Explaining International Differences in Genetically Modified Food Labeling Policies*

Guillaume P. Gruère, Colin A. Carter, and Y. Hossein Farzin

Abstract

Many countries have adopted labeling policies for genetically modified (GM) food, and the regulations vary considerably across countries. We evaluate the importance of political-economic factors implicit in the choice of GM food labeling regulations. Using an analytical model, we show that production and trade-related interests play a prominent role in labeling decision-making. This conclusion is validated by an empirical analysis of GM food labeling policy choices. We find that countries producing GM crops are more likely to have less stringent labeling policies. Food and feed exporters to the European Union (EU) and Japan are more likely to have adopted stricter labeling policies. Labeling regulations in Asia and Europe are similar to those of Japan and the EU. Countries with no labeling policies are less developed, with important rural sectors and are more likely to have ratified the Cartagena Protocol on Biosafety.

1. Introduction

The main international players in food trade have adopted dramatically different positions on the labeling of genetically modified (GM) food. In total, more than 40 countries have adopted labeling regulations, and the characteristics of the regulations vary greatly. At one end of the spectrum, the United States is the largest producer of GM crops, and has published voluntary labeling guidelines for non-GM food.1 At the other end of the spectrum, the European Union (EU) has stringent mandatory labeling regulations, and requires the labeling of GM food and GM ingredients with a 0.9% tolerance level for the accidental presence of approved GM ingredients in non-GM products.

Eastern European countries and Russia adopted labeling regulations comparable to those in the EU. At the same time, certain Southeastern Asian countries (such as Vietnam and Indonesia) have adopted regulations similar to those in Japan. Some other developing countries have taken a position on GM food, sometimes adopting mandatory labeling policies that do not seem to respond to genuine consumer concerns and that may be unenforceable.

Previous literature has acknowledged the difficulty associated with explaining the heterogeneous pattern of labeling regulations across countries. Caswell (2000) argued that this “patchwork of regulation” is the result of domestic rational choices. Mitchell (2002) provided an early empirical comparative study of international labeling regulations. Using international cross-sectional data, she used logit regressions to explain the presence of GM food labeling requirements. She finds that higher-income countries are associated with mandatory labeling. Countries with biotechnology crop trials are more likely to mandate labeling, but export dependence does not make a country more

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likely to have labeling requirements. She also found that importers of food from the United States are less likely to have labeling requirements. Mitchell concluded that more work needs to be done to explain international labeling regulations.

Fulton and Giannakas (2004) analytically compared different GM labeling and regulation scenarios, and found that labeling regulations and adoption decisions raise conflicts of interest among consumers, farmers, and seed companies, and that there is no simple explanation as to why different labeling regulations have been introduced in different countries. Anderson and Jackson (2003) used a general-equilibrium model to simulate the effects of the EU moratorium on new GM crops. They found that EU producers benefit from restrictive policies in the EU, whereas US producers would benefit if there were no regulatory barriers in the EU and elsewhere. They conclude that producer differences may explain the dramatically different regulatory approaches between the EU and the United States. Graff and Zilberman (2004) expand this argument, by observing that farmers and agriculture chemical producers in the EU benefit from having strong regulations covering GM crops and GM food.

In this paper, we use an empirical approach based on a political-economic framework to explain international choices of GM food labeling policies. Our aim is to measure what may have motivated different countries to choose their specific set of regulations.

2. Analytical Framework

We present a model of decision-making regarding the adoption of mandatory labeling. This stylized model is adapted from the proportional voting model in Persson and Tabellini (2000). We assume that labeling policies are decided under the influence of pressure groups and public opinion. Depending on the constitutional system, countries may allocate more weight to certain pressure groups, to voters, or to neither of these and make an arbitrary decision.

Our mixed model combines the effects of voters and electoral pressure and the effects of political and financial contributions of pressure groups. To do so, we assume that voters and pressure groups contribute to the result in vote equivalents. Most democratic countries need to submit a labeling policy to a parliament or a council, and obtain a majority vote. For instance, if the whole population is against a new measure, but some pressure groups are effectively campaigning in favor of it, the result may be measured in the number of votes at the parliamentary level.

