Herding Among Bureaucrats

Branko Bo_skovic
David. P. Byrne
Arvind Magesan

July 2012

Research Paper Number 1153

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

July 26, 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

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 are 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 (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 health professionals. These experts neither want to risk recommending a drug that is ultimately of poor quality nor advising against a drug of high quality. Such concerns can be exacerbated should an

---

[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.

1

expert find herself not in the consensus established by her peers. In this way, the pressure to conform that Shiller alludes to 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.[3] 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 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

---

[3]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.

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.[4]

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.[5] Our empirical results provide a reason for caution against an unbridled move to technocratic 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.[6]

---

[4]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.

[5]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.

[6]The debate over who should form policy has recently come to the forefront of political and economic debates in the face of

Many papers in a wide range of contexts attempt to identify social learning in decision-making.[7] This paper is most closely related to Buera et. al's (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.[8] 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.[9] 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 level.[10] 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, 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

---

recent financial and macroeconomic events in Europe. See "Europe: The Rise of the Technocracy" in *The Guardian*, November 13, 2011.

[7]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, Brock, Durlauf, and Ioannides (2010) for a survey of this literature.

[8]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).

[9]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.

[10]The Canadian territories also offer their own health insurance programs.

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 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)).

---

[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.

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 finding ways to solve health problems. 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). Making such errors is likely detrimental to their reputations as being informed health professionals, which may adversely affect their future labor market opportunities within the private or public healthcare industry in Canada or internationally.

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) examine 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 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.[14] 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.

---

[14]See http://www.cadth.ca/index.php/en/cdr/cdr-overview for succinct history and overview of the CDR.

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.[15] 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.[16] 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 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

---

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

[16]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.

number of provinces that have not listed the drug.[17] 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 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

---

[17]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.

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.[18] 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, 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

---

[18]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.

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. We extract data on each drug's DIN, listing status and date by province, and the Patented Medicine Pricing Review Board's (PMPRB)[19] 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).[20]

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).[21] 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.

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

---

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

[20]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.

[21]In online Appendix C, we provide details on how we construct the initial stock of drugs on each province's formulary, and further discuss data collection and variable construction.

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.[22]

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.[23]

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 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.

---

[22]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).

[23]See http://www.electionalmanac.com/canada/.

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.[25] The only main difference is that only one of the 22 breakthrough drugs in the sample is reviewed by the CDR.

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 whether either of these mechanisms drive observed 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 combines the effects from social learning and career concerns, by using a benchmark empirical interactions-based model (see 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

---

[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.

[25]Statistical tests of differences in means for CDR and non-CDR reviewed drugs are available upon request.

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 the following 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. The vector $\mathbf{X}_{ijt}$ contains various controls that affect formulary listings.[26] Province i's observed listing decision list_{ijt} is a discrete choice defined by:

$$\text{list}_{ijt} = 1 \quad \text{if } \text{list}^*_{ijt} > 0$$

$$\text{list}_{ijt} = 0 \quad \text{otherwise}$$

Province i's listing probability is thus calculated as:

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

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 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.[27]

The parameters in equation (3) are estimated using logit 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

---

[26]This specification is also consistent with the discrete time hazard model used by Kyle (2006, 2007) who models irreversible pharmaceutical entry into healthcare markets.

[27]We have estimated numerous models based on a number of plausibly valid weighting schemes that define list_{-ijt-1}, and different functional forms for $f(\cdot, \boldsymbol{\beta})$ including higher-order polynomials and splines. Our empirical findings throughout the paper remain unchanged under the many alternative specifications arising from different combinations of weighting schemes and functional forms. These results are readily available upon request.

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; the logit model cannot since it suffers from an incidental parameter problem. Moreover, calculating marginal effects of changing list_{-ijt-1} on province i's listing decisions for many specifications of $f(\cdot, \boldsymbol{\beta})$ is much simpler with a linear probability model than with logit. 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.

