THE UNIVERSITY OF MELBOURNE

Department of Economics

Working Paper Series

Herding Among Bureaucrats

Branko Boskovic, David P.Byrne, Arvind Magesan

September 2012

Research Paper Number 1158

ISSN: 0819 2642
ISBN: 978 0 7340 4509 6

Department of Economics
The University of Melbourne
Parkville VIC 3010
www.economics.unimelb.edu.au

Herding Among Bureaucrats*

Branko Bošković
University of Alberta
boskovic@ualberta.ca

David P. Byrne
University of Melbourne
byrned@unimelb.edu.au

Arvind Magesan
University of Calgary
anmagesa@ucalgary.ca

September 6, 2012

Abstract

The herding of expert opinions is often rationalized as the outcome of social learning. However, experts are typically individuals with career concerns. As a result, herding can also arise from the fear of opposing consensus opinion and the potential career consequences of being wrong. We empirically test for social learning and career concerns using novel data on bureaucrats' expert opinions over whether to publicly provide health insurance for pharmaceuticals. We find robust evidence that career concerns are an important source of herd behavior in these policy choices. Our findings have implications for the delegation of policy-making to experts.

Keywords: Experts; Social learning; Career Concerns; Bureaucrats; Pharmaceuticals
JEL Codes: D80, H77, I18

*We thank IMS Brogan for providing data. We have received helpful comments from Anthony Harris, Aidan Hollis, Don Husereau, Sacha Kapoor, Simon Loerschter, Scott Taylor, Tom Wilkening, and participants at many departmental seminars and conferences. We especially thank Francisco Gonzalez and a Co-editor for invaluable feedback. Cecilia Garcia has provided excellent research assistance. Any errors, omissions, or views expressed in this paper are solely those of the authors.

From my own experience on expert panels, I know firsthand the pressures that people – might I say mavericks? – may feel when questioning the group consensus.

- Robert J. Shiller in "Challenging the Crowd in Whispers, Not Shouts", *New York Times*, 11/01/08

1 Introduction

Experts tasked with making recommendations in an uncertain environment often reach similar conclusions. Examples of this phenomenon abound: the tendency of financial market experts to reach consensus on subjects ranging from financial forecasts to firms' credit ratings has received a great deal of attention both from academics and the popular press; scientists tend to reach consensus on contentious issues such as the causes and consequences of global warming.

The simplest explanation for the prevalence of consensus in such varied settings is that experts are knowledgeable individuals with the best means to independently arrive at the one correct answer. However, experts are quite often found to be wrong (Freedman (2010)), making this explanation somewhat unsatisfactory. The herding literature in economics, pioneered by Banerjee (1992) and Bikchandani et al. (1992), offers another explanation. If experts' recommendations partially reveal their private information, then experts may learn from the recommendations made by those before them, and a consensus can arise.[1]

While this type of social learning among experts presents one plausible rationale for herd behavior, Shiller's *New York Times* piece hints at another: the fear for one's reputation and career prospects associated with going against consensus opinion. In this case, an expert whose own belief is at odds with the prevailing consensus may have the incentive to disregard his better judgement to follow the herd (Janis (1972), Scharfstein and Stein (1990)). If career concerns play an important role in shaping individuals' decisions, social learning among experts may be obstructed: if experts care only for conforming to consensus opinion, their individual decisions reflect no private information and thus are uninformative to others.

In this paper, we use a novel dataset to study social learning and career concerns as sources of herd behavior in the policy recommendations of expert bureaucrats. To our knowledge, ours is the first study that separately identifies these two sources of herd behavior in decision-making in a context where both potentially matter. Specifically, we study the recommendations of medical experts who determine which drugs to list on the respective public healthcare plans of Canadian provinces. Social learning is potentially important since evaluating the quality of new drugs is a costly and highly uncertain process.[2] These experts can thus benefit from learning from the publicly disclosed recommendations made in other jurisdictions. Our experts also have career concerns since their positions are largely based on their reputation for being well-informed academic and bureaucratic researchers.[3] These experts neither want to risk recommending a

[1] Bikchandani et al. (1992) term this phenomenon an "information cascade."

[2] Quality in this context is determined by the cost-effectiveness and efficacy of the drug relative to existing alternative therapies. We provide a detail discussion of drug quality in Section 2.

[3] As shown by Collins (1992), a researcher appointed to scientific organizations, such as a policy advisor role, can lead to a

drug that is ultimately of poor quality nor advising against a drug of high quality. Such concerns can be exacerbated should an expert find herself not in the consensus established by her peers. In this way, the pressure to conform that Shiller alludes to – the fear of being ostracized or even terminated – can play a significant role in determining experts' recommendations in this context.

Using an empirical interactions-based model (Brock and Durlauf (2001)), we first establish that experts are indeed influenced by the recommendations of other experts. The well-known identification problem in these models lies in disentangling "endogenous" effects (the effects of interest) from "contextual" and "correlated" effects (Manski (1993)). Our panel dataset contains a large number of irreversible, binary policy choices (i.e., expert recommendations of whether to publicly insure a drug) across a small number of jurisdictions. The richness of these data enables us to flexibly control for numerous confounding factors that generate contextual or correlated effects in policy choices, most notably drug-specific unobserved heterogeneity. These features of the data, combined with the fact that we study a simple, well-defined policy choice that is publicly disclosed, makes this context particularly conducive for credibly identifying endogenous effects. Our results indicate large and statistically significant effects of other experts' recommendations on the recommendation of experts in a given province that are robust across various model specifications.

Having established interdependency in expert recommendations, we investigate the roles of social learning and career concerns in generating the interdependency. Separately identifying these two forces is challenging because both imply that experts have a positive influence on each others' recommendations. For identification, we exploit two sources of exogenous variation in the degree of uncertainty about drug quality to test for social learning and career concerns in experts' policy choices.

First, we exploit a unique federal policy intervention that, for a subset of drugs in our sample, provides our experts with credible information about a drug's efficacy and cost-effectiveness. The policy is equivalent to an ex-ante shock to public information about drug quality, applied randomly to different drugs.[4] For drugs that are subject to the policy, social learning plays a diminished role in generating interdependency in experts' recommendations because there is less uncertainty about drug quality. The information shock does not, however, affect the career cost associated with going against popular opinion and being wrong. These facts provide us with a simple hypothesis test: if we observe that interdependency in expert recommendations is not statistically different across drugs that are subject to the policy and those that are not, we fail to reject the hypothesis that career concerns exist. That is, if much of the incentive for social learning is removed and we still see herding in experts' decisions, we conclude that career concerns drive this herd behavior.

Our second set of tests exploit exogenous variation in drug novelty. For each drug in our data, we observe

more favorable review of his research that are currently under peer review, which in turn can generate further career rewards. However, being associated with failures – such as being terminated from an advisory role – can similarly lead his research to be viewed more skeptically, thereby decreasing his professional stature.

[4]Importantly, below we discuss any potential selection bias inherent in this policy. We also provide evidence from the federal government that the information stemming from this policy is informative and useful for the expert bureaucrats.

a measure of drug novelty that indicates the degree of therapeutic advance that a drug yields relative to existing alternatives. The more novel a drug is, the more uncertain its quality. Thus, the scope for social learning in generating herd behavior in expert recommendations is at least partly muted for non-novel drugs such as generics. This affords us with another test for career concerns that is similar to the one discussed above: if the interdependency in expert recommendations for drugs with little novelty is not statistically different from the interdependency for the average drug, we fail to reject the hypothesis that career concerns exist. As before, if we remove much of the incentive for social learning and still observe herding among experts, we conclude that career concerns play an important role in generating this herd behavior.

Our empirical test based on the federal policy intervention suggests that career concerns play an important role in generating interdependency in expert recommendations: drugs that are exposed to the public information shock have identical estimated endogenous effects as those that are not. Our empirical test based on drug novelty further confirms this finding. The estimated interdependency across experts is statistically and economically significant for the least novel drugs in the sample.[5]

Overall, our results indicate career concerns are an important source of herd behavior in policy-making in a context where social learning likely plays a role as well. This suggests that social learning is potentially obstructed by the career concerns of experts. Expert decisions reveal less information about their private knowledge because of the expert's incentive to ignore his own private information in the face of consensus opinion. This has important implications for the delegation of policy decisions in two different dimensions. The first concerns the decentralization of policy-making. A potential benefit of decentralized policy-making within a federation is that policy makers can incorporate the information generated by others' decisions in their own decision process. This can be quite invaluable for less populous jurisdictions with limited finances, since learning from the decisions of others is less costly than paying for more in-depth policy evaluations. Our findings suggest that this particular benefit to decentralization of policy-making may be compromised by career concerns that prevent individuals from optimally using their information when making decisions.

Our findings also have implications regarding who should be tasked with making public policy. It is often argued that non-elected expert bureaucrats, sometimes labelled technocrats, should replace politicians as policy makers because they are better able to make non-political, evidence-based decisions. Politically-motivated politicians may be less knowledgeable and face time-inconsistency problems in forming optimal policy over time.[6] Our empirical results provide a reason for caution against an unbridled move to techno-

[5] We also rule out the possibility that this interdependency arises from political concerns. We discuss anecdotes and research findings that indicate our medical experts' decisions are devoid of politics. Further, we investigate whether interdependency in policy choices is higher around provinces' election years, periods where political pressure to match the health insurance decisions of other jurisdictions is potentially heightened. We find interdependency is unchanged during these periods.

[6] Rogoff (1985) is a classic reference that prescribes the use of experts as policy makers in the context of monetary policy. He shows that having an independent central banker who places a large weight on inflation in conducting monetary policy can increase social welfare. Alesina and Tabellini (2007) show that bureaucrats with career concerns are preferable to politically-driven politicians for technical tasks where ability is more important than effort.

cratic rule. While politicians have incentives that can prevent them from choosing the technically optimal policy, the career concerns of technocrats can likewise prevent them from forming optimal policy when they are evaluated relative to their peers.[7]

Many papers in a wide range of contexts attempt to identify social learning in decision-making.[8] This paper is most closely related to the Buera et al. (2011) study of social learning in the context of historical country-level decisions to pursue market-oriented policies. Empirical studies of career concerns as a source of herding in decision-making are less exhaustive, and mainly focus on financial decision-making.[9] For example, Chevalier and Ellison (1999) empirically investigate how career concerns lead younger mutual fund managers to herd into popular sectors in managing their portfolios. This article bridges across these two literatures that respectively study herd behavior in decision-making. Our identification strategy that exploits differences in uncertainty over drug quality is novel, and is what allows us to separately identify career concerns and social learning as sources of herd behavior in decision-making.

We also contribute to a health economics literature that examines pharmaceutical entry into healthcare markets. Kyle (2006, 2007) provides global analyses of the roles of firm characteristics and country-level price controls in determining the likelihood a pharmaceutical enters a particular national market.[10] A key novelty of our study is to show that health insurers make interdependent decisions when evaluating pharmaceuticals. This finding has implications for the lobbying strategies of drug manufacturers since they can leverage this interdependency to get their drugs onto as many health plans as possible.

2 Context

Healthcare in Canada is universally provided by publicly-funded health insurance systems that are administered at the provincial and territorial level. Provinces receive federal transfer payments to help finance healthcare expenditures; however, the delivery and coverage of the public health plans are at the sole discretion of the provincial governments. Despite this decentralized approach, the public health insurance systems are very similar across provinces, with the exception of prescription drug coverage (Anis et al. (2001)).

To sell a drug in Canada, a drug manufacturer must first obtain federal approval from Health Canada,

[7] The debate over who should form policy has recently come to the forefront of political and economic debates in the face of recent financial and macroeconomic events in Europe. See "Europe: The Rise of the Technocracy" in *The Guardian*, November 13, 2011.

[8] Applications include technology adoption in developmental settings (Besley and Case (1994), Foster and Rosenzweig (1995)), the diffusion of home computers (Goolsbee and Klenow (2002)), movie demand at the box office (Moretti (2010)) or employees' choices of health plans (Sorensen (2006)). See Blume et al. (2010) for a survey of this literature.

[9] There is an established literature in labor economics on the role career concerns play in the design of optimal incentive contracts that dates back to the seminal work of Holmstrom (1982). In an equilibrium model of labor market with forward-looking workers, career concerns arise because firms develop perceptions of a worker's ability over time. The higher the perception, the higher a wage a worker can command. In our context, medical experts are largely concerned with the potential impact of ignoring their peers and subsequently being wrong has on their perceived ability by potential future employers (such as hospitals, medical schools, pharmaceutical companies, government healthcare agencies, and so on).

[10] In a similar vein of research, Stern (1996), Berndt et al. (1997) and Lichtenberg and Philipson (2002) examine the importance of within and between drug class substitution in pharmaceutical market entry.

which evaluates the safety of new drugs. If a drug passes Health Canada's evaluation, it receives a Notice of Compliance (NOC) and a Drug Identification Number (DIN). Upon receiving an NOC, a drug manufacturer may apply to a province to have their drug listed on its formulary (i.e., the list of drugs citizens receive cost reimbursement for under the provincial health plan). Alternatively, companies can penetrate the market directly and sell to consumers who potentially have private insurance for pharmaceutical costs.

Each provincial formulary is managed by a committee of experts including biostaticians, chemists, economists, epidemiologists, pharmacologists, and physicians. Committee members are typically appointed by provincial Ministers of Health based on their expertise and reputations as health professionals. In deciding whether to list a drug on their formulary, a committee evaluates research and clinical studies on the safety, efficacy, and cost-effectiveness of a drug relative to its therapeutic substitutes.[11] Drug companies also provide research aimed at establishing their drug's innovativeness and improved cost-effectiveness over existing therapies as part of their formulary listing applications. Ultimately, each committee's objective is to ensure that publicly insured drugs yield a high "bang-for-the-buck" in terms of public health outcomes per tax dollar spent. A quote from a physician on the British Columbia formulary from Armstrong et al. (2008) summarizes the drug quality versus cost trade-off inherent to drug evaluations:

> *Can we stretch our dollar and have more medications if we don't accept the most expensive medication (...) If we decline the Mercedes and take the Ford, we can spend that extra money on the other things we might not otherwise have.*

2.1 Sources of interdependency in formulary listings

Three key facts about the healthcare system suggest that formulary committees have the ability and incentive to learn from other committees' listing decisions. First, formulary reviews are costly in terms of the time and cost of employing expert drug reviewers (Government of Canada (2007)). Second, after inspecting published historical formularies for the provinces, we find that formulary updates and recent drug reviews are mainly published at quarterly frequencies and are publicly available. Third, drug evaluations are uncertain processes whose difficulty depend on the novelty of the drug.[12] *Generic* and *me-too* drugs[13] do not involve complex cost-benefit or efficacy analyses since committee members are well-informed about these drugs and their therapeutic alternatives. In contrast, evaluating innovative *breakthrough* drugs (i.e., drugs that establish new therapies altogether) and *line extensions* (i.e., drugs that potentially yield non-negligible

[11] The listing decisions committees have a non-negligible impact on provinces' healthcare budgets. For example, in 1998 Ontario spent $1.5 billion dollars covering drug costs, representing 2.6% of the entire provincial budget.

[12] In online Appendix C, we provide an example evaluation from 2007 by Ontario's formulary committee for Novartis' drug Darifenacin (branded Enablex). The committee concludes that Enablex "has not been proven to work better than standard options available" and thus should not be listed on the formulary. The decision is based on eight clinical trials, two of which find no statistically significant differences in efficacy and side-effects between Enablex and a substitute product on the formulary, Oxybutinin. This example highlights one form of uncertainty in drug evaluations, namely weighing the quality and importance of various conflicting clinical trials that test the efficacy of a drug and its therapeutic substitutes.

