Overconfidence and the Diffusion of Medical Technology

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Abstract:

A variety of models explain why new technologies such as hybrid corn, agricultural fertilizer, and new medical treatments diffuse so slowly. A common characteristic of these models is that agents (or countries) quickest to diffuse do so optimally because of relative gains from the new technology; the debate is around why others are so slow. In this paper, we develop a nested Bayesian model of diffusion and learning with heterogeneous agents that allows for *overconfidence*, which can cause early innovators to exhibit below-average productivity. We apply the model to the case of implantable cardiac defibrillators (ICDs), a medical device approved in 2005 to help prevent cardiac death in patients with weakened hearts (congestive heart failure). Using a unique clinical registry of every ICD implanted during 2006-13 linked to Medicare claims data, we find remarkable variations in the speed of diffusion across hospitals and regions. The structural model matches both aggregate moments, and individual hospital-level trajectories, of mortality and utilization. We find that overconfidence raises mortality by 8% on average (and more among those most overconfident), and can explain roughly three-quarters of variation in diffusion rates and risk-adjusted mortality. In addition, the model predicts, correctly, that the most overconfident hospitals are the ones that scale back quickest. These results suggest caution in equating rapid diffusion to productivity gains, particularly in health care.

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I. Introduction

The productivity literature in economics has traditionally focused on understanding why there are such large differences in the diffusion rates of new innovations (Comin and Hobijn, 2004, 2009; Skinner and Staiger, 2015). For example, Grilliches (1958) emphasized differences in the profitability of hybrid-corn adoption, while Comin and Hobijn (2007) and Caselli and Coleman (2006) rely on heterogeneity across agents in the value of the new technology. Non-adopters may also optimally hold back because they are waiting for the price to decline or are better at the old technology (Jovanovic and Nyarko, 1996), or because they face higher costs from suppliers (Suri, 2011).

A related literature seeking to explain slow diffusion instead as the consequence of poorly informed agents who lack appropriate education or information about potentially profitable innovations (e.g., Foster and Rosenzweig, 1995; Conley and Udry, 2010; Rogers, 2010; Skinner and Staiger, 2007) or time-inconsistency and a lack of commitment devices (Duflo, Kremer, and Robinson, 2008). All of these papers seek to explain why diffusion is so slow despite the clear economic benefits of doing so, and the implications of this slow diffusion for productivity growth (Comin and Hobijn, 2010).

In this paper, we address a closely related question: Why are some so quick to adopt and diffuse a new technology across a wide swath of applications? Nearly all of the previous studies assume that rapid diffusers effect change more rapidly because of greater profitability, better information, and superior relative advantage in the new technology. But the rapid diffusers could be overly optimistic either about the value of the new technology, or about their own skill in using the new technology. Overconfidence as a cause for rapid diffusion has received some attention in the finance and management literature (e.g., Malmendier and Tate, 2005; Barber and Odean, 2001, Glaser and Weber, 2007; O'Neill, Pouder; and Buchholtz, 1998), and in industrial organization (Camerer and Lovallo, 1999), but to our knowledge overconfidence has received little attention in the productivity literature.

We first present empirical patterns of diffusion using as an example implantable cardioverter defibrillators (ICDs), an expensive medical device that has been used for many years to treat patients who had experienced, but survived, a sudden cardiac arrest. In 2005, following several large randomized clinical trials (RCTs), ICDs were allowed by Medicare in the U.S. to be used as a preventive device for patients with weakened hearts (congestive heart

failure, or CHF) who had not yet experienced a cardiac arrest, thus expanding the population of those eligible for ICDs dramatically. We use the Medicare claims data linked to a Centers for Medicare and Medicaid Services (CMS) clinical registry of every ICD implanted during 2006-13 with detailed information on key clinical variables such as the severity of their CHF, ejection fraction, family history of heart failure, and ventricular fibrillation. Using the Medicare claims data, we find that between 2002 and 2006, rates of ICD use doubled nationally, but with considerable variation in the speed of diffusion. Rates in some regions such as Terre Haute IN and McAllen TX exhibiting very rapid rates of growth, while rates in other areas, such as Seattle and Minneapolis, exhibited only modest growth. By 2006, age-sex-race-adjusted rates of ICD use varied by a factor of ten. Since that time rates have steadily declined, so that by 2013, the national rate of ICD use had dropped by a fifth relative to 2006. Indeed, hospitals with the most rapid increase in utilization rates for 2002-05 were quickest to "exnovate" (Bekelis et al. 2017) or scale back on utilization, during 2006-13.

We also found wide differences in hospital-level risk-adjusted mortality rates, which we report at the regional level. They ranged from 2-year risk-adjusted rates of 18 percent in Minneapolis to 26 percent in Munster, IN. The reduced-form correlation between utilization of ICDs and risk-adjusted mortality was 0.22 ($p < .001$), suggesting that patients seeing most rapid diffusers of the new technology experienced, on average, worse outcomes.

To explain these empirical puzzles, we developed a model in which potential innovators face uncertainty about the value of the technology for specific scenarios (e.g., whether to use fertilizer for a given plot of land, or whether to implant a medical device in an actual patient). In a rational model, Bayesian agents who are early diffusers do so because they are more skilled in applying the technology, and thus optimally can the technology more quickly and more intensively with higher returns (Currie and MacLeod, 2013; Currie, MacLeod, and Van Parys, 2015). Not surprisingly, those with lower skill levels are predicted to be slower in diffusing into the new technology because there are fewer potential uses of the technology with positive net returns.

Nested within this model, however, is the possibility of overconfidence; that some agents believe their skill is better than it really is. We show that with overconfidence in skill, agents go "deeper" into the distribution of potential applications, such that the (objective) net benefit could be negative at the margin. Yet innovators may still learn; it's possible that initially overconfident

diffusers realize that they are not yielding such favorable results, and subsequently scale back. The model therefore captures Bayesian learning in a dynamic framework; innovators may realize that they have been overly confident rather than skilled, so our model has implications as well for the dynamic pathways of new innovations.

We estimate the model parameters by fitting to the aggregate moments of the ICD data, and find strong statistical support for the overconfidence model. Differences in the extent of overconfidence across hospitals explained roughly three-quarters of the variation in utilization, and nearly three-quarters of the variation in risk-adjusted mortality. The higher rates of mortality in the most rapidly diffusing regions are, surprisingly, not as much about low skill, but more about reaching into less appropriate patients. In sum, both the model and the reduced form estimates suggest that the hospitals exhibiting the most rapid diffusion of ICDs were also those with the lowest productivity.

The empirical patterns of ICD use exhibited rapid scaling back in utilization rates after 2006, which is consistent with the out-of-sample prediction of our Bayesian learning model. Using hospital-level longitudinal data, the model predicts all of the subsequent decline in ICD rates between 2006-13, and captures nearly half of the variance in the hospital-specific declines. Unlike other studies of clinical learning-by-doing (e.g., Jovanovic and Nyarko, 1995; Gong, 2017), however, we find no empirical evidence that physicians improved outcomes over the period of 2006-13; risk-adjusted mortality rates barely budged.

Our results differ from earlier analyses of diffusion, in which early adopters were the "innovators" and slow diffusers "laggards" (Rogers, 2004). Why? One reason may be that we are studying health care markets, where patients cannot always determine quality and financial incentives to do more are often present. Supportive of this view is the investigation and multiple malpractice cases now pending in Munster, Indiana, an area with among the most rapid diffusion rates in the country, and with the highest risk-adjusted mortality (Creswell, 2015). Yet even in health care, hospitals with the greatest productivity in treating heart attacks are more likely to attract a growth in patients (Chandra et al., 2016). Furthermore, Currie, MacLeod and Van Parys (2015) find that the most aggressive physicians in treating heart attacks (according to then-current standards) gained the best results. Our finding can be reconciled with theirs by noting that for heart attacks, the new and then unproven technology turned out *ex post* to have been far

more advantageous than expected, while the medical consensus appears to be that ICDs are less successful in practice than first envisioned (McMurray, 2016).

While the model is developed in the framework of overconfidence, we note that there are a variety of other types of behavior that are observationally equivalent with overconfidence. For example, supplier-induced demand models (see Chandra et al., 2011) predict physicians provide less appropriate treatments in pursuit of profit, generating equivalent correlations between utilization and health outcomes. Even insistent patients could generate a similar pattern. Yet such models require that physicians understand that they are harming patients. By contrast, there is growing clinical evidence pointing to overconfidence, rather than pure supplier-induced demand, as a primary factor in misdiagnosis and poorer health outcomes (Berner and Graber, 2008; Cutler et al. 2017).

Can our results be generalized to diffusion across non-health sectors of the economy? Like other studies in the non-medical sector, we find substantial heterogeneity in productivity across institutions, as in (e.g.) Pavcnik (2002). But many studies of diffusion focus on successful innovations, where overconfidence *ex ante* could look like prescience *ex post*. In practice, the association among overconfidence, rapid diffusion rates, and below-average productivity may be more common than previously thought.

In the next section, we consider both clinical aspects of ICD use and expansion, as well as documenting the empirical patterns of ICD diffusion and mortality from 2002 to 2013. Section 3 develops a model that can potentially explain these patterns, while Section 4 presents model estimates and simulation; Section 5 concludes.

2. Implantable Cardioverter Defibrillators (ICDs)

Congestive heart failure (CHF) is a very common illness especially among elderly people (Rogers, 2013), with a prevalence of 5.8 million people in the U.S. It is thus more common than heart attacks (or acute myocardial infarctions), of which there are approximately 715,000 annually. While heart attacks are sudden medical emergencies treated (often successfully) with a variety of medical interventions, CHF is a chronic illness whose progression can only be slowed by appropriate medical management. The typical progress of CHF is from the New York Heart Association Class I (the least severe) through to Class IV (the most severe), at which point the annual mortality rate ranges between 20-50%. (Ahmed et al., 2006)

An important risk facing CHF patients is a sudden cardiac arrest, which occurs when the heart suddenly stops functioning, typically because of arrhythmia, or irregular heart rhythm. This causes rapid and unsynchronized heartbeat, leading to little or no blood being pumped from the heart, and a complete absence of a heartbeat (van Reys, 2014). Implantable cardioverter defibrillators (ICDs) are small electronic devices that are surgiccally implanted in the pectoral region of the chest and connected with wire "leads" to key locations of the heart. These leads serve two functions. The first is to monitor the rhythm and detect tachycardia (irregular or weak heart beats), and the second is, when necessary, to shock the heart with a strong electrical current, effectively "rebooting" the conduction system. (Popular entertainment shows often show physicians using paddles to administer electrical shocks; ICDs are internal automated versions.) Over time ICDs have become more effective and entailed fewer complications as the size of the ICD shrunk, and the sophistication of the computer programs designed to detect arrhythmias improved.

Initially, ICDs were developed in the 1980s and 1990s for people who had already experienced and survived a cardiac arrest, and were at risk of experiencing another one. As ICDs became more compact and reliable, attention turned to the larger group of people with congestive heart failure (CHF) at risk of cardiac arrest but who had not yet experienced the life-threatening event; for these patients the ICD is deemed "preventive." A large 2005 randomized trial, SCD-HeFT, found substantial mortality benefits of up to 7 percentage point increases in survival 5 years after the procedure. It is important to note that ICDs provide no other benefit to patients other than a "reboot" in the case of sudden cardiac arrest; thus mortality as a measure of health outcomes is a particularly apposite measure. As well, ICDs carry with them risks of broken leads or infection during the initial procedure.

It is important to note that the SCD-HeFT trial included only the intermediate Class II and Class III CHF patients with low "ejection fractions" or the heart's ability to pump blood to the rest of the body.[1] The reason why the trial was limited to only these two groups was the consensus that for Class I (the least serious) CHF patients, the risks outweighed potential benefits given the rarity of sudden cardiac arrest in this group, while for the more severe Class

[1] As well, the ejection fraction should be 35% or less in patients with Class II or III Heart Failure. Despite the rarity of older patients in the randomized trials, there are no guidelines that recommend against the use of ICDs on the basis of age.

IV patients, the heart is so weakened that it can no longer sustain pumping, no matter how many times it reboots. For these patients, ICDs can lead to a series of successive and painful shocks, sometimes delaying an otherwise peaceful demise as the ICD continues to go off until the batteries are drained (Friedrich and Bohm, 2007). Despite these guidelines, a sizeable fraction of ICD procedures were done for those with either Class I or Class IV heart failure, and for considerably older patients where the treatment value is unknown.

2.1 Patterns of ICD Diffusion in the Medicare Population

We use the 100% Medicare claims data for the fee-for-service over-65 Medicare population to derive rates of utilization by age population-based rates of ICD use from the claims data, and assign rates to patients and then to hospitals (as described below). Because of possible changes over time in coding standards, we develop measures for all ICD use during 2002-13, and not simply those for preventive purposes.[2] To measure utilization, we use population-based rates at the hospital referral region (HRR) level, of which there are 306 in the U.S.[3] These utilization measures are based on the residence of the patient; if a resident of the Jackson Tennessee HRR received their ICD in Atlanta, the ICD would be assigned to the Jackson HRR rather than Atlanta. Rates are adjusted by age, sex, and race.

Rates of ICD diffusion between 2002-13 for the U.S., and for selected regions, are shown in Figure 1. We first focus on the temporal diffusion between 2002 and 2005-6; we discuss the scaling back (or "exnovation," as in Bekelis et al., 2017) of ICD use below. Note first that U.S. rates in 2002, while low (0.12 per 100 Medicare enrollees), is still consequential; the near doubling of ICD rates through 2005 therefore represents the diffusion of procedure use to a new population – those with CHF but who have not yet experienced sudden cardiac arrest – rather than the innovation of a new treatment protocol or device. For this reason, we might not expect as much "learning-by-doing" in the skill of the already-experienced physician, although we do

[2] We begin the analysis using the claims data in 2002, when the sample of Part B claims data relevant for analysis is 20% of all fee-for-service enrollees; the sample rises to 40% in 2003-05, and becomes 100% thereafter.

[3] HRRs were first developed by the Dartmouth Atlas project in the 1990s to create regions based on the migration patterns of individuals to their hospitals. Thus HRR boundaries will often follow (e.g.) interstate highways and cross state lines. Each HRR includes a major tertiary hospital that performs neurosurgery and cardiac surgery. We use HRRs rather than the smaller hospital service areas (HSAs) for better sample precision.

expect that physicians may learn over time about which of these newly eligible patients benefit from ICDs, and which don't.