5.1.1 Identification and covariates

As discussed in Section 2, formulary committees meet and make listing decisions at quarterly frequencies. Armstrong et. al (2008) report that committees make decisions based on recommendations already made by other formulary committees as opposed to making conjectures about the current or future decisions of others. Thus, modeling listing decisions at a quarterly frequency and assuming that current listing decisions are a function only of past listing decisions of other committees is appropriate. Our ability to make this assumption hinges on 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 $\mathbf{X}_{ijt}$ contains control 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 listing decisions because they have common 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.[28]

We consider a number of drug-specific controls. These include our citation-based drug quality measure and dummy variables for the PMPRB drug 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

---

[28]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.

increases (decreases) the chances province i lists. We also include drug class fixed effects in all regressions. In our richest specification, we include drug fixed effects which account for all permanent heterogeneity across drugs, in particular unobserved drug quality which potentially is an important source of correlated effects.[29]

We also include a number of province-drug related variables that largely help control for contextual effects. Importantly, we 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.[30] We include the number of drugs that drug j's manufacturer currently has on province i's formulary (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. 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.[31] Drug manufacturer fixed effects are also included in all regressions.

A number of additional time-varying provincial characteristics are also controlled for. We control for government debt and 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. We also control for annually-reported demographics such as population and its square, GDP per capita, unemployment rate, median age, and fraction of the population older than 65. Additional fixed effects are included in $\mathbf{X}_{ijt}$ for province, season/quarter, year, and NOC year.

5.1.2 Results

The parameter estimates and corresponding average partial effects of each covariate on listing probabilities (which account for any estimated non-linear relationships) are presented in Table 3. Four models are estimated: baseline logit and linear probability models (LOGIT and LPM1), and linear probability models that incrementally add province-drug class fixed effects (LPM2) and drug fixed effects (LPM3) to the baseline model. Average partial effects for list$_{-ijt-1}$ are computed by increasing list$_{-ijt-1}$ from 0 to 0.22 (a one-standard deviation increase). This is a "typical" change in other provinces' listing decisions in the data.

The parameter estimates for β_1 and β_2 that govern the endogenous effects are statistically significant, and indicate that the formulary listings of other provinces have a positive but diminishing effect on a given

---

[29]Other sources of permanent drug-specific heterogeneity include dosage size, strength, and form (i.e., pill vs tablet).

[30]Such "within-class competition" among drugs has been documented by a number of authors including Berndt et. al (1997) and Kyle (2006, 2007).

[31]Kyle (2006, 2007) shows jurisdiction-specific preferences across drug classes are important to control for in predicting pharmaceutical entry in to healthcare markets.

committee's listing decisions. Estimated marginal effects on quarterly listing probabilities of increasing list_{-ijt-1} from 0 to 0.22 are somewhat higher under LPM1 (6.1%) than LOGIT (4.7%). The LPM3 marginal effect of 5.5% is similar in magnitude to the LOGIT estimate; its decline from 6.8% under LPM2 highlights the importance of accounting for drug-specific heterogeneity in quantifying endogenous effects. All of these marginal effects are large in magnitude relative to the average quarterly listing probability of 4.8% in the data. Figure 4 plots the predicted average listing probabilities as list_{-ijt-1} varies from 0 to 0.5.[32] The figure depicts similar diminishing marginal effects of list_{-ijt-1} on listing probabilities across the four specifications. It further highlights the large impact of the decisions of other formulary committees on listing probabilities relative to the 4.8% average listing probability. Under the LPM3 specification, the average predicted quarterly listing probability is 8.1% at $\text{list}_{-ijt-1} = 0.2$, rising to 10.2% when $\text{list}_{-ijt-1} = 0.4$.

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 3% and 2% under the LPM2 specification. Higher quality drugs have a statistically significant and positive impact on listing probabilities for all specifications. Line extensions and me-too drugs are 2% to 3% 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 LPM3, a one-drug increase in the number of a drugs a manufacturer has on a given formulary increases its listing probability by 16.5%. Portfolio effects are statistically significant as well. Under LOGIT and LPM1, they have surprising positive signs, whereas they have expected negative and diminishing effects signs under LPM2 and LPM3 once province-drug fixed effects are controlled for. As Kyle (2006) points out, this sign reversal highlights the importance of accounting for underlying jurisdiction-specific demand for particular drug classes when modeling pharmaceutical entry into healthcare markets.[33]

The 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.[34]

---

[32]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. They are available upon request.

[33]Borrowing an example from Kyle (2006), suppose residents of Manitoba had a strong preference for anti-ulcer drugs while residents of New Brunswick did not. Further suppose each province's formulary committee responds to their constituents' demands, resulting in 5 and 2 anti-ulcer drugs 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. Without controlling for Manitoba's and New Brunswick's demand 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.