[13] Me-too drugs yield minimal improvement or are near replicas of existing products in the market.

therapeutic advances within a drug class) is a more difficult and uncertain process. Committee members are less familiar with these products, clinical research on their efficacy is less abundant, and defining relevant therapeutic alternatives (if any exist) is far less clear (PausJennsen et al. (2003)).

Given these features of the healthcare system, formulary committees can save on costs and reduce their uncertainty in drug reviews by inferring any relevant information from the public disclosure of the listing decisions of other provinces. This scope for learning from others – or "social learning" – may be useful for all provinces, especially for smaller provinces who have fewer resources for drug evaluations (Government of Canada (2007)).

Career concerns of formulary committee members likely affect listing decisions as well. As noted above, the expertise and reputation of committee members is what gets them appointed to formulary committees in the first place. Committee members such as physicians, pharmacists, and epidemiologists make their careers by consistently being correct in their diagnoses, prescriptions, and research. In evaluating drugs, these experts want to avoid: (1) listing drugs that turn out to have low-cost-effectiveness (Type I error); and (2) not listing drugs that have high-cost-effectiveness (Type II error).[14] Making such errors is likely detrimental to their reputations as being informed health researchers, which may adversely affect their future labor market opportunities within the healthcare industry or academia, within Canada or internationally. It is difficult to determine the exact adverse effects for any individual committee members, since individual formulary listing recommendations are highly confidential.[15] As such, we cannot match individual committee members' decisions to any subsequent career outcomes.

To the extent that these errors are exacerbated if a committee is alone in listing (not listing) a drug while the other committees do not list (list) a drug, formulary committees will have an incentive to mimic the decisions of other committees as a result of the career concerns of committee member. Alesina and Tabellini (2007) allude to this notion of career concerns in the decision-making of bureaucrats and its implications for how policy tasks should be divided among elected politicians and independent bureaucrats. That career concerns can yield herd behavior in the decisions of bureaucrats is analogous to herding in financial decision-making among investors, bankers, and other professionals in finance whose decisions are influenced by career concerns; see Scharfstein and Stein (1990), Chevalier and Ellison (1999), among others.

One final point of note is that politics likely play a minimal role in formulary listings. Listings decisions are mainly based on committee evaluations of the efficacy and cost-effectiveness of drugs, and in general are

[14] An example of a poor formulary listing decision is the decision to list varenicline (sold under the brand name Champix in Canada and Chantix in the U.S.) that allegedly caused several suicides and suicide attempts, resulting in negative local media coverage for the individual provincial governments. See "Controversy around province's choice of stop-smoking drug" in *Times Colonist*, May 13, 2012.

[15] Jasanoff (1990) provides various examples of the impact of expert opinions on policymaking, and how the public perceives government-appointed experts. For example, the report by Dr. Dante Picciano to the Environmental Protection Agency on the effects of the Love Canal disaster on its residents, that was adopted by government agencies in the U.S., subsequently generated a strong public backlash against the respective agencies and expert(s).

intended to be devoid of political concerns (PausJennsen et al. (2003)). One anecdote from our discussions with various provincial formulary committee members is particularly relevant. An entire formulary committee once threatened to quit in response to an elected official asking them to change their recommendation from "do not list" to "list" for perceived political reasons. The committee members wanted their opinions as healthcare experts taken seriously, and valued their independence in evaluating drugs. Politics may, however, have some effect, which like social learning and career concerns would create positive correlation in formulary listing decisions. Accordingly, we address this in our empirical analysis below.

2.2 The Common Drug Review

In March 2002, the Canadian federal government created a third-party drug review process called the Common Drug Review (CDR), which began accepting submissions from drug companies in September 2003. The CDR sees the federally-appointed Canadian Drug Expert Committee (CDEC) evaluate the safety, efficacy and cost-effectiveness of new drugs relative to existing therapies. The CDR provides a report detailing the results of this evaluation for a given drug and makes an initial "list" or "do not list" recommendation to the provincial formulary committees. The provincial committees ultimately decide whether to list a drug, taking into account the CDR's analysis and recommendation. Drug manufacturers are not required to submit their products to the CDR over our sample period, which is a potential source of endogeneity that we must confront in our empirical analysis.

The CDR has two primary objectives (Government of Canada (2007)): (1) reduce duplication of drug review costs across the provincial formularies, and (2) establish a baseline level of informativeness among the provinces to ensure evidence-based, objective and rigorous drug formulary listing decisions. The CDR effectively provides an initial shock of public information to the provinces with the goal of minimizing total drug evaluation and research costs sunk by the provincial formulary committees in making their listing decisions. By all accounts, the CDR has been successful in achieving its two main goals. In its comprehensive 2007 evaluation of the CDR (see Government of Canada (2007)), the federal government consulted with the formulary committees of the provinces and territories, who collectively confirmed that

> *... drug plan processes for reviewing overall cost-effectiveness and making formulary listing recommendations on new drugs have been replaced by the single CDR process. In their view, the CDR process saves time, effort and money. It has reduced duplication of effort across the provincial, territorial and federal drug plans and has allowed all jurisdictions large and small to have equal access to a high level of evidence and expert advice from the CDR. They also told the Committee that the CDR has rapidly become a respected peer among review processes on the global stage.*

3 Model

We develop a simple theoretical model of social learning and career concerns among experts in the spirit of Scharfstein and Stein (1990) to illustrate how these phenomena generate correlated listing patterns. In our empirical analysis, we further use the model to interpret our findings and develop strategies for empirically identifying the presence of social learning and career concerns in listing decisions.

A firm develops a single pharmaceutical drug of unknown value V, which may be of high (H) or low (L) value. We interpret value as drug quality or its innovativeness over known therapeutic alternatives. Consistent with information disclosed to us by pharmaceutical industry representatives, we assume the firm applies for formulary listing to the province whose experts are most likely to list the drug, and then continues to the next most likely, and so on.

Experts on the different provincial formulary committees have a common prior belief above the drug's value. Once approached by the firm, province i's formulary committee is faced with two decisions. First, it can choose to conduct an evaluation to gain more information about the drug's value at cost c_e, the outcome of which is a private signal, $Y \in \{h, l\}$. We assume that the signal is identically informative in either state: $P(Y = h|V = H) = P(Y = l|V = L) = p \geq \frac{1}{2}$. Upon observing the signal, the committee updates its belief about the drug's unknown value using Bayes' rule. Second, irrespective of its evaluation choice, the committee must choose whether to recommend listing the drug on province i's formulary. We assume that recommendations are binding decisions whereby provinces list any drug recommended by the formulary committee.[16] A positive choice is accompanied by a listing cost, c_ℓ^i, that mainly represents the per-capita fiscal cost of publicly insuring the drug.[17] We assume that drug values and c_ℓ^i are such that, with perfect knowledge of a drug's value, any formulary committee would recommend listing a high value drug, and not recommend listing otherwise.

The committee makes its recommendation to minimize the expected costs associated with listing a low value drug and not listing a high value drug. Denoting the belief of province i's formulary committee as γ^i, the cost of not listing a high value drug is given by $\gamma^i\lambda_1$, where $\lambda_1 > 0$ and the subscript denotes a Type I error. Similarly, the cost associated with a Type II error (i.e., listing a low value drug) is $(1 - \gamma^i)\lambda_2 + c_\ell^i$, where $\lambda_2 > 0$.

As formulary committees have the option to evaluate drugs before making listing decisions, their listing

[16] This is consistent with our discussion above that politics likely play a relatively minor role in determining which drugs get listed on a formulary.

[17] Province-specific drug cost reimbursement schemes largely determine per-capita formulary listing costs. Provinces either have "full" or "partial" reimbursement policy for their residents, though differences in user fees, deductibles and co-payments can vary considerably across provinces for a given drug. Some provinces use a "means test" or "ability to pay" criteria in determining the scale of deductibles or co-payments (Saskatchewan, Ontario or Newfoundland), while others do not (British Columbia or Nova Scotia). See Anis et al. (2001) for a detailed analysis of differences in subsidy schemes across the provinces. In our empirical analysis below, we allow for various forms of provincial heterogeneity that controls for the impact of reimbursement schemes on formulary listing hazards.

decisions may reveal information about the outcome of the evaluations. Thus, formulary committees use the past listing decisions of other provinces to make inferences about the unknown quality of the drug. This represents the first source of herding in our model. A large number of past listings suggests that evaluations revealed good news about the quality of the drug, while few listings suggests the opposite.

To allow for the possibility that formulary committee members are experts with career concerns, we assume that the error cost functions, λ_1 and λ_2, depend on the "net" number of provinces that have listed the drug. Specifically, let n^i represent the number of provinces other than i that have listed the drug less the number of provinces that have not listed the drug.[18] We assume that the cost of not listing a high value drug is larger if the formulary committees of other provinces have listed the drug, and smaller if other provinces have not listed the drug: $\partial\lambda_1(n^i)/\partial n_i \geq 0$. Similarly, we assume that $\partial\lambda_2(n^i)/\partial n^i \leq 0$, which implies that the cost of listing a bad drug is lower if other provinces' formulary committees have made the same mistaken recommendation. This represents career concerns of experts in our model: province i's formulary committee sacrifices less reputation when it makes a mistake if many other committees do so as well.

Given its current (post-evaluation) belief γ^i and the net number of other provinces that have listed the drug, n^i, province i's formulary committee makes its recommendation by minimizing the sum of statistical error and listing costs. The payoff from doing so is given by:

$$\min \ \{\gamma^i\lambda_1(n^i),\ (1-\gamma^i)\lambda_2(n^i) + c_{\ell_i}\}. \tag{1}$$

Figure 1a depicts province i's listing decision problem. From the figure, we see that to the left of the intersection of $\gamma^i\lambda_1(n^i)$ and $(1-\gamma^i)\lambda_2(n^i)+c_{\ell_i}$, the expected cost of not listing is lower than the cost of listing, so the formulary committee recommends "do not list." To the right of the intersection, $(1-\gamma^i)\lambda_2(n^i)+c_{\ell_i} < \gamma^i\lambda_1(n^i)$ and the committee recommends to "list."

Given this ex-post listing decision rule for a given belief γ^i, province i's committee makes an ex-ante evaluation decision, $d_i \in \{0,1\}$, that solves:

$$\min_{d_i\in\{0,1\}} \left\{ E\big[\ \min\{\lambda_1\gamma_1^i, \lambda_2(1-\gamma_1^i) + c_\ell^i\}|d_i, \gamma_0^i\big] + d_i c_e \right\}, \tag{2}$$

where the expectation is with respect to the results of the evaluation. The committee undertakes an evaluation if the expected value of the evaluation is significant relative to the costs. It is immediate from this condition that a formulary will undertake an evaluation only if the outcome of the evaluation can influence its listing decision: good news leads to a listing and bad news leads to non-listing. That is, if the committee knows that, given preferences, beliefs and the technology available for evaluation (i.e., the precision of the signal p) it will make the same recommendation regardless of the outcome of the evaluation, then there is no

[18] n_i can be positive or negative. For example, if province i's formulary committee is the 5th to make a listing decision and three of the previous four committees have listed the drug, then n_i=3-1=2. If only one of the other four committees have listed the drug, then n_i=1-3=-2.

benefit to paying the cost of an evaluation. Together with the assumptions of common belief and common knowledge of preferences, this implies that a province that evaluates a drug publicly reveals the results of the evaluation through its decision.

Equation (2) defines a range of beliefs such that the formulary committee will undertake an evaluation. This range of beliefs is depicted by the lightly shaded region in Figure 1b. If the belief falls into the dark shaded region to the left or the white region to the right, the prior belief about drug quality is so low or high that an evaluation cannot influence the committee's decision. Holding all else constant, as the cost of an evaluation c_e increases or the precision p decreases, the size of the lightly shaded region shrinks, and there is no belief at which the committee evaluates the drug prior to making a listing decision.

To see how social learning and career concerns can yield similar (or even observationally equivalent) patterns of recommendation, consider first a case where there are no career concerns, so that one committee's listing recommendation can only affect another's through its informational content. Formally, suppose that $\lambda_1(n^i) = \lambda_1$ and $\lambda_2(n^i) = \lambda_2$. This case is illustrated in Figure 2a, which depicts Type II error functions for two provinces i and j that differ only in listing costs with $c_i < c_j$. Given our assumption that drug manufacturers first apply for listing to provinces more likely to list their drugs, the committee for low-cost province i makes its drug evaluation and recommendation first.[19] At the belief γ_0, province i's formulary committee undertakes an evaluation, and province j's does not. Suppose province i's evaluation reveals good news, such that the belief about drug quality increases, and province i lists the drug. Province j will update its belief to incorporate the information contained in province i's decision. If the belief about drug quality shifts to γ_1', province j's committee will undertake a drug evaluation, and may or may not subsequently list the drug. If the new belief shifts to γ_1'', province j's committee recommends to list the drug with no further evaluation. On the other hand, if committee i's drug evaluation delivers bad news, neither province lists the drug. If from the outset there were neither drug evaluations nor social learning, then at belief γ_0 the low-cost province i would list and the high-cost province j would not. Thus, committees learning from one another's listing choices generates a positive correlation in recommendations where none would exist otherwise.

To see that career concerns also produce correlated recommendations, suppose that provinces never undertake a drug evaluation, either because c_e is too large or drug evaluations are uninformative, $p = \frac{1}{2}$. Thus, provinces cannot learn from one another. However, the costs of Type I and Type II errors depend on the recommendations of other committees. Returning to our example, at belief γ_0, the low-cost province i's committee is biased towards recommending listing, while the high-cost committee j is biased towards recommending not listing. The drug manufacturer approaches province i first, and its formulary committee recommends listing. After province i lists the drug, both the Type I and II error functions for j shift,

[19] It is straightforward to show that for any given belief γ_0, provinces with high listing costs reject without evaluation, and low listing costs list without evaluation, and provinces with intermediate listing costs evaluate a drug and make a decision based on the outcome of the evaluation.

reflecting that it is now more costly for j not to list the drug if it turns out to be of high value, and less costly to list the drug if it turns out to be low value: $\lambda_1(1) > \lambda_1(0)$ and $\lambda_2(1) < \lambda_2(0)$. Under the same belief about drug quality γ_0, but with a different set of Type I and II error functions due to career concerns, province j's optimal recommendation is now in agreement with province i.

In summary, interdependency in listing recommendations by formulary committees may be driven by two different forces: informational spillovers and career concerns of formulary committee members. Any correlations in provincial formulary listing decisions observed in the data are likely to be a result of one or both of these forces.

4 Data

The primary data source is IMS Brogan's Formulary Acceptance: Monitoring and Evaluation (FAME) database. It contains the universe of formulary listings for the Canadian provinces between 1994 and 2007.[20] We extract data on each drug's DIN, listing status and date by province, and the Patented Medicine Pricing Review Board's (PMPRB)[21] drug novelty classifications: breakthrough, line extensions, minimal improvement/me-too, and generic. Throughout, we focus on the eight most populous provinces of Canada: British Columbia (BC), Alberta (AB), Saskatchewan (SK), Manitoba (MB), Ontario (ON), Québec (QC), New Brunswick (NB), and Nova Scotia (NS).[22]

We also collect data from Health Canada's Notice of Compliance Data Extract, a database containing information on the universe of drugs that have been approved for sale in Canada since 1991. Key variables include a drug's DIN, NOC date, drug class, manufacturer, brand name, and active ingredient. Health Canada's drug class definitions correspond to the 3-digit classifiers from the Anatomical Therapeutic Chemical Classification System. We further track all pharmaceutical company mergers since 1985 to identify the parent company of each drug manufacturer over time.