We separate the stakeholders into three aggregate groups: farmers and producer lobbies noted $P$, voting consumers reflecting public opinion noted $C$, and other pressure groups from civil society $O$ (such as consumer unions and green parties). Each of these specific groups is allocated a weight $\alpha_s \geq 0$, $s \in \{P, C, O\}$, and the total sum of weights is equal to one: $\alpha_P + \alpha_C + \alpha_O = 1$. These weights depend on the political regimes and constitutions and the political orientations in each country but they may also depend on political contributions (bribes) of each group.

In each group $s$, an individual voting member $i$ prefers mandatory labeling ($ML$) to no labeling ($NL$) if and only if: $W^s(ML) \geq W^s(NL) + \sigma_i$, where $W^s(\cdot)$ is the welfare function associated with a labeling policy, and $\sigma_i$ is an idiosyncratic parameter representing voter $i$’s belief. For simplicity we assume that $\sigma_i$ is drawn from a uniform distribution, over a range centered on zero, i.e. $\sigma_i \sim U[-1/(2\phi^c), 1/(2\phi^c)]$ (with $\phi^c > 0$). In each group, the indifferent member (or swing voter) is defined by the parameter $\sigma_i$ such that $\sigma_i < \sigma$ prefers mandatory labeling, and conversely any individual voter $j$ such that $\sigma_j > \sigma$ opposes mandatory labeling.
Each group determines its position according to a vote. The intensity of the message delivered by each group depends on the proportion of its members approving it. This proposition reflects the classical result of Olson (1965)—organized groups will be more effective at pressuring governments. The adoption decision by policymakers will be made according to the weighted sum of support of each group (in vote equivalents). We compute the probability of voting or the proportion of vote equivalents for mandatory labeling as: \( V(ML) = \Sigma \alpha' F(\sigma') \) where \( F(\cdot) \) is the cumulative distribution function (c.d.f.) of \( \sigma \). Substituting the Uniform distribution into the c.d.f. gives:

\[
V(ML) = \sum \alpha' \varphi' (\sigma' + 1/(2\varphi')) = \frac{1}{2} + \sum \alpha' \varphi' \sigma'.
\] (1)

To obtain a majority of vote equivalents for mandatory labeling, the second term has to be positive: \( \Sigma \alpha' \varphi' \sigma' \geq 0 \). According to this proportional model, three factors affect the decision of a country to adopt mandatory labeling: the weight given to each group in the final decision (\( \alpha' \)), the degree of homogeneity (also defined as the responsiveness) in each group (\( \varphi' \)), and the welfare change associated with the new policy for each group (\( \sigma' \)).

To derive consumer welfare changes with labeling (\( \sigma' \)), we use an adaptation of the classical vertical differentiation model of Mussa and Rosen (1978), applied to two distinct groups of consumers. We assume that in any country a share \( \beta_1 \) of consumers trust government regulations on GM food and only see a quality difference with a change in label (i.e. they are noted trusting consumers). In contrast, distrusting consumers (with share \( \beta_2 = 1 - \beta_1 \) of consumers) are using their own ways to obtain information on GM food, and tend to be cautious in their purchase of food.\(^5\)

The indirect utility \( V_{kj} \) of an individual \( j \) for a product of variant \( k = g, n \) (GM or non-GM)\(^6\) is defined as:

\[
V_{kj} = a - p_k + \Psi_k(\lambda) \theta_j + I_{ml}(u, -T),
\] (2)

where \( a \) is the basic utility from consuming the good, \( p_k \) is the price of variant \( k \) (GM or non-GM); the expression \( \Psi_k(\lambda) \theta_j \) represents the utility shifter for the quality component of the product, \( I_{ml} \) is an indicator variable equal to one under mandatory labeling, zero otherwise; \( u \) represents the indirect utility of product variety in the presence of labeling;\(^7\) and \( T \) is the tax imposed with labeling.\(^8\)

The function \( \Psi_k(\lambda) \) stands for the overall perception of the quality of the product, and it is the same across all consumers in a given country. \( \lambda \) can be interpreted as the maximum willingness to pay for the absence of GM.\(^9\) The quality component captures the perception of both human health effects and the environmental impacts of GM food production. \( \Psi_k(\lambda) \) is defined based on the type of consumer as shown in Table 1. For distrusting consumers, \( \Psi_k(\lambda) = \lambda > 0 \) for the non-GM variant and \( \Psi_k(\lambda) = -\lambda \) for the