[34]This impact of budgets is mentioned by committee members in Armstrong et. al's (2008) study of formulary listing processes.

17

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.[35] 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.[36] 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

---

[35]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.

[36]That the CDR reduces provincial formulary committees' drug evaluation efforts, and provides substitute information for making listing decision directly relates to our discussion from Section 2.2 on the two main goals of the CDR, and the committees' comments to the federal government in 2007 on the success of the CDR in achieving these goals. If the CDR recommendations are sufficiently informative that provincial formulary committees do not undertake evaluations for CDR-reviewed drugs (as suggested by the committees in the Government of Canada (2007) federal CDR study), then all remaining interdependency in formulary listings without the CDR should strictly be driven by the career concerns of committee members.

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.[37] 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.[38]

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.[39] 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.

---

[37]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).

[38]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, 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.

[39]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.

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 the LPM3 specification with drug fixed effects, except that we replace $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$ with its specification from equation (7). The LPM3a column of Table 4 presents the estimation results for the parameters of interest only. The estimate of 0.033 for β_1^{cdr} with a standard error of 0.036 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 higher values of list_{-ijt-1} on province i's probability of listing a drug is identical in the LPM3 column of Table 3 and the LPM3a column of Table 4. This finding is evidence against the 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.[40]

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 alternatives.

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.[41] As in the case of CDR-reviewed drugs, there are two reasons

---

[40]To be clear, this is not to say that CDR reviews are uninformative. Recall the estimates in columns 1-3 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 $\boldsymbol{\beta}$.

[41]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

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.[42]

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.[43]

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 0.22 increases a province's listing probability by 5.4%, and 5.2% for me-toos and generics. These marginal effects are large relative to the average quarterly listing probabilities of 6.0%, and 2.7% 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 5.5% for the LPM3 specification reported in Table 3.[44]

Figure 6 further illustrates how the marginal effect changes as list$_{-ijt-1}$ varies from 0 to 0.5. The initial

---

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.

[42]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 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.

[43]We have also estimated the model for line extensions, the results of which are available upon request. Unfortunately, we do not observe enough breakthrough drugs in our sample with which to estimate our rich social interactions models.

[44]The estimated (unreported) marginal effect for 262 Line Extensions in the sample is 9.4% 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.

listing probabilities for me-toos and generics are 1.7% and 1.6%. As list$_{-ijt-1}$ rises, the listing probabilities for me-toos and generics increase to 8.2% and 6.3%. 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 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 $f(\text{list}_{-ijt-1}, \boldsymbol{\beta})$:

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

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 LPM3 specification 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 LPM3b-LPM3e 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 0.01%. 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, a context where social learning is also a likely driver of herd behavior in decision-making. We find robust evidence that experts are influenced by each others' policy recommendations. We exploit a unique policy intervention and exogenous variation in drug novelty to show that career concerns are an important source of herd behavior among experts in a context where social learning is 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 federation 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.

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.

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.

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.

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.

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.

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*.