As shown in Figure 1, Miami exhibited a high use of ICDs even in 2002, with a rate of 0.19 per 100 patients in 2002, rising to 0.34 in 2006 before gradually declining to 0.18. The three most rapid adopters in the graph were McAllen TX (from 0.14 in 2002 to 0.37 in 2006), Munster IN (from 0.19 in 2003 to 0.45 in 2006) and Terre Haute IN (from 0.13 in 2003 to 0.54 in 2006); these all scaled back quickly, but still ended up with rates more than double those in Seattle and (e.g.) Savannah GA, which never expanded their use of ICDs by much.

Figure 2 provides a map for the entire U.S. of 2006 ICD utilization rates by HRR. There is even more geographic disparity in the use of ICDs across the entire U.S., with rates ranging as low as 0.04 in Lynchburg, VA.[4] There is a "patchwork quilt" pattern of treatment rates, suggesting that it's not just (e.g.) higher cardiovascular rates in the South that accounts for the variations. While we are currently preparing fully adjusted rates to control for health behaviors of individuals (e.g., smoking, obesity), we note that these rates do not show an overly strong association with underlying health status: the Medicare age-sex-race-adjusted mortality rate in Munster is almost identical to Lynchburg's, despite the nearly 10-fold difference in utilization rates.[5]

Why did rates decline between 2006-13? If the population of eligible patients suddenly expanded in 2006, then why the gradual decline of ICDs, as shown by the US average in Figure 1? One explanation is a "stock-flow" imbalance; there were a large stock of people deemed appropriate for treatment, and once physicians worked through this stock, they then relied only on new flows of patients. However, this does not explain the continued decline after 2010, when presumably the stock of potential patients had been exhausted.

Another possibility is that during this period, alternative treatments were developed that could substitute for ICDs, for example a new drug regimen for CHF. While during this time, there was greater emphasis on adherence to guideline-directed drug prescriptions, we know of

[4] One might be concerned with small-sample bias in these relatively small HRRs, but the patterns show a strong temporal trend; high rates in 2006 are matched (or even exceeded) by high rates in 2005 and 2007.

[5] Mortality data are drawn from the 2006 mortality data in www.dartmouthdiffusion.org

no new alternative treatments based on literature and discussion with cardiologists and electrophysiologists.

The best explanation of the decline was that physicians had learned from experience that ICDs were not so helpful to many of their patients. Matchett et al. (2009) for example, referred to the ICD expansion as a "Hype Cycle" with one phase reflecting "inflation expectations ... through media endorsements and clinical trial data..." followed by "the trough of disillusionment...consistent with device recalls and increased concern regarding cost." When ICDs discharge and reboot (which patients say is like a bomb going off in the chest[6]) multiple times, patients become anxious, with one estimate of nearly half of ICD recipients depressed in part because of worry about the next "kick" (Matchett et al., 2009).

As shown in Figure 3, which shows the HRR-level rate of growth in ICDs between 2002-05 correlated with the change between 2006-13, the regions with the most rapid growth also experienced the most rapid decline. Despite this overall decline, however, the coefficient of variation (the standard deviation divided by the mean) declined only slightly, from 0.29 in 2006 to 0.27 in 2013. This general pattern is consistent with a model in which there is learning-by-doing with regard to the choice of patient most appropriate for the device, so that those with the greatest degree of overconfidence would scale back most quickly.

2.2. Diffusion and Variation in Health Outcome Following ICD Implantation

When CMS approved the use of ICDs for preventive purposes, it was done with the understanding that hospitals would send detailed clinical information about the patient to CMS. We use this 100% registry, linked to the Medicare denominator file for people age 65+, during 2006-13, which allows us to mortality rates based on Medicare denominator files available through 2015. The registry includes detailed information on the registry that includes whether the ICD was for patients with CHF (e.g., preventive), their risk class (I through IV) as well as ejection fraction and many other clinically relevant factors such as having ventricular tachycardia, family history of cardiac arrest, the exact ejection fraction, and other measures, along with the identity of the hospital performing the procedure.[7] These data are far more

[6] https://www.everydayhealth.com/atrial-fibrillation/living-with/shocking-truths-about-heart-defibrillators/

[7] One complexity associated with identifying hospitals is that in some cases, the hospital was not identified; only the NPI for the provider who performed the procedure. We are grateful to Andrea Austin for providing a cross-

detailed than what could ever be recovered from Medicare billing claims. To estimate outcomes, we focus on a relatively homogenous group of CHF patients who have never had an ICD implanted; we implicitly assume that the hospital-specific mortality effect estimated using these patients is similar to the effect for other patients receiving an ICD.

Ideally, we would be able to measure true treatment effects; the benefit of an ICD relative to the status quo of medical management for CHF. However, our estimates and modeling are specific to mortality rates only among those treated. We discuss this concern, and how we address it, in the modeling section in Section 4.

Table 1 provides summary statistics of the ICD sample (N = 253,613). The average age among the Medicare enrollees (all of whom are 65+) is 74.5, and just 28 percent are female. Note that the mortality rate barely budged between 2006 and 2013. We also include summary statistics for additional covariates from the registry, including the ejection fraction, prior cardiac arrest, family history, prior heart attack, and other variables.

Hospital-level risk-adjusted mortality is modeled using the following structure:

$$M_{ijt} = \Psi_{it} + X_{ijt}\beta + \zeta_{ijt}$$

where $\Psi_{it} = Z_{it}\Gamma + \nu_{it}$.

Mortality M_{ijt} is a binary variable that depends on characteristic of patient X_{ijt}, and the physician/hospital Ψ_{it}, which in turn is a function of observable provider-level characteristics Z_{it} such as patient volume, the utilization rate for ICDs, and the use of guideline-consistent medical treatment for CHF patients. We are particularly interested in the variance of Ψ_{it}, which depends both on the predictable characteristics of the hospital, Var($Z_{it}\Gamma$), as well as the provider-specific error term Var(ν_{it}). Our preferred specification is a random-effects model clustered at the level of the provider, which allows us to "shrink" the estimate of the provider residual towards the fitted value $Z_{it}\hat{\Gamma}$ depending on the sample size of the provider. To preserve linear variance additivity, we use linear probability models; we begin with a least-squares

walk from ICD-capable providers to the hospital where they performed the plurality of procedures, which we used to create our dataset.

regression, consider the random-effects model, and then briefly consider a fixed-effect model at the provider level.

The benefits inherent in ICD implantation arise only after several years (Bardy et al., 2005) so we focus on both 1-year and 2-year mortality. For the random-effects model, we estimate the distribution of Ψ_{it} in Figure 4, which shows the risk-adjusted two-year variation in hospital quality, expressed in hospital-specific mortality rates. The standard deviation is 3.2 percentage points, and a low-quality hospital exhibits a mortality rate nearly double that of a high-quality hospital.[8] These (large) variations arise both from differences in physician and more generally hospital staff skill, and the choice of patients based on factors unobservable even in the clinical registry data.

2.3 The Reduced-Form Correlation Between ICD Diffusion and Mortality

For the model specification, we will need to know a variety of reduced-form parameters such as the variance in mortality across hospitals, the variance in utilization, and diffusion patterns for individual hospitals. As well, a critical reduced-form parameter is the correlation between the rate of diffusion and risk-adjusted mortality by hospital. We therefore combine the utilization data (Section 2.1) and the outcome estimates (Section 2.2) to estimate a generalized model of mortality and utilization. In Table 2, we report summary estimates of the OLS, random effect, and fixed-effect models, limited to just two-year mortality; regression results are reported in the Appendix for OLS in Table A.1, random effects in Table A.2, and hospital fixed-effects in Table A.3 that also include one-year mortality.

As shown in Table 2, there is a consistent positive correlation and significant correlation between the rate of use of ICDs in a given year, and risk-adjusted mortality rates, in both the OLS and random-effects model, suggesting in the reduced form that patients of the most rapid diffusers experience worse outcomes. The point estimates are much smaller and not significant in the fixed-effect model; this is because most of the identification is from cross-sectional variation; within a hospital there is relatively little improvement in skill, leading to almost no temporal variation.

[8] Recall that these estimates are derived from the random-effects model, and are therefore already shrunken towards the mean; a fixed-effects model would have exhibited even more variability.

While one can argue that volume is itself a key component of quality, we also include the log of annual volume of all ICDs for the over-65 population (including non-CHF patients) as a control. The coefficients on these variables are as expected; an increase in log-volume of 1 leads to a 1.3 percentage-point decline in 2-year mortality in the random-effects model (Column 4 of Table 2). In addition, we also include the HRR-level rate of guideline-appropriate medical treatments for ICD candidates (Roth et al., 2016) to adjust for our concern that the correlation between utilization and mortality is driven by poor medical management – that high utilization of ICDs is because health systems are so poor at medical management, and the poor medical management in turn adversely affects mortality (e.g. Chandra and Staiger, 2007). And while low rates of medical management are clearly bad for mortality, including them as controls does not significantly attenuate the coefficient on utilization.

Another concern is to derive appropriate measures of utilization rates. It is straightforward to measure the number of ICDs performed at a given hospital, but measuring the denominator, the population of potential recipients of the treatment for a hospital in a city with multiple hospitals, is more difficult. To assign utilization rates to each hospital, we used the utilization rate for the patient's HRR of origin to create a measure that reflected the population of people in that hospital receiving care. Typically, hospitals will draw the plurality of patients from their local HRR, but patients do travel for ICDs.

Figure 5 shows the correlation between the average (2006-13) ICD utilization rate, and the fully risk-adjusted relevant hospital-level mortality. There is a strong positive correlation (as shown above and in Table 2), but this graph labels several of the more interesting regions. In particular, some regions exhibit both low mortality rates and low use of ICDs (the Minneapolis-St. Paul HRR); others are in-between, while others exhibit very high rates of ICD use, coupled with relatively high rates of mortality.

Munster, IN is an interesting case, because it is among the most rapid diffuser of ICDs, yet as Figure 5 shows, it also has among the handful of regions with the highest two-year (and 1-year) risk-adjusted mortality rates. An obvious question is why Munster is so different from other nearby regions. (Even Terre Haute, which is 120 miles away, exhibited far lower mortality rates.) One explanation could have been an unusually entrepreneurial cardiologist practicing in Munster during this time. A 2015 *New York Times* article (Creswell, 2015) described how the cardiologist, Dr. Gandhi, was under investigation for inappropriate cardiac procedures:

> When Dr. Mark Dixon, then the medical director of Community Hospital's electrophysiology lab, where defibrillators were implanted, raised concerns to a hospital executive in 2005 about whether Dr. Gandhi and other physicians were qualified to implant the devices, he said he was shut down.

While anecdotal, it is at least suggestive that the variations we observe in the data are not an artifact, but instead represent real differences in provider skills and patient choice. By contrast, many regions in the U.S. exhibited very slow diffusion, and with much lower risk-adjusted mortality.

To sum up, we find wide variation in rates of diffusion across the U.S. with regard to ICD use; reversion to the mean with regard to utilization, in the sense that regions with the most rapid growth were most likely to "exnovate" or scale back on their use; wide variability in ICD mortality rates across hospitals, and a positive correlation between diffusion and mortality. We turn next to developing a model that can potentially explain these empirical patterns.

3. The Model

Our goal is to develop a model of technology diffusion to better understand the empirical patterns of ICD diffusion (and exnovation) and mortality. It builds on an optimizing Bayesian framework where both doctors and patients are heterogeneous and health outcomes are uncertain. Patients differ in the potential benefits from an ICD implant while doctors differ in their ability in implanting ICDs. Additionally, we allow doctors to have a biased perception of their true ability. We first focus on the decision to implant an ICD taking as fixed the doctor's perceived skill. In section 2.2, we study the model dynamics by making endogenous the doctor's prior distribution of skill through learning.

3.1 Static setting

We begin with the decision problem from the perspective of the doctor. There is a continuum of patient types j that differ in their potential net value of the treatment. Let μ_j denote the difference between the patient's potential value of being treated v_j or not treated w_j. The patient's type (μ_j) is not directly observed by doctors. We assume that the distribution of patient's net value from treatment, μ_j, is normal with mean $\bar{\mu}$, and variance σ_μ^2. The precision of

the prior of μ_j is denoted by $\rho_\mu = \frac{1}{\sigma_\mu^2}$. The two components of the net value from treatment, v_j and w_j, are normally distributed and, for the time being, we assume that they are independent.[9]

In addition to the patient's type, the value of the ICD depends on the doctor' skill, a_i. In particular the net value of implanting an ICD to a patient of type μ_j by a doctor with skill a_i is $\mu_j + a_i$.[10]

Doctors do not know a_i; a_i^p denotes the mean of the doctor's prior distribution of a_i. We refer to a_i^p as perceived skill. The gap between the perceived and true skill is the overconfidence bias, o_i. If $a_i^p > a_i$ the patient is overconfident on his skill, while if $a_i^p < a_i$ he is under-confident. If $a_i^p = a_i$ the doctor is unbiased.

Information structure. Before deciding the treatment, doctors observe an imperfect signal on the patient's type. Specifically, we assume that the distribution of patient's value from treatment, μ_j, is normal with mean $\bar{\mu}$, and variance σ_μ^2. The precision of the prior of μ_j is denoted by $\rho_\mu = \frac{1}{\sigma_\mu^2}$.

The noisy signal, s_j, is related to the patient's true type, μ_j, as follows:

$$s_j = \mu_j + \varepsilon \tag{1}$$

where ε is normal with mean 0 and variance σ_ε^2.

Treatment decision. Given this information structure, the posterior distribution of the patient's type is distributed as

$$\mu_j | s_j \sim N(\bar{\mu}_j^p, \frac{\sigma_\mu^2 \sigma_\varepsilon^2}{\sigma_\mu^2 + \sigma_\varepsilon^2}) \tag{2}$$

The posterior mean is

$$\bar{\mu}_j^p = (1 - \alpha)\bar{\mu} + \alpha s_j, \tag{3}$$

with $\alpha = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\varepsilon^2}$.

[9] We explore the effects of relaxing this assumption in the robustness checks section.
[10] Without loss of generality, we normalize the costs of implanting an ICD to 0.

