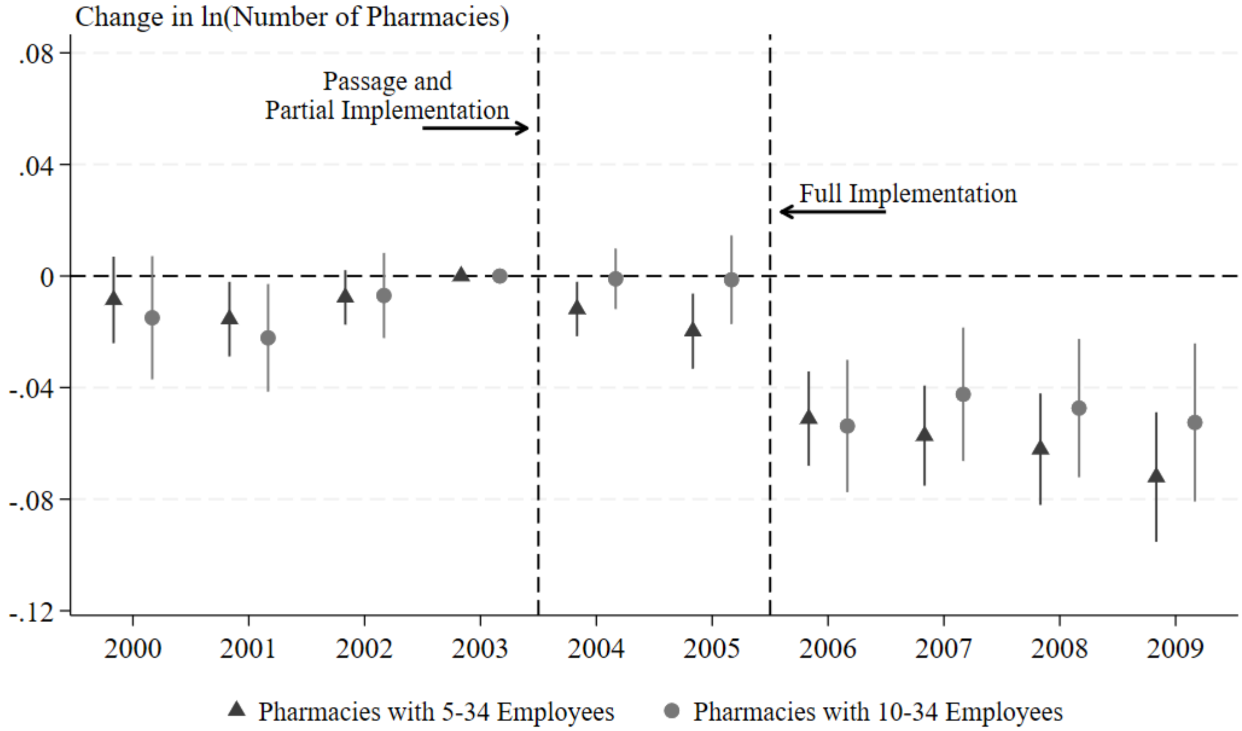
11. Appendix B: Figures and Tables

Appendix Figure B1: Comparison of the Actual Result to 100 Placebo Estimates



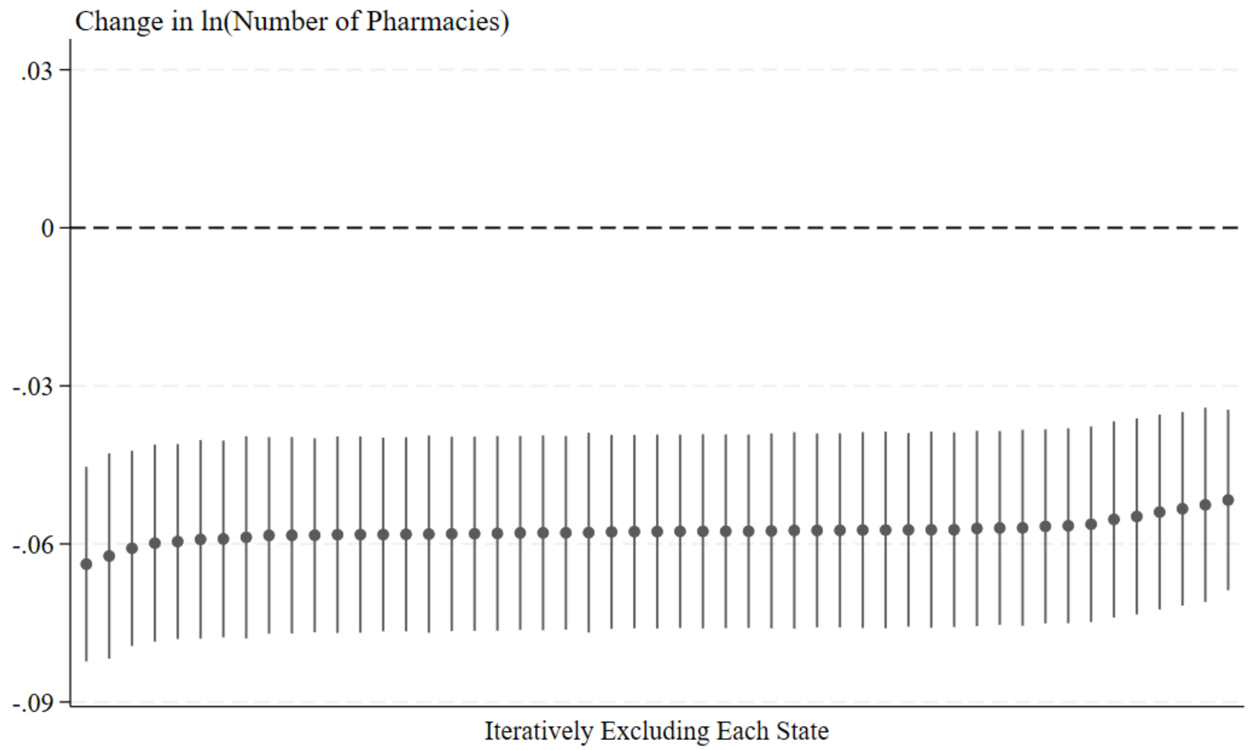
Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The independent variable of interest captures how the number of pharmacies changed following the passage of Medicare Part D in counties with an above-median share of the population made up 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 (4). 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 B2: The Relationship Between Medicare Part D and the Number of Pharmacies is Robust to Excluding the Smallest and Largest Establishments