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 Estimates

	LOGIT		LPM1		LPM2		LPM3	
	Est	MFx	Est	MFx	Est	MFx	Est	MFx
List$_{-ijt-1}$	5.255**	0.047**	0.333**	0.061**	0.361**	0.068**	0.318**	0.055**
	(0.423)	(0.001)	(0.028)	(0.002)	(0.029)	(0.002)	(0.035)	(0.003)
(List$_{-ijt-1}$)^2	-4.040**		-0.274**		-0.260**		-0.329**	
	(0.514)		(0.036)		(0.037)		(0.043)	
CDR: Do Not List	-1.471**	-0.059**	-0.020**	-0.020**	-0.030**	-0.030**		
	(0.327)	(0.013)	(0.005)	(0.005)	(0.006)	(0.006)		
CDR: List	0.639**	0.025**	0.023**	0.023**	0.020**	0.020**		
	(0.161)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)		
Drug Quality	0.534**	0.021**	0.016**	0.016**	0.018**	0.018**	-0.001	-0.001
	(0.139)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.017)	(0.017)
Breakthrough Drugs	0.522**	0.021**	0.013**	0.013**	0.002	0.002		
	(0.189)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)		
Line Extensions	0.831**	0.033**	0.026**	0.026*	0.023**	0.023**		
	(0.089)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)		
Me-too Drugs	0.823**	0.033**	0.027**	0.027**	0.023**	0.023**		
	(0.092)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)		
Prov-Mfgr Experience	3.460**	0.085**	0.146**	0.090**	0.124**	0.079**	0.222**	0.165**
	(1.039)	(0.023)	(0.038)	(0.024)	(0.039)	(0.025)	(0.045)	(0.031)
(Prov-Mfgr Experience)^2	-4.157*		-0.187**		-0.151*		-0.192**	
	(1.844)		(0.064)		(0.059)		(0.064)	
# of Drugs in Class on Formulary	3.351**	0.102**	0.119*	0.096**	-0.619**	-0.544**	-0.944**	-0.870**
	(1.227)	(0.037)	(0.048)	(0.038)	(0.084)	(0.069)	(0.120)	(0.104)
(# of Drugs in Class on Formulary)^2	-3.376*		-0.109*		0.357**		0.352**	
	(1.367)		(0.050)		(0.095)		(0.113)	
# of Drugs with NOC in Class	0.547	0.011	0.010	0.004	0.058**	0.043**	0.023	0.014
	(0.394)	(0.011)	(0.010)	(0.008)	(0.012)	(0.010)	(0.033)	(0.027)
(# of Drugs with NOC in Class)^2	-0.232		-0.005*		-0.014**		-0.008	
	(0.121)		(0.002)		(0.003)		(0.007)	
Election Year	-0.061	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.069)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year Before Election	-0.022	-0.001	-0.001	-0.001	-0.000	-0.000	0.000	0.000
	(0.082)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year After Election	-0.142	-0.006	-0.006	-0.006	-0.005	-0.005	-0.005	-0.005
	(0.082)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Government Debt Level	-0.331**	-0.013**	-0.010*	-0.010*	-0.010*	-0.010*	-0.009*	-0.009*
	(0.102)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Prov Demographic Controls		Y		Y		Y		Y
Prov-Drug Class Fixed Effects		N		N		Y		Y
Drug Fixed Effects		N		N		N		Y
N		69375		69375		69375		69375
R^2		-		0.085		0.109		0.133
LL		-1.03e+04		11631.94		12879.61		14244.21

Notes: Standard errors are in parentheses and are clustered at the (province, drug class) level . **, * at the 1% and 5% levels. All specifications include fixed effects for province, drug age (in terms of quarters), quarter/season, year, NOC year, drug class and manufacturer. Separate drug age dummies are estimated for each province. 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 non-dummy variables are average partial effects for a one-unit change from a covariate's value in the data. Marginal effects for dummy variables are average partial effects for a change in a covariate's value in the data to a "1". 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

	LPM3a		LPM3b		LPM3c		LPM3d		LPM3e	
	Est	MFx	Est	MFx	Est	MFx	Est	MFx	Est	MFx
List_{-ijt-1}	0.314**	0.055**	0.312**	0.055**	0.325 **	0.054**	0.314**	0.054**	0.311**	0.055**
	(0.035)	(0.026)	(0.036)	(0.026)	(0.035)	(0.026)	(0.035)	(0.026)	(0.036)	(0.026)
$(\text{List}_{-ijt-1})^2$	-0.327**		-0.330**		-0.329**		-0.329**		-0.328**	
	(0.043)		(0.043)		(0.043)		(0.043)		(0.043)	
$\text{List}_{-ijt-1} \times 1\{\text{CDR-reviewed drug}\}$	0.033								0.034	
	(0.036)								(0.036)	
$\text{List}_{-ijt-1} \times 1\{\text{Election year}\}$			0.023						0.022	
			(0.016)						(0.016)	
$\text{List}_{-ijt-1} \times 1\{\text{Year before election}\}$					-0.035*				-0.033*	
					(0.016)				(0.017)	
$\text{List}_{-ijt-1} \times 1\{\text{Year after election}\}$							0.021		0.017	
							(0.018)		(0.018)	
N	69375		69375		69375		69375		69375	
R^2	0.133		0.133		0.133		0.133		0.133	

Notes: Standard errors are in parentheses and are clustered at the (province, drug class) level . **, * at the 1% and 5% levels. Results are based on the LPM3 specification with drug fixed effects; refer to Table 3 for the full list of control variables. Marginal effects for non-dummy variables are average partial effects for a one-unit change from a covariate's value in the data. Marginal effects for dummy variables are average partial effects for a change in a covariate's value in the data to a "1". 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 5: Drug Novelty Class Model Parameter Estimates