The doctor's perceived skill is the only relevant statistic of the prior distribution of a_i for the treatment decision. A doctor with perceived skill a_i^p will treat a patient with signal s_j if and only if $\bar{\mu}_j^p + a_i^p \geq 0$.[11] That is, if the signal s_j is greater than a threshold $s(a_i^p)$ defined by:

$$s_j \geq s(a_i^p) \equiv -\frac{(1-\alpha)}{\alpha}\bar{\mu} - \frac{a_i^p}{\alpha}. \quad (4)$$

ICD usage. The probability of implanting an ICD for a doctor with perceived skill a_i^p is

$$\Pr\left(ICD = 1|a_i^p\right) = \int_{s(a_i^p)}^{\infty} f(s)\, ds, \quad (5)$$

where $s(a_i^p)$ is defined by equation (4) and where *f(.)* is the pdf of the signal s_j. That is, it is a normal distribution with mean $\bar{\mu}$, and variance $\sigma_\mu^2 + \sigma_\varepsilon^2$.

Proposition 1 (Determinants of diffusion). Ceteris paribus, the use of ICDs increases with perceived skilled, a_i^p.

Proof:

$\frac{\partial \Pr\left(ICD=1|a_i^p\right)}{\partial a_i^p} = -f\left(s\left(a_i^p\right)\right) * \frac{\partial s(.)}{\partial a_i^p} > 0$, because, from expression (4), $\frac{\partial s(.)}{\partial a_i^p} < 0$.□

Intuitively, the threshold signal required to implant an ICD decreases with perceived skill. Therefore, doctors that think have a high skill are more likely to observe a patient' signal above their threshold. Note that what matters for the incidence of ICDs is the doctors perceived signal, a_i^p. (Recall that $a_i^p = a_i + o_i$.) Therefore, for a given skill, a_i, the use of ICDs increases with over-confidence, o_i. Similarly, for a given level of overconfidence, higher (true) skill induces a greater use of ICDs.

Outcomes. Most empirical studies on technology adoption do not have access to adopter-level proxies for the outcomes after adopting the technology. Our dataset has the advantage of containing information on the patients' mortality after they have received an ICD. Our model can capture the event of death in a short horizon as a low ex-post realization. Naturally, the further in the future the patient dies, the higher the ex-post utility of the patient.

[11] Note that because doctors are risk neutral, they only take into account their average perceived skill (and the patient' signal) to determine whether they should implant an ICD.

This logic allows us to establish a mapping between mortality and utility. In particular, we interpret the death of the patient within *x* years as an ex-post utility below a threshold $\underline{\kappa}_x$, where $\underline{\kappa}_x$ is increasing in *x*.

Now we can compute the *x*-years mortality rate conditional on ICD implant for a doctor with perceived skill, a_i^p, and actual skill, a_i, is:

$$Pr\left(v_j + a_i \leq \underline{\kappa}_x \middle| ICD = 1, a_i^p, a_i\right) = \frac{\Pr\left(v_j \leq \underline{\kappa}_x - a_i \cap ICD = 1\right)}{\Pr\left(ICD = 1 | a_i^p\right)} = \frac{\int_{-\infty}^{\infty} f_\varepsilon(\varepsilon\prime)\left(\int_{s(a_i^p)-\varepsilon}^{\underline{\kappa}_x - a_i} f_v(v\prime)dv\prime\right)d\varepsilon\prime}{\int_{s(a_i^p)}^{\infty} f_s(s\prime)ds\prime} \quad (6)$$

where $f_\varepsilon(.)$ is the pdf for ε, $f_v(.)$ is the pdf for patient's type v_j, and $f_s(.)$ is the pdf for the signal *s*. While utilization is affected only by perceived skill, conditional mortality is affected by both the doctor' true skill and perceived skill.

Proposition 2 (Determinants of mortality conditional on ICD implant). Here we show that (i) the probability of death conditional on implanting an ICD (but not adjusting for patient characteristics) increases with overconfidence, and (ii) skill has an ambiguous effect on the physician's post-ICD (unconditional) mortality rate.

Proof: The proofs are as follows:

(i)

$$\frac{\partial \Pr(v_j + a_i \leq \underline{\kappa}_x | \, ICD = 1, a_i^p, a_i)}{\partial o_i} =$$

$$\left[1 - Pr(v_j \leq \underline{\kappa}_x | \, ICD = 1, a_i^p, a_i)\right]\left(-\frac{\partial \bar{s}}{\partial o_i}\right)\left[\frac{\int_{-\infty}^{\infty} f_\varepsilon(\varepsilon\prime) f_v(s(a_i^p) - \varepsilon\prime)d\varepsilon\prime}{\int_{-\infty}^{\infty} f_\varepsilon(\varepsilon\prime)\left(\int_{s(a_i^p)-\varepsilon}^{\infty} f_v(v\prime)dv\prime\right)d\varepsilon\prime}\right] > 0 \quad (7)$$

Both the first and third terms are positive, but the key is the middle expression; that when overconfidence rises, the "hurdle" point at which the physician does the procedure declines, thus expanding the number of patients for which the net benefit is negative.

(ii)

$$\frac{\partial \Pr(v_j + a_i \leq \underline{\kappa}_x | \, ICD = 1, a_i^p, a_i)}{\partial a_i} = -\left[\frac{\int_{-\infty}^{\infty} f_\varepsilon(\varepsilon') f_v(\underline{\kappa}_x - a_i)d\varepsilon'}{\int_{-\infty}^{\infty} f_\varepsilon(\varepsilon')\left(\int_{s(a_i^p)-\varepsilon}^{\infty} f_v(v')d\,v'\right)d\varepsilon'}\right]$$

$$+\frac{\left[1 - Pr(v_j \leq \underline{\kappa}_x | \, ICD = 1, a_i^p, a_i)\right]}{\alpha}\left[\frac{\int_{-\infty}^{\infty} f_\varepsilon(\varepsilon\prime) f_v(s(a_i^p) - \varepsilon\prime)d\varepsilon\prime}{\int_{-\infty}^{\infty} f_\varepsilon(\varepsilon\prime)\left(\int_{s(a_i^p)-\varepsilon}^{\infty} f_v(v\prime)dv\prime\right)d\varepsilon\prime}\right] \quad (8)$$

Here we show that the net effect of skill on mortality is to both improve outcomes for patients who would have been treated anyway, but to also bring in more patients with net benefit, but whose underlying mortality probability could be higher as well.[12] This result holds only for unconditional mortality; once we adjust for characteristics of patients, skill exerts an unambiguously positive effect on health outcomes.

3.2 Dynamics through learning

We explore the dynamic properties of the model by allowing doctors to learn about their true skill. The learning problem we pose is one where doctors are uncertain both about the level of their skill and about the precision of the signals they receive. By allowing for an unknown precision, we can investigate the relevance of heterogeneity in confidence about the precision of the prior distribution of skill to explain the evolution of perceived skill in the data.

We start by describing the nature of the signals and the priors. After implanting *n* ICDs for patients newly covered by the CMS rules, doctors receive *n* imperfect signal, $\{s_{ik}^{a}\}_{k=1}^{n}$. Signals are random draws from a normal distribution with unknown value of the mean a_i and known value of the precision ρ_{sa}. In particular, the signal $s_{ik}^{a} = a_i + \xi_{ik}$, where the noise term ξ_{ik} is distributed according to a normal with zero mean and precision ρ_{ξ}. Therefore, the precision of the signal net of noise is $\rho_a = \frac{\rho_{sa}\rho_{\xi}}{\rho_{\xi}-\rho_{sa}}$. The doctor's prior of the distribution of a_i is normal with mean a_i^p and precision τ_i such that $\tau_i>0$ and $-\infty < a_i^p < \infty$.

There are two possible biases in the doctor's prior. The first is the familiar bias between true and perceived skill (overconfidence). The second is a bias in the precision of the conditional prior distribution of skill. This bias is reflected by the gap between the precision in the prior distribution of skill, τ_i, and the precision of the signal net of noise, ρ_a. To explore the evolution of perceived skill, we use the following lemma to compute the posterior distribution of skill.

Lemma 1 (Posterior distribution of skill) The posterior distribution of a_i is normal with mean $a_i^{p\prime}$ and precision $\tau_i+n\rho_{sa}$, where

[12] This is one reason why some highly-skilled physicians may appear to be lower quality; because they end up with the most difficult patients.

$$a_i^{p\prime} = \frac{\tau_i a_i^p + n\rho_{sa}\overline{s_i^a}}{\tau_i + n\rho_{sa}} \quad (9)$$

and $\overline{s_i^a} = \frac{\sum_{k=1}^{n} s_{ik}^a}{n}$.

Proof: See De Groot (1971), page 167. □

Lemma 1 describes the evolution in perceived skill. Subtracting a_i in both sides of expression (9) and substituting the tildes by time subscripts we obtain

$$a_{i,t+1}^p - a_{i,t}^p = -\alpha_{it}^a * \left(a_{i,t}^p - a_i\right) + \alpha_{it}^a * \sum_{k=1}^{n} \xi_{it} \quad (10)$$

where

$$\alpha_{it}^a = \frac{n\rho_{sa}}{\tau_i + n\rho_{sa}} \quad (11)$$

Replacing in $\bar{a}_{i,t}^p - a_i$ by $o_{i,t}$, we obtain[13]

$$a_{i,t+1}^p - a_{i,t}^p = -\alpha_{it}^a * o_{i,t} + \alpha_{it}^a * \sum_{k=1}^{n} \xi_{it} \quad (12)$$

Because α_{at} is independent of the overconfidence bias, equation (12) shows that the larger the bias in perceived skill, the larger the expected correction in the perceived skilled. Adding and subtracting a_i to the left-hand-side of (12), we can express the law of motion for overconfidence as

$$o_{i,t+1} - o_{i,t} = -\alpha_{it}^a * o_{i,t} + \alpha_{it}^a * \sum_{k=1}^{n} \xi_{it} \quad (13)$$

Equation (13) shows that learning induces mean-reversion in the level of doctor overconfidence.

The speed of learning in our model is captured by coefficient α_{it}^a. Expression (11) shows that α_{it}^a varies across doctors. Other things equal, α_{it}^a decreases in the precision of the prior precision of skill (τ_i), and increases in the precision of the signal (ρ_{sa}) and in the number of signals/ICD implants (n).[14]

[13] Subtracting and adding a_i to the right-hand side of (14) we obtain the following expression for the evolution of overconfidence:

$$\Delta o_{i,t+1} = -\alpha_{at} * o_{i,t} + \alpha_{at} * \xi_t \text{ where } \Delta o_{i,t+1} = o_{i,t+1} - o_{i,t}.$$

[14] Furthermore, α_{it}^a evolves over time. In particular, combining equation (11) and the evolution of precision of the prior distribution of skill (from Lemma 1), variance of perceived skill, $\sigma_{a_t^p}^2$, we can write the following difference equation for α_{at}:

4. Analysis and Model Estimation

We next use the model to explore the determinants of empirical patterns documented in Section 2. Our strategy has three steps. First, we use the reduced form parameters from Section 2 to calibrate the key parameters of the economy-wide distributions of patient type, and doctor true and perceived skill so as to match aggregate moments. Note that these parameters are common across hospitals. Second, using the common parameters and the data on usage rate of ICDs and mortality conditional on ICD at each hospital and year, we identify the hospital-level true and perceived skill, a_{it} and a_{it}^{p}. Note that these parameters are specific for each hospital/year. Third, we use the identified parameters to validate some of the model assumptions and explore determinants of ICD use and conditional mortality in the cross-section and time series, including out-of-sample predictions.

4.1 Identification

Thus far the model has considered the decision-making process of individual physicians, while the unit of observation in our analysis is the hospital. Because our data is at the hospital level, thus reflecting utilization decisions and outcomes for the entire team of physicians, nurses, and other health workers, we are not able to measure the specific contribution of the cardiologist or electrophysiologist who performs the procedure. That said, typically there are typically only a few physician (or just one) who performs to the procedure at a given hospital.[15]

Estimating treatment effects. As noted above, we measure mortality rates accurately at the hospital level, but our primary interest is in treatment effects, or the beneficial outcomes of an ICD relative to not being treated with an ICD. To address this concern, we use published data

$$\alpha_{at+1} = \frac{\alpha_{at}}{1+\alpha_{at}} \tag{14}$$

The solution to this difference equation is

$$\alpha_{at} = \frac{\alpha_{0i}}{1+t*\alpha_{0i}} \tag{15}$$

where $\alpha_{0i} = \frac{\sigma^2_{a_0^p}}{\sigma^2_{a_0^p}+\sigma^2_{i\xi}}$ is the learning coefficient in the initial period.

[15] To avoid identifying specific hospitals, we translate the hospital-level mortality predictions back to the HRR level for presentation. For example, the patient from Jackson TN whose procedure was done in Atlanta would have her outcome transferred back to the Jackson HRR. That said, health care is still quite local, so that an HRR-level rate is heavily weighted towards patients in the same HRR.

from Medicare Part D claims describing regional rates of guideline-appropriate drug treatments in the months leading up to ICD implantation (Roth et al., 2016).[16]

Aggregate parameters. We start by calibrating the parameters that are common across hospitals. Without loss of generality can normalize the average skill in population, $\bar{a}_i$, and the average utility of a patient with heart failure in the absence of ICD treatments, $\bar{w}$, to 0. These parameters are isomorphic to $\bar{v}$ in the ICD use equation (5).

An important aspect of the calibration is to bridge the (conceptual) gap between the units in the model (i.e., utility) and in the outcomes we observe (i.e., years of survival after ICD implant). We do this by calibrating the thresholds $\underline{\kappa_x}$ to match the unconditional mortality rates for patients with congestive heart failure (CHF).[17] Specifically, we set $\underline{\kappa_x}$ so that the cdf of $w_j$is equal to the x-years mortality of patients with CHF.

These leaves 7 parameters to calibrate, the average level in population of overconfidence and the value of ICDs ($\bar{o}$ and $\bar{v}$), and the variance in population of three patient-level parameters, v_j, w_j, ε_j, and two hospital/doctor level parameters a_i and o_i ($\sigma_v^2, \sigma_w^2, \sigma_\varepsilon^2, \sigma_a^2, \sigma_o^2$). To calibrate these parameters, we use 8 moments: the mean and variance ICD use rate across hospitals, the mean and variance conditional 1- and 2-year mortality across hospitals, and the cross-hospital correlations between the ICD use rate and the 1- and 2-year conditional mortality rates.[18] Note that our system is over-identified.