The third data source comes from the provinces' most recently published formularies as of September 2011. For each province, we digitize the list of DINs that defines its current formulary. Using these data in conjunction with the FAME and NOC Data Extract databases, we construct an initial list of drugs/DINs that were on each province's formulary in 1994 (i.e., the start of the FAME sample period). Starting from these initial formularies, we use the FAME data to track how the portfolio of drugs on each province's formulary evolves over time. In online Appendix C, we provide details on how we construct the initial stock

[20] Unfortunately, we do not have information on prescription rates by drug and province. This implies we cannot model how intensely a drug is prescribed in a province conditional on formulary listing. As such, we only model the formulary listing decisions of provinces.

[21] The PMPRB is a national regulatory body in Canada that regulates the prices of all patented drugs.

[22] Data for Prince Edward Island, Newfoundland, and the Canadian territories is poorly recorded. According to the 2011 Census, these jurisdictions have approximately 2% of the Canadian population. Given their small size, we do not expect the formulary listing decisions in these jurisdictions to have a large impact on other provinces' formularies. As such, dropping these provinces and territories from the sample should have little impact on our results.

of drugs on each province's formulary, and further discuss data collection and variable construction.

An important variable to account for in identifying interdependencies in formulary listings is drug "quality." From a formulary committee's perspective, a high quality drug is one that yields non-trival therapeutic value relative to existing therapies to its province's constituents at a reasonable cost. Provinces are more likely to list (not list) a high (low) quality drug, which generates spurious correlation in provincial formulary listings. To control for the impact of drug quality on formulary listings, we construct a quality measure based on medical journal citations (Dranove and Meltzer (1994), Kyle (2006, 2007)). We collect data on Medline citation counts from the U.S. National Library of Medicine's website (http://www.ncbi.nlm.nih.gov/pubmed/) for the active ingredient in every drug listed in Health Canada's NOC Data Extract. We measure a drug's quality as a function of its share of the total stock of citations within its class. This measure assumes a drug's true quality is correlated with medical journal citation counts a drug receives over time. See online Appendix C for details on how we construct this quality measure, and a discussion of its shortcomings.[23]

There are three final data sources of note. We obtain all "list" or "do not list" CDR recommendations from 2003-2010 from the CDR's website, and match these to the FAME data. To account for the impact that provincial demographics or elections have on formulary listing decisions, we collect data on provincial demographics, government debt, and election years. Data on population, GDP per capita, median age, fraction of the population older than 65, unemployment, and government debt are collected from Statistics Canada's CANSIM II database. Provincial election dates and results are collected from an election almanac.

As noted in Section 2, we have deduced from historical formulary publications that that provincial formulary updates occur at a quarterly frequency. Our empirical analysis is therefore based on quarterly listing decisions. We study listing decisions up to 12 quarters after a drug's NOC date, and drop DINs where listing decisions are made beyond three years from the NOC quarter (which occurs in less than 1% of all DINs in the FAME database). After removing outliers and observations with missing data, our estimation sample consists of 991 DINs that were up for formulary listing between 1994 and 2007. The estimation sample has 69,375 (drug, province, quarter) observations that span 475 active ingredients, 85 drug classes, and 54 drug manufacturers.

4.1 Estimation sample and summary statistics

We study listing decisions up to 12 quarters after a drug's NOC date, and drop DINs where listing decisions are made beyond three years from the NOC quarter (which occurs in less than 1% of all DINs in

[23]This measure of drug quality is far from perfect. However, we can consistently construct this quality metric for all drugs in the NOC Data Extract back to 1991. Alternative quality measures could be constructed using Prescrire International's annual Drug Awards, or the World Health Organization's (WHO) Essential Medicines list. The Prescrire awards are given to a handful of drugs annually, which is small relative to the more than 475 active ingredients that we require quality measures for. The WHO Essential Medicines list is updated bi-annually, which does not yield high enough frequency updates on drug quality given that (1) provinces make listing decisions on a quarterly basis, and (2) conditional on listing a drug, most decisions are made within 1.5 years (discussed below).

the FAME database). After removing outliers and observations with missing data, our estimation sample consists of 989 DINs that were up for formulary listing between 1994 and 2007. The sample's 989 drugs consist of 22 (2%) breakthroughs, 262 (26%) line extensions, 357 (36%) me-toos, and 348 (35%) generics.

Figure 3 presents a histogram that tabulates formulary listing counts across all provinces by drug age (in terms of the number of quarters since a drug receives an NOC). Listing rates generally follow a hump shape: there are few listings within two quarters of a drug's NOC date, the majority of listings occur between three and five quarters after a drug receives an NOC, and listing rates then gradually fall off over time. The negative duration dependence in listing rates from four quarters onwards suggests that committees conclude a drug is not worth listing if it is not listed within a year and a half of its NOC date.

Table 1 contains statistics that highlight differences in the listing propensity and speed of provincial formulary committees. Quebec and Saskatchewan have relatively optimistic committees that recommend listing for 560 (57%) and 490 (50%) drugs in the sample. These committees are also the fastest in reaching list recommendations, which on average are made 295 (s.d.=184) and 317 (s.d.=171) days after a drug's NOC date. New Brunswick, the least populous province in the sample, is the least likely to list (321 listings) and takes the longest to make list decisions (519 days on average (s.d.=222)). Table 1 generally does not point to systematic relationships between province size, listing rates or speed. For example, the most populous province of Ontario lists the 5th most drugs, and is the 7th fastest in making positive list recommendations. Rather, provincial heterogeneity in listing behavior reflects differences in various factors beyond population, including the structure of provinces' reimbursement schemes, or the fraction of provincial governments' budgets devoted to healthcare expenditures.[24] Overall, the table makes clear that provincial heterogeneity is an important contextual factor to account for in identifying interdependencies in the listing decisions of formulary committees empirically.

Table 2 presents summary statistics that describe CDR drug reviews. Between 2003 and 2007, 143 of 362 total drugs are reviewed under the CDR, 72 of which received a "list" recommendation. Thus, if a drug manufacturer submits a drug for review to the CDR, it has a 50/50 chance of receiving a positive recommendation in our sample. In terms of observable characteristics, drugs that are reviewed by the CDR do not differ significantly from those that are not reviewed by the CDR. The only main difference is that only one of the 22 breakthrough drugs in the sample is reviewed by the CDR. Statistical tests of differences in means of characteristics for CDR and non-CDR reviewed drugs are available upon request.

[24] Differences in reimbursement schemes, healthcare budgets, and the number of drugs on the formularies likely reflects differences in provinces' attitudes toward public health insurance. For example, despite being a rural province, Saskatchewan's government has historically been a large proponent of comprehensive public health insurance. In fact, Saskatchewan became the first province in Canada to offer universal health insurance in 1946 under Premier Tommy Douglas. This province-specific preference for public health insurance is likely reflected in Saskatchewan's high formulary listing rate and speed in our sample.

5 Econometric analysis

Sections 2 and 3 suggest that a province's listing choices may be affected by the choices of other provinces by either informational spillovers, career concerns, or both. For the remainder of the paper, we investigate the roles these mechanisms play in generating interdependency in listing decisions. Our empirical analysis proceeds in two steps. First, we aim to credibly identify and estimate "endogenous effects" (i.e., independencies in formulary listings), which includes the effects of both social learning and career concerns, by using an empirical interactions-based model (Brock and Durlauf (2001)). We argue that our context allows us to overcome well-known difficulties in identifying endogenous effects. Second, we allow our endogenous effects to be a function of CDR reviews and drug novelty classes to determine whether the endogenous effects are driven by information spillovers, career concerns, or both. We also investigate whether endogenous effects change around provincial elections to see if committees are more responsive to the formulary listings of other provinces during periods of enhanced political pressure.

5.1 Baseline analysis

We formally study interdependency in the drug listing decisions of provinces using a discrete choice model that predicts province i's latent utility list^*_{ijt} of listing drug j in quarter t:

$$\text{list}^*_{ijt} = f(\text{list}_{-ijt-1}, \boldsymbol{\beta}) + \mathbf{X}'_{ijt}\delta_x + \epsilon_{ijt}, \tag{3}$$

where $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$ is a function of other provinces' past listing decisions for drug j, and $\mathbf{X}_{ijt}$ contains various controls that affect formulary listings. Assuming that list_{-ijt-1} enters equation (3) with a lag is appropriate given Armstrong et al.'s (2008) finding that committees tend make decisions based on recommendations already made by other formulary committees as opposed to making conjectures about the current or future decisions of others. Since list_{-ijt-1} enters equation (3) with a lag, we must drop the first quarter when a given drug receives an NOC in estimation. Province i's observed listing decision is a discrete choice defined by:

$$\begin{aligned} \text{list}_{ijt} &= 1 \text{ if } \text{list}^*_{ijt} > 0 \\ \text{list}_{ijt} &= 0 \text{ otherwise} \end{aligned}$$

Province i's listing probability is thus calculated as:

$$\text{Prob}(\text{list}_{ijt-1} = 1) = \text{Prob}\big(\epsilon_{ijt} > f(\text{list}_{-ijt-1}, \boldsymbol{\beta}) + \mathbf{X}'_{ijt}\delta_x\big) \tag{4}$$

Consistent with our empirical observation that formulary de-listings rarely occur, we assume listing decisions are irreversible: $\text{list}_{ijt} = 1 \Rightarrow \text{list}_{ij\tau} = 1 \ \forall \ \tau > t$. Thus, we estimate the model using sequences of binary listing decisions for a given province up to and including the quarter where $\text{list}_{ijt} = 1$. This

modeling strategy is analogous to using a discrete time hazard model like that used in Kyle's (2006, 2007) studies of pharmaceutical entry into national healthcare markets. Empirically modeling listing decisions at a quarterly frequency is appropriate given committees generally meet and make recommendations at quarterly frequencies, as discussed in Section 2. Our preliminary analyses of provinces' listing decisions further confirms this fact: conditional on listing, decisions tend to be made in March, June, September, and December. Thus, there is little within-quarter variation in listing decisions to otherwise exploit in estimation.

We assume the listing decisions of other provinces affect province i's listing decisions through the variable list_{-ijt-1} and the function $f(\cdot, \boldsymbol{\beta})$. We specify list_{-ijt-1} as a weighted average:

$$\text{list}_{-ijt-1} = \sum_{k \neq i} \frac{POP_{kt-1}}{\sum_{k \neq i} POP_{kt-1}} \text{list}_{kt-1}. \tag{5}$$

This specification puts greater weight on the lagged quarterly listing decisions of more populous provinces. These larger provinces typically undertake more extensive reviews and thus likely have a greater effect on what other provinces do, be it through information spillovers or career concerns. The function f is specified as a second-order polynomial in other provinces' listing decisions:

$$f(\text{list}_{-ijt-1}, \boldsymbol{\beta}) = \beta_0 + \beta_1 \text{list}_{-ijt-1} + \beta_2 \text{list}^2_{-ijt-1} \tag{6}$$

The vector $\boldsymbol{\beta}$ thus governs the causal effect of interest: the effect of past listing choices of other provinces on province i's listing choice.[25]

We have estimated the parameters in equation (3) using logit, probit, and linear probability models. The latter replaces list^*_{ijt} with list_{ijt} and estimates the parameters by linear regression. In our context, the linear probability model is particularly useful as it allows us to include a number of dummy variables in $\mathbf{X}_{ijt}$ that account for time-, province-, manufacturer-, and drug-specific heterogeneity. Our richest models include 989 drug fixed effects to account for unobserved (and difficult to measure) drug quality, which is critical for identifying endogenous effects. The linear probability model can be estimated under such a specification; logit/probit models cannot since they suffer from an incidental parameter problem. The main drawback of the linear probability model is that it does not necessarily yield fitted choice probabilities between 0 and 1. We find this to be a minor issue in our sample: at worst, 6%, of our fitted values for an estimated model are either less than 0 or greater than 1. As such, we present results based on linear probability models below, and provide robustness checks based on alternative model specifications in supplemental Appendix C.3. Our findings are robust to the use of logit and probit models and higher-order polynomials for $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$.

[25] We have estimated numerous models based on a number of plausibly valid weighting schemes based on population or geographic distance that could define list_{-ijt-1} and find little differences in our results. See Appendix C.3 for results based on uniform weights of other province's previous listings.

5.1.1 Identification

Critical to our empirical strategy of identifying $\boldsymbol{\beta}$ is our assumption that a province's current listing decision depends on the lagged listing decisions of other provinces at quarterly frequencies. Our ability to make this assumption hinges on the institutional features of our empirical environment and the richness of our data, namely that we have exact NOC approval and formulary listing dates. If we only observed decisions at an annual frequency, we would instead have to allow for contemporaneous effects, which would potentially introduce reverse causality in listing decisions and further complicate the identification of $\boldsymbol{\beta}$.

The vector $\mathbf{X}_{ijt}$ in equation (3) contains controls for variables that simultaneously explain the drug listing decisions of committees. Using Manski's (1993) nomenclature, these covariates account for "correlated" and "contextual" effects that would otherwise compromise the identification of $\boldsymbol{\beta}$. Contextual effects arise when formulary committees make similar (dissimilar) listing decisions because they have common (uncommon) exogenous characteristics. Correlated effects arise when there is a common drug-specific variable that affects the decisions of all committees, and thereby affects the degree of correlation in listing decisions independently of endogenous effects.[26] To be clear, our goal is not to accurately quantify the individual marginal effects of the many province- and drug-specific factors that drive formulary listings such as a drug's therapeutic advance, price, and so on. Rather, we aim to credibly identify endogenous effects in formulary listings using an econometric design that holds these important factors fixed.

We consider a number of province-specific controls that account for contextual effects. These include time varying observable province characteristics that could affect public health insurance decisions for pharmaceuticals including government debt, indicators of whether province i is currently in an election year (i.e., within two quarters before or after an election), is in a year prior to an election year, or is in a year following an election year, and annually-reported demographics including population and its square, GDP per capita, unemployment rate, median age, and fraction of the population older than 65. We include province-specific quarter-of-the-year (or seasonal) dummies in $\mathbf{X}_{ijt}$ to account for systematic differences in listing decisions across provinces during different quarters of the year. These could arise from unobserved bureaucratic differences across provinces that cause certain provinces to list drugs in particular quarters. We also include year and province dummies in $\mathbf{X}_{ijt}$ to account for any other unobserved trends in listing rates over time, or province-specific differences in the propensity to list drugs on their formularies.

We also include a number of province-drug related variables $\mathbf{X}_{ijt}$ that largely help control for contextual effects. We control for the number of drugs that drug j's manufacturer currently has on province i's formulary

[26] A third factor that often confounds identification of endogenous effects arises when agents sort themselves in groups while accounting for group characteristics. In such instances, group members tend to make similar decisions because they have similar observed or unobserved characteristics. This can introduce self-selection bias if endogenous effects are estimated assuming exogenous group formation. Our context enables us to avoid such self-selection bias since we estimate endogenous effects for a fixed group of eight provinces using cross-drug variation in listing decisions over time.

(i.e., successful listings prior to quarter t) to capture any economies of scope drug manufacturers realize from previous experience in dealing with province i. We also control for the number of drugs in drug j's class currently listed on province i's formulary. This accounts for substitution/portfolio effects across drugs within a given drug class: all else equal, if province i has many drugs on its formulary in a particular drug class, the marginal benefit to listing another drug in the class should be relatively lower, thus reducing the probability of listing. Further, recall from our discussion of Table 1 that provinces systematically differ in their listing rates and times. To flexibly control for these differences, we include a vector of dummies for drug age (in quarters) since its NOC approval for each province. We also allow for province-specific preferences across the 85 drug classes by including province-drug class dummies in $\mathbf{X}_{ijt}$. Similarly, we include drug province-manufacturer dummies in our specifications to account for any unobserved time-invariant province-drug manufacturer specific relationships that could affect provinces' listing decisions.

