# Effect of Electronic Prescribing With Formulary Decision Support on Medication Use and Cost

*Michael A. Fischer, MD, MS; Christine Vogeli, PhD; Margaret Stedman, MPH; Timothy Ferris, MD, MPH; M. Alan Brookhart, PhD; Joel S. Weissman, PhD*

**Background:** Electronic prescribing (e-prescribing) with formulary decision support (FDS) prompts prescribers to prescribe lower-cost medications and may help contain health care costs. In April 2004, 2 large Massachusetts insurers began providing an e-prescribing system with FDS to community-based practices.

**Methods:** Using 18 months (October 1, 2003, to March 31, 2005) of administrative data, we conducted a pre-post study with concurrent controls. We first compared the change in the proportion of prescriptions for 3 formulary tiers before and after e-prescribing began, then developed multivariate longitudinal models to estimate the specific effect of e-prescribing when controlling for baseline differences between intervention and control prescribers. Potential savings were estimated using average medication costs by formulary tier.

**Results:** More than 1.5 million patients filled 17.4 million prescriptions during the study period. Multivariate models controlling for baseline differences between prescribers and for changes over time estimated that e-prescribing corresponded to a 3.3% increase (95% confidence interval, 2.7%-4.0%) in tier 1 prescribing. The proportion of prescriptions for tiers 2 and 3 (brand-name medications) decreased correspondingly. e-Prescriptions accounted for 20% of filled prescriptions in the intervention group. Based on average costs for private insurers, we estimated that e-prescribing with FDS at this rate could result in savings of $845 000 per 100 000 patients. Higher levels of e-prescribing use would increase these savings.

**Conclusions:** Clinicians using e-prescribing with FDS were significantly more likely to prescribe tier 1 medications, and the potential financial savings were substantial. Widespread use of e-prescribing systems with FDS could result in reduced spending on medications.

*Arch Intern Med. 2008;168(22):2433-2439*

ESCALATING HEALTH CARE costs are a major policy concern, and health information technology has been promoted as a tool for realizing large savings,[1,2] although the evidence for how effectively this technology can reduce costs remains limited.[3] Prescription drug costs account for a significant proportion of medical spending and have been increasing rapidly.[4,5] Insurers and policymakers have tried several measures to control drug costs. The Veterans Health Administration reduced spending by instituting a narrow drug formulary.[6] Some states have enacted regulations requiring that pharmacists substitute a generic medication whenever one is available,[7] and some insurers have used financial incentives for physicians who prescribe more generic medications.[8]

Another method for encouraging use of lower-cost medications is variable cost sharing, generally implemented as tiered copayments.[9] In these systems, insurers identify preferred medications, often generic medications, and designate them "tier 1" with the lowest copayment. The second tier, generally requiring a higher copayment, may include moderately priced brand-name medications. Third-tier drugs are generally expensive brand-name agents for which generic alternatives are available in lower copayment tiers, or so-called lifestyle medications.

A key limitation of tiered copayment systems is prescribers' inability to keep track of differing copayment tiers across insurance plans' formularies. Electronic prescribing (e-prescribing) systems offer one method of addressing this problem. By providing formulary decision support (FDS) at the point of prescribing, e-prescribing can allow clinicians to prescribe preferred medications more frequently. The ability of e-prescribing systems to influence prescriber action has been demonstrated in inpatient settings or closed de-

**Author Affiliations:** Division of Pharmacoepidemiology and Pharmacoeconomics, Brigham and Women's Hospital (Drs Fischer and Brookhart and Ms Stedman), and Institute for Health Policy, Massachusetts General Hospital (Drs Vogeli, Ferris, and Weissman), Harvard Medical School, Boston.

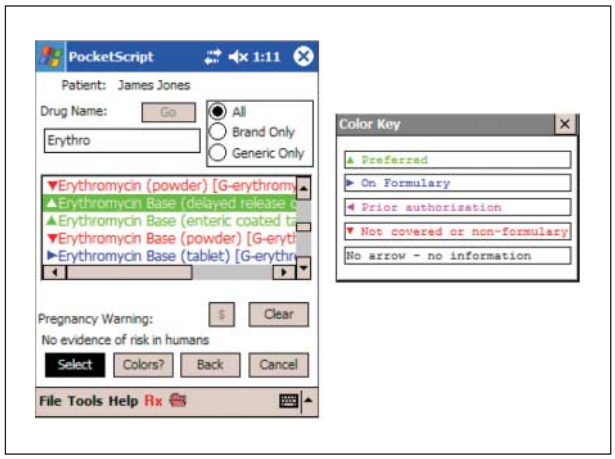


**Figure 1.** Sample prescribing screen for the PocketScript (Zix Corporation, Dallas, Texas) e-prescribing system with formulary decision support. Preferred formulary medications appear in green text, nonpreferred formulary medications in blue, and nonformulary medications in red.

livery systems (like the Veterans Health Administration).[10] However, most prescribing occurs in community-based practices, and the potential effect of e-prescribing in these settings has not been fully described.