A narrative for the model identification is as follows.[19] For the time being, let's take as given the values of the variance of the three patient level variables M = ($\sigma_v^2, \sigma_w^2, \sigma_\varepsilon^2$). Given these, the average level of overconfidence, $\bar{o}$, and ICDs value, $\bar{v}$, determine the average ICD use rate, while the variance of perceived skill ($\sigma_a^2 + \sigma_o^2$) determines the variance of ICD use across

[16] These are, of course, different guidelines, and relate to appropriate drugs to treat the congestive heart failure medically. Often these combinations of drugs will improve the functioning of the heart sufficiently to avoid having to require an ICD at all.

[17] The rate of ICD use among potentially appropriate patients, 18.5 percent, is derived from Al Khatab et al. (2012) based on their study of ICD use in a cohort of CHF patients; we assume that variation in this parameter is proportional to observed variation in population-based utilization, which is of course much lower. We know the mortality rate among those treated with an ICD, but we impute the mortality for those without an ICD (and the average treatment effect μ_j) used estimates from the largest randomized trial, which showed no impact after one year, and an approximately 2.5 percentage point reduction in mortality after 2 years (Bardy et al., 2005).

[18] All of these moments are computed over the period 2006-2013.

[19] In reality, some of the parameters impact more than one moment for example, the variances of all hospital level variables affect the variance of ICD use rates as well as the one- and two-year conditional mortalities.

hospitals. Conditional mortality across hospitals is determined by M, $\bar{o}$, and the average value of the ICD, $\bar{v}$,, while the variance of one- and two-year conditional mortality helps us pin down the variance of true skill across hospitals/doctors and the relative variance of v and w.

The variance of μ, $(\sigma_v^2 + \sigma_w^2)$, and the noise of the signals (σ_ε^2) is identified from the correlation between ICD use rates and conditional mortalities. Intuitively, α_i is identified by the correlation between ICD use and one-year mortality conditional on ICD implant; a high α reduces the sensitivity of the decision of implanting an ICD to the level of perceived skill, a_i^p. Therefore, those doctors with higher perceived skill, and hence higher ICD use, will not go as deep into the distribution of patients when α_i is low. For this reason, their marginal patient has a higher μ, leading to lower mortality rates. As a result, a higher α is associated with a lower correlation between ICD use and mortality conditional on having an ICD.

The model does a good job of matching aggregate moments. Table 3 reports the data and moment implied moments. The only target that the model misses is the average 2-year mortality. Table 4 reports the calibrated values for the aggregate parameters. First, we find that on average doctors are overconfident. Second, the cross-hospital variance of overconfidence is more than three times larger than the variance in true skill. This suggests the coexistence of overconfident and under-confident hospitals. Third, the variance of patient-level variables is more than thirty times larger than the variance of hospital-level variables. This is necessary to match the relatively low cross-sectional dispersion of conditional mortality rates.

Hospital level parameters. Once we have calibrated the common parameters, we identify for each hospital and year the true skill and overconfidence that produce the observed ICD use rate and (1-year) conditional mortality. Proposition 1 has shown that the ICD use rate is increasing in the perceived skill of the hospital. Therefore, we can identify perceived skill from the ICD use rat. Proposition 2 shows that, for a given perceived skill, the conditional mortality is decreasing in true skill. Therefore, we can invert equation (6) to identify the hospital/year true skill level.

We start by analyzing the identified levels of a_i and o_i; reassuringly, the variance of the distributions are close to the estimates of σ_a^2 and σ_o^2 identified in the calibration of the aggregate

parameters.[20] Figure 6 plots in a US map the average identified levels of o_i for each hospital. There are significant geographic differences in overconfidence. The regions with greater overconfidence are in the South (e.g. Texas), South-East, and Great Lakes (Michigan, Indiana, Ohio).[21] Our estimates imply that hospitals with greater skill are more overconfident since the correlation between a_i and o_i is 0.38. Given that risk-adjusted mortality is also higher in high-utilization regions, these estimates imply that in high-use hospitals, the adverse effects on clinical quality of overconfidence more than compensates for the somewhat higher skill levels.

To further understand the nature of variation in the hospital level estimates of skill and overconfidence we conduct a variance covariance decomposition. Specifically, let x_{it} be the estimate of *x* in hospital *i* and year *t*, for $x_{it} = \{a_{it}^p, a_{it}, o_{it}\}$. Then we can decompose the variance of x_{it} into the "within hospital" over time component, and the "between hospital" component (See Table 6).[22] For all three parameters, the variance of the within component is smaller than the variance of the between component. However, there is significant variation in the relative contribution of the within and between components across the three variables. For perceived skill and overconfidence, the variance of the within component is approximately half the variance of the between component; this means there is significant learning-by-doing about the appropriateness of ICDs over time. By contrast, for skill, the variance of the within component is less than one fourth the variance of the between component, which is consistent

[20] The variance of overconfidence is equal to 0.032 in the hospital-level identification vs. 0.0292 in the aggregate calibration while the variance of skill is 0.0068 in the hospital-level identification vs. 0.0092 in the aggregate calibration.

[21] Interestingly, we find a strong correlation between overconfidence and life expectancy at the bottom quartile of the income distribution (Chetty et al.).

[22] Specifically, let T_i denote the number of observations corresponding o hospital *i*, $\bar{x}_i$ the average of *x* in hospital *i*, and $\bar{\bar{x}}$ be the average of *x* across all hospitals. Then the within hospital *i* variance of *x* is

$$Var_i = \frac{\sum_t (x_{it} - \bar{x}_i)^2}{T_i} \quad (16)$$

The between hospital variance is defined as

$$Var_{be} = \frac{\sum_i (\bar{x}_i - \bar{\bar{x}})^2}{N_i} \quad (17)$$

Then variance of x_{it} can be expressed as:

$$Var(x_{it}) = \frac{\sum_i Var_i}{N_i} + Var_{be} \quad (18)$$

with our earlier findings suggesting very little learning-by-doing with regard to hospital-level skill over time.

4.2 Analysis

Now that we have identified the key parameters of the model at both the aggregate and hospital level, we can return to our primary goal, which is to test whether the presence and magnitude of hospital-specific skill and overconfidence is strongly predictive of the evolution of ICD utilization and health outcomes.

Effects of skill and overconfidence. We start by exploring the empirical consequences of skill and overconfidence for ICD use and mortality. To this end, we alternatively eliminate hospital-level variation in skill and overconfidence and use the model to compute the ICD use rate and conditional mortality rates in each hospital. The model predicts that getting rid of overconfidence would reduce one-year mortality by 8 percent, from 11.3 to 10.5 percentage points; reducing the variation in overconfidence, however would have little impact on average mortality.

We also calculate the fraction of the variation in ICD use (conditional mortality) that can be attributed to hospital variation in skill by the covariance between the actual ICD use (conditional mortality) and the vector of ICD usage rates (conditional mortality rates) that emerges if overconfidence is equal to the mean value in all hospitals, divided by the actual variance of ICD use (conditional mortality). The fraction of the variation in ICD use (conditional mortality) attributable to overconfidence is the complementary share. The decomposition indicates that 76% of the hospital variation in ICD utilization is because of variation in overconfidence, with the remaining 24% because of variation in skill. Similarly, over 70% of the hospital variation in mortality is due to variation in overconfidence, while variation in true skill accounts for 29% of the variation across hospitals in the one-year mortality conditional on ICD use. Therefore, we conclude that overconfidence is significantly more important than true skill to account for the large variation we observe in ICD use rates and conditional mortality.

Determinants of time variation in overconfidence. Next, we turn our attention to the time variation in overconfidence, and in perceived skill. In particular, we study whether the learning model we have posed in section 2 does a good job in explaining the evolution of perceived skill and conditional mortality. To this end, we estimate the following econometric counterpart of equation (12)

$$a^{p}_{i,t+1} - a^{p}_{i,t} = \alpha_{0i} - \alpha^{a}_{it} * o_{i,t} + u_{i,t}. \quad (19)$$

Comparing specification (19) with equation (12), it follows that the intercept captures the average realization of $\alpha_{ait} * \xi_{it}$ for hospital i.[23] We estimate two versions of (19), the first (reported in column I of Table 7) allows for a hospital-specific intercept and learning coefficient. The second (in column II) imposes the same intercept and learning coefficient across hospitals.[24] Despite its simplicity, the learning model fits quite well the evolution of perceived skill. In the baseline specification, the learning model accounts for 49% of the variation in the change of perceived skill, while in the version where both the intercept and learning coefficients are restricted to be the same across hospitals, the R^2 still is 23%. As predicted by our model, the median learning coefficient α_{ai} is significantly positive and between zero and one. The median point estimate is 0.47 which implies that the variance of the noise in the signal about the doctor's skill is approximately the same as the variance of the prior of perceived skill. Nevertheless, there is significant variation in the estimated learning coefficients. The standard deviation of α_{ai} across hospitals is 0.6.[25]

To gain further insights about the determinants of learning, we explore the association between the learning coefficient and initial overconfidence and ICD volume in the hospital, which we measure as the annual rate of utilization across all types of ICD implantation using the registry data. We find that hospitals with lower learning coefficient α_{ai} have greater initial overconfidence and higher ICD volume. This observation suggests that more overconfident hospitals also have tighter priors about their skill. As a result, they perform more ICD procedures and, despite the greater number of signals, they learn more slowly about their true skill.

We conclude our analysis by exploring whether the decline in ICD use and conditional mortality between 2006 and 2013 can be a consequence of learning about overconfidence. To explore this hypothesis, we use the estimates of the learning model (column I of Table 8) to build a counterfactual measure of perceived skill due to learning. Then, we use our model to simulate the ICD use and conditional mortality levels in 2006 and 2013 for the counterfactual measures of

[23] Equation (19) abstracts from the possibility that α_{ait} varies over time.

[24] The difference in the number of observations between both specifications is due to the fact that we require hospitals to have at least four observations to estimate the hospital-specific parameters.

[25] In 8% of the hospitals the estimate of the learning coefficient is negative, while in 21% it is greater than one.

perceived skill. Then we compare the evolution of the relevant moments under the counterfactual with those observed in the data. Table 8 presents the results from this exercise.

The first three columns of Table 8 report the moments with respect to the ICD use rate, with the first two rows for 2006 and the second two rows for 2013. The moments in 2006 are very similar in both model and data by construction. However, the model's out-of-sample predictions for 2013 also provide a close match to actual 2013 values. The key finding is that the learning model fully accounts for the observed 6.8 percentage point decline in ICD. The learning model also predicts the reduced dispersion in ICD usage rates across hospitals and the correlation between skill and ICD use by similar amounts observed in the data.

The second three columns report the moments for the conditional mortality rate. In the data, we observed a mild decline in the one-year conditional mortality rate from 12.8% to 12.0%. Our learning model fully accounts for this reduction in the conditional mortality. Furthermore, the cross-sectional distribution of conditional mortality in 2013 and its correlation with true skill across hospitals is very similar in the model and in the counterfactual. Thus the evolution of physician beliefs about the efficacy of ICDs for this new population of CHF patients can explain both the sharp exnovation in the use of ICDs during this period, as well as a more modest decline in conditional mortality rates.

5. Discussion and Conclusion

What drives the diffusion of new technologies? Research in economics has focused on factors primarily related to rates of return, whether because of input prices, differential factor productivity, or higher rates of return; the puzzle has often been why so many economic agents diffuse so slowly. In this paper, we test for a different determinant of technological diffusion, overconfidence, in which an individual's perception of their own skill and ability causes them to step up the use of a new technology, even when true skills fall short of their beliefs. For the case of a specific medical technology, implantable defibrillators (ICDs), these behavioral biases appear to be important quantitatively and explain otherwise puzzling empirical regularities.

While we have interpreted the parameter $o_{i,}$ we acknowledge that there are several competing interpretations that are isomorphic in the context of our model. For example, it can reflect biases in the doctor's prior about the mean net value of ICD, $\bar{\mu}$; that is, the physician may have strongly-held beliefs about treatment efficacy that are inconsistent with clinical evidence

(as in Cutler et al., 2017). Second, it can capture classic supplier-induced demand, in which the individual physician in pursuit of monetary profits treats patients beyond the point where they might benefit, or other variants of principal-agent models.[26] Finally, we have not addressed potential demand-side factors – e.g., patient pressures to seek the procedure – that could also lead to systematically overusing or underusing the procedure. Thus the parameter o_i should be broadly interpreted as a "portmanteau" of additional factors that affect physician behavior. The behavioral and policy implications of these different interpretations of overconfidence, however, are similar, even if the prescribed policy prescriptions are different.[27]

Many studies of learning-by-doing find improvements in mortality over time (Gong, 2017; Jovanovik and Nyarko, 1995; although see Huesch, 2009). The lack of strong progress in mortality that we observe may be explained by the long years of experience many physicians already have with implanting ICDs in other types of patients. Thus the innovation that was introduced in 2006 – which, based on the rapid rise prior to 2006, appeared to have been anticipated by physicians – is the expansion of the patient population. It is perhaps less surprising then that the learning that we observe in the data was with regard to appropriateness for patients, rather than technical skill *per se*.

Still, one might expect to see a sharp decline in ICD implantation rates for hospitals with the poorest mortality outcomes (as in Chandra et al., 2016). Yet there was little or no way for most physicians (or referral physicians) to observe their own skill, and to know whether their own risk-adjusted rates were above or below average. The SCD-HeFT trial could have provided a rough guideline for mortality (roughly 8 percent mortality in the first year), but the patient mix in the community was substantially older than in randomized trials, so community-level physicians had no benchmark against which they could compare outcomes in their patients compared to the trial physicians.

There are several limitations of the study. One is that we are considering just one specific technology that has turned out to perhaps yield less than expected in net benefits. By contrast, Currie, MacLeod, and Van Parys (2015) found that cardiologists who were more

[26] For example, one study by Cutler et al. (2017) used survey and vignette data to find that that physician beliefs about the effectiveness of technologies with uncertain (or even adverse) clinical effects were the single largest predictor of risk-adjusted utilization.