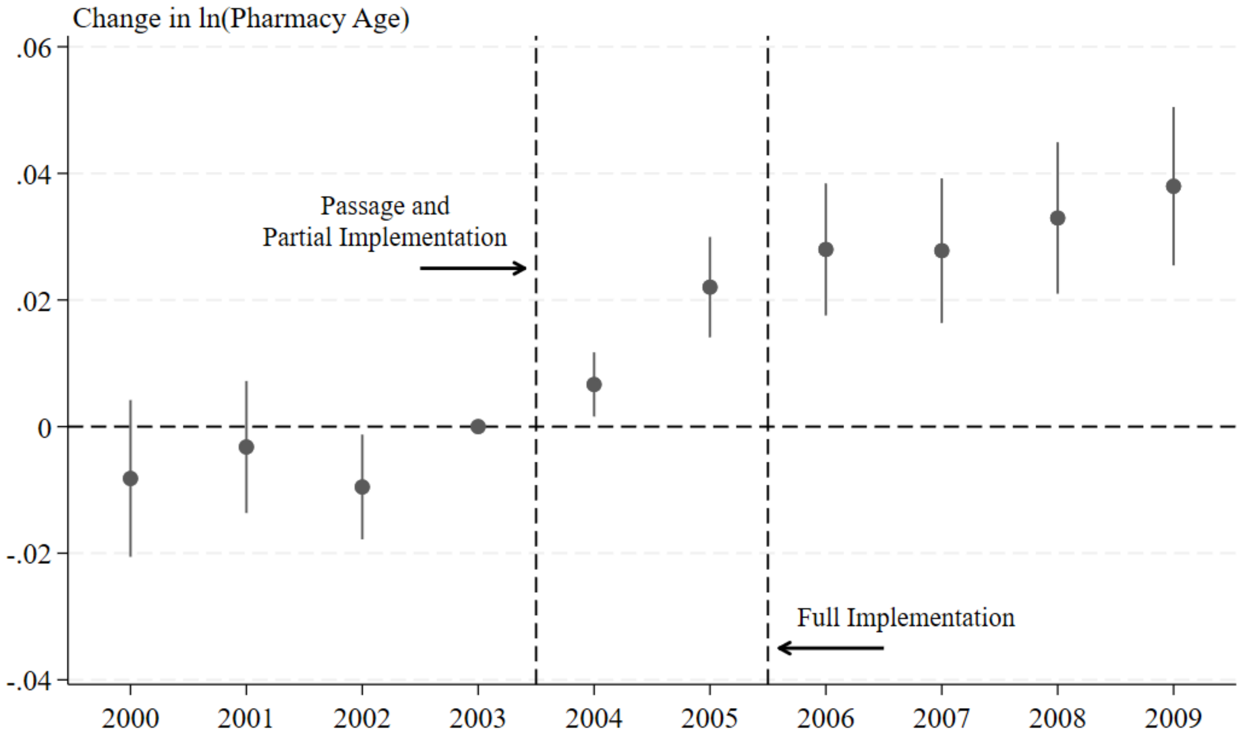
Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The markers indicate the coefficients and the vertical lines the 95 percent confidence intervals obtained from the event study specification shown in equation (5) comparing counties that had an above-median share of the population made up 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 B3: The Relationship Between Medicare Part D and the Number of Pharmacies is Robust to Iteratively Excluding Observations from Each State