In late 2003, 2 insurers in Massachusetts embarked on what was at the time the largest rollout of a community-based e-prescribing system with FDS in the country. The program is heavily subsidized, and anecdotal reports from payers suggest that even in Massachusetts, where law mandates generic substitution by pharmacists unless the prescriber explicitly specifies a branded product, e-prescribing reduces overall spending on pharmaceuticals, justifying further support of the program. However, such a claim has not been rigorously analyzed. We, therefore, evaluated the first year of this statewide program to determine its effect on medication use and costs.

## METHODS

### STUDY DESIGN

To understand the effect of e-prescribing with FDS on medication use, we performed a pre-post analysis with intervention and control groups. We calculated the proportion of prescriptions written in each of 3 formulary tiers for 6 months before and up to 12 months after the start of e-prescribing. The individual prescription was the unit of analysis, and we controlled for data clustering at the patient and prescriber level. Clinician use of e-prescribing defined the intervention prescriptions, and all prescriptions written by unenrolled prescribers served as controls. We applied the estimated effect of e-prescribing with FDS to patient-level data to estimate the potential savings per patient per month. The Partners Institutional Review Board (parent organization of Massachusetts General Hospital and Brigham and Women's Hospital) approved the study.

### INTERVENTION

In October 2003, Blue Cross Blue Shield of Massachusetts, Tufts Health Plan, and Zix Corporation formed the eRx Collaborative. Under the program, PocketScript software from Zix Corporation (Dallas, Texas) was distributed to Massachusetts outpatient providers. The eRx Collaborative identified high-volume prescribers and offered them the e-prescribing system, with costs paid by the insurance companies. Participants in the program received a free wireless mobile device, access to a secure Web portal, licensing, and wireless carrier service. The program was available to any high-volume prescriber; however, because many hospital-based clinicians were already using electronic medical records, enrollees in the eRx Collaborative were overwhelmingly from community-based practices.

Clinicians began enrolling during the second quarter of 2004. The program subsequently expanded to include additional insurers and e-prescribing companies; however, for the purposes of this study we focused exclusively on Blue Cross Blue Shield of Massachusetts, Tufts Health Plan, and Zix Corporation.

The e-prescribing software included formulary-based color-coding for drug names (**Figure 1**). Tier 1 medications required the lowest copayment and were all generic medications. Medications with preferred formulary status (generally tier 1) appeared in green text. Nonpreferred medications appeared in blue, and those that were not covered appeared in red. The system did not prevent users from prescribing nonpreferred medications; the color-coding served only as a reminder.

### DATA SOURCES

We obtained data on prescriptions written with the e-prescribing system (e-prescribing data) and prescriptions filled and paid for by the 2 participating health plans (claims data). All identifiable characteristics were removed from the data before transmission to the research team. Encrypted patient and clinician identifiers were created so records could be linked across the data sets while preserving confidentiality. The e-prescribing data covered 12 months, from April 1, 2004, through March 31, 2005, and the claims data included those 12 months and the 6 preceding months.

The e-prescribing data included prescriber identification number (ID), patient ID, prescription date, drug name, dosage, form (pill, tablet, etc), and insurance plan. The paid claims data included patient ID, prescription fill date, prescriber ID, and copayment tier. Drugs were identified in the claims data by the national drug code, which specifies the medication, dosage, and form. Prescriber IDs were linked to files from the Zix Corporation and the insurance plans to obtain specialty, age, sex, and practice size. Patient IDs were linked to enrollment files to obtain age, sex, and insurance plan.

The e-prescribing data recorded all e-prescriptions, regardless of whether they were filled or not. Therefore, to identify paid claims written electronically, we linked the 2 data sources using patient identifiers and drug names, requiring that the prescription fill date was on or after the date of e-prescribing.

### ANALYSES

Patients with at least 1 drug claim during the study period were included. Prescriptions from medication benefit plans that did not use tiered copayment systems were excluded. The intervention group included all prescribers who wrote at least 1 e-prescription, with all other clinicians (whether they were offered e-prescribing or not) serving as controls. Some paid claims (7%) were excluded because the prescriber field could not be linked to a single clinician; this generally occurs when placeholder identifiers are used for trainees or out-of-state prescribers. An additional 3% of claims were excluded because of incomplete or missing data.

We first examined the unadjusted data using a simple pre-post descriptive analysis. We calculated the proportion of filled prescriptions that were in each copayment tier and compared

the proportion of medications in each tier before and after e-prescribing began. For intervention prescribers, we used all filled claims in the 6 months before April 1, 2004 as baseline data. During the intervention period, we examined the data using 2 approaches: an "e-prescriptions only" analysis including just those prescriptions written electronically (including refills) and an "all prescriptions" analysis including all filled claims for each e-prescribing clinician on or after the date on which they wrote their first e-prescription through the end of our data period.