We consider a number of drug-specific controls that account for correlated effects. These include our citation-based drug quality measure and dummy variables for the PMPRB drug novelty classes (with generics being the baseline group). We also control for the number of drugs in drug j's class that have received an NOC (irrespective of whether they are submitted for formulary listing). This accounts for aggregate trends in the number of drugs within drug j's class that have penetrated the Canadian market. $\mathbf{X}_{ijt}$ also includes two dummy variables for "list" and "do not list" CDR recommendations. All else equal, we expect that a "list" ("do not list") recommendation increases (decreases) the chances province i lists. We also include NOC year dummies to account for any unobserved drug "vintage" effects in formulary listings.

In our richest specification, we include 989 drug fixed effects in $\mathbf{X}_{ijt}$. These are perhaps the most important covariates for accounting for correlated effects; they control for the impact that time-invariant unobserved drug quality has on formulary listings. Recall that a drug's price and its therapeutic advance over existing therapies determine its quality: all else equal, drugs with lower prices or higher therapeutic benefits are of higher quality. In practice, formulary committees judge a drug's quality based on forecasts of its fiscal impact on public healthcare budgets, and existing clinical research on its efficacy and safety (PausJennsen et al. (2003), Armstrong et al. (2008)). Over the three year post-NOC period that we study, and in particular over the initial 18 month period when most listing decisions are made, it is not unreasonable to assume that these assessments of drug cost and therapeutic advance are largely fixed. To the extent that these drug quality assessment criteria are similar across provinces, our drug fixed effects will account for these important time-invariant factors that affect provinces' formulary listings.[27]

The main caveat to our empirical specification is that we do not explicitly control for province-specific drug prices. Data on these prices are not readily available. Moreover, the effective price that a province

[27]Drug fixed effects also control for the impact that drug-specific characteristics like dosage size, strength, and form (i.e,. pill vs. tablet) have on formulary listing decisions.

pays per pill depends on how a province reimburses its citizens for a given drug's cost. These reimbursement schemes vary by drug across the provinces, and they change over time within the provinces. Constructing a consistent price index across the provinces for the 989 drugs in our sample dating back to 1994 is simply infeasible given the lack of price data and the complexities of provinces' time varying reimbursement schemes.

Despite being unable to construct such a price index to include $\mathbf{X}_{ijt}$, we believe that four sets of our covariates jointly control for price effects. As just discussed, our drug fixed effects control for the time-invariant common price effect for a given drug on provinces' formulary listings. Second, to the extent that our medical citations-based measure of drug quality is correlated with drug prices over time (i.e., if more cost-effective drugs receive more citations), our quality control will help account for time varying price changes for a given drug that are not captured by our drug fixed effects. Third, we control for the number of drugs in drug j's class currently listed on province i's formulary. This further helps account for province-specific within-class time varying price effects since a province's level of cost reimbursement (and hence effective per unit fiscal cost) for a given drug largely depends on the number of within-class substitutes currently on a province's formulary. Finally, our inclusion of drug class fixed effects by province controls for any province-specific willingness to pay for a given class of drugs, and hence province-specific price effects at the drug-class level for 86 drug classes. Given the combined impact of these controls in accounting for price effects, we are confident that any residual time varying province- and drug-specific price effects will not severly undermine identification of endogenous effects.

5.1.2 Results

We present parameter estimates for eight specifications of equation (3) in Table 3. These specifications allow us to assess the sensitivity of our endogenous effects estimates to the control variables included in $\mathbf{X}_{ijt}$. We also report average partial effects of increasing our variable of interest list_{-ijt-1} from 0 to 0.223 (a one-standard deviation increase) in Table 3. This is a typical change in other provinces' listing decisions in the data. We further illustrate our baseline estimated endogenous effects in Figure 4, which plots the predicted average listing probabilities for specifications (6)-(8) as list_{-ijt-1} varies from 0 to 0.5.[28]

The positive and negative parameter estimates for β_1 and β_2 respectively, which govern the endogenous effects, are statistically significant across all specifications. As Figure 4 illustrates, these estimates indicate that the formulary listings of other provinces have a positive but diminishing effect on a given committee's listing decisions. However, the estimated marginal effects differ in important ways across the eight specifications in Table 3, and highlight the importance of controlling for contextual and correlated effects. Without any controls, the marginal effect from increasing list_{-ijt-1} from 0 to 0.223 increases a province's quarterly

[28]This is the relevant range for quantifying the magnitude of spillovers in our sample, as over 85% of all listing decisions are made where $\text{list}_{-ijt-1} \leq 0.5$. The sample mean and median values for list_{-ijt-1} are 0.173 and 0. We do not plot standard errors in these figures for the sake of clarity since they are indistinguishable from the sample averages of the predicted choice probabilities. The standard errors for the plots in Figures 4 and 6 are available upon request.

listing probability by 4.9%. This is a large effect relative to the average quarterly listing probability of 4.8% in the sample. As we add controls for provincial characteristics such as demographics and fixed effects for election periods, years, provinces, and quarter-of-the-year (by province) in columns (2) and (3), the marginal effect estimates for list_{-ijt-1} increase to 5.2% and 5.9%. This suggests that dissimilarity in observable and unobservable provincial characteristics results in lower intertemporal correlation in formulary listings across the provinces. Once these confounding contextual effects are controlled for, the magnitude of estimated endogenous effects rises.

Columns (4)-(6) of Table 3 incrementally add province-drug controls to $\mathbf{X}_{ijt}$. The estimated marginal effect of list_{-ijt-1} on the probability of listing is largely unchanged in columns (3)-(5), while it jumps to 6.7% in column (6). This latter result highlights the importance of the inclusion province-drug class fixed effects in our model for identifying endogenous effects. To the extent that province-specific preferences for particular drug classes exist (due to demographics, provinces' cost reimbursement schemes or other unobserved reasons), there will be disagreement among committees' listing decisions that is independent of endogenous effects stemming from social learning or career concerns. If these province-specific preferences exist and are not controlled for, they will potentially create downward bias in our endogenous effects estimates. The change in our estimated β_1 and β_2 parameters and marginal effects of list_{-ijt-1} in columns (5) and (6) suggest this is indeed the case.

Further evidence of province-specific preferences across drug classes can be found by comparing the coefficient estimates for our portfolio variable ("# of Drugs in Class on Formulary") and its square in columns (5) and (6) of Table 3. Portfolio effects are statistically significant under both specifications, however the column (5) (without province-drug class fixed effects) estimates suggest a surprising positive effect of having additional drugs within a given drug's class on its listing probability. In contrast, the column (6) (with province-drug class fixed effects) estimates indicate an expected negative portfolio effect. As Kyle (2006) originally points out, this sign reversal highlights directly speaks to jurisdiction-specific preferences for particular drug classes that also confound identification of portfolio effects.[29]

The final two columns in Table 3 add observable drug-specific characteristics and individual drug fixed effects to $\mathbf{X}_{ijt}$. The change in our parameter estimates in columns (6) and (7) and the corresponding fall in the marginal effect of list_{-ijt-1} to 6.2% indicates that our drug-specific controls for quality, CDR recommendations, and PMPRB novelty classes capture correlated effects in formulary listings. The statistically

[29] Borrowing an example from Kyle (2006), suppose residents of Manitoba have a strong preference for anti-ulcer drugs while residents of New Brunswick do not. Further suppose each province's formulary committee responds to their constituents' demands, resulting in 5 and 2 anti-ulcer drugs being listed on Manitoba's and New Brunswick's formularies. If a new anti-ulcer drug came up from listing and Manitoba's preferences were relatively strong enough, Manitoba would be more likely to list the drug. In contrast, New Brunswick's weak preference for anti-ulcer drugs would cause it to not list the drug. Without controlling for Manitoba's and New Brunswick's province-specific preferences for anti-ulcer drugs, we would incorrectly conclude that formularies are more likely to list drugs that already have many drugs within a given class, confounding our portfolio effects estimates. Province-drug class fixed effects control for these province-specific preferences for drug classes. Once this unobserved heterogeneity is controlled for, our estimated porfolio effects have their expected signs in columns (6)-(8) of Table 3.

significant 0.017 coefficient estimate on drug quality in column (7) indicates that higher quality drugs are more likely to be listed on formularies. The relatively large decline in marginal effects to 5.0% in column (8) illustrates the importance of drug fixed effects for identifying endogenous effects. As discussed, drug fixed effects account for unobserved drug quality/cost-effectiveness that generates correlation in province's formulary listings, and potentially compromises identification of β_1 and β_2. The importance of using drug fixed effects can also be seen from Figure 4; endogenous effects increase at a slower rate as list_{-ijt-1} rises under specification (8) relative to specifications (6) and (7). Further note that the coefficient estimate on drug quality falls to -0.008 and becomes statistically insignificant in column (8). Even though our drug quality measure is time-varying, our drug fixed effects seem to largely account for the impact of drug quality on listing decisions over the three year time horizon that we study.

Table 3 has a number of secondary empirical results that we summarize here. CDR recommendations have a large impact on the listing decisions of provinces: "do not list" and "list" recommendations decrease and increase listing probabilities by 4.6% and 1.6% under the column (7) specification. Line extensions and me-too drugs are 2.5% and 2.4% more likely to be listed on formularies than generics. Province-manufacturer experience has as positive, diminishing effect on the ability of companies to get their drugs listed onto formularies. Under model (8), a one-drug increase in the number of a drugs a manufacturer has on a given formulary increases its listing probability by 16.5%. The (unreported) fiscal controls for election periods show the listing probabilities of formulary committees do not change just prior to, during, or just following provincial elections. This further speaks to our discussion in Section 2 that committee members act as expert government bureaucrats and not politicians. The magnitude of a government's debt level has a statistically significant negative impact on formulary listing rates across all specifications. This highlights the impact that budgets have on the cost-benefit analyses of formulary committees: the greater the provincial debts, the fewer drugs that get added to the formulary.

5.2 Identifying career concerns

While identifying interdependency in listing decisions across committees is interesting in and of itself, we now go one step further and try to uncover the source of this interdependency. Most studies that identify endogenous effects in a given setting are unable to pin down what drives the endogenous effect due to data limitations. We are fortunate to have three sources of exogenous variation to identify which are the relevant channels through which interdependencies in formulary listings arise: (1) the introduction of the Common Drug Review (CDR) partway through our sample; (2) differences in the uncertainty about drug quality as measured by the PMPRB drug novelty classifications; and (3) provincial elections.

5.2.1 The Common Drug Review

For a subset of drugs in the sample, the CDR makes a binary public recommendation of "list" or "do not list" as part of the CDR policy.[30] By providing information to formulary committees about drug quality, the CDR ostensibly reduces a committee's reliance on the informational content contained in the listing decisions of other committees for two reasons. First, committees that would typically evaluate drugs in the absence of the CDR no longer do so or perhaps conduct a less thorough evaluation, and therefore their listing decisions contain less information. Second, committees that would typically incorporate the information contained in the decisions of other committees into their own information sets no longer need to do so since: (1) the information in the CDR recommendation substitutes for that information; and (2) the decisions of other committees contain less information conditional on a CDR review. Thus, even if there remains some uncertainty about drugs following the CDR review, the interdependency in formulary listings due purely to informational spillover will be lower than for non-CDR-reviewed drugs.

Using our model, we formalize this intuition in Figure 5. The figure illustrates an instance where the CDR allows us to identify whether career concerns help to explain committee recommendations. The lightly shaded rectangle represents the set of beliefs at which the low listing cost committee i would be willing to conduct a costly evaluation; the darkly coloured rectangle represents the same for the higher cost committee j. The initial belief about drug quality is given by γ_0. At this belief, committee i would be willing to evaluate the drug before making a listing decision; committee j would choose not to list without further evaluation.

Recall that we assume the pharmaceutical firm first applies for listing to provinces most likely to list, in our example, province i. Before any evaluation or listing decisions are made, the CDR evaluates the drug and makes a recommendation of either "list" or "do not list". Figure 5 depicts a case where the CDR recommends to "list" and the common belief about the quality of the drug increases to γ_1.[31] At this new belief, committee i lists the drug with no further evaluation since γ_1 lies to the right of its light gray evaluation range. If there are no career concerns, province j still chooses to not list the drug with no evaluation since γ_1 lies to the left of its darker gray evaluation region. However, if career concerns are present and are strong enough, then committee j's expected cost of not listing the drug twists up to $\lambda_1(1)\gamma$, and the expected cost of listing the drug twists down to $\lambda_2(1)(1-\gamma) + c_\ell^2$. In this case, committee j either evaluates the drug, or lists it without further evaluation. That is, when the CDR evaluates a drug, it reduces the incentive for early movers to undertake drug evaluations, and their decisions can only influence later movers if career concerns are strong enough.[32]

[30] Recall from Table 2 that the CDR does not review all drugs after the 2003 introduction of the CDR. Thus, we use variation in CDR reviews over time, and across drugs within a given year in the post-CDR period to examine CDR effects.

[31] Formally, we may assume that the CDR recommendation is a costless signal with some precision q which may or may not be larger than p, the precision of private signals generated by a provincial formulary committee's evaluation (see Section 3 above).

[32] Note that the CDR evaluation may shift sufficiently far to the right (left) to induce both provinces to list (not list) the drug. In this case, the provinces' decisions would be positively correlated not because of informational spillovers or career concerns,

To identify the importance of informational spillovers and career concerns as forces that generate interdependency in provincial listing decisions, we modify our empirical specification to allow for heterogeneous endogenous effects as follows:

$$f(\text{list}_{-ijt-1}, \boldsymbol{\beta}) = \beta_0 + \beta_1 \text{list}_{-ijt-1} + \beta_1^{cdr} 1\{\text{CDR } j\} \cdot \text{list}_{-ijt-1} + \beta_2 \text{list}^2_{-ijt-1} \tag{7}$$

where $1\{\text{CDR } j\}$ is an indicator that equals 1 if the CDR reviews drug j.[33] We argue that identifying β_1 and β_1^{cdr} allows us to determine whether informational spillovers, career concerns, or both play a role in formulary committee decision-making. If career concerns do not play a role in decision-making, all of the observed interdependency is driven by informational spillovers and social learning among formulary committees. Since the CDR resolves at least some uncertainty about the quality of the drugs it evaluates (if not most, as suggested by the provinces in the Government of Canada (2007) review of the CDR policy), given our argument from the model above, it must be that β_1^{cdr} is negative, and almost as large as β_1. That is, any remaining interdependency in formulary listings for CDR-reviewed drugs should be negligible if: (1) informational spillovers are the primary driver of endogenous effects; and (2) CDR-reviews yield much lower informational spillovers in formulary listing decisions.

If both informational spillovers and career concerns drive the endogenous effect, then β_1^{cdr} should be negative, though it may be small in magnitude. That is, informational spillovers are much weaker for CDR-reviewed drugs, but they are not the only source of interdependency across the listing decisions of formulary committees. In this case, the endogenous effect should be smaller, but not necessarily negligible for CDR-reviewed drugs.

If career concerns dominate social learning in driving the endogenous effect, then it must be that $\beta_1^{cdr} = 0$. In this case, the CDR policy that provides public information to reduce provinces' expenditures on drug evaluations and ensure a minimum level of informativeness in decision-making (which thereby reduces informational spillovers) does not break the interdependency that exists through career concerns.

We re-estimate equation (5) under specification (8) with drug fixed effects, except that we replace $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$ with its specification from equation (7). Table 4 presents the estimation results for the parameters of interest only. The estimate of -0.008 for β_1^{cdr} with a standard error of 0.020 in column (1) of the table suggests that the CDR reviews have virtually no impact the degree of interdependency among provincial formulary listings. The β_1^{cdr} estimate is effectively zero, and is certainly not negative which would otherwise speak to a reduction in informational spillovers from formulary listings arising from the policy. Relatedly, the marginal effect of increasing list_{-ijt-1} from 0 to 0.223 on province i's probability of listing a drug is identical in column (1) of Table 3 and column (8) of Table 4. This finding is evidence against the

but from the correlated effect of the CDR's review. This does not pose an identification problem for us since we able able to account for the direct (time-invariant) effect of the CDR review on perceived drug quality through drug fixed effects.