[27] One additional way to generalize the model is to introduce (and estimate) a potential correlation between skill and overconfidence; low-skilled physicians may also be overconfident.

aggressive than then-current guidelines for percutaneous coronary interventions (PCI) gained better results. One difference between PCIs and ICDs is that the value of PCIs were underestimated while the value of ICDs was overestimated. Which characteristic of new medical technology is more common? Some argue that "Scott's Parabola" of high expectations followed by discouraging reports and a decline in use, is a not unreasonable paradigm. For example, Jupiter and Burke (2013) write:

> Artelon® arthroplasty, thermal shrinkage, Vioxx®, metal-on-metal hip arthroplasty, and Infuse® bone grafting in the spine—all had come onto the "market" with enthusiastic reports only to fall from grace to unhappy outcomes, permanent disabilities, and malpractice litigation. (p. 249).

A better understanding of the long-term value of new innovations would be useful, particularly given hysteresis in the extent to which existing and ineffective technologies remain in practice (Duffy and Farley, 1992).

A second limitation is that we may not be adjusting adequately for differences across regions in the demand for ICDs, so that unmeasured confounding, in which high rates of ICD use are correlated with (e.g.) socioeconomic status, which in turn adversely affects mortality conditional on risk-adjusters. While preliminary estimates including zip code income did not affect our mortality results, we are pursuing additional strategies to test the sensitivity of our results to risk-adjustment for utilization rates. One challenge to risk adjustment is to avoid measures such as CHF hospitalizations where "risk-adjusters" are themselves reflective of practice style (Song et al., 2010; Finkelstein et al., 2017).

How generalizable are ICDs to technology outside of health care? The result that physicians overestimate their skill is certainly consistent with other data from laboratory experiments in which hypothetical entrepreneurs are overconfident about their own ability and enter into markets or games where failure is likely (Camerer and Lovallo, 1999). And a pattern of overconfidence is common across non-physicians, as for example with regard to individual assessment of one's own driving skills (Svenson, 1981). Whether this translates as well into more rapid diffusion of new and less-effective technologies is less well-understood, but certainly the complexity of the "production process" in involving a large team of health professionals, from diagnosis to implementation and subsequent ICD maintenance, is not inconsistent with

complex technology in the non-medical sectors of the economy. Further data and case studies are clearly required, but despite these caveats, it would appear that for elderly people with congestive heart failure, living in a region where their physicians exhibit less rather than more overconfidence is likely to have been good for their health.

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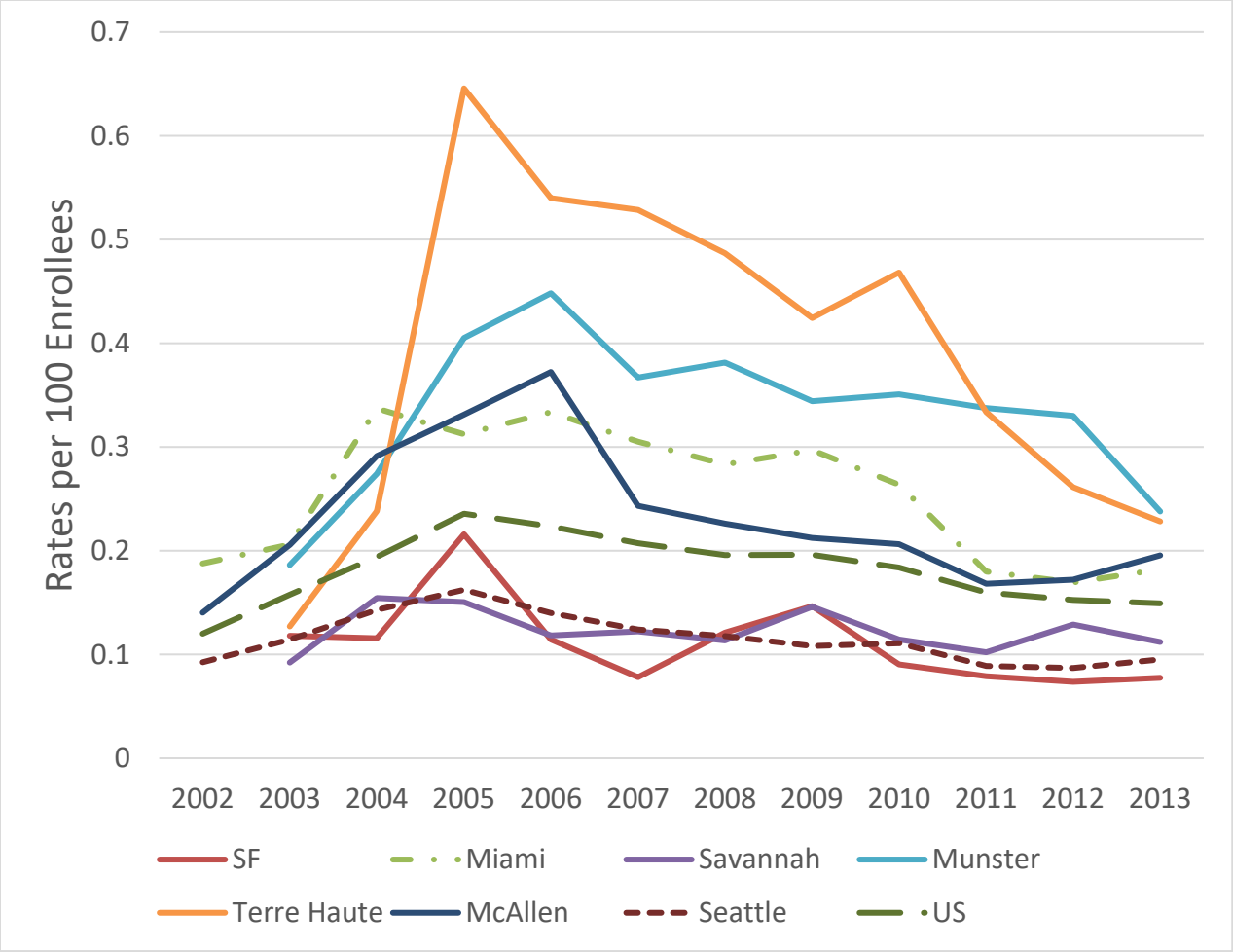

Figure 1: Rates of ICD use per 100 Medicare Enrollees for Selected Hospital Referral Regions, and the U.S. Average, 2002-13.

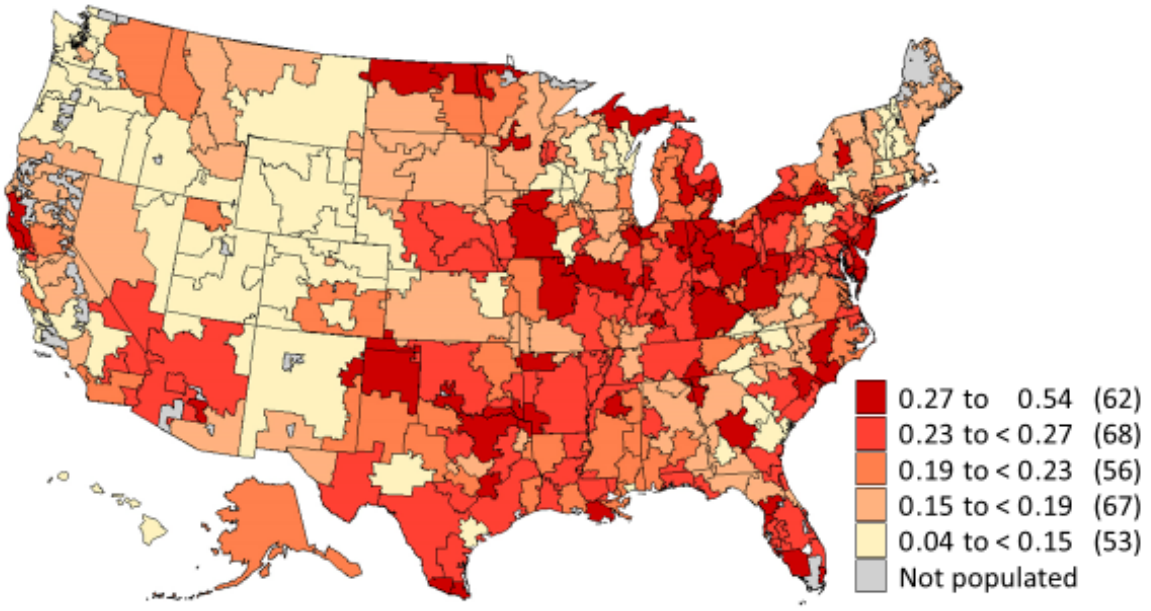

Figure 2. Implantable Cardioverter Defibrillator (ICD) rates per 100 Medicare enrollees, 2006. Age-sex-race-adjusted, for the over-65 Medicare Fee-for-service population.

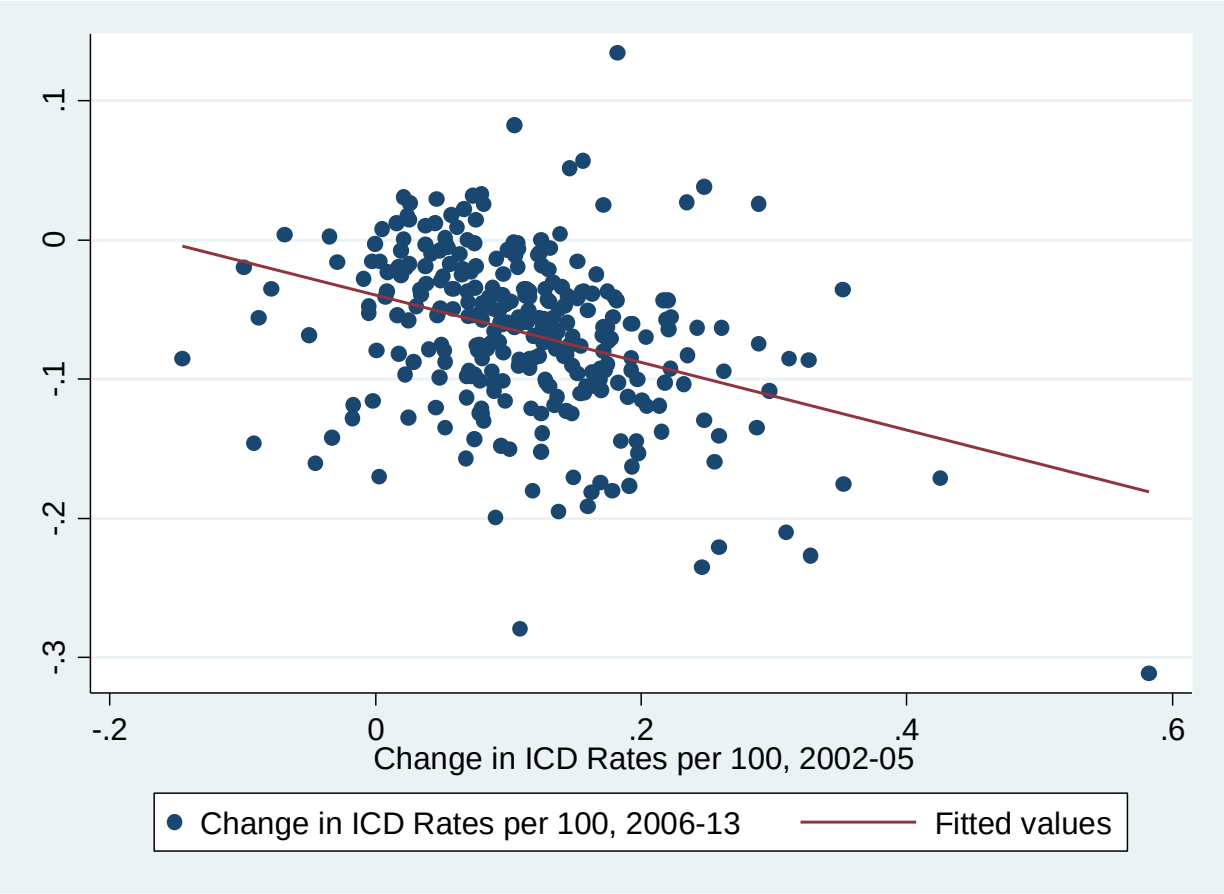

Figure 3: Correlation between 2002-05 and 2006-13 ICD Utilization Rates, at the HRR level (Rates per 100 Medicare enrollees for all types of ICDs).

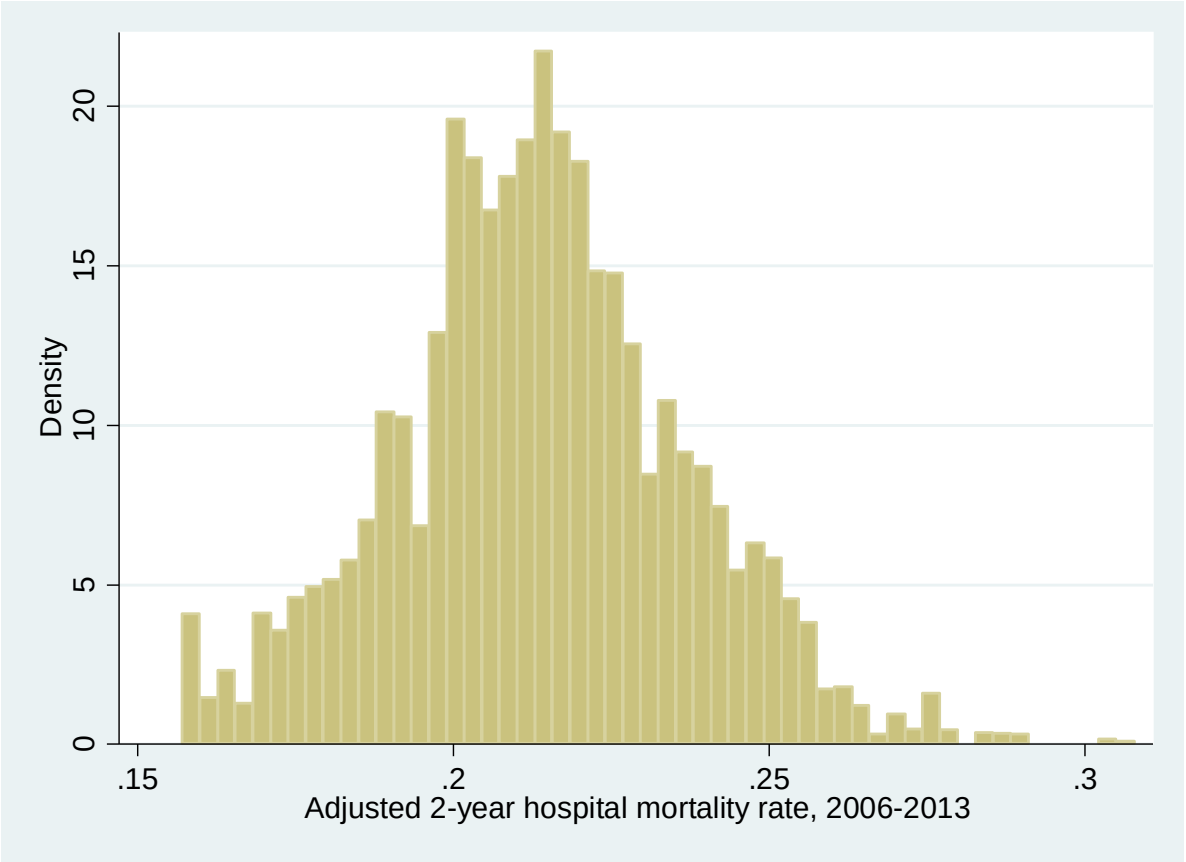

Figure 4: Distribution of Risk-adjusted Random-Effects 2-Year Mortality by Hospital: 2006-13