For control prescribers, we defined the baseline period as described previously to include all their filled claims in the 6 months before April 1, 2004, and the intervention period to include those claims filled during the following 12 months. The same set of prescribing data for the controls was used for the e-prescriptions only and the all prescriptions analyses. We compared the change from the baseline period to the intervention period across the control and intervention groups, using bootstrapped standard errors to create 95% confidence intervals (CIs) around the change for each tier and treatment group so that nonoverlapping CIs could be interpreted as statistically significant. To provide a visual display of the effect of e-prescribing, we recategorized the data by "relative months" before and after prescribers first wrote e-prescriptions and generated a graph depicting tier 1 prescribing for each group over time.

The descriptive analysis does not account for differences between the e-prescribing and control groups, including baseline characteristics, or the variable time gap between the baseline and intervention periods, which occurred because e-prescribing start dates were distributed throughout the study period. The unadjusted analysis also does not account for the fact that, even after enrollment, prescriptions could be written either electronically or on paper. Therefore, we developed regression models to quantify more precisely the effect of e-prescribing. In these models we used the individual prescription as the unit of analysis and modeled the probability that a prescription would be in a given copayment tier. Because each prescription event has 3 possible outcomes (ie, tier 1, 2, or 3), we developed multinomial logistic regression models,[11] using tier 1 as the reference group.

Indicator variables identified nonelectronic prescriptions written by intervention clinicians before and after they began e-prescribing, thereby measuring the differences between intervention and control prescribers when not e-prescribing (ie, baseline differences). We included a term for calendar month to control for secular trends. A final indicator variable identified whether an intervention clinician's prescription was actually e-prescribed. Among prescribers using the e-prescribing system, the parameter estimate for this variable measures the change in the likelihood of a prescription being in a given tier for those written electronically vs nonelectronically. We used the fitted model to generate the predicted probabilities of prescriptions being in a given tier. Standard errors were adjusted for within-clinician correlation by a grouped bootstrapping. (Full model details are available from the corresponding author.)

In preliminary development of our models, we included baseline characteristics of patients (age and sex) and prescribers (age, sex, and medical specialty). None of these variables changed the results significantly, so they were dropped from the final models. (Results of adjusted models are available from the corresponding author.) Analyses were performed using SAS statistical software, version 8.2,[12] and Stata statistical software, version 9.0.[13]

We used the model results to estimate the potential financial effect of e-prescribing with FDS and provide a range of possible financial effects. We began with a limited estimate, taking into account the actual use of e-prescribing as observed in our study,[14,15] and assumed that broader e-prescribing availability and use would increase these savings in a linear fashion. We assumed that patients filled 1 prescription per month, a representative utilization rate for privately insured patients. We used prevailing average monthly medication costs for major health plans in our region, corresponding to $28 for tier 1, $115 for tier 2, and $139 for tier 3. We multiplied the number of prescriptions per patient per month by the average cost for each tier and the projected change in percentage of prescriptions in each tier. We multiplied this result by 0.20 to reflect that only 20% of medications in our sample were e-prescribed. We explored the change in financial effect when we varied drug utilization rates and costs. Full details of the financial calculations are available from the corresponding author.

**Table 1. Patient and Prescriber Characteristics[a]**

| Characteristic | Intervention Group (e-Prescription) | Control Group[b] (No e-Prescription) | Total |
|---|---|---|---|
| **Patients** | | | |
| No. of participants | 64 749 | 1 466 564 | **1 531 313** |
| Sex | | | |
| Male | 27 458 (42.4) | 643 375 (43.9) | **670 833** (43.8) |
| Female | 37 291 (57.6) | 823 189 (56.1) | **860 480** (56.2) |
| Age, y | | | |
| ≤18 | 8 214 (12.7) | 308 756 (21.1) | **316 970** (20.7) |
| 19-34 | 10 203 (15.8) | 320 556 (21.9) | **330 759** (21.6) |
| 35-54 | 28 989 (44.8) | 552 989 (37.7) | **581 978** (38.0) |
| 55-64 | 11 885 (18.4) | 193 121 (13.2) | **205 006** (13.4) |
| ≥65 | 5458 (8.4) | 91 142 (6.2) | **96 600** (6.3) |
| **Prescribers** | | | |
| No. of participants | 1198 | 34 453 | **35 651** |
| Sex | | | |
| Male | 593 (49.5) | 22 495 (65.3) | **23 088** (64.8) |
| Female | 460 (38.4) | 10 138 (29.4) | **10 598** (29.7) |
| Missing data | 145 (12.1) | 1820 (5.3) | **1965** (5.5) |
| Age, y | | | |
| ≤35 | 138 (11.5) | 1784 (5.2) | **1922** (5.4) |
| 36-54 | 696 (58.1) | 9017 (26.2) | **9713** (27.2) |
| ≥55 | 200 (16.7) | 3651 (10.6) | **3851** (10.8) |
| Missing data | 164 (13.7) | 20 001 (58.1) | **20 165** (56.6) |
| Specialty[c] | | | |
| Internal medicine | 365 (30.5) | 9988 (29.0) | **10 353** (29.0) |
| Pediatrics | 300 (25.0) | 3208 (9.3) | **3508** (9.8) |
| Family practice | 186 (15.5) | 2125 (6.2) | **2311** (6.5) |
| Other | 321 (26.8) | 19 682 (57.1) | **20 003** (56.1) |
| Missing data | 137 (11.4) | 110 (0.3) | **247** (0.7) |