	Me-toos		Generics	
	Est	MFx	Est	MFx
List$_{-ijt-1}$	0.337**	0.054**	0.208**	0.052**
	(0.060)	(0.004)	(0.058)	(0.005)
(List$_{-ijt-1}$)^2	-0.288**		-0.208**	
	(0.073)		(0.078)	
Drug Quality	-0.012	-0.012	0.058	0.058
	(0.019)	(0.019)	(0.031)	(0.031)
Prov-Mfgr Experience	0.324**	0.221**	0.051	0.045
	(0.102)	(0.060)	(0.056)	(0.045)
(Prov-Mfgr Experience)^2	-0.320		-0.022	
	(0.172)		(0.061)	
# of Drugs in Class on Formulary	-0.928**	-0.970**	-0.562**	-0.467**
	(0.237)	(0.198)	(0.141)	(0.122)
(# of Drugs in Class on Formulary)^2	-0.228		0.425**	
	(0.322)		(0.147)	
# of Drugs with NOC in Class	0.040	0.029	-0.173**	-0.153**
	(0.061)	(0.051)	(0.035)	(0.030)
(# of Drugs with NOC in Class)^2	-0.010		0.021**	
	(0.013)		(0.006)	
Election Year	-0.001	-0.001	-0.005	-0.005
	(0.005)	(0.005)	(0.004)	(0.004)
Year Before Election	0.000	0.000	0.005	0.005
	(0.007)	(0.007)	(0.004)	(0.004)
Year After Election	-0.010	-0.010	0.003	0.003
	(0.006)	(0.006)	(0.005)	(0.005)
Government Debt Level	-0.010	-0.010	0.001	0.001
	(0.007)	(0.007)	(0.006)	(0.006)
Prov Demographic Controls		Y		Y
Prov-Drug Class Fixed Effects		Y		Y
Drug Fixed Effects		Y		Y
N		24595		17632
R^2		0.199		0.149

Notes: Standard errors are in parentheses and are clustered at the (province, drug class) level . **, * at the 1% and 5% levels. Results are based on the LPM3 specification with drug fixed effects; refer to Table 3 for the full list of control variables. Marginal effects for non-dummy variables are average partial effects for a one-unit change from a covariate's value in the data. Marginal effects for dummy variables are average partial effects for a change in a covariate's value in the data to a "1". 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.

B Figures

Figure 1: Formulary Listing Model Decisions

(a) Listing Decisions

$\lambda_1(n^i)\gamma$

$\lambda_2(n^i)(1-\gamma) + c_l^i$

γ

Do Not List   List

(b) Evaluation Decisions

$\lambda_1(n^i)\gamma$

$\lambda_2(n^i)(1-\gamma) + c_l^i$

γ
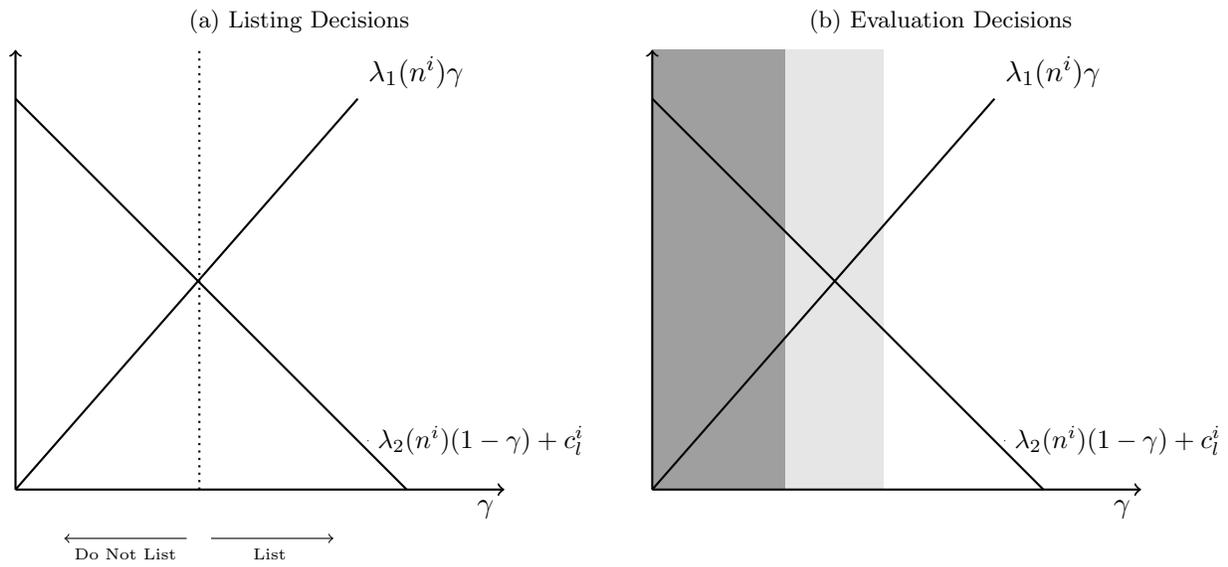
Figure 2: Strength in Numbers and Formulary Listing Decisions