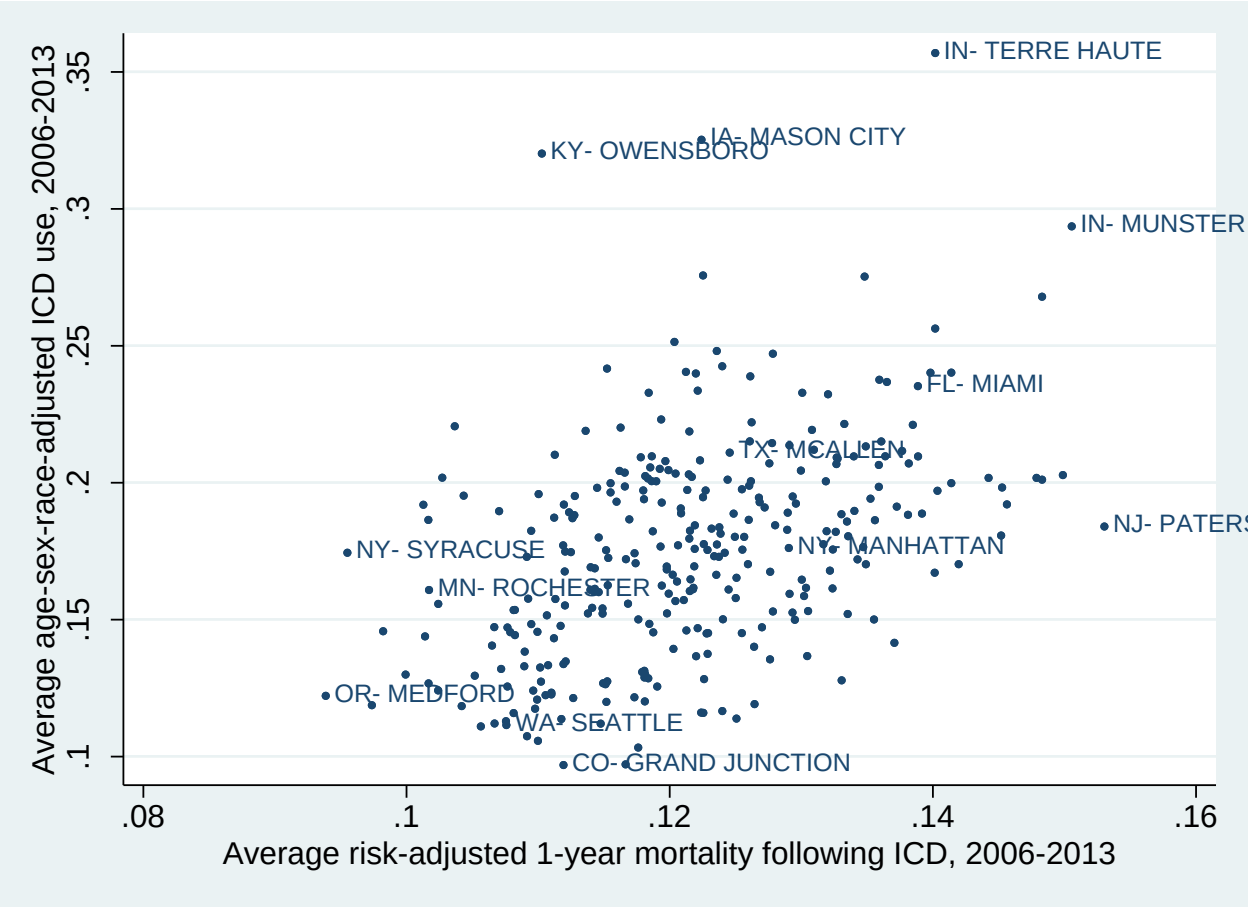

Figure 5: Correlation Between Average ICD Utilization (2006-13) and 2-Year Risk-adjusted Mortality

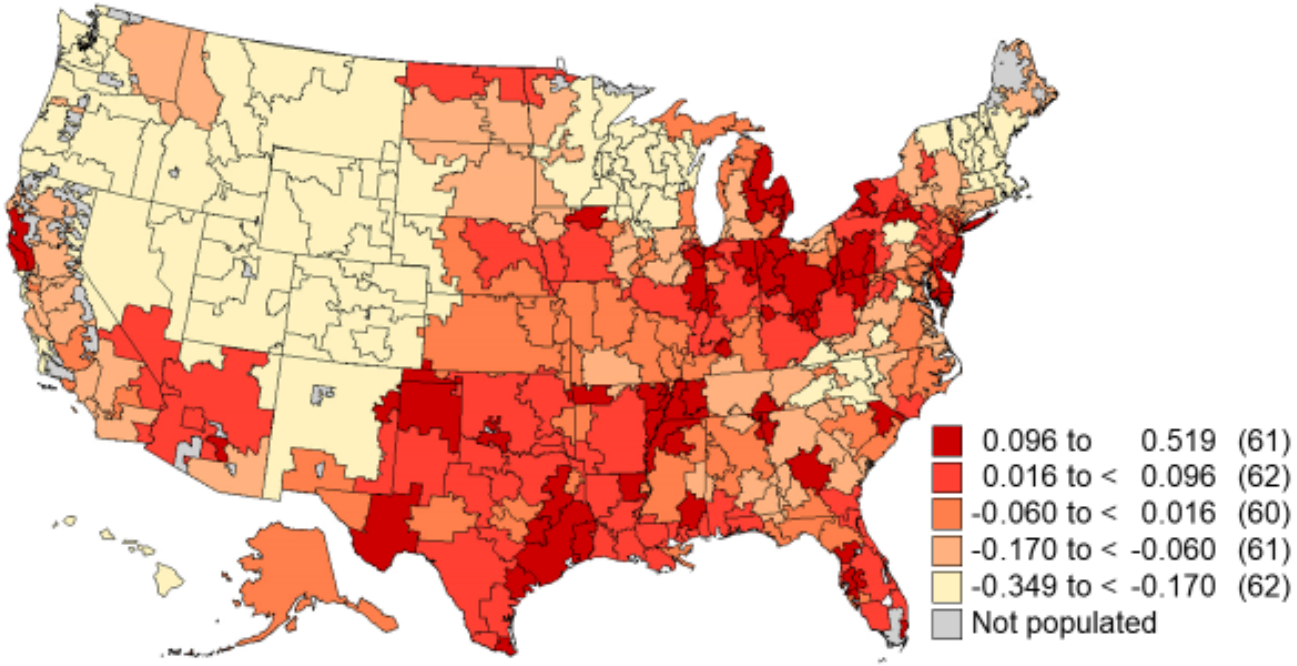

Figure 6: Estimated Overconfidence Parameter by Region

Table 1: Summary Statistics from ICD Registry Data (N = 253, 613)

Variable	Mean	Standard Deviation
2-Year Mortality: 2006-13	0.218	0.413
2-Year Mortality: 2006	0.219	0.414
2-Year Mortality: 2013	0.216	0.411
1-Year Mortality: 2006-13	0.123	0.328
1-Year Mortality: 2006	0.122	0.328
1-Year Mortality: 2012	0.118	0.323
Fraction Inappropriate	0.098	0.297
Ejection Fraction (Percentage)	25.766	7.319
Fraction with EF > 35%	0.034	0.182
Fraction Class I	0.029	0.169
Fraction Class IV	0.043	0.202
Age	74.897	6.248
Previous cardiac arrest	0.020	0.142
Family history: Sudden death	0.030	0.171
Ventricular tacchycardia	0.225	0.418
Non-ischemic dilated cardiomyopathy	0.320	0.467
Ischemic heart disease	0.696	0.460
Previous myocardial infarction	0.548	0.498
Previous CABG	0.395	0.489
Previous PCI	0.345	0.475
Electrophysiology study	0.083	0.276
VT indication (ES study)	0.021	0.143
Female	0.282	0.450
Black	0.101	0.301
Hispanic (Medicare)	0.052	0.222
Other race	0.025	0.157
Hispanic ethnicity (Registry)	0.051	0.219

Table 2: Regression Coefficients for OLS, Random, and Fixed Effects Models: Two-Year Mortality

VARIABLES	(1) OLS	(2) OLS	(3) Random Effect	(4) Random Effect	(5) Fixed Effect	(6) Fixed Effect
HRR-level ICD Rate	0.136***	0.159***	0.128***	0.147***	0.0445	0.071
	(0.0298)	(0.0289)	(0.0263)	(0.0261)	(0.0470)	(0.0479)
Ln(volume)		-0.014***		-0.014***		-0.009***
		(0.001)		(0.001)		(0.003)
HRR-level Rx Rate		-0.110***		-0.115***		-0.091
		(0.018)		(0.018)		(0.101)
Observations	253,247	252,613	253,247	252,613	253,247	252,613
R-squared	0.046	0.047			0.057	0.057
Number of Groups			1,548	1,542		

Note: Covariates included in all regressions – see Appendix Tables A.1 (OLS), A.2 (Random Effects), and A.3 (Fixed Effects) for full sets of estimates. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Aggregate Moments from Empirical Data and Model Estimates

Moments	Data	Model
One-year mortality rate conditional on an ICD	0.122	0.113
Two-year mortality rate conditional on an ICD	0.218	0.308
One-year mortality rate for a candidate not receiving an ICD	0.122*	0.122
Two-year mortality rate for a candidate not receiving an ICD	0.243*	0.243
Standard deviation of one-year mortality rate conditional on ICD across hospitals	0.023	0.02
Standard deviation of two-year mortality rate conditional on ICD across hospitals	0.031	0.036
Average use of ICDs among candidates for an ICD	0.185	0.186
Standard deviation (risk-adjusted) of the use of ICDs across hospitals	0.050	0.044
Correlation between ICD use and one-year mortality rate conditional on ICD use, across hospitals	0.231	0.218
Correlation between ICD use and two-year mortality rate conditional on ICD use, across hospitals	0.204	0.207

Notes: All data from CMS ICD registry merged to claims data, unless otherwise noted.
* Using the SCD-HeFT trial estimates of survival gain (Bardy et al, 2005) of roughly 2.5 percentage points at 2 years, 0 at 1 year, subtracted from observed mortality conditional on receiving an ICD.

Table 4: Calibration, Identification, and Aggregate Parameters

Parameter	Value
$\sigma^2_{w_j}$	1.06
$\sigma^2_{o_i}$	0.03
$\sigma^2_{a_i}$	0.01
$\sigma^2_{\varepsilon j}$	1.05
$\sigma^2_{\varepsilon_j}$	0.83
$\bar{o}$	0.06
$\bar{v} - \bar{w} + \bar{a}$	-1.06

Table 5: Model Estimates of the Mean and Standard Deviation in Risk-adjusted Mortality and Utilization Rates

	Data	Baseline	obar=0	abar=.1	Var (oi)=0	Var(ai)=0
ICD Use	0.185	0.186	**0. 163**	**0.21**	0.187	0.186
Conditional Mortality	0.122	0.113	0.105	**0.097**	0.112	0.112
Std(ICD)	0.05	0.044	0.04	0.05	**0.0218**	0.038
Std(Cond-Mort)	0.023	0.02	0.019	0.018	0.0159	**0.0145**
Corr(ICD, Cond Mortality)	0.23	0.22	0.22	0.21	**-0.8465**	**0.84**

Table 6: Variance Covariance Decomposition of Hospital-Level Parameters

	a_p	a	o
Within Component	0.0181	0.0013	0.0101
Between Component	0.0328	0.0056	0.0225
Total Variance	0.051	0.0068	0.0327

Table 7: Regression Estimates from the Learning Model

	I	II
α_0	-0.023*	0.0281
	(0.0013)	(0.0113)
α_a	0.471*	0.1953
	(0.007)	(0.0067)
N	7776	8359
R^2	0.49	0.23

Note: Standard deviation of estimates in Parenthesis. * Median estimate across hospitals

Table 8: Predicted Evolution of Overconfidence and Utilization, 2006-13

		ICD Use			Conditional Mortality		
		Mean	Std	Correlation with a_i	Mean	Std	Correlation with a_i
2006	**Data**	0.21	0.053	0.94	0.128	0.016	0.65
	Model	0.21	0.053	0.94	0.129	0.018	0.695
2013	**Data**	0.142	0.033	0.905	0.1205	0.0152	0.644
	Model	0.142	0.032	0.895	0.1198	0.0174	0.708

Appendix

Expression (4) defines the diffusion of ICD for a doctor/hospital with a given perceived skill. To compute the aggregate diffusion of ICDs we just need to compute the expectation of (4) over the initial distribution of perceived skills across hospitals. Formally, the diffusion of ICD in population is given by

$$\Pr(ICD) = \int_{-\infty}^{\infty} f_{a^p}(q) \Pr(\ ICD = 1|q) dq = \int_{-\infty}^{\infty} f_{a^p}(q) \left(\int_{\bar{s}(q)}^{\infty} f(s)\, ds \right) dq \qquad \text{(A.1)}$$

where $f_{a^p}(.)$ is the distribution of perceived skill in population.