[a] Data are given as the number (percentage) of participants unless otherwise indicated.

[b] Control prescribers were identified separately in the 2 participating insurance plans, so individuals may have contributed 2 observations to the control cohort.

[c] Since clinicians may have multiple specialties, categories for specialty are not mutually exclusive. Column percentages for specialty do not sum to 100.

## RESULTS

**Table 1** shows the demographic and practice characteristics of the study population. More than 1.5 million patients filled prescription claims, and 64 749 patients filled a prescription that was e-prescribed. Patients receiving e-prescriptions were slightly more likely to be female and were older than patients who did not receive e-prescriptions. The data included more than 35 000 clinicians, of whom 1198 wrote e-prescriptions. Prescribers in the intervention group were slightly younger and were more likely to be female. The specialties of internal medicine,

**Table 2. Baseline and Intervention Period Prescriptions by Formulary Tier**

| Formulary Tier | Baseline[a] | Intervention Period | | | |
|---|---|---|---|---|---|
| | | e-Prescriptions Only[b] | | All Prescriptions[c] | |
| | | No. (%) of Prescriptions | Change (95% CI), % | No. (%) of Prescriptions | Change (95% CI), % |
| Tier 1 | | | | | |
| Intervention | 526 635 (54.8) | 130 352 (61.4) | 6.6 (5.9 to 7.3) | 638 904 (58.5) | 3.7 (3.2 to 4.1) |
| Control[d] | 3 012 208 (53.2) | NA | NA | 6 429 208 (55.8) | 2.6 (2.5 to 2.7) |
| Tier 2 | | | | | |
| Intervention | 343 334 (35.8) | 64 947 (30.6) | –5.2 (–5.9 to –4.5) | 353 300 (32.3) | –3.4 (–3.8 to –3.0) |
| Control[d] | 2 061 171 (36.4) | NA | –NA | 3 883 160 (33.7) | –2.7 (–2.8 to –2.6) |
| Tier 3 | | | | | |
| Intervention | 90 327 (9.4) | 16 985 (8.0) | –1.4 (–1.8 to –1.0) | 100 386 (9.2) | –0.2 (–0.5 to 0.0) |
| Control[d] | 590 434 (10.4) | NA | NA | 1 220 318 (10.6) | 0.2 (0.1 to 0.2) |

Abbreviations: CI, confidence interval; NA, not applicable.
[a] Defined as October 1, 2003, through March 31, 2004.
[b] Includes filled pharmacy claims that were matched to prescriptions written electronically.
[c] Includes all filled pharmacy claims, from both electronic and nonelectronic prescriptions, written by prescribers in the intervention group on or after the first date they wrote an e-prescription.
[d] Includes all filled claims for prescribers not using the e-prescribing system.

pediatrics, and family practice accounted for about 70% of the intervention group, a higher proportion than in the control group. There were a total of 17.4 million filled prescriptions during the entire study period, more than 212 000 of which were e-prescriptions.

The proportions of prescriptions in each copayment tier for intervention and control groups, before and after e-prescribing began, are shown in **Table 2**. Baseline proportions for the controls were 53.2%, 36.4%, and 10.4% in tiers 1, 2, and 3, respectively. Prescribers in the intervention group had a slightly higher tier 1 prescribing rate and lower tier 2 and 3 prescribing rates during the baseline period (54.8%, 35.8%, and 9.4%, respectively). After intervention, clinicians began e-prescribing; tier 1 prescribing increased sharply for e-prescriptions. During the intervention period, 61.4% of e-prescriptions were in tier 1, an increase of 6.6% (95% CI, 5.9%-7.3%) over baseline, compared with the 2.6% (95% CI, 2.5%-2.7%) increase in the control group. The tier 2 prescription rate was 30.6%, a decrease of 5.2% (95% CI, –5.9% to –4.5%) compared with a 2.7% decrease (95% CI, –2.8% to –2.6%) for controls. The tier 3 proportion was 8.0%, a decrease of 1.4% (95% CI, –1.8% to –1.0%), compared with a 0.2% increase for controls (95% CI, 0.1%-0.2%). e-Prescriptions represented only about 20% of all prescriptions written by the intervention group, and the all-prescriptions analysis demonstrated a diminished, although still positive, effect on tier 1 prescribing. Even when not e-prescribing, intervention prescribers were more likely than controls to prescribe tier 1 drugs before and after the start of e-prescribing (**Figure 2**). However, when the intervention group did use e-prescribing, they prescribed tier 1 medications at higher rates.