[33] We have also considered models where we interact $\{\text{CDR } j\}$ with higher order terms in the polynomial that governs the endogenous effects. Doing so yields little difference in the empirical results.

hypothesis that social learning is the sole channel through which endogenous effects arise. Career concerns and fear of going against the decisions of other committees is sufficiently strong such that it overwhelms any impact of the CDR's informational shock on the degree of interdependency in decision-making.[34]

5.2.2 Drug novelty

The exogenously given novelty of a drug provides an additional opportunity to test whether informational spillovers or career concerns drive interdependency in listing decisions. Recall from Section 4 that the PMPRB classifies pharmaceuticals as belonging to one of four novelty classes: breakthrough, line extensions, me-too, and generic. Breakthrough drugs are the most novel and generic drugs are the least. Generics should have little uncertainty in their underlying therapeutic value since they are bio-equivalent to branded alternatives that have been under patent for 17 years, and often marketed for more than a decade. Formulary committee experts are more likely to have hands-on experience with generic drugs and their alternatives relative to innovative breakthroughs or line extensions, and, as a result, can readily evaluate their efficacy. The same can be said for me-too drugs that, as their name suggests, are almost identical to branded drugs.

In the context of our model, drug novelty can be measured by the initial prior γ_0. The more that is known ex-ante about a drug, the closer γ_0 is to 0 or 1, and the lower the ex-ante value to sinking the cost c_e and undertaking a drug evaluation. If γ_0 is close to 0 (close to 1), it almost certainly does not (does) yield therapeutic value over alternative therapies.[35] As in the case of CDR-reviewed drugs, there are two reasons why social learning should not play a significant role in driving interdependency in decision-making across committees for non-innovative drugs like generics and me-toos. First, committees are less likely to undertake evaluations of drugs with less uncertainty in their therapeutic value since the value to expending resources on an evaluation is lower. This implies that listing decisions for less novel drugs contain less information from which others can make inferences. Second, committees that typically use the information contained in the decisions of other committees to make decisions have less incentive to do so for less novel drugs because their beliefs are so certain for non-novel drugs that more information is unlikely to change their minds. Consistent with the findings from PausJennsen et al. (2003) discussed in Section 2, the model thus predicts that less innovative drugs like generics and me-toos are less likely to involve extensive drug evaluations. As a result, there should be little scope for informational spillovers across formulary committees regarding therapeutic value.[36]

[34] This is not to say that CDR reviews are uninformative. Recall the estimates from model (7) from Table 3 that CDR reviews have a statistically and economically significant effect on provinces listing probabilities, which indicates that formulary committees take into account the CDR recommendations. However, this common impact of CDR reviews on committees' listing decisions is a correlated effect that our drug fixed effects account for in identifying $\boldsymbol{\beta}$.

[35] To be more precise, the higher the prior belief γ_0, the more likely (ex-ante) the outcome of an evaluation is positive. But at high beliefs, positive evaluations have little effect on the belief of a committee. If positive evaluations are very likely relative to negative ones, and positive ones have little effect on the belief, there is little value to evaluating a drug. A symmetric claim can be made at low beliefs.

[36] This does not imply that no uncertainty about non-novel drugs exists, since committees may still remain uncertain about a drug's cost-effectiveness. In particular, committees are uncertain about the propensity of consumers to substitute from branded

To examine how endogenous effects vary across drug novelty classes, we estimate our baseline model in equation (5) on two different sub-samples of novelty types: me-toos and generics. Given the preceding discussion, if interdependency in formulary listings is only driven by informational spillovers, then the estimated endogenous effects for generics and me-toos should not be different from 0.

Table 5 presents our estimation results based on sub-samples of 357 Me-too and 348 Generic drugs. The coefficient estimates for β_1 and β_2 are statistically significant for both drug classes. The estimates yield economically significant marginal effects of the past listing decisions of other committees on province i's listing decision for drug j for all novelty classes. A one-standard deviation increase in list_{-ijt-1} from 0 to 0.223 increases a province's listing probability by 5.4%, and 3.2% for me-toos and generics. These marginal effects are large relative to the average quarterly listing probabilities of 3.2%, and 4.3% for these two novelty classes. Moreover, assuming that social learning is more important for the average drug than me-toos and generics, if there are no career concerns, then the marginal effect of other jurisdictions' listing decisions for me-toos and generics should be significantly less than the baseline marginal effects. This is not the case: the marginal effect estimates for me-toos and generics are similar in magnitude to the analogous baseline marginal effect of 5.0% for the column (8) specification in Table 3.[37]

Figure 6 further illustrates how the marginal effect changes as list_{-ijt-1} varies from 0 to 0.5. The initial listing probabilities for me-toos and generics are 3.2% and 4.3%. As list_{-ijt-1} rises, the listing probabilities for me-toos and generics increase to 14.5% and 11.8%. These results provide further evidence against the hypothesis that social learning is the sole driver of endogenous effects in provincial formulary listings. Despite the fact that generics and me-toos have little scope for generating informational spillovers regarding their therapeutic value, formulary committees continue to be influenced by the decisions of other committees. We again attribute this result to expert committee members' fear of going against group consensus regarding public health insurance decisions for pharmaceuticals.

5.2.3 Provincial elections

As mentioned in Section 2.1, the listing recommendations of health experts are to be devoid of provincial politics. This is one of the benefits of delegating policy to experts in the first place. Nonetheless, politics may have an impact on interdependency in listing decisions either through its direct effect on committee members, or indirectly through politicians pressuring experts to make politically-favourable listing recommendations because of interjurisdictional "yardstick competition" (Besley and Case (1995)). The latter effect arises if

products toward non-novel drugs like generics, should the latter be listed on the formularies. As a result, the ultimate fiscal cost of listing a non-novel drug is uncertain, although it undoubtedly possesses less overall uncertainty than a novel drug like a Breakthrough.

[37] The estimated (unreported) marginal effect for 262 Line Extensions in the sample is 7.8% and is statistically significant at the 1% level. This is evidence that the interdependency in formulary listings indeed varies with drug novelty. Moreover, this finding is consistent with the idea that social learning is a source of interdependency given that Line Extensions are much more uncertain in their therapeutic advance relative to existing drugs within a therapeutic class. Details pertaining to these line extensions results are available upon request.

politicians influence experts on the formulary committees while trying to please an electorate that judges them by comparing their province's health plans to those of other provinces. Irrespective of the reason, if formulary committees mimic the past decisions of other committees because of political pressure, then politics will impact listing decisions in the same way career concerns do. To investigate whether political concerns matter, we consider another specification of $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$:

$$f(\text{list}_{-ijt-1}, \boldsymbol{\beta}) = \beta_0 + \beta_1 \text{list}_{-ijt-1} + \beta_1^{pol} 1\{\text{Election Period } t\} \cdot \text{list}_{-ijt-1} + \beta_2 \text{list}^2_{-ijt-1} \tag{8}$$

The coefficient β_1^{pol} governs the change in the endogenous effect around an election period, which occurs every three to five years for a given province. We consider three types of election periods for $1\{\text{Election Period } t\}$, specifically if a province i is: (1) within two quarters either before or after (one-year) of a provincial election; (2) within four quarters prior to an election; and (3) within four quarters following an election. If yardstick competition is more intense around elections, and formulary experts respond to this by matching the listing decisions of other provinces, then β_1^{pol} should be positive, implying endogenous effects are larger around elections.

Similar to our analysis from Section 5.2.1, we estimate equation (5) under the specification (8) from Table 3 with drug fixed effects, except we replace $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$ with its definition from equation (8). The estimates for the coefficients of interest are listed in columns (2)-(5) of Table 4. Looking across the columns, the estimated coefficients on β_1 and β_2 are largely the same, and the marginal effect of list_{-ijt-1} on province i's listing decisions is virtually unchanged if we allow for differential endogenous effects within, just before, or just after an election period. The only statistically significant election-related estimate is the β_1^{pol} coefficient for one year before an election. It suggests a lower endogenous effect just before an election that reduces the marginal effect of list_{-ijt-1} by a negligible 0.02%. Overall, the results from Table 4 support published documentation from the provincial public health plans, and evidence from Armstrong et al. (2008) that listings are minimally impacted by politics. These results support our interpretation of endogenous effects as being driven by social learning and the career concerns of experts as opposed to political concerns.

6 Conclusion

Experts often have career concerns. As such, herd behavior among experts can potentially be explained by the incentive to conform to popular opinion when making uncertain recommendations. In doing so, experts avoid any negative repercussions associated with being the dissenting expert who is found to be wrong ex-post. In this paper, we have developed empirical tests for career concerns in the recommendations of expert bureaucrats over public health insurance of pharmaceuticals. We find robust evidence that experts are influenced by each others' policy recommendations. Using a novel identification strategy that exploits a policy intervention and exogenous variation in drug novelty, we show that career concerns are an important

source of herd behavior among experts in a context where social learning likely matters as well.

Our findings yield two key implications for the delegation of policy decisions. First, a potential benefit of decentralizing policy-making within a given set of jurisdictions is that policy makers can learn from the decisions of others when making their own decisions. This is of particular importance in jurisdictions where resources are limited and in-depth policy evaluations are infeasible. Our findings suggest that these benefits of decentralized policy-making are muted by the career concerns of those making the policy choices. Career concerns prevent bureaucrats from optimally, in a statistical sense, using information available to them when making decisions. In our pharmaceutical context, this implies that the health care delivery system is inefficient and the menu of drugs available to patients is potentially suboptimal.[38]

Second, our findings have implications for who should be tasked with making government policy. It is often argued that non-elected expert bureaucrats should replace politicians as policy makers because they are better able to make dispassionate, evidence-based decisions. In contrast, politicians are potentially less knowledgeable and may suffer from time-inconsistency problems that prevent them from forming optimal policy over time. Our results provide new empirical insights that suggest a reason for caution against an unchecked move to technocratic rule. While politically-driven politicians have incentives that can prevent them from choosing the optimal policy, environments where career concerns exist and technocrats are evaluated relative to their peers can inhibit experts from forming optimal policy as well.

We believe the main thrust of our results extends beyond our public health context. In particular, both social learning and career concerns likely affect policymaking across countries, states or provinces when government-appointed bureaucrats make uncertain decisions regarding common issues. Inter-jurisdictional policy choices in a range of contexts, from financial regulation to environmental policy, are likely affected by these economic forces. For example, countries may be pursuing suboptimal climate change policies because their experts are inhibited by career concerns to learn about the costs associated with available policy options from what other countries do.

In future work, we plan on imposing more structure on the formulary decision-making process to jointly identify how province-specific preferences across drug classes and career concerns of committee members drive equilibrium formulary listings. With the parameters of such a structural model in hand, we can quantify the magnitude of inefficiencies created by career concerns and evaluate policies that centralize policy-making, such as the Common Drug Review.

[38] One possibility is that the cost of being wrong is much larger for an inexperienced expert near the beginning of his career than for a more established late career expert. In this case, if the same provinces (the ones with smaller budgets for drug evaluation, for example) tend to have inexperienced individuals making listing decisions, one may argue that career concerns does not pose an issue for efficiency. These individuals would make less informed decisions in any case, and perhaps conforming to the consensus created by more established experts is the least of all evils. However, as there is no single formulary listing committee that is *always*, or even very often, the first to make a decision in any given year, it must be the case that experts on the *average* committee are subject to the pressure of existing expert opinion when making listing decisions. That is, it is not the case that only inexperienced experts of less repute conform to the consensus set by more prominent experts.

References

Alesina, A., and G. Tabellini (2007): "Bureaucrats or Politicians? Part I: A Single Policy Task," *American Economic Review*, 97, 169–179.

Anis., A. H., D. Guh, and X. hua Wang (2001): "A Dog's Breakfast: Prescription Drug Coverage Varies Widely Across Canada," *Medical Care*, 39, 315–326.

Armstrong, K., C. Mitton, B. Carleton, and J. Shoveller (2008): "Drug Formulary Decision-Making in Two Regional Health Authorities in British Columbia, Canada," *Health Policy*, 88, 308–316.

Banerjee, A. V. (1992): "A Simple Model of Herd Behavior," *Quarterly Journal of Economics*, 107, 797–817.

Berndt, E., L. Bui, D. Lucking-Reily, and G. Urban (1997): "The Roles of Marketing, Product Quality and Price Competition in the Growth and Composition of the US Anti-Ulcer Drug Industry," in *The Economics of New Goods*, T. Bresnahan and R. Gordon (Eds.), University of Chicago Press for the National Bureau of Economic Research.

Besley, T., and A. Case (1994): "Diffusion as a Learning Process: Evidence from HYV Cotton," Discussion Paper 174, Research Program in Developmental Studies, Princeton University.

Besley, T., and A. Case (1995): "Incumbent Behavior: Vote-Seeking, Tax-Setting, and Yardstick Competition," *American Economic Review*, 85, 26–45.

Bikhchandani, S., D. Hirshleifer, and I. Welch (1992): "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 100, 992–1026.

Blume, L. E., W. A. Brock, S. N. Durlauf, and Y. M. Ioannides (2010): "Identification of Social Interactions," in *Handbook of Social Economics*, ed. by J. Benhabib, A. Bisin, and M. Jackson. North Holland.

Brock, W. A., and S. N. Durlauf (2001): *Interaction Based Models*. Chapter 54 Handbook of Econometrics.

Buera, F. J., A. Monge, and G. Primiceri (2011): "Learning the Wealth of Nations," *Econometrica*, 79, 1–45.

Chevalier, J., and G. Ellison (1999): "Career Concerns of Mutual Fund Managers," *Quarterly Journal of Economics*, 114, 389–432.

Collins, H. M. (1992): *Changing Order: Replication and Induction in Scientific Practice*. University of Chicago Press.

Dranove, D., and D. Meltzer (1994): "Do Important Drugs Reach the Market Sooner?," *Rand Journal of Economics*, 25, 402–423.

Foster, A. D., and M. R. Rosenzweig (1995): "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture," *Journal of Political Economy*, 103, 1176–1209.

Freedman, D. H. (2010): *Wrong: When Experts Keep Failing Us – And How to Know When to Trust Them*. Little, Brown and Co.

Goolsbee, A., and P. J. Klenow (2002): "Evidence on Learning and Network Externalities in the Diffusion of Home Computers," *Journal of Law and Economics*, 45, 317–343.

Government of Canada, . (2007): "Prescription Drugs Part 1 – Common Drug Review: an F/P/T Process," Report of the Standing Committee on Health, 39th Parliament, 2nd Session.

Holmstrom, B. (1982): "Managerial Incentive Schemes - A Dynamic Perspective," in *Essays in Economics and Management in the Honor of Lars Wahlbeck*.

Janis, I. L. (1972): *Victims of Groupthink: A Psychological Study of Foreign-Policy Decisions and Fiascos*. Houghton Mifflin.

Jasanoff, S. (1990): *The Fifth Branch: Science Advisors as Policymakers*. Harvard University Press.

Kyle, M. K. (2006): "The Role of Firm Characteristics in Pharmaceutical Product Launches," *Rand Journal of Economics*, 37, 602–618.

——— (2007): "Pharmaceutical Price Controls and Entry Strategies," *Review of Economics and Statistics*, 89, 88–99.

Lichtenberg, F. R., and T. J. Philipson (2002): "The Dual Effects of Intellectual Property Regulations: Within-and Between-Competition in the US Pharmaceuticals Industry," *Journal of Law and Economics*, 45, 643–672.