Similarly, we can compute the standard deviation of the use of ICD's across hospitals as

$$Std(ICD_i) = SQRT\left[\int_{-\infty}^{\infty} f_{a^p}(q) (\Pr(\ ICD = 1|q) - \Pr(ICD))^2 dq \right] \qquad \text{(A.2)}$$

The mortality rate conditional on ICD implant is

$$Pr\left(v_j + a_i \leq \underline{\kappa} \middle| ICD = 1\right) = \frac{\Pr\left(v_j \leq \underline{\kappa} - a_i \cap\ ICD = 1\right)}{\Pr(\ ICD)}$$

$$= \frac{\int_{-\infty}^{\infty} f_{a,a^p}(q,q^p) \left(\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{\varepsilon}(\varepsilon') f_w(w') \left(\int_{\bar{s}(q^p)-\varepsilon'-w'}^{\underline{\kappa}-q} f_{\mu}(\mu') d\mu' \right) d\varepsilon' dw' \right) dq dq^p}{\Pr(\ ICD)} \qquad \text{(A.3)}$$

where $f_{a,a^p}(.,.)$ is the joint distribution of the duple skill, and perceived skill in population.

The standard deviation of mortality rates across hospitals is computed as

$$Std(Mort_i) = SQRT\left[\int_{-\infty}^{\infty} f_{a,a^p}(q,q^p) \left(Pr\left(v_j + a_i \leq \underline{\kappa} \middle| ICD = 1, q^p, q\right) - Pr\left(v_j + a_i \leq \underline{\kappa} \middle| ICD = 1\right) \right)^2 dq\, dq^p \right] \qquad \text{(A.4)}$$

Finally, the correlation between mortality and ICD use across hospitals is computed as

$$\rho_{Mort_i, ICD_i} = \frac{Covar(ICD_i, Mort_i)}{Std(ICD_i) Std(Mort_i)} \qquad \text{(A.5)}$$

Table A.1: Mortality (One & Two Years) OLS Regression

VARIABLES	(1) death1yr	(2) death1yr	(3) death1yr	(4) death2yr	(5) death2yr	(6) death2yr
HRR-level ICD Rate	0.116***	0.153***	0.127***	0.136***	0.195***	0.159***
	(0.0217)	(0.0218)	(0.0213)	(0.0298)	(0.0297)	(0.0289)
Ln(volume)		-0.00903***	-0.00888***		-0.0142***	-0.0141***
		(0.00108)	(0.00107)		(0.00139)	(0.00138)
HRR-level Rx Rate			-0.0823***			-0.110***
			(0.0141)			(0.0185)
Ejection Fraction (EF) <20%	-0.00344***	-0.00345***	-0.00347***	-0.00443***	-0.00444***	-0.00448***
	(0.000382)	(0.000381)	(0.000381)	(0.000472)	(0.000470)	(0.000470)
EF 20-25%	-0.00460***	-0.00460***	-0.00459***	-0.00546***	-0.00545***	-0.00543***
	(0.000406)	(0.000406)	(0.000406)	(0.000503)	(0.000502)	(0.000503)
EF 25-30%	-0.00223***	-0.00226***	-0.00225***	-0.00388***	-0.00393***	-0.00394***
	(0.000355)	(0.000355)	(0.000357)	(0.000451)	(0.000450)	(0.000452)
EF 30-35%	-0.000754*	-0.000747*	-0.000748*	-0.00111**	-0.00110**	-0.00108*
	(0.000413)	(0.000412)	(0.000413)	(0.000557)	(0.000554)	(0.000554)
EF > 35%	0.00153***	0.00152***	0.00150***	0.00198***	0.00196***	0.00191***
	(0.000326)	(0.000325)	(0.000325)	(0.000395)	(0.000395)	(0.000396)
EF Missing	0.0219***	0.0203***	0.0202***	0.0312***	0.0287***	0.0274***
	(0.00725)	(0.00727)	(0.00730)	(0.00976)	(0.00976)	(0.00970)
NY Heart Assoc. Class II	0.00266	0.00215	0.00137	0.00621	0.00541	0.00443
	(0.00342)	(0.00339)	(0.00338)	(0.00486)	(0.00479)	(0.00478)
NY Heart Assoc. Class III	0.0478***	0.0473***	0.0464***	0.0711***	0.0703***	0.0691***
	(0.00346)	(0.00341)	(0.00340)	(0.00487)	(0.00477)	(0.00478)
NY Heart Assoc. Class IV	0.154***	0.152***	0.151***	0.191***	0.188***	0.187***
	(0.00584)	(0.00583)	(0.00584)	(0.00726)	(0.00721)	(0.00722)
NY Heart Assoc. Class missing	0.0554***	0.0526***	0.0521***	0.0934***	0.0889***	0.0885***
	(0.0113)	(0.0113)	(0.0112)	(0.0138)	(0.0136)	(0.0137)
Age 70-74	0.0151***	0.0152***	0.0154***	0.0278***	0.0279***	0.0279***
	(0.00165)	(0.00165)	(0.00165)	(0.00206)	(0.00205)	(0.00206)
Age 75-79	0.0365***	0.0367***	0.0367***	0.0647***	0.0649***	0.0649***
	(0.00181)	(0.00181)	(0.00181)	(0.00227)	(0.00226)	(0.00227)
Age 80-84	0.0631***	0.0632***	0.0633***	0.109***	0.109***	0.109***
	(0.00212)	(0.00213)	(0.00213)	(0.00258)	(0.00257)	(0.00257)
Age 85-89	0.102***	0.102***	0.101***	0.175***	0.175***	0.174***
	(0.00331)	(0.00332)	(0.00332)	(0.00408)	(0.00411)	(0.00409)
Age 90+	0.181***	0.181***	0.181***	0.273***	0.273***	0.273***
	(0.0107)	(0.0107)	(0.0107)	(0.0124)	(0.0124)	(0.0124)
Previous cardiac arrest	0.0586***	0.0577***	0.0577***	0.0590***	0.0577***	0.0579***
	(0.00552)	(0.00552)	(0.00553)	(0.00633)	(0.00634)	(0.00636)
Family history sudden arrest	-0.0118***	-0.0121***	-0.0118***	-0.0191***	-0.0196***	-0.0193***
	(0.00398)	(0.00390)	(0.00389)	(0.00490)	(0.00479)	(0.00478)
Ventricular tacchycardia	0.0444***	0.0445***	0.0444***	0.0566***	0.0567***	0.0565***
	(0.00194)	(0.00194)	(0.00194)	(0.00230)	(0.00230)	(0.00231)

Non-ischemic dilated cardiomyopathy	-0.0219***	-0.0212***	-0.0210***	-0.0319***	-0.0307***	-0.0304***
	(0.00247)	(0.00247)	(0.00247)	(0.00316)	(0.00316)	(0.00316)
Ischemic heart disease	0.0164***	0.0169***	0.0168***	0.0261***	0.0270***	0.0269***
	(0.00271)	(0.00271)	(0.00271)	(0.00333)	(0.00333)	(0.00333)
Previous myocardial infarction	0.00777***	0.00811***	0.00820***	0.0125***	0.0130***	0.0132***
	(0.00171)	(0.00171)	(0.00171)	(0.00224)	(0.00223)	(0.00223)
Previous CABG	0.00864***	0.00873***	0.00851***	0.0202***	0.0203***	0.0202***
	(0.00165)	(0.00165)	(0.00165)	(0.00200)	(0.00199)	(0.00199)
Previous PCI	-0.00980***	-0.00980***	-0.00981***	-0.0125***	-0.0125***	-0.0125***
	(0.00163)	(0.00163)	(0.00163)	(0.00198)	(0.00198)	(0.00199)
Electrophysiology study	-0.0189***	-0.0174***	-0.0179***	-0.0277***	-0.0253***	-0.0257***
	(0.00301)	(0.00289)	(0.00292)	(0.00414)	(0.00395)	(0.00401)
VT indication (ES study)	-0.00564	-0.00472	-0.00497	-0.00700	-0.00555	-0.00590
	(0.00512)	(0.00513)	(0.00510)	(0.00664)	(0.00665)	(0.00673)
Female	-0.00729***	-0.00732***	-0.00730***	-0.0166***	-0.0166***	-0.0165***
	(0.00148)	(0.00148)	(0.00148)	(0.00186)	(0.00187)	(0.00187)
Black	0.0344***	0.0341***	0.0336***	0.0551***	0.0546***	0.0541***
	(0.00239)	(0.00238)	(0.00236)	(0.00297)	(0.00292)	(0.00291)
Hsipanic (Medicare)	0.0126**	0.0116**	0.0123**	0.0185***	0.0168***	0.0169***
	(0.00507)	(0.00506)	(0.00506)	(0.00646)	(0.00647)	(0.00647)
Other race	0.0162***	0.0151***	0.0146***	0.0237***	0.0220***	0.0210***
	(0.00425)	(0.00424)	(0.00422)	(0.00543)	(0.00544)	(0.00542)
Hispanic ethnicity (Registry)	0.00798	0.00642	0.00530	0.00437	0.00191	0.00121
	(0.00499)	(0.00499)	(0.00502)	(0.00631)	(0.00635)	(0.00639)
2007.year	0.00453*	0.00636***	0.00592**	0.00588*	0.00877***	0.00799***
	(0.00240)	(0.00240)	(0.00239)	(0.00301)	(0.00304)	(0.00302)
2008.year	0.0101***	0.0124***	0.0117***	0.00974***	0.0132***	0.0122***
	(0.00259)	(0.00260)	(0.00258)	(0.00339)	(0.00341)	(0.00338)
2009.year	0.00959***	0.0121***	0.0111***	0.0122***	0.0161***	0.0147***
	(0.00273)	(0.00272)	(0.00273)	(0.00348)	(0.00347)	(0.00347)
2010.year	0.0141***	0.0163***	0.0151***	0.00985***	0.0133***	0.0115***
	(0.00288)	(0.00289)	(0.00288)	(0.00352)	(0.00355)	(0.00352)
2011.year	0.0104***	0.0122***	0.0106***	0.0148***	0.0177***	0.0153***
	(0.00300)	(0.00303)	(0.00305)	(0.00381)	(0.00385)	(0.00385)
2012.year	0.0162***	0.0174***	0.0155***	0.0182***	0.0201***	0.0173***
	(0.00321)	(0.00322)	(0.00322)	(0.00397)	(0.00401)	(0.00399)
2013.year	0.0161***	0.0175***	0.0154***	0.0238***	0.0261***	0.0231***
	(0.00316)	(0.00317)	(0.00317)	(0.00393)	(0.00394)	(0.00391)
Constant	0.0874***	0.118***	0.175***	0.151***	0.199***	0.276***
	(0.00947)	(0.00993)	(0.0137)	(0.0126)	(0.0128)	(0.0181)
Observations	253,247	253,247	252,613	253,247	253,247	252,613
R-squared	0.034	0.035	0.035	0.046	0.047	0.047

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A2: Mortality (One & Two Years) Random Effects Regression

VARIABLES	(1) death1yr	(2) death1yr	(3) death1yr	(4) death2yr	(5) death2yr	(6) death2yr
HRR-level ICD Rate	0.108***	0.139***	0.120***	0.128***	0.176***	0.147***
	(0.0204)	(0.0203)	(0.0205)	(0.0263)	(0.0259)	(0.0261)
Ln(volume)		-0.00902***	-0.00890***		-0.0136***	-0.0136***
		(0.00102)	(0.00102)		(0.00130)	(0.00130)
HRR-level Rx Rate			-0.0843***			-0.115***
			(0.0143)			(0.0183)
Ejection Fraction (EF) <20%	-0.00358***	-0.00358***	-0.00359***	-0.00466***	-0.00466***	-0.00468***
	(0.000342)	(0.000342)	(0.000342)	(0.000428)	(0.000428)	(0.000428)
EF 20-25%	-0.00461***	-0.00460***	-0.00459***	-0.00547***	-0.00547***	-0.00545***
	(0.000394)	(0.000394)	(0.000395)	(0.000494)	(0.000493)	(0.000494)
EF 25-30%	-0.00224***	-0.00225***	-0.00224***	-0.00389***	-0.00390***	-0.00390***
	(0.000384)	(0.000384)	(0.000384)	(0.000480)	(0.000480)	(0.000481)
EF 30-35%	-0.000791*	-0.000781*	-0.000787*	-0.00110*	-0.00109*	-0.00108*
	(0.000466)	(0.000466)	(0.000466)	(0.000583)	(0.000583)	(0.000584)
EF > 35%	0.00152***	0.00152***	0.00151***	0.00199***	0.00199***	0.00195***
	(0.000294)	(0.000294)	(0.000295)	(0.000368)	(0.000368)	(0.000369)
EF Missing	0.0183***	0.0177**	0.0181***	0.0265***	0.0256***	0.0249***
	(0.00694)	(0.00694)	(0.00696)	(0.00869)	(0.00869)	(0.00872)
NY Heart Assoc. Class II	0.00207	0.00204	0.00154	0.00537	0.00534	0.00476
	(0.00394)	(0.00394)	(0.00394)	(0.00493)	(0.00493)	(0.00494)
NY Heart Assoc. Class III	0.0474***	0.0475***	0.0470***	0.0707***	0.0709***	0.0703***
	(0.00387)	(0.00387)	(0.00387)	(0.00485)	(0.00484)	(0.00485)
NY Heart Assoc. Class IV	0.154***	0.153***	0.152***	0.189***	0.189***	0.188***
	(0.00492)	(0.00491)	(0.00492)	(0.00616)	(0.00615)	(0.00616)
NY Heart Assoc. Class missing	0.0513***	0.0500***	0.0498***	0.0880***	0.0861***	0.0860***
	(0.0120)	(0.0120)	(0.0120)	(0.0150)	(0.0150)	(0.0150)
Age 70-74	0.0152***	0.0152***	0.0154***	0.0279***	0.0280***	0.0279***
	(0.00182)	(0.00182)	(0.00182)	(0.00228)	(0.00228)	(0.00228)
Age 75-79	0.0365***	0.0366***	0.0367***	0.0647***	0.0648***	0.0648***
	(0.00183)	(0.00183)	(0.00184)	(0.00230)	(0.00230)	(0.00230)
Age 80-84	0.0625***	0.0626***	0.0628***	0.108***	0.109***	0.109***
	(0.00201)	(0.00201)	(0.00201)	(0.00252)	(0.00251)	(0.00252)
Age 85-89	0.0998***	0.0999***	0.0999***	0.172***	0.172***	0.172***
	(0.00288)	(0.00288)	(0.00288)	(0.00361)	(0.00361)	(0.00361)
Age 90+	0.177***	0.177***	0.177***	0.268***	0.268***	0.269***
	(0.00783)	(0.00783)	(0.00783)	(0.00980)	(0.00980)	(0.00981)
Previous cardiac arrest	0.0570***	0.0565***	0.0565***	0.0567***	0.0561***	0.0562***
	(0.00456)	(0.00456)	(0.00456)	(0.00571)	(0.00571)	(0.00571)
Family history sudden arrest	-0.0117***	-0.0117***	-0.0117***	-0.0185***	-0.0185***	-0.0185***
	(0.00378)	(0.00378)	(0.00378)	(0.00474)	(0.00473)	(0.00473)
Ventricular tacchycardia	0.0444***	0.0444***	0.0443***	0.0567***	0.0566***	0.0565***
	(0.00161)	(0.00160)	(0.00161)	(0.00201)	(0.00201)	(0.00201)
Non-ischemic dilated cardiomyopathy	-0.0205***	-0.0202***	-0.0201***	-0.0299***	-0.0294***	-0.0293***
	(0.00231)	(0.00231)	(0.00231)	(0.00290)	(0.00289)	(0.00290)
Ischemic heart disease	0.0169***	0.0172***	0.0172***	0.0269***	0.0274***	0.0274***