We performed multivariate analyses to account for variable start dates, baseline differences among prescribers, and actual use of e-prescribing by intervention group prescribers. These results are summarized in **Table 3**, which shows the predicted probabilities of prescriptions in each tier during the intervention period, adjusting for temporal trends. The intervention group prescribed 1.4% more (95% CI, 0.6%-2.0%) tier 1 medications, 0.3% fewer (95% CI, –0.8% to 0.2%) tier 2 medications, and 1.0% fewer (95% CI, –1.4% to –0.7%) tier 3 medications than the control group. Table 3 also shows the specific effect of e-prescribing with FDS, controlling for time and baseline differences between groups and accounting for whether prescriptions were written electronically or nonelectronically by intervention prescribers. These effects correspond to an increase of 3.3% (95% CI, 2.7%-4.0%) in tier 1 prescriptions, a decrease of 1.9% (95% CI, –2.5% to –1.3%) in tier 2 prescriptions, and a decrease of 1.5% (95% CI, –1.8% to –1.1%) in tier 3 prescriptions.

Using the assumptions of prescription volume per patient and the average cost per copayment tier presented in the "Methods" section, use of e-prescribing with FDS at the level that we observed (20%) would reduce costs by $0.70 per patient per month. This is equivalent to $845 000 annual savings in prescription drug spending per 100 000 insured patients filling prescriptions. The potential savings increase with more availability and use of e-prescribing[14,15]; for complete e-prescribing use, the projected savings are $3.91 million per 100 000 patients per year. The financial effect of these changes also varies with the volume of medication use and medication costs. Full details of the financial calculations are available from the corresponding author.

## COMMENT

We evaluated the first year of large-scale implementation of an office-based e-prescribing system in community-based medical practices. The e-prescribing system encourages prescribers to choose medications with lower copayments by using point-of-prescribing FDS. We found that clinicians who used the e-prescribing system prescribed a higher proportion of tier 1 medications. Al-