Manski, C. (1993): "The Reflection Problem," *Review of Economic Studies*, 60, 531–542.

Moretti, E. (2010): "Social Learning and Peer Effects in Consumption: Evidence from Movie Sales," *Review of Economic Studies*.

PausJennsen, A. M., P. A. Singer, and A. S. Detsky (2003): "Ontario's Formulary Committee: How Recommendations Are Made," *Pharmacoeconomics*, 21, 285–294.

Rogoff, K. (1985): "The Optimal Degree of Commitment to an Intermediate Monetary Target," *Quarterly Journal of Economics*, 100, 1169–1189.

Scharfstein, D. S., and J. C. Stein (1990): "Herd Behavior and Investment," *American Economic Review*, 80, 465–479.

Sorensen, A. T. (2006): "Social Learning and Health Plan Choice," *Rand Journal of Economics*, 37, 929–945.

Stern, S. (1996): "Market Definition and the Returns to Innovation: Subsitution Patterns in Pharmaceutical Markets," MIT POPI Working Paper.

A Tables

Table 1: Formulary Listing Decisions and Day-to-List by Province

Province	Drugs Listed	Fraction Listed	Days-to-List Mean	Days-to-List Std. Dev.
British Columbia	335	33.87%	379.19	(235.48)
Alberta	388	39.23%	347.97	(183.12)
Saskatchewan	490	49.54%	317.28	(170.81)
Manitoba	465	47.02%	371.99	(175.28)
Ontario	383	38.73%	452.49	(205.31)
Québec	560	56.62%	294.73	(184.86)
New Brunswick	321	32.45%	519.04	(222.73)
Nova Scotia	402	40.65%	402.23	(189.52)

Notes: Total number of drugs in the sample is 989. Days-to-List is the difference in number of days between a drug's formulary listing date in a given province and the date it receives its Notice of Compliance.

Table 2: Common Drug Review Counts and Recommendations

NOC Year	Total Drugs	CDR Reviewed	CDR Says "list"	Fraction CDR Reviewed	Fraction CDR Says "List"
2003	73	11	6	15.07%	54.55%
2004	89	37	13	41.57%	35.14%
2005	80	36	20	45.00%	55.56%
2006	70	34	20	48.57%	58.82%
2007	50	25	13	50.00%	52.00%
Total	362	143	72	39.50%	50.35%

Notes: N/A.

Table 3: Baseline Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
List_{-ijt-1}	0.247**	0.262**	0.291**	0.290**	0.300**	0.326**	0.307**	0.268**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.019)
$(\text{List}_{-ijt-1})^2$	-0.189**	-0.195**	-0.197**	-0.196**	-0.206**	-0.210**	-0.202**	-0.256**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.023)
Marginal Effect of List_{-ijt-1}	0.049**	0.052**	0.059**	0.059**	0.061**	0.067**	0.062**	0.050**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Province-Manufacturer Experience				0.045**	-0.040	0.039	0.039	0.186**
				(0.015)	(0.035)	(0.036)	(0.036)	(0.054)
(Province-Manufacturer Experience)^2				-0.076**	-0.031	-0.098$^+$	-0.107$^+$	-0.179*
				(0.029)	(0.055)	(0.057)	(0.057)	(0.073)
# of Drugs in Class on Formulary				0.084**	0.077**	-0.559**	-0.591**	-0.915**
				(0.015)	(0.017)	(0.057)	(0.057)	(0.067)
(# of Drugs in Class on Formulary)^2				-0.104**	-0.099**	0.302**	0.356**	0.371**
				(0.021)	(0.024)	(0.074)	(0.075)	(0.094)
# of Drugs with NOC Within Class				0.007*	0.008*	0.059**	0.059**	0.023
				(0.003)	(0.004)	(0.009)	(0.009)	(0.019)
(# of Drugs with NOC Within Class)^2				-0.002*	-0.003*	-0.014**	-0.015**	-0.006
				(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Drug Quality							0.017**	-0.008
							(0.004)	(0.011)
CDR: Do Not List							-0.046**	
							(0.004)	
CDR: List							0.016**	
							(0.005)	
Line-Extensions							0.025**	
							(0.003)	
Breakthrough Drugs							-0.004	
							(0.006)	
Me-too Drugs							0.024**	
							(0.002)	
Provincial Demographic Controls	N	Y	Y	Y	Y	Y	Y	Y
Fixed Effects Controlled For								
Election Period	N	Y	Y	Y	Y	Y	Y	Y
Year	N	Y	Y	Y	Y	Y	Y	Y
Province	N	N	Y	Y	Y	Y	Y	Y
Province-Quarter-of-Year	N	N	Y	Y	Y	Y	Y	Y
Province-Drug Age	N	N	Y	Y	Y	Y	Y	Y
Drug Manufacturer	N	N	N	N	Y	Y	Y	Y
Province-Drug Manufacturer	N	N	N	N	Y	Y	Y	Y
Drug Class	N	N	N	N	N	Y	Y	Y
Province-Drug Class	N	N	N	N	N	Y	Y	Y
Individual Drug	N	N	N	N	N	N	N	Y
R-Squared	0.018	0.026	0.074	0.075	0.086	0.117	0.120	0.147
Observations	69375	69375	69375	69375	69375	69375	69375	69375

Notes: Standard errors are in parentheses and are clustered at the (province, drug class) level . **, * at the 1% and 5% levels. Controls for provincial demographics including population and its square, GDP per capita, unemployment rate, median age, and fraction of the population older than 65 is also included in each specification. Marginal effects for List_{-ijt-1} are average partial effects from a changing List_{-ijt-1}=0 to List_{-ijt-1}=0.223 (a one standard deviation increase in List_{-ijt-1}); see the text for why these values are chosen. Drug counts for "Prov-Mfgr Experience", "# of Drugs in Class on Formulary", and "# of Drugs with NOC in Class" are in terms of 100 drugs.

Table 4: CDR and Elections Impact on Endogenous Effects

	(1)	(2)	(3)	(4)	(5)
List_{-ijt-1}	0.270**	0.263**	0.275**	0.267**	0.273**
	(0.020)	(0.019)	(0.019)	(0.019)	(0.020)
$(\text{List}_{-ijt-1})^2$	-0.257**	-0.257**	-0.256**	-0.256**	-0.258**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
$\text{List}_{-ijt-1} \times 1\{\text{CDR-reviewed drug}\}$	-0.008				-0.008
	(0.020)				(0.020)
$\text{List}_{-ijt-1} \times 1\{\text{Election year}\}$		0.019			0.029
		(0.016)			(0.020)
$\text{List}_{-ijt-1} \times 1\{\text{Year before election}\}$			-0.025**		-0.035**
			(0.009)		(0.010)
$\text{List}_{-ijt-1} \times 1\{\text{Year after election}\}$				0.004	-0.012
				(0.009)	(0.010)
Marginal Effect of List_{-ijt-1}	0.050**	0.051**	0.048**	0.050**	0.051**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-Squared	0.147	0.147	0.147	0.147	0.148
Observations	69375	69375	69375	69375	69375

Notes: All estimates are based on specification (8) from Table 3; refer to that table for the full list of controls. Standard errors are listed in parentheses and are clustered at the (province, drug class) level. **, *, and + indicates statistical significance at the 1%, 5%, and 10% levels. Marginal effects for List_{-ijt-1} are average partial effects from a changing List_{-ijt-1}=0 to List_{-ijt-1}=0.223 (a one standard deviation increase in List_{-ijt-1}); see the text for discussion of why these values are chosen.

Table 5: Drug Novelty Class Regressions

	Me-toos	Generics
List_{-ijt-1}	0.297**	0.166**
	(0.032)	(0.039)
$(\text{List}_{-ijt-1})^2$	-0.242**	-0.097+
	(0.037)	(0.055)
Marginal Effect of List_{-ijt-1}	0.054**	0.032**
	(0.005)	(0.004)
Prov-Mfgr Experience	0.420**	-0.113
	(0.100)	(0.087)
(Prov-Mfgr Experience)^2	-0.389**	0.233+
	(0.135)	(0.139)
# of Drugs in Class on Formulary	-0.789**	-0.506**
	(0.135)	(0.106)
(# of Drugs in Class on Formulary)^2	-0.154	0.248
	(0.232)	(0.178)
# of Drugs with NOC in Class	0.054	-0.163**
	(0.035)	(0.027)
(# of Drugs with NOC in Class)^2	-0.014+	0.025**
	(0.007)	(0.006)
Drug Quality	-0.014	0.052*
	(0.015)	(0.025)
R-Squared	0.197	0.135
Observations	24610	17617

Notes: All estimates are based on specification (8) from Table 3; refer to that table for the full list of controls. Standard errors are listed in parentheses and are clustered at the (province, drug class) level. **, *, and + indicates statistical significance at the 1%, 5%, and 10% levels. Marginal effects for List_{-ijt-1} are average partial effects from a changing List_{-ijt-1}=0 to List_{-ijt-1}=0.223 (a one standard deviation increase in List_{-ijt-1}); see the text for discussion of why these values are chosen. Drug counts for "Prov-Mfgr Experience", "# of Drugs in Class on Formulary", and "# of Drugs with NOC in Class" are in terms of 100 drugs.