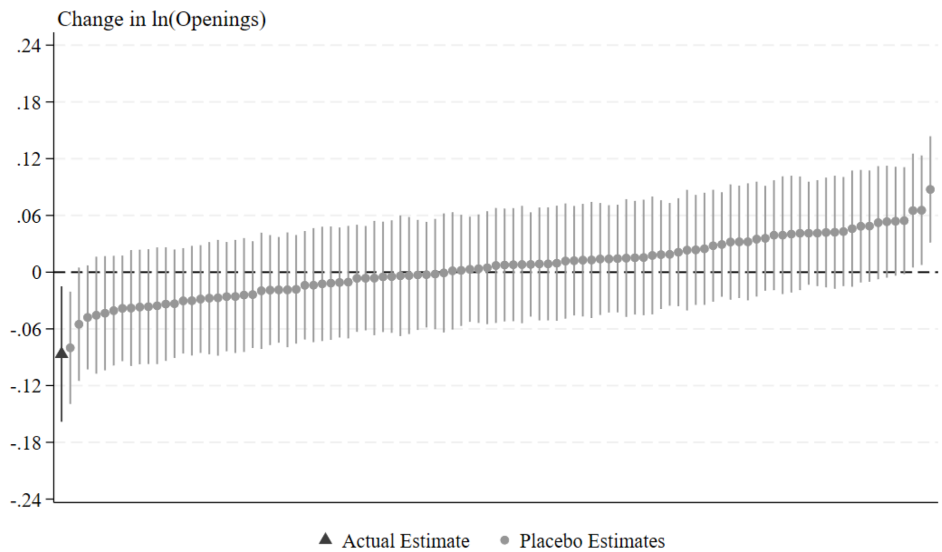
Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the number of pharmacies in a county. The independent variable of interest captures how the number of pharmacies changed following the passage of Medicare Part D in counties with an above-median share of the population made up 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 (4). 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 B4: Medicare Part D Was Associated with an Increase in Pharmacy Age

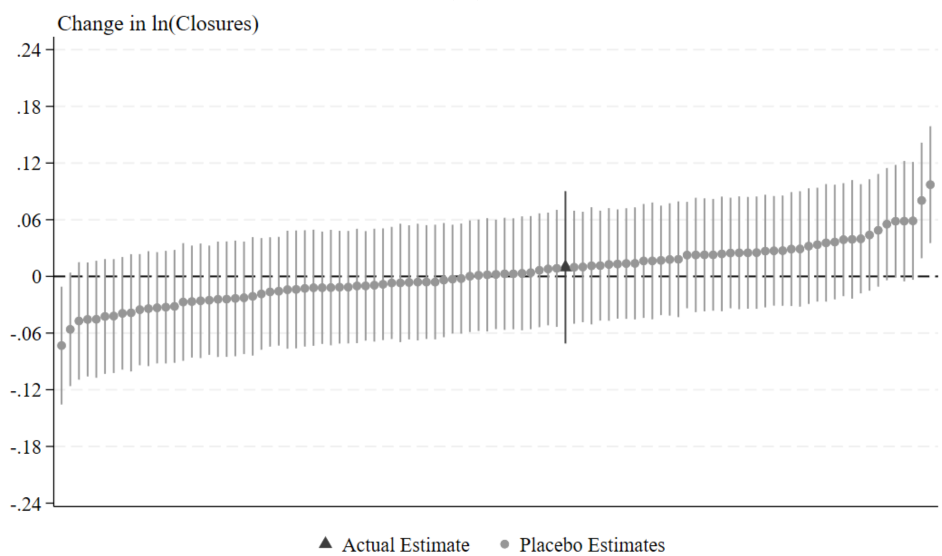


Source: National Establishment Time-Series, 2000-2009.
Note: The dependent variable is the age of the pharmacy. The grey circles indicate the coefficients and the vertical lines the 95 percent confidence intervals obtained from a modified version of the event study specification shown in equation (5) comparing counties that had an above-median share of the population made up 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 B5: 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 made up 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 (4). 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 Table B1: 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 B2: 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 B3: Event Study Estimates