	(0.00246)	(0.00246)	(0.00247)	(0.00309)	(0.00309)	(0.00309)
Previous myocardial infarction	0.00870***	0.00877***	0.00882***	0.0133***	0.0134***	0.0135***
	(0.00165)	(0.00165)	(0.00165)	(0.00207)	(0.00207)	(0.00207)
Previous CABG	0.00870***	0.00872***	0.00857***	0.0203***	0.0203***	0.0202***
	(0.00156)	(0.00156)	(0.00156)	(0.00195)	(0.00195)	(0.00196)
Previous PCI	-0.00992***	-0.00991***	-0.00996***	-0.0124***	-0.0124***	-0.0125***
	(0.00153)	(0.00153)	(0.00153)	(0.00191)	(0.00191)	(0.00192)
Electrophysiology study	-0.0190***	-0.0181***	-0.0183***	-0.0268***	-0.0255***	-0.0256***
	(0.00277)	(0.00277)	(0.00277)	(0.00347)	(0.00347)	(0.00347)
VT indication (ES study)	-0.00443	-0.00406	-0.00402	-0.00548	-0.00490	-0.00485
	(0.00523)	(0.00522)	(0.00523)	(0.00655)	(0.00654)	(0.00655)
Female	-0.00734***	-0.00734***	-0.00733***	-0.0166***	-0.0166***	-0.0165***
	(0.00147)	(0.00147)	(0.00147)	(0.00184)	(0.00184)	(0.00184)
Black	0.0298***	0.0297***	0.0296***	0.0492***	0.0491***	0.0491***
	(0.00226)	(0.00225)	(0.00226)	(0.00283)	(0.00283)	(0.00283)
Hsipanic (Medicare)	0.00922*	0.00884*	0.00975*	0.0140**	0.0135**	0.0137**
	(0.00506)	(0.00506)	(0.00507)	(0.00634)	(0.00634)	(0.00635)
Other race	0.0124***	0.0120***	0.0118***	0.0186***	0.0180***	0.0175***
	(0.00418)	(0.00417)	(0.00418)	(0.00524)	(0.00523)	(0.00524)
Hispanic ethnicity (Registry)	0.00442	0.00388	0.00293	8.57e-05	-0.000684	-0.00118
	(0.00515)	(0.00515)	(0.00516)	(0.00645)	(0.00645)	(0.00646)
2007.year	0.00446*	0.00630**	0.00598**	0.00587*	0.00864***	0.00801***
	(0.00247)	(0.00248)	(0.00248)	(0.00309)	(0.00310)	(0.00311)
2008.year	0.00975***	0.0119***	0.0115***	0.00920***	0.0125***	0.0117***
	(0.00255)	(0.00256)	(0.00257)	(0.00320)	(0.00321)	(0.00322)
2009.year	0.00904***	0.0115***	0.0108***	0.0115***	0.0153***	0.0142***
	(0.00257)	(0.00258)	(0.00258)	(0.00322)	(0.00323)	(0.00324)
2010.year	0.0129***	0.0151***	0.0143***	0.00810**	0.0115***	0.0101***
	(0.00269)	(0.00269)	(0.00270)	(0.00338)	(0.00338)	(0.00339)
2011.year	0.00895***	0.0106***	0.00958***	0.0128***	0.0154***	0.0137***
	(0.00294)	(0.00293)	(0.00294)	(0.00370)	(0.00369)	(0.00370)
2012.year	0.0148***	0.0159***	0.0146***	0.0162***	0.0179***	0.0158***
	(0.00304)	(0.00302)	(0.00303)	(0.00382)	(0.00380)	(0.00382)
2013.year	0.0146***	0.0160***	0.0145***	0.0216***	0.0237***	0.0216***
	(0.00307)	(0.00305)	(0.00307)	(0.00386)	(0.00384)	(0.00386)
Constant	0.0955***	0.124***	0.180***	0.163***	0.206***	0.283***
	(0.00904)	(0.00958)	(0.0135)	(0.0114)	(0.0121)	(0.0172)
Observations	253,247	253,247	252,613	253,247	253,247	252,613
Groups	1,548	1,548	1,542	1,548	1,548	1,542

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Mortality (One & Two Year) OLS Fixed Effects Regression

VARIABLES	(1) death1yr	(2) death1yr	(3) death1yr	(4) death2yr	(5) death2yr	(6) death2yr
HRR-level ICD Rate	0.0552	0.0720*	0.0734*	0.0445	0.0703	0.0709
	(0.0368)	(0.0374)	(0.0376)	(0.0470)	(0.0475)	(0.0479)
Ln(volume)		-0.00577***	-0.00598***		-0.00890***	-0.00925***
		(0.00221)	(0.00223)		(0.00277)	(0.00280)
HRR-level Rx Rate			-0.0643			-0.0913
			(0.0791)			(0.101)
Ejection Fraction (EF) <20%	-0.00368***	-0.00368***	-0.00369***	-0.00482***	-0.00482***	-0.00485***
	(0.000380)	(0.000380)	(0.000381)	(0.000470)	(0.000470)	(0.000471)
EF 20-25%	-0.00457***	-0.00456***	-0.00454***	-0.00542***	-0.00542***	-0.00539***
	(0.000408)	(0.000408)	(0.000408)	(0.000503)	(0.000503)	(0.000504)
EF 25-30%	-0.00224***	-0.00224***	-0.00224***	-0.00387***	-0.00386***	-0.00387***
	(0.000356)	(0.000356)	(0.000357)	(0.000452)	(0.000452)	(0.000453)
EF 30-35%	-0.000750*	-0.000750*	-0.000763*	-0.00104*	-0.00104*	-0.00103*
	(0.000412)	(0.000412)	(0.000412)	(0.000551)	(0.000551)	(0.000552)
EF > 35%	0.00153***	0.00153***	0.00152***	0.00199***	0.00199***	0.00195***
	(0.000318)	(0.000318)	(0.000318)	(0.000387)	(0.000387)	(0.000388)
EF Missing	0.0156**	0.0155**	0.0162**	0.0241**	0.0240**	0.0239**
	(0.00773)	(0.00772)	(0.00779)	(0.0102)	(0.0102)	(0.0102)
NY Heart Assoc. Class II	0.00201	0.00205	0.00160	0.00541	0.00548	0.00496
	(0.00348)	(0.00348)	(0.00349)	(0.00494)	(0.00494)	(0.00495)
NY Heart Assoc. Class III	0.0477***	0.0478***	0.0475***	0.0713***	0.0714***	0.0712***
	(0.00351)	(0.00351)	(0.00352)	(0.00494)	(0.00494)	(0.00495)
NY Heart Assoc. Class IV	0.154***	0.154***	0.153***	0.189***	0.189***	0.189***
	(0.00586)	(0.00586)	(0.00587)	(0.00731)	(0.00731)	(0.00733)
NY Heart Assoc. Class missing	0.0469***	0.0468***	0.0467***	0.0848***	0.0847***	0.0848***
	(0.0119)	(0.0119)	(0.0119)	(0.0151)	(0.0151)	(0.0151)
Age 70-74	0.0152***	0.0152***	0.0153***	0.0280***	0.0280***	0.0278***
	(0.00166)	(0.00166)	(0.00167)	(0.00206)	(0.00206)	(0.00206)
Age 75-79	0.0365***	0.0365***	0.0365***	0.0646***	0.0647***	0.0647***
	(0.00182)	(0.00182)	(0.00183)	(0.00228)	(0.00228)	(0.00228)
Age 80-84	0.0618***	0.0618***	0.0620***	0.108***	0.108***	0.108***
	(0.00215)	(0.00215)	(0.00215)	(0.00258)	(0.00258)	(0.00258)
Age 85-89	0.0975***	0.0975***	0.0976***	0.170***	0.170***	0.170***
	(0.00329)	(0.00329)	(0.00330)	(0.00410)	(0.00410)	(0.00410)
Age 90+	0.172***	0.172***	0.172***	0.263***	0.263***	0.264***
	(0.0107)	(0.0107)	(0.0107)	(0.0125)	(0.0125)	(0.0125)
Previous cardiac arrest	0.0549***	0.0548***	0.0546***	0.0542***	0.0541***	0.0542***
	(0.00553)	(0.00553)	(0.00553)	(0.00634)	(0.00634)	(0.00635)
Family history sudden arrest	-0.0116***	-0.0116***	-0.0116***	-0.0178***	-0.0178***	-0.0178***
	(0.00362)	(0.00362)	(0.00361)	(0.00468)	(0.00468)	(0.00468)
Ventricular tacchycardia	0.0441***	0.0442***	0.0440***	0.0564***	0.0564***	0.0562***
	(0.00193)	(0.00193)	(0.00193)	(0.00229)	(0.00229)	(0.00230)
Non-ischemic dialated	-0.0190***	-0.0190***	-0.0190***	-0.0282***	-0.0281***	-0.0280***
	(0.00243)	(0.00243)	(0.00244)	(0.00315)	(0.00315)	(0.00315)
ischemichd	0.0181***	0.0181***	0.0181***	0.0284***	0.0285***	0.0286***

	(0.00264)	(0.00264)	(0.00265)	(0.00330)	(0.00330)	(0.00331)
prevmi	0.00920***	0.00922***	0.00929***	0.0135***	0.0135***	0.0136***
	(0.00172)	(0.00172)	(0.00172)	(0.00222)	(0.00222)	(0.00222)
prevcabg	0.00876***	0.00874***	0.00864***	0.0201***	0.0201***	0.0201***
	(0.00165)	(0.00165)	(0.00165)	(0.00200)	(0.00200)	(0.00200)
prevpci	-0.00991***	-0.00992***	-0.0100***	-0.0123***	-0.0123***	-0.0124***
	(0.00164)	(0.00164)	(0.00164)	(0.00201)	(0.00201)	(0.00201)
epstudy	-0.0193***	-0.0193***	-0.0193***	-0.0263***	-0.0263***	-0.0261***
	(0.00282)	(0.00282)	(0.00283)	(0.00380)	(0.00381)	(0.00382)
epsvtind	-0.00425	-0.00410	-0.00382	-0.00630	-0.00606	-0.00582
	(0.00513)	(0.00513)	(0.00513)	(0.00661)	(0.00662)	(0.00663)
female	-0.00735***	-0.00733***	-0.00732***	-0.0168***	-0.0168***	-0.0167***
	(0.00147)	(0.00147)	(0.00147)	(0.00187)	(0.00187)	(0.00187)
raceblack	0.0255***	0.0255***	0.0257***	0.0444***	0.0444***	0.0448***
	(0.00232)	(0.00232)	(0.00232)	(0.00293)	(0.00293)	(0.00293)
racehisp	0.00489	0.00492	0.00596	0.00951	0.00954	0.00996
	(0.00511)	(0.00511)	(0.00512)	(0.00646)	(0.00646)	(0.00648)
raceother	0.00780*	0.00776*	0.00784*	0.0138**	0.0137**	0.0136**
	(0.00426)	(0.00425)	(0.00427)	(0.00554)	(0.00553)	(0.00553)
hispethnicity	0.000518	0.000507	-0.000397	-0.00397	-0.00398	-0.00436
	(0.00500)	(0.00500)	(0.00500)	(0.00629)	(0.00629)	(0.00630)
2007.year	0.00373	0.00484*	0.00495*	0.00462	0.00634**	0.00634**
	(0.00250)	(0.00253)	(0.00254)	(0.00308)	(0.00314)	(0.00314)
2008.year	0.00832***	0.00962***	0.00976***	0.00692**	0.00893**	0.00902**
	(0.00269)	(0.00274)	(0.00275)	(0.00350)	(0.00358)	(0.00359)
2009.year	0.00702**	0.00852***	0.00849***	0.00875**	0.0111***	0.0110***
	(0.00280)	(0.00287)	(0.00287)	(0.00355)	(0.00362)	(0.00364)
2010.year	0.00997***	0.0113***	0.0114***	0.00348	0.00557	0.00553
	(0.00310)	(0.00316)	(0.00315)	(0.00382)	(0.00386)	(0.00386)
2011.year	0.00473	0.00569	0.00607*	0.00605	0.00753*	0.00790*
	(0.00352)	(0.00354)	(0.00354)	(0.00455)	(0.00457)	(0.00458)
2012.year	0.0102***	0.0109***	0.0109***	0.00873*	0.00979**	0.00963**
	(0.00383)	(0.00384)	(0.00385)	(0.00483)	(0.00483)	(0.00485)
2013.year	0.0100***	0.0108***	0.0110***	0.0139***	0.0152***	0.0153***
	(0.00388)	(0.00388)	(0.00389)	(0.00481)	(0.00481)	(0.00483)
Constant	0.106***	0.127***	0.168***	0.180***	0.212***	0.270***
	(0.0115)	(0.0139)	(0.0517)	(0.0147)	(0.0178)	(0.0659)
Observations	253,247	253,247	252,613	253,247	253,247	252,613
R-squared	0.045	0.045	0.045	0.057	0.057	0.057

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1