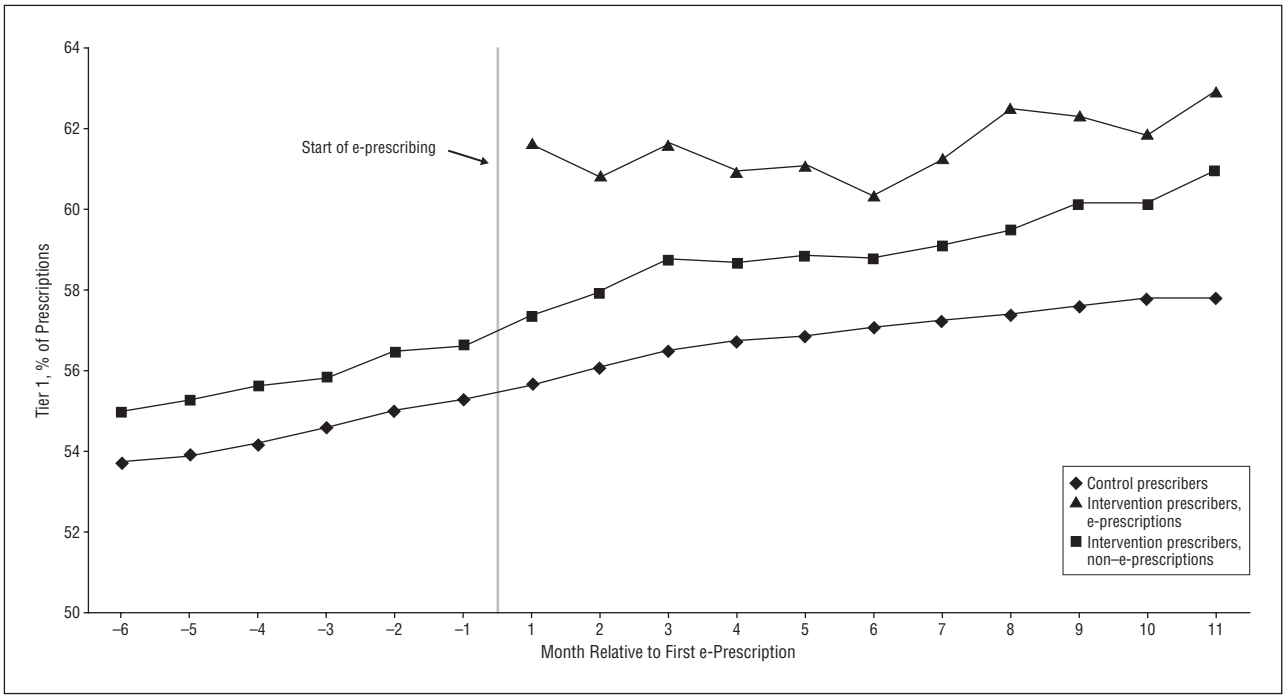


**Figure 2.** Percentage of filled prescriptions in copayment tier 1 (generic) medications for control vs intervention prescribers over time.

**Table 3. Predicted Prescribing by Tier Based on e-Prescribing Status**

| | Formulary Tier,%[b] | | |
|---|---|---|---|
| Predicted Probability[a] | Tier 1 | Tier 2 | Tier 3 |
| Control | 55.0 (54.7 to 55.2) | 34.5 (34.3 to 34.7) | 10.5 (10.4 to 10.7) |
| Intervention | | | |
| Nonelectronic prescription | 56.3 (55.7 to 57.0) | 34.1 (33.7 to 34.7) | 9.5 (9.2 to 9.8) |
| Electronic prescription | 59.7 (58.9 to 60.5) | 32.3 (31.6 to 33.0) | 8.0 (7.7 to 8.4) |
| Risk difference | | | |
| Baseline (no e-prescribing)[c] | 1.4 (0.6 to 2.0) | –0.3 (–0.8 to 0.2) | –1.0 (–1.4 to –0.7) |
| e-Prescribing vs no e-prescribing[d] | 3.3 (2.7 to 4.0) | –1.9 (–2.5 to –1.3) | –1.5 (–1.8 to –1.1) |

[a] Predicted probability of a prescription being in a given tier, adjusted for month.
[b] Data are given as the predicted probability of an individual prescription being in a given tier (95% confidence interval, adjusted for clustering within prescriber and patient).
[c] An estimate of the difference in the probability for prescriptions that were not e-prescribed being in a given tier for intervention vs control prescribers.
[d] An estimate the difference in the probability of a prescription in the intervention group being in a given tier for prescriptions written electronically vs nonelectronically, controlling for all other effects.

though the size of the effect may appear modest (3.3% adjusted increase in tier 1 medications vs controls), the potential financial effect is substantial. The size of the financial effect depends critically on the extent to which e-prescribing is available and used. In Massachusetts, the proportion of e-prescribing may well increase over time because health plans have recently begun offering physician incentives for increased use of e-prescribing (incentives were not in place at the time of this study).

Previous research has identified considerable potential savings on prescription drugs if generic medications were more widely prescribed[16-18] or if lower-cost alternative medications were used for common conditions.[19] Prescribing medications with lower copayments may have clinical benefits such as increased patient adherence.[20] Despite physician incentives for generic prescribing[8] and pharmacy-level generic substitution requirements,[7] drug costs continue to rise. By providing information at the point of prescribing, e-prescribing with FDS offers advantages over these approaches. Our results provide empirical verification of this potential.

There are several possible explanations for our findings. The modest effect for intervention prescribers when not e-prescribing suggests that users did not learn from the FDS but required the information at the moment of prescribing. Massachusetts mandates generic substitution by pharmacists, so simple generic substitution is unlikely to explain our findings, suggesting that prescribers using the system may have chosen different agents with preferred formulary status. It is possible, although unlikely, that differences in tier 1 prescribing among intervention clinicians when not e-prescribing resulted from deliberate choices to use paper when prescribing tier 2 and 3 medications. Our lack of information about paper

prescriptions prevents us from exploring this issue further. Additional research on why physicians decline to use e-prescribing and how adopters actually use it will help us better understand how these systems achieve the effect that we observed.

Our findings could have important financial implications. Understanding the economic effect of e-prescribing is a priority for physicians, practices, and payers; without such information, the potential return on investment from e-prescribing cannot be properly estimated. In our 2004-2005 study period, the availability and use of e-prescribing with FDS were relatively limited, and exploratory calculations of the economic effect of our results showed potential savings of $845 000 for a population of 100 000 patients with average levels of medication use. As e-prescribing systems become more widely available and easier to use,[14,15] uptake rates are likely to increase and complete use of e-prescribing system with FDS could reduce prescription drug spending by up to $3.9 million per 100 000 patients per year. The potential economic benefits of this change would have to be balanced against the costs of implementing e-prescribing; recent government estimates of approximate first-year costs were $3000 per prescriber.[21] At observed use rates, a clinician would need to treat 355 patients in a year (with savings of $8.45 per patient) to generate $3000 in system savings to match the cost of e-prescribing; savings from higher e-prescribing uptake or increased patient volume would represent a net gain for the system.