(a) Social Learning Only

$\gamma\lambda_1(n)$

$\lambda_2(1-\gamma) + c_\ell^j$

$\lambda_2(1-\gamma) + c_\ell^i$

γ_0 γ_1' γ_1'' γ

(b) Career Concerns Only

$\gamma\lambda_1(1)$ $\gamma\lambda_1(0)$

$\lambda_2(1)(1-\gamma) + c_\ell^j$

γ_0 γ
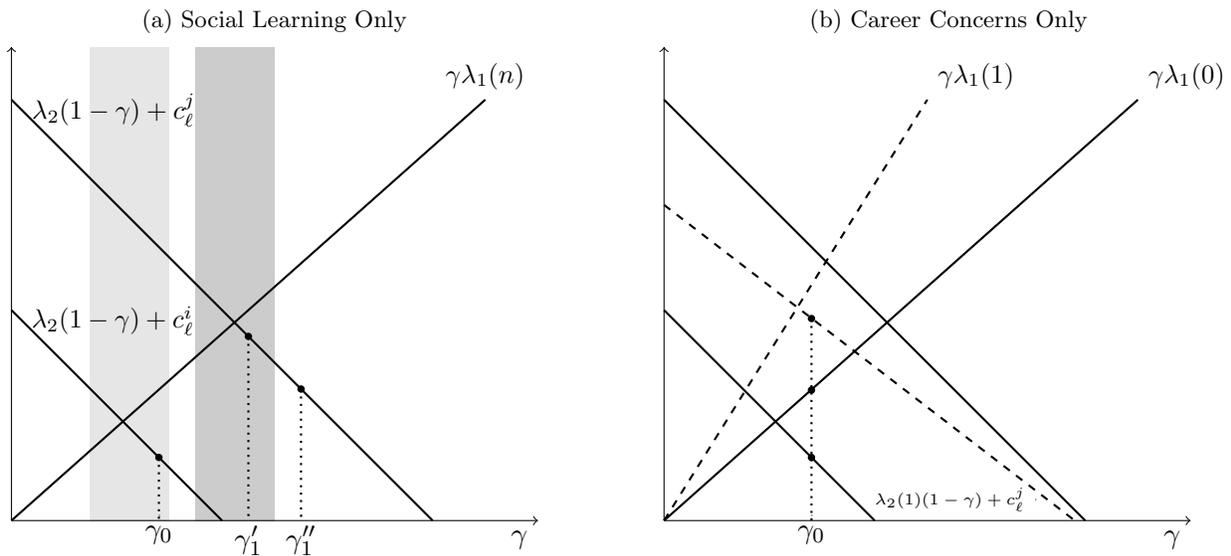
Figure 3: Listing Counts by Qtrs Since NOC

Distribution of Listing Quarters
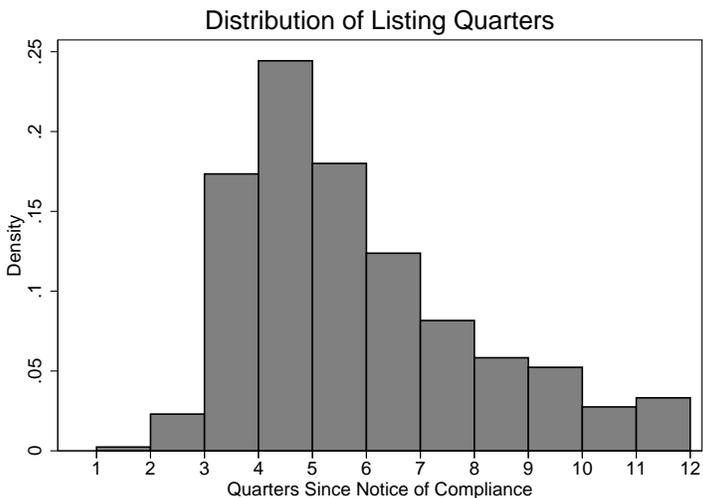
Figure 4: Baseline Endogenous Effects