B Figures

Figure 1: Formulary Listing Model Decisions

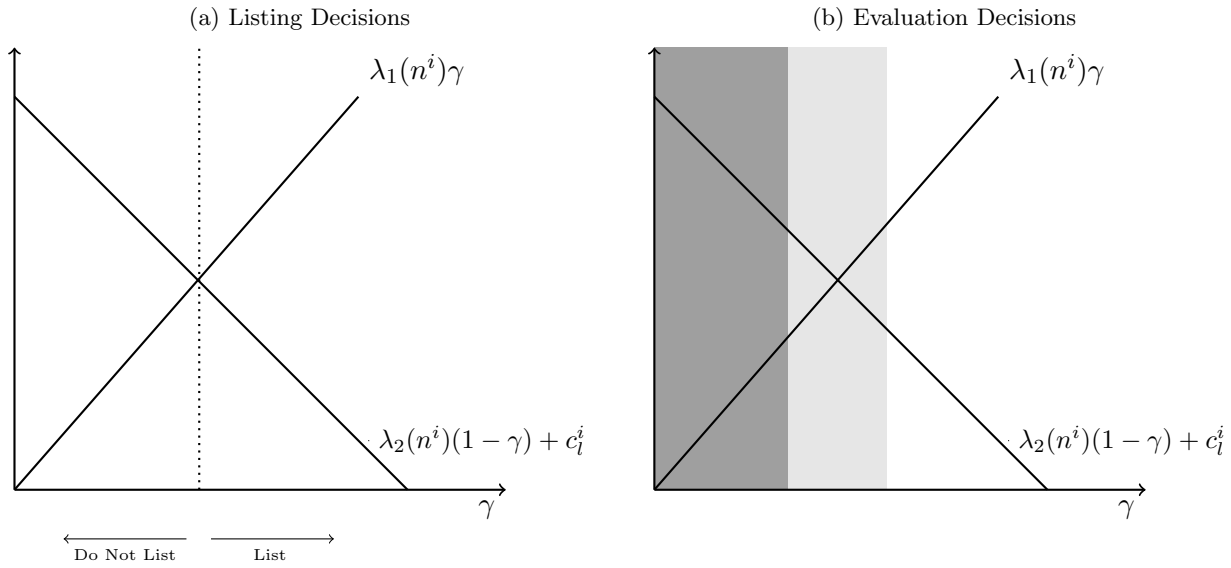


Figure 2: Strength in Numbers and Formulary Listing Decisions

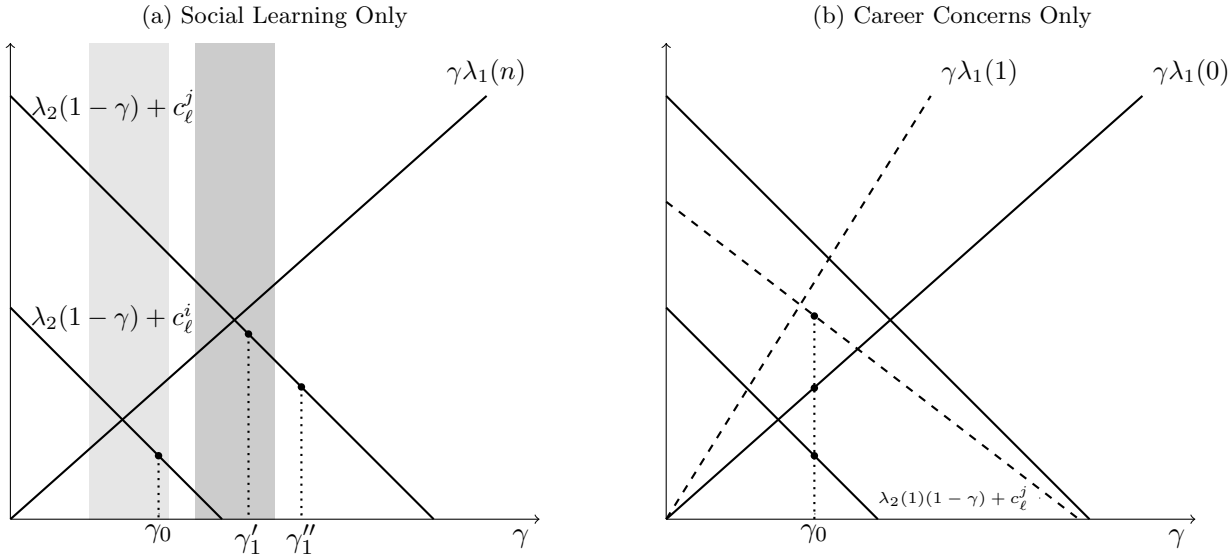


Figure 3: Listing Counts by Qtrs Since NOC

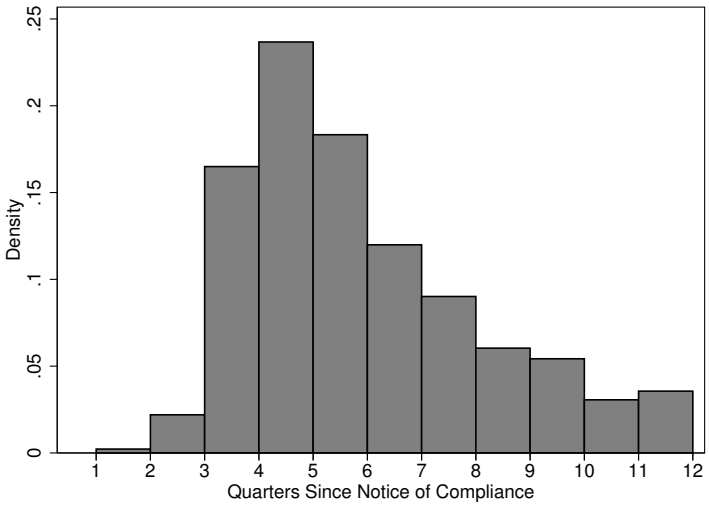


Figure 4: Baseline Endogenous Effects

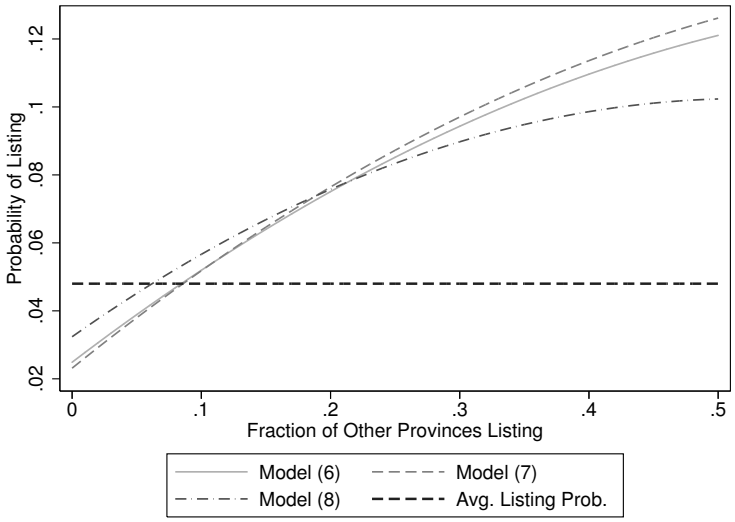


Figure 5: Identification of Career Concerns with the CDR

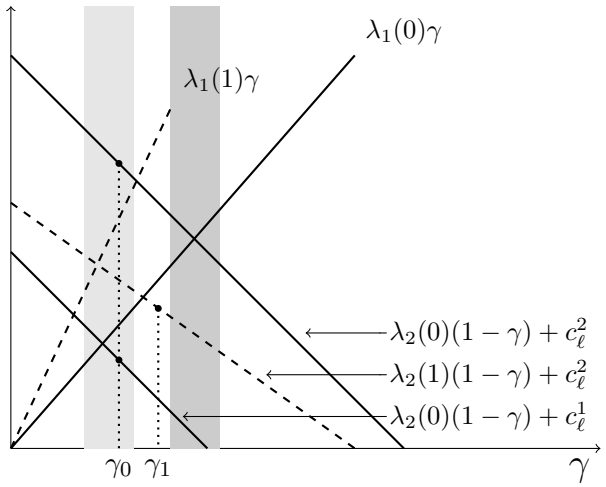
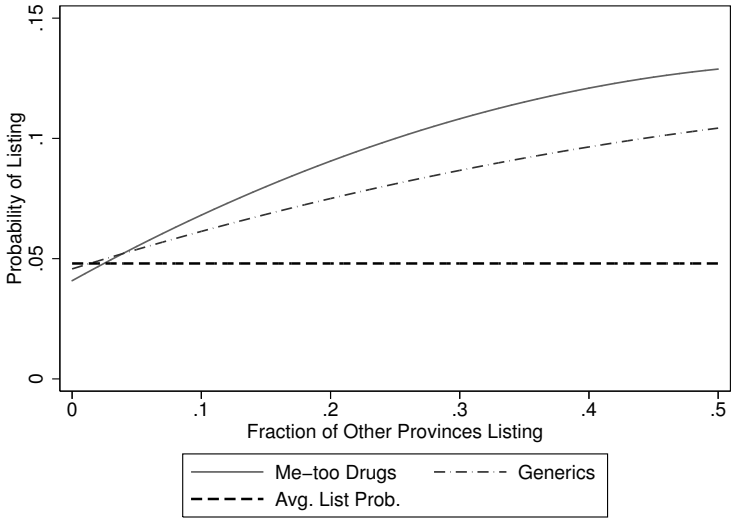


Figure 6: Novelty Class Endogenous Effects



C Supplemental material (not for publication)

C.1 Dataset construction

The data sources and variables used in the paper are listed in Table C.1. As can be seen from the table, the key variable for matching all the drug-specific data sources is a drug's Drug Identification Number (DIN).

C.1.1 Digitizing current formularies

The provincial formularies for British Columbia, Alberta, Saskatchewan, Ontario, and New Brunswick are all available in spreadsheet-ready formats and report Drug Identification Numbers for all listed drugs. Manitoba's, Quebec's, and Nova Scotia's formularies are available in PDF format. Quebec's and Nova Scotia's formularies report Drug Identification Numbers, enabling us to directly extract them from their formulary PDFs to a spreadsheet-ready format. Manitoba's formulary does not report Drug Identification Numbers, but does report brand names, active ingredients, and manufacturer names for all the drugs listed on its formulary. Using this information, combined with the drug-specific information on drug class, manufacturer, brand name, and active ingredient from Health Canada's Notice of Compliance Extract and the other seven formularies, we are able to "hand-match" of all the Drug Identification Numbers listed drugs on Manitoba's formulary.

C.1.2 Constructing initial formularies for 1994

We construct the initial formularies from 1994 for all the provinces as follows:

1. Match the NOC date to all drugs currently listed on the eight formularies using the NOC Data Extract and each drug's DIN. Not all drugs will be matched since the NOC Data Extract goes back to 1991, while the eight current formularies entail drugs with NOC dates from potentially before 1991.

2. Match the NOC date to all drugs in the IMS Brogan FAME database (for the entire database, not just the estimation sample) using the NOC Data Extract and each drug's DIN. All drugs are matched since the FAME database runs from 1994-2007 and the NOC Data Extract runs from 1991-2011. Using this match, we double-check that all drugs in the FAME database have an NOC date between 1994 and 2007. We also cross-reference Health Canada's reported NOC dates with those reported by IMS Brogan.

3. Find all DINs that are in the IMS Brogan FAME database, but are *not* in the dataset of drugs currently listed on the eight formularies. Remove all drugs that are in both datasets. Going forward, denote the remaining unmatched DINs the "Initial DIN List" for each province.

4. Remove all DINs whose NOC date is after 2007 from each province's Initial DIN List. All remaining DINs either have an NOC date between 1991 and 1994 (i.e. NOC dates that run back to the start of the NOC Data extract), or do not have an NOC date possibly because it is before 1991.

5. For the DINs without an NOC date, we obtain drug-specific information on drug class, manufacturer, brand name, and active ingredient that is reported in various current formularies. Saskatchewan's and Alberta's formularies were particularly useful for constructing these variables for DINs without an NOC date.

6. For the DINs without an NOC date, use information on their drug manufacturer, brand name, and active ingredient to ensure the drug was plausibly made by a company that has existed since before 1991. Searching through various drug manufacturers' online histories and product lists is the primary way in which this hand check was done.

7. After conducting steps 1-5, we arrive at a final Initial DIN List in 1994 for each of the eight provinces in the estimation sample.

With the Initial DIN List and the FAME Database, we construct a number of drug-specific variables. We track Province-Manufacturer drug counts (i.e., to account for drug company – province relations in formulary listings) by tabulating the cumulative number of drugs a manufacturer has on a province's formulary by a given quarter. We track Province-Drug Class drug counts (i.e., to account for portfolio or within-class competition effects in formulary listings) by tabulating the cumulative number of drugs that are listed within a drug class on a province's formulary by a given quarter. We track the total number of drugs in the Canadian market within a drug class (irrespective of whether the drug was applied for formulary listing or not) by tabulating the cumulative number of drugs that receive an NOC by a given quarter.

C.1.3 Constructing citations-based drug quality measure

Our citation-based measure for our drug quality control variable follows Dranove and Meltzer (1994) and Kyle (2006). We first obtain citation counts from the U.S. National Library of Medicine's Medline website. Using a spider programmed in Ruby, we scrape the citation counts for each active ingredient in the sample from this website's online database of medical journals. An individual citation corresponds to a mention of an active ingredient in the title or abstract from a Clinical Trial, Meta Analysis, Practice Guideline, or Randomized Controlled Trial based on humans from a medical journal in Medline. The citation counts used in the paper were scraped on September 17, 2011.

We denote the total number of medical journal citations as of September 17 for the active ingredient for drug j in drug class k as Ncite_j. Recall that the 86 drug classes in the sample are taken from Health Canada's NOC Data Extract. Let Ndrug_{kt} be the number of drugs in class k that have received an NOC as of quarter t in the sample. Ndrug_{kt} is tabulated using all DINs from the NOC Data Extract dating back to 1991, and all other unique drugs from the provinces' Initial DIN Lists described above. We set the NOC dates for the drugs from the Initial DIN Lists to 1991, which introduces some unavoidable measurement error. Let T_j be quarter that drug j received an NOC such that $t - T_j$ is the number of quarters since drug j received an NOC as of quarter t. Let $\delta \in (0, 1)$ be the quarterly discount factor for citation counts for a given drug. The citation-based quality measure for drug j in quarter t used in the paper is computed as the discounted share of all citations with drug j's class k:

$$\text{quality}_{jt} = \frac{\delta^{t-T_i} \cdot \text{Ncite}_j}{\sum_{i=1}^{\text{Ndrug}_{kt}} \delta^{t-T_i} \cdot \text{Ncite}_i}$$

Our results on the paper are based on $\delta = 0.025$. We find little difference in our estimates and calculations when δ is set to 0.015, 0.035, 0.05 or 0.075. Any results from the paper based on different values of δ can readily be produced upon request.

Dranove and Meltzer's (1994) study of whether important drugs reach markets faster considers a number of other measures in addition to measures based on medical journal citations. These alternative quality measures are based on citations of a drug's active ingredient (or "new molecular entity in their study) in medical textbooks, citations in patent applications, the number of countries a drug is introduced in worldwide, and sales (though only for a subset of the drugs in their sample). We only consider one of these measures as our quality variable largely serves as a control rather that being a covariate of interest as in Dranove and Meltzer (1994). Moreover, our use of drug fixed effects accounts for the time-invariant component of drug quality around a drug's release date in Canada that we are chiefly concerned with controlling for across drugs in identifying endogenous effects in formulary listings. In our richest specifications, the time varying

quality measure controls for residual time varying quality, which as discussed in the text has a statistically insignificant effect on formulary listings once drug fixed effects are controlled for.

The key assumption in using this quality control variable is that a drug's true importance relative to alternative therapies is correlated with the number of medical journals it is cited in. Kyle (2006) notes a number of shortcomings of this measure that are relevant to our study including: (1) citations might not reflect other drug-specific characteristics other than importance, such as how dangerous a drug is; and (2) larger drug manufacturers may have resources to generate more citations from clinical trials for their products independent of a drug's true importance. Moreover, our 86 drug-class classifications may be to coarse to properly define the set of relevant therapeutic substitutes for a given drug which would introduce further measurement error. These are unavoidable shortcomings in using this citation-based control variable of drug quality, and reflect the difficulty in finding or constructing an alternative quality measure that is consistently reported across all drug classes from 1991 to present.

C.1.4 Data sources

Table C.1: Summary of Data Sources and Variables

IMS Brogran Formulary Acceptance: Monitoring and Evaluation Database	
Coverage: 1994-2007, 10 provinces and 3 territories, 1200 DINs	
Drug Identification Number	Numeric
Province	String
Listing date	Date
PMPRB drug novelty classification	String
Health Canada Notice of Compliance Data Abstract	
Coverage: 1991-2011, 11,999 DINs	
http://www.hc-sc.gc.ca/dhp-mps/prodpharma/notices-avis/noc-acc/noc_acc_data_extract-eng.php	
Drug Identification Number	Numeric
Notice of Compliance date	Date
Drug class	String
Drug manufacturer	String
Drug brand name	String
Drug active ingredient	String
Medline/PubMed	
Coverage: 462 active ingredients	
http://www.ncbi.nlm.nih.gov/pubmed/	
Number of medical journal citations	Count
Common Drug Review Decisions	
http://www.cadth.ca/en/products/cdr/search/	
Coverage: 2003-2007, 162 DINs	
Drug Identification Number	Numeric
Common Drug Review recommendation	String
Statistics Canada Demographics	
Coverage: 1990-2011, 10 provinces	
http://cansim2.statcan.ca/	
Population	Count (in 1000s)
GDP per capita	2002 Constant Dollars (in 1000s)
Median age	Numeric
Government debt	Numeric (in 1,000,000,000s)
Unemployment	Fraction
Population older than 65	Fraction
Elections Almanac	
Coverage: 1962-2011, 10 provinces	
http://www.electionalmanac.com/canada/	
Province election date	Date
Current Provincial Formularies	
Coverage: As of September 2011, 8 provinces	
BC: http://www.health.gov.bc.ca/pharmacare/formulary	
AB: https://www.ab.bluecross.ca/dbl/publications.html	
SK: http://www.health.gov.sk.ca/formulary	
MB: http://www.gov.mb.ca/health/mdbif/	
ON: http://www.health.gov.on.ca/english/providers/program/drugs/odbf_mn.html	
QC: http://www.ramq.gouv.qc.ca/en/regie/legal-publications/pages/list-medications.aspx	
NB: http://www.gnb.ca/0212/nbpdpformulary-e.asp	
NS: http://www.gov.ns.ca/health/pharmacare/formulary.asp	
Drug Identification Number	Numeric

Notes: All website links are active as of September 6, 2012. Current provincial formularies are as of September 2011.

C.2 Robustness Checks

C.2.1 Alternative weighting functions in constructing list_{-ijt-1}

We re-estimate our linear probability models using the following definition for list_{-ijt-1} where the listing decisions of all other provinces (other than i) are given equal weight:

$$\text{list}_{-ijt-1} = \sum_{k \neq i} (1/7) \cdot \text{list}_{kt-1}$$

The resulting baseline estimates, analogous to those from Table 3 in the paper, are listed in Table C.2 below. The statistical and economic significance of our estimates are largely unchanged under this construction of list_{-ijt-1}. The estimated endogenous effects are slightly larger than those reported in the paper.

C.2.2 Higher order polynomials of list_{-ijt-1} in $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$

We re-estimate our linear probability models using cubic and quartic functions in defining $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$:

$$f(\text{list}_{-ijt-1}, \boldsymbol{\beta}) = \beta_0 + \beta_1 \text{list}_{-ijt-1} + \beta_2 \text{list}^2_{-ijt-1} + \beta_3 \text{list}^3_{-ijt-1}$$

$$f(\text{list}_{-ijt-1}, \boldsymbol{\beta}) = \beta_0 + \beta_1 \text{list}_{-ijt-1} + \beta_2 \text{list}^2_{-ijt-1} + \beta_3 \text{list}^3_{-ijt-1} + \beta_4 \text{list}^4_{-ijt-1}$$

The resulting baseline estimates are listed in Table C.3 below. These results are based on the population-weighted average definition of list_{-ijt-1} from equation (5). If anything, using higher order polynomials in constructing list_{-ijt-1} result in *larger* endogenous effects in formulary listings among provinces. The endogenous effects are also diminishing in list_{-ijt-1}, like that found with the quadratic specification.

C.2.3 Logit and Probit Models

We re-estimate our listing model from equation (3) under the following latent-utility specification for modeling province i's listing decision for drug j in quarter t:

$$\text{list}^*_{ijt} = f(\text{list}_{-ijt-1}, \boldsymbol{\beta}) + \mathbf{X}'_{ijt}\delta_x + \epsilon_{ijt},$$

where province i's observed listing decision list_{ijt} is a discrete choice defined by:

$$\begin{aligned} \text{list}_{ijt} &= 1 \text{ if } \text{list}^*_{ijt} > 0 \\ \text{list}_{ijt} &= 0 \text{ otherwise} \end{aligned}$$

Province i's listing probability is calculated as:

$$\text{Prob}(\text{list}_{ijt-1} = 1) = \text{Prob}\big(\epsilon_{ijt} > f(\text{list}_{-ijt-1}, \boldsymbol{\beta}) + \mathbf{X}'_{ijt}\delta_x\big)$$

We estimate the model's parameters assuming ϵ_{ijt} follows a standard logistic distribution (Logit) and a standard normal distribution (Probit). The resulting estimates are listed in Table C.4 below. These results are based on the population-weighted average definition of list_{-ijt-1} from equation (5). The table contains linear probability, logit and probit estimates for the sake of comparison. We cannot report estimates for rich models that include province-drug class fixed effects or drug fixed effects because the logit and probit models suffer from an incidental parameter problem under these specifications. All models yield statistically significant endogenous effects. The magnitude of the endogenous effects is 1 to 1.5% smaller under the Logit and Probit models in Table C.4. Note, however, that these models do not account for province-drug class fixed effects nor drug fixed effects, both of which are important controls in identifying endogenous effects.