	(1)	(2)	(3)
Outcome →	ln(Establishments)	ln(Openings)	ln(Closures)
Pre-Period			
1{Year = 2000} × **1**{Above-Median Share}	0.008	-0.014	-0.002
	(0.009)	(0.082)	(0.077)
1{Year = 2001} × **1**{Above-Median Share}	0.002	-0.090	0.057
	(0.008)	(0.074)	(0.079)
1{Year = 2002} × **1**{Above-Median Share}	0.008	0.051	-0.135*
	(0.006)	(0.064)	(0.080)
Post-Period			
1{Year = 2004} × **1**{Above-Median Share}	-0.011***	-0.122*	0.037
	(0.004)	(0.073)	(0.072)
1{Year = 2005} × **1**{Above-Median Share}	-0.043***	-0.245***	0.062
	(0.006)	(0.063)	(0.078)
1{Year = 2006} × **1**{Above-Median Share}	-0.059***	-0.128**	-0.092
	(0.008)	(0.053)	(0.081)
1{Year = 2007} × **1**{Above-Median Share}	-0.060***	-0.030	-0.044
	(0.009)	(0.079)	(0.093)
1{Year = 2008} × **1**{Above-Median Share}	-0.065***	-0.013	-0.007
	(0.010)	(0.069)	(0.085)
1{Year = 2009} × **1**{Above-Median Share}	-0.076***	-0.017	-0.024
	(0.011)	(0.068)	(0.084)
Pre = 0?	χ^2= 6.93	χ^2 = 2.69	χ^2 = 5.81
	p = 0.074	p = 0.442	p = 0.121
Post = 0?	χ^2 = 72.10	χ^2 = 28.61	χ^2 = 5.480
	p = 0.000	p = 0.000	p = 0.484
Pre = Post?	χ^2 = 78.30	χ^2 = 36.93	χ^2 = 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 (5) comparing counties that had an above-median share of the population made up 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 chi-squared 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 B4: 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} ×	-0.058***		
1{High Share 65+ in 2000}	(0.009)		
1{Year ≥ 2004} ×		-0.048***	
1{Q2 Share 65+ in 2000}		(0.011)	
1{Year ≥ 2004} ×		-0.080***	
1{Q3 Share 65+ in 2000}		(0.012)	
1{Year ≥ 2004} ×		-0.085***	
1{Q4 Share 65+ in 2000}		(0.013)	
1{Year ≥ 2004} ×			-1.024***
Share 65+ in 2000			(0.130)
Pseudo-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 (4). 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 made up of elderly individuals in the year 2000 was in the 2^{nd}, 3^{rd}, or 4^{th} 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 made up 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 B5: Medicare Part D was Not Associated with Changes in Pharmacy Access When Using the Poverty Rate in the Year 2000 to Define Treatment

	(1)	(2)	(3)	(4)
1{Year ≥ 2004} ×	0.002	-0.003	-0.002	-0.015
1{High Share in Poverty in 2000}	(0.019)	(0.015)	(0.015)	(0.012)
Pseudo-R^2	0.918	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 (4). 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 poverty rate 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 made up of Black individuals and the share of the prime-age county population made up 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.

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

Appendix Table B6: 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)
Pseudo-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 (4). 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 made up 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 made up 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 B7: 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} × **1**{High Share 65+ in 2000}	-0.158**	-0.104	0.001	0.050
	(0.063)	(0.084)	(0.049)	(0.066)
Pseudo-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 (4). 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 10-34 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 B8: The Relationship Between Medicare Part D, Pharmacy Openings, and Pharmacy Closures, by Standalone Status

	(1)	(2)
Sample →	Standalone Pharmacies	Non-Standalone Pharmacies
	Panel A: Change in ln(Openings)	
1{Year ≥ 2004} × **1**{High Share 65+ in 2000}	-0.111**	-0.038
	(0.045)	(0.059)
Pseudo-R^2	0.680	0.590
Observations	29,340	29,340
	Panel B: Change in ln(Closures)	
1{Year ≥ 2004} × **1**{High Share 65+ in 2000}	-0.119*	0.137**
	(0.064)	(0.060)
Pseudo-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 (4). 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 B9: 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 a modified version of equation (4) 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 conducts the analysis at the county level. Panel B conducts the analysis at the establishment level and includes time-invariant establishment fixed effects. Standard errors, shown in parentheses, are clustered at the county level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Appendix Table B10: Medicare Part D and Mortality, by Demographic Characteristics

	(1)	(2)	(3)	(4)
Deaths →	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	0.894	0.874	0.902	0.907
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 (6) 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 age-race- and age-sex specific populations. Panel A examines all counties, Panel B examines counties that had an above-median share of the population made up of adults aged 65 or older in the year 2000, and Panel C examines counties that had a below-median share of the population made up of elderly adults in the year 2000. Panel D examines all counties and is estimated using equation (6) where we interact the independent variable of interest with an indicator for whether the county had a above-median share of the population made up 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$