Listing Probability vs. Peers Listing Decisions
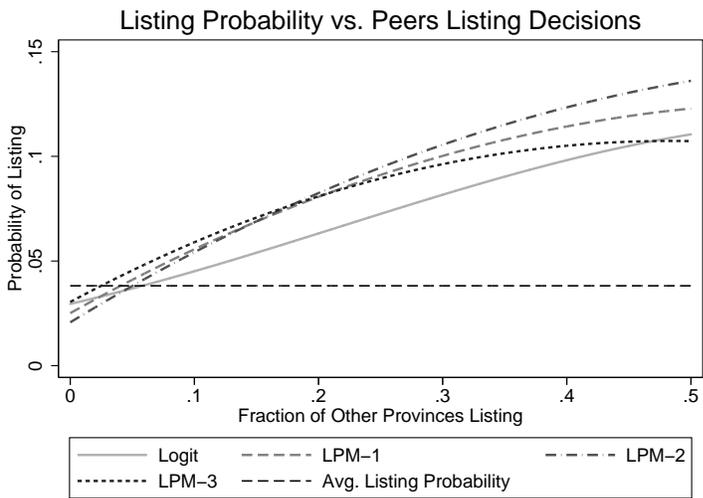
Figure 5: Identification of Career Concerns with the CDR
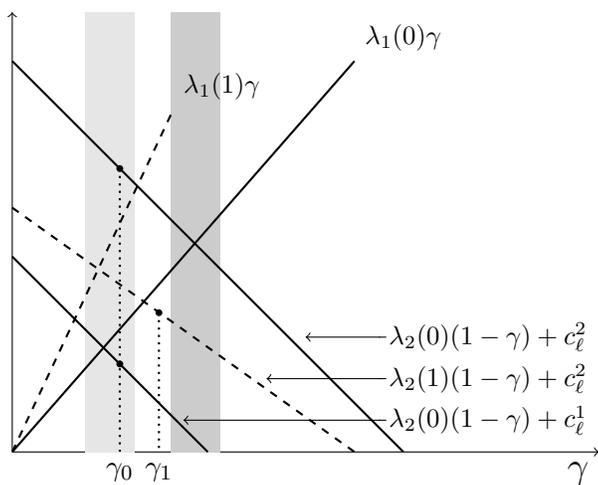
Figure 6: Novelty Class Endogenous Effects

Listing Probability vs. Peers Listing Decisions
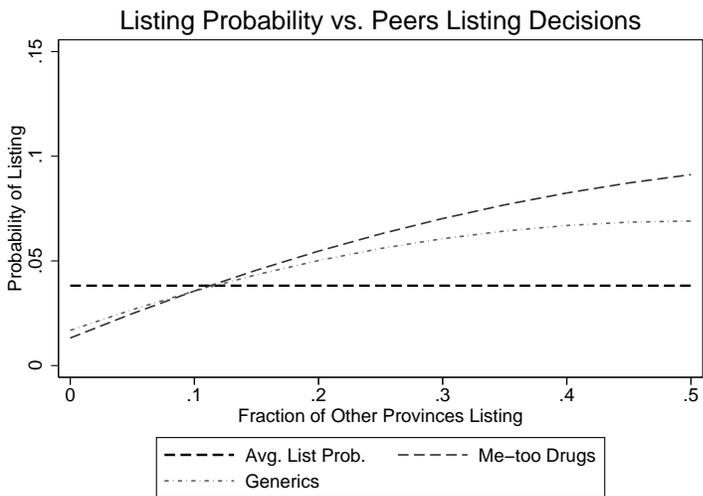
C Supplemental material (not for publication)

C.1 Dataset construction

The data sources and variables used in the paper are listed in Table 6. 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.2 Supplemental tables and figures

Table 6: 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 July 26, 2012. Current provincial formularies are as of September 2011.

Figure 7: Example Formulary Listing Decision: Darifenacin in Ontario

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.

Ministry of
Health and Long-Term Care

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