Table C.2: Regressions with Uniform Weights of Other Provinces' Decisions in Constructing list_{-ijt-1}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
List_{-ijt-1}	0.281**	0.293**	0.334**	0.333**	0.347**	0.390**	0.368**	0.338**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.021)
$(\text{List}_{-ijt-1})^2$	-0.219**	-0.222**	-0.228**	-0.226**	-0.239**	-0.268**	-0.256**	-0.341**
	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.026)
Marginal Effect of List_{-ijt-1}	0.052**	0.054**	0.063**	0.063**	0.065**	0.074**	0.069**	0.058**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.003)
Province-Manufacturer Experience				0.053**	-0.019	0.063+	0.063+	0.189**
				(0.015)	(0.035)	(0.036)	(0.036)	(0.054)
(Province-Manufacturer Experience)^2				-0.084**	-0.054	-0.113*	-0.121*	-0.173*
				(0.029)	(0.055)	(0.057)	(0.057)	(0.073)
# of Drugs in Class on Formulary				0.079**	0.071**	-0.558**	-0.580**	-0.909**
				(0.016)	(0.017)	(0.057)	(0.057)	(0.068)
(# of Drugs in Class on Formulary)^2				-0.103**	-0.093**	0.303**	0.343**	0.358**
				(0.022)	(0.024)	(0.075)	(0.076)	(0.094)
# of Drugs with NOC Within Class				0.004	0.005	0.055**	0.056**	0.021)
				(0.003)	(0.004)	(0.009)	(0.009)	(0.019)
(# of Drugs with NOC Within Class)^2				-0.001	-0.002+	-0.013**	-0.014**	-0.006
				(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Drug Quality							0.017**	-0.002
							(0.004)	(0.011)
CDR: Do Not List							-0.037**	
							(0.004)	
CDR: List							0.014**	
							(0.005)	
Line-Extensions							0.022**	
							(0.003)	
Breakthrough Drugs							-0.002	
							(0.006)	
Me-too Drugs							0.022**	
							(0.002)	
Provincial Demographic Controls	N	Y	Y	Y	Y	Y	Y	Y
Fixed Effects Controlled For								
Election Period	N	Y	Y	Y	Y	Y	Y	Y
Year	N	Y	Y	Y	Y	Y	Y	Y
Province	N	N	Y	Y	Y	Y	Y	Y
Province-Quarter-of-Year	N	N	Y	Y	Y	Y	Y	Y
Province-Drug Age	N	N	Y	Y	Y	Y	Y	Y
Drug Manufacturer	N	N	N	N	Y	Y	Y	Y
Province-Drug Manufacturer	N	N	N	N	Y	Y	Y	Y
Drug Class	N	N	N	N	N	Y	Y	Y
Province-Drug Class	N	N	N	N	N	Y	Y	Y
Individual Drug	N	N	N	N	N	N	N	Y
R-Squared	0.022	0.029	0.079	0.080	0.091	0.122	0.125	0.149
Observations	69375	69375	69375	69375	69375	69375	69375	69375

Notes: Standard errors are in parentheses and are clustered at the (province, drug class) level . **, * at the 1% and 5% levels. Controls for provincial demographics including population and its square, GDP per capita, unemployment rate, median age, and fraction of the population older than 65 is also included in each specification. Marginal effects for List_{-ijt-1} are average partial effects from a changing List_{-ijt-1}=0 to List_{-ijt-1}=0.223 (a one standard deviation increase in List_{-ijt-1}); see the text for why these values are chosen. Drug counts for "Prov-Mfgr Experience", "# of Drugs in Class on Formulary", and "# of Drugs with NOC in Class" are in terms of 100 drugs.

Table C.3: Regressions With $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$ Specified as a Cubic or Quartic Function of list_{-ijt-1}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cubic Specification								
List_{-ijt-1}	0.469**	0.477**	0.529**	0.521**	0.524**	0.530**	0.509**	0.460**
	(0.033)	(0.034)	(0.032)	(0.033)	(0.033)	(0.034)	(0.034)	(0.041)
$(\text{List}_{-ijt-1})^2$	-0.978**	-0.962**	-1.027**	-1.000**	-0.982**	-0.924**	-0.910**	-0.903**
	(0.112)	(0.112)	(0.107)	(0.107)	(0.108)	(0.111)	(0.110)	(0.127)
$(\text{List}_{-ijt-1})^3$	0.612**	0.595**	0.639**	0.619**	0.597**	0.551**	0.546**	0.490**
	(0.087)	(0.087)	(0.083)	(0.083)	(0.084)	(0.086)	(0.086)	(0.096)
Marginal Effect of List_{-ijt-1}	0.065**	0.068**	0.077**	0.076**	0.078**	0.082**	0.078**	0.065**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.007)
R-Squared	0.020	0.027	0.076	0.077	0.087	0.118	0.121	0.148
Observations	69375	69375	69375	69375	69375	69375	69375	69375
Quartic Specification								
List_{-ijt-1}	0.640**	0.613**	0.693**	0.678**	0.681**	0.764**	0.726**	0.788**
	(0.069)	(0.070)	(0.066)	(0.066)	(0.068)	(0.069)	(0.069)	(0.083)
$(\text{List}_{-ijt-1})^2$	-2.008**	-1.783**	-2.011**	-1.938**	-1.925**	-2.324**	-2.210**	-2.818**
	(0.388)	(0.390)	(0.366)	(0.367)	(0.374)	(0.379)	(0.378)	(0.440)
$(\text{List}_{-ijt-1})^3$	2.429**	2.043**	2.370**	2.269**	2.255**	3.019**	2.841**	3.823**
	(0.667)	(0.669)	(0.627)	(0.628)	(0.640)	(0.648)	(0.647)	(0.739)
$(\text{List}_{-ijt-1})^4$	-0.972**	-0.774*	-0.924**	-0.880**	-0.884**	-1.320**	-1.228**	-1.767**
	(0.356)	(0.357)	(0.335)	(0.335)	(0.341)	(0.344)	(0.344)	(0.388)
Marginal Effect of List_{-ijt-1}	0.068**	0.070**	0.080**	0.080**	0.081**	0.087**	0.082**	0.073**
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)	(0.008)
R-Squared	0.020	0.027	0.076	0.077	0.088	0.118	0.122	0.149
Observations	69375	69375	69375	69375	69375	69375	69375	69375

Notes: With the exception of the higher order polynomial terms, specifications (1)-(8) are identical to those in Table 3; refer to that table for the full list of controls. For the sake of brevity we do not report parameter estimates for all other covariates; they are available upon request. Standard errors are in parentheses and are clustered at the (province, drug class) level . **, * at the 1% and 5% levels. Marginal effects for List_{-ijt-1} are average partial effects from a changing List_{-ijt-1}=0 to List_{-ijt-1}=0.223 (a one standard deviation increase in List_{-ijt-1}); see the text for why these values are chosen.

Table C.4: Linear Probability, Logit, and Probit Regressions

	Linear Probability			Logit			Probit		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
List_j	0.288**	0.297**	0.276**	5.608**	5.437**	4.694**	2.797**	2.682**	2.390**
	0.015	0.015	0.015	0.227	0.235	0.247	0.113	0.120	0.122
$(\text{List}_j)^2$	-0.189**	-0.228**	-0.218**	-3.520**	-3.599**	-3.510**	-1.771**	-1.958**	-1.790**
	0.019	0.019	0.019	0.266	0.274	0.281	0.132	0.138	0.140
Marginal Effect of List_{-ijt-1}	0.059**	0.058**	0.054**	0.043**	0.041**	0.038**	0.044**	0.040**	0.038**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.005)	(0.002)	(0.004)	(0.005)
Province-Manufacturer Experience	0.046**	0.138**	0.145**	1.365**	2.795**	3.698**	0.575**	1.701**	1.742**
	0.015	0.025	0.025	0.358	0.613	0.683	0.175	0.321	0.331
(Province-Manufacturer Experience)^2	-0.079**	-0.176**	-0.190**	-1.934**	-3.580**	-4.544**	-0.809*	-2.130**	-2.097**
	0.030	0.038	0.039	0.679	0.960	1.115	0.333	0.505	0.532
# of Drugs in Class on Formulary	0.084**	0.112**	0.107**	2.109**	1.990**	3.146**	1.020**	1.539**	1.507**
	0.016	0.024	0.024	0.353	0.382	0.655	0.170	0.299	0.308
(# of Drugs in Class on Formulary)^2	-0.104**	-0.103**	-0.095**	-2.595**	-2.510**	-3.126**	-1.249**	-1.442**	-1.394**
	0.022	0.028	0.028	0.535	0.579	0.823	0.253	0.362	0.378
# of Drugs with NOC in Class	0.006*	0.011	0.013	0.118	0.081	0.490$^+$	0.064$^+$	0.181$^+$	0.220
	0.003	0.008	0.008	0.077	0.079	0.298	0.037	0.108	0.134
(# of Drugs with NOC in Class)^2	-0.002*	-0.005**	-0.006**	-0.045	-0.050$^+$	-0.236**	-0.023$^+$	-0.074**	-0.101**
	0.001	0.002	0.002	0.027	0.026	0.085	0.013	0.026	0.037
Drug Quality			0.015**			0.523**			0.227**
			0.004			0.104			0.049
CDR: Do Not List			-0.034**			-1.808**			-0.797**
			0.004			0.227			0.097
CDR: List			0.016**			0.456**			0.229**
			0.005			0.115			0.056
Breakthrough Drugs			0.027**			0.883**			0.416**
			0.003			0.070			0.034
Line-Extension Drugs			0.006			0.490**			0.251**
			0.005			0.184			0.086
Me-too Drugs			0.028**			0.863**			0.396**
			0.002			0.073			0.035
Provincial Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects Controlled For									
Election Period	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province-Quarter-of-Year	Y	Y	Y	Y	Y	Y	Y	Y	Y
Drug Age	Y	Y	Y	Y	Y	Y	Y	Y	Y
Drug Manufacturer	N	Y	Y	N	Y	Y	N	Y	Y
Drug Class	N	Y	Y	N	Y	Y	N	Y	Y
R-Squared	0.065	0.079	0.082						
Log Likelihood				-11019	-10851	-10323	-11039	-10538	-10368
Observations	69375	69375	69375	69375	69375	69375	69375	69375	69375

Notes: Standard errors are in parentheses and are clustered at the (province, drug class) level . **, * at the 1% and 5% levels. Controls for provincial demographics including population and its square, GDP per capita, unemployment rate, median age, and fraction of the population older than 65 is also included in each specification. Marginal effects for List_{-ijt-1} are average partial effects from a changing List_{-ijt-1}=0 to List_{-ijt-1}=0.223 (a one standard deviation increase in List_{-ijt-1}); see the text for why these values are chosen. Drug counts for "Prov-Mfgr Experience", "# of Drugs in Class on Formulary", and "# of Drugs with NOC in Class" are in terms of 100 drugs.

C.3 Supplemental figures

Figure C.1: Example Formulary Listing Decision: Darifenacin in Ontario

Committee to Evaluate Drugs (CED)

Recommendations and Reasons

This document posted
July 2007

Darifenacin

Product:
DARIFENACIN (Enablex®)

Class of drugs:
Antispasmodic

Indication:
Treatment of overactive bladder

Manufacturer:
Novartis Pharmaceuticals Canada Inc.

CED Recommendation

The CED recommended that darifenacin (Enablex) not be listed on the Ontario Drug Benefit (ODB) Formulary, on the basis that it is not more effective than available alternatives, and is more expensive.

Executive Officer Decision

Based on the CED recommendation, the Executive Officer has decided not to list darifenacin (Enablex).

Status

No funding through the Ontario Public Drug Programs.

Highlights of Recommendation:

- Darifenacin (Enablex) is used to treat overactive bladder, which may cause urinary incontinence, increased frequency of urination, or an increased urge to urinate.
- Studies suggest that darifenacin (Enablex) works as well as alternatives available on the Ontario Drug Benefit Formulary (e.g. oxybutynin, tolterodine) in patients with overactive bladder. Oxybutinin is available as a general benefit on the Formulary. Tolterodine is another alternative listed on the Formulary as a Limited Use benefit.
- At $1.58 per day, darifenacin (Enablex) is significantly more expensive than regular oxybutinin ($0.50 - $0.75 per day) but slightly less expensive than tolterodine.
- The Committee felt that the class of drugs used to treat overactive bladder may be overused, especially in the elderly. These agents may cause significant side effects that can occur more frequently in the elderly, including dry mouth, constipation, dizziness, vision problems and delirium.
- **Overall, the Committee noted that darifenacin (Enablex) has not been proven to work better than standard options available for overactive bladder, and darifenacin (Enablex) is more expensive. The Committee also noted that this class of drugs is overused and strategies need to be put in place to reduce inappropriate use.** The Committee recommended that darifenacin (Enablex) not be listed on the ODB Formulary.

Background:

Overactive bladder refers to the involuntary spasm of the bladder muscle or a patient's inability to control bladder muscle contractions. The condition may result in a strong need to urinate right away, with or without leakage or wetting accidents caused by a sudden, unstoppable urge to urinate, and an increased need to urinate throughout the day and/or night (frequent bathroom visits).

Darifenacin (Enablex) is an antispasmodic agent used to treat overactive bladder. The medication works by blocking involuntary contractions of the bladder muscle that allow muscles to relax, resulting in better control of the bladder.

The principles of treating overactive bladder are to increase the total amount of urine expressed per bathroom visit, reduce the number of bathroom visits, and to reduce the number of incontinence episodes through lifestyle interventions, bladder training (such as pelvic exercises to strengthen the muscles of the bladder), drug therapy or surgery. First-line drug treatments generally involve the use of antispasmodic drugs.

Oxybutinin and tolterodine are alternatives to darifenacin (Enablex) and are available on the ODB Formulary.

Detailed Discussion:

- The manufacturer, Novartis Pharmaceuticals Canada Inc., asked the Ministry of Health and Long-Term Care to consider listing darifenacin (Enablex) on the ODB Formulary.
- The Committee considered eight randomized controlled trials that evaluated the efficacy of darifenacin (Enablex). For five of the eight trials that were placebo-controlled, patients on active treatment with darifenacin (Enablex) experienced improved efficacy but more side effects.
- One study compared darifenacin (Enablex) to tolterodine. It showed comparable efficacy and tolerability between the two treatments.
- Two studies evaluated darifenacin (Enablex) versus oxybutynin. No differences in efficacy or side-effect profile were demonstrated between the two agents.
- At $1.58 per day, darifenacin (Enablex) is significantly more expensive than immediate release oxybutynin ($0.50 - $0.75 per day) but slightly less expensive than tolterodine.
- Given the prevalence of the inappropriate use of drugs to treat overactive bladder and the significant risk of clinically important side effects, especially in the geriatric population, the Committee indicated expanding the use of this class of drugs could negatively effect the overall health of the Ontario population.
- The Committee also indicated that the Formulary should not consider reimbursing darifenacin (Enablex) unless it offers a therapeutic and/or a cost advantage compared with formulary alternatives, and unless programs to reduce inappropriate use are put in place.

CEDAC Recommendation:

(http://www.cadth.ca/index.php/en/cdr/recommendations)

The Canadian Expert Drug Advisory Committee recommended that darifenacin (Enablex) not be listed.

continued…

Ministry of
Health and Long-Term Care

Ontario

Ontario

Ministry of
Health and Long-Term Care
Ontario Public Drug Programs

For more information, please contact:

Ministry of Health and Long-Term Care
Ontario Public Drug Programs
415 Yonge Street, Suite 1601
Toronto, Ontario M5B 2E7
or click: www.moh.on.gov.ca/dss/ced