These economic calculations must be regarded as preliminary, and any attempt to generalize the findings must consider the context in which our study was done. We evaluated e-prescribing in one location, a state that already has mandatory generic substitution requirements for pharmacists and widespread use of physician pay-for-performance incentives based on prescribing more generic medications. Massachusetts had a large number of prescribers using e-prescribing systems other than the one we studied (mostly those using an electronic medical record system at major medical centers), which would tend to reduce differences between the intervention and control groups. Even in the context of pay-for-performance incentives, pharmacy regulations, and increasing overall use of generics, we still found a large potential savings from e-prescribing. Only 14 states mandate generic substitution; if our results are generalizable to states with lower baseline generic prescribing, the potential savings could be larger than those identified in our study. More sophisticated interventions to increase appropriate prescribing across other dimensions (eg, encouraging thiazides for hypertension) could result in additional savings. Such interventions are not available in most current e-prescribing systems, but our results demonstrate their potential to affect prescribing.

There are other potential limitations that must be considered in interpreting these results. Our study was observational; practices were not randomly assigned to receive the e-prescribing system but were selected by the health insurance plans if they were high-volume prescribers. We observed differences in prescribing patterns between the intervention and control groups, both in the baseline and intervention periods. Although the use of a control series in our analyses provides some adjustment for baseline differences, there may be residual selection bias owing to unobserved and unaccounted for reasons that a clinician decided to e-prescribe, which may limit the generalizability of our results. Primary care specialties were overrepresented in the intervention group; when we restricted the control group to primary care specialties (results not shown) the control group had slightly higher rates of tier 1 prescriptions, but the main results were unchanged.

Prescriber identification information in the prescriptions claims files did not always correspond to an individual, so about 10% of prescription claims were excluded from our analyses. We reran all analyses, treating the placeholder prescriber identifiers as if they were individual clinicians, and none of our effect estimates changed. As noted, many qualitative factors could affect whether clinicians choose to prescribe electronically for any given prescription, and we did not capture those characteristics. Previous studies have identified barriers to adoption, such as the financial cost of acquiring new systems and the time required to learn how to e-prescribe.[22-25] Additional research on why clinicians decline to use e-prescribing and how adopters actually use it will help to understand better how these systems achieve the effect that we observed.

In conclusion, we found that an office-based e-prescribing system with FDS at the point of prescribing, used in a cross-section of community practices, could have a significant effect on the prescribing of less expensive medications. However, this effect was only observed for prescriptions written with the e-prescribing system. Our results suggest that there are important economic gains achievable through the broader use of e-prescribing with FDS but that merely providing e-prescribing systems to clinicians will not necessarily achieve those savings. Rather, prescribers need to adopt the e-prescribing systems fully for these gains to be realized. Making those changes represents an important goal for physicians, insurers, and all those with a stake in the cost of prescription medications.

**Accepted for Publication:** April 8, 2008.
**Correspondence:** Michael A. Fischer, MD, MS, Division of Pharmacoepidemiology and Pharmacoeconomics, Brigham and Women's Hospital, 1620 Tremont St, Ste 3030, Boston, MA 02120 (mfischer@partners.org).
**Author Contributions:** Dr Fischer had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis. *Study concept and design*: Fischer, Stedman, Ferris, Brookhart, and Weissman. *Acquisition of data*: Fischer and Weissman. *Analysis and interpretation of data*: Fischer, Vogeli, Stedman, Ferris, Brookhart, and Weissman. *Drafting of the manuscript*: Fischer and Weissman. *Critical revision of the manuscript for important intellectual content*: Fischer, Vogeli, Stedman, Ferris, Brookhart, and Weissman. *Statistical analysis*: Fischer, Stedman, and Brookhart. *Obtained funding*: Weissman. *Administrative, technical, and material support*: Fischer, Vogeli, Stedman, and Weissman. *Study supervision*: Weissman.
**Financial Disclosure**: None reported.

**Funding/Support:** This study was supported by grant R01 HS15175 from the Agency for Healthcare Research and Quality and career development grant AG12084 (Dr Brookhart) from the National Institutes of Health.
**Role of Sponsors:** The investigators retained control over all aspects of the analyses and presentation of results.
**Previous Presentation:** This study was presented in part at the Society of General Internal Medicine Annual Meeting; April 27, 2007; Los Angeles, California; and at the International Conference on Pharmacoepidemiology; August 21, 2007; Quebec City, Quebec, Canada.
**Additional Contributions:** We gratefully acknowledge the assistance of Blue Cross Blue Shield of Massachusetts, Tufts Health Plan, and Zix Corporation in providing data for this research.

## REFERENCES

1. Hillestad R, Bigelow J, Bower A, et al. Can electronic medical record systems transform health care? potential health benefits, savings, and costs. *Health Aff (Millwood).* 2005;24(5):1103-1117.
2. Walker J, Pan E, Johnston D, Adler-Milstein J, Bates DW, Middleton B. The value of health care information exchange and interoperability. *Health Aff (Millwood).* 2005(suppl Web exclusives):W5-10–W5-18.
3. Sidorov J. It ain't necessarily so: the electronic health record and the unlikely prospect of reducing health care costs. *Health Aff (Millwood).* 2006;25(4): 1079-1085.
4. Heffler S, Smith S, Keehan S, et al. Health spending projections through 2013. *Health Aff (Millwood).* 2004(suppl Web exclusives):W4-79-93.
5. Hoffman JM, Shah ND, Vermeulen LC, et al. Projecting future drug expenditures: 2004. *Am J Health Syst Pharm.* 2004;61(2):145-158.
6. Huskamp HA, Epstein AM, Blumenthal D. The impact of a national prescription drug formulary on prices, market share, and spending: lessons for Medicare? *Health Aff (Millwood).* 2003;22(3):149-158.
7. National Institute for Health Care Management. *A Primer: Generic Drugs, Patents, and the Pharmaceutical Marketplace.* Washington, DC: National Institute for Health Care Management Foundation; 2002.
8. Endsley S, Baker G, Kershner BA, Curtin K. What family physicians need to know about pay for performance. *Fam Pract Manag.* 2006;13(7):69-74.
9. Huskamp HA, Deverka PA, Epstein AM, Epstein RS, McGuigan KA, Frank RG. The effect of incentive-based formularies on prescription-drug utilization and spending. *N Engl J Med.* 2003;349(23):2224-2232.
10. Chaudhry B, Wang J, Wu S, et al. Systematic review: impact of health information technology on quality, efficiency, and costs of medical care *Ann Intern Med.* 2006;144(10):742-752.
11. Agresti A. *Categorical Data Analysis.* New York, NY: John Wiley & Sons; 1990.
12. SAS Institute. *SAS Statistical Software.* Version 8.2. Cary, NC: SAS Institute; 2003.
13. StataCorp. *Stata Statistical Software.* Release 9.0. College Station, TX: Stata Corp; 2005.
14. Leonard KJ, Sittig DF. Improving information technology adoption and implementation through the identification of appropriate benefits: creating IMPROVE-IT. *J Med Internet Res.* 2007;9(2):e9. doi:10.2196/jmir.9.2.e9.
15. Sittig DF, Shiffman RN, Leonard K, et al. A draft framework for measuring progress towards the development of a national health information infrastructure. *BMC Med Inform Decis Mak.* 2005;5(1):14. doi:10.1186/1472-6947-5-14.
16. Fischer MA, Avorn J. Economic consequences of underuse of generic drugs: evidence from Medicaid and implications for prescription drug benefit plans. *Health Serv Res.* 2003;38(4):1051-1063.
17. Fischer MA, Avorn J. Potential savings from increased use of generic drugs in the elderly: what the experience of Medicaid and other insurance programs means for a Medicare drug benefit. *Pharmacoepidemiol Drug Saf.* 2004;13(4):207-214.
18. Haas JS, Phillips KA, Gerstenberger EP, Seger AC. Potential savings from substituting generic drugs for brand-name drugs: medical expenditure panel survey, 1997-2000. *Ann Intern Med.* 2005;142(11):891-897.
19. Fischer MA, Avorn J. Economic implications of evidence-based prescribing for hypertension. *JAMA.* 2004;291(15):1850-1856.
20. Shrank WH, Hoang T, Ettner SL, et al. The implications of choice: prescribing generic or preferred pharmaceuticals improves medication adherence for chronic conditions. *Arch Intern Med.* 2006;166(3):332-337.
21. Centers for Medicare and Medicaid Services. *Medicare Program: Proposed Standards for e-Prescribing Under Medicare Part D.* Washington, DC: Dept of Health and Human Services; 2007. Publication GAO-08-690R.
22. Elson RB. Electronic prescribing in ambulatory care: a market primer and implications for managed care pharmacy. *J Manag Care Pharm.* 2001;7(2):115-120.
23. Grossman JM, Gerland A, Reed MC, Fahlman C. Physicians' experiences using commercial e-prescribing systems [Web exclusives]. *Health Aff (Millwood).* 2007; 26(3):w393-w404.
24. Miller RA, Gardner RM, Johnson KB, Hripcsak G. Clinical decision support and electronic prescribing systems: a time for responsible thought and action. *J Am Med Inform Assoc.* 2005;12(4):403-409.
25. Overhage JM, Perkins S, Tierney WM, McDonald CJ. Controlled trial of direct physician order entry. *J Am Med Inform Assoc.* 2001;8(4):361-371.