**Table 1. Quality Function \( \Psi_k(\lambda) \) for Trusting and Distrusting Consumers**

<table>
<thead>
<tr>
<th>Product</th>
<th>Trusting</th>
<th>Distrusting</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GM</td>
<td>Non-GM</td>
</tr>
<tr>
<td>No labeling</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mandatory (“Contains GM”)</td>
<td>-( \lambda )</td>
<td>0</td>
</tr>
</tbody>
</table>
GM variant, regardless of the absence or presence of labeling. In contrast, trusting consumers make an informed choice according to the label and do not see non-GM as superior if it is not indicated on the label. Finally, $\theta_j$ is the idiosyncratic consumer preference. It represents the taste parameter of each consumer $j$ in the population. Consumers with $\theta_j = 0$ are indifferent to the GM/non-GM quality dimension, and consumers with $\theta_j = 1$ are anti-GM. For simplicity, we use a uniform distribution of tastes over $[0, 1]$.

The share of consumers purchasing GM is obtained by setting the utility of consuming GM equal to that of those consuming non-GM and obtaining the shifting parameter $\theta^{GM}$. The welfare effects are derived as the integral of the utility function for all GM or non-GM consumers. Derivations are shown in the Appendix. Under no labeling, a product is sold at a unique price $p_0$; with mandatory labeling, the market is segregated into GM (or potentially GM) products with price $p_g$ and pure non-GM products with price $p_n$. Because GM products are seen as lower quality, the burden of proof is on the non-GM producers, and we assume that $p_g \leq p_0 \leq p_n$. The complete utility expressions under no labeling (variables with superscript 0) and for GM and non-GM consumers under labeling (with superscripts GM and NGM) are shown in the Appendix.

The change in consumer welfare with labeling is defined as $\Delta U = (U^{GM} + U^{NGM}) - U^0$. By replacing these utilities with their complete expressions (see the Appendix), we find that $\Delta U > 0$ if and only if $2\beta_\lambda + u_\lambda > T + (p_n - p_0) + (1 - \Theta)(p_g - p_\beta)$, where $\Theta$ is the total share of consumers purchasing the GM product. This inequality balances the benefits of labeling for distrust ing consumers ($\beta_\lambda$) and the utility associated with a new product ($u_\lambda$), on the one hand, with the costs of labeling, represented by the tax rate ($T$), the difference between the old and new price for non-GM ($p_n - p_0$), and the new premium for non-GM ($p_n - p_g$) applied to non-GM consumers $(1 - \Theta)$, on the other. We also find that the change in consumer welfare will increase with the share of distrust ing consumers ($\partial \Delta U / \partial \beta_\lambda$) $\geq 0$, and that it will also increase with the maximum willingness to pay for non-GM ($\partial \Delta U / \partial \lambda$) $\geq 0$ as long as $\beta_\lambda \geq 0.4$ (see the Appendix).

Therefore, in countries that have a small share of distrust ing consumers ($\beta_\lambda \leq 0.4$), with low GM concerns ($\lambda$ small), a high aversion to taxes, and whose market is already covered with GM products (resulting in $p_0 \approx p_g$ but a large difference between $p_n$ and $p_0$), such as the United States, the swing-voting consumer will likely be indifferent or opposed to labeling (i.e. $\sigma^C \leq 0$). In contrast, in countries with a majority of distrust ing consumers ($\beta_\lambda \geq 0.4$), high GM concerns (relatively high $\lambda$), that especially value quality and a large share of non-GM consumers, with a market largely covered with non-GM ($p_0 \approx p_n$), like countries in the EU, the swing-voting consumer will prefer mandatory labeling (i.e. $\sigma^C > 0$).

On the producer side, we define welfare changes as expected profit changes. Profits are defined as $\Pi_k = pQ - c_k(Q)Q$, where $p$ and $Q$ are the prices and quantities, and $c_k(\cdot)$ is the unit cost function for variant $k$. We assume that the unit cost functions are differentiable and nondecreasing in $Q$ and that GM food is produced at a lower unit cost, i.e. for all $Q$ positive, $c'_g(Q) < c'_n(Q)$. With labeling, a fixed cost $FC_{ml}$ is subtracted from the profits, and we also include a variable cost of segregation for non-GM producers ($c_{ml} > 0$) under labeling. We distinguish three groups of producers, GM producers, non-GM producers, and GM producers switching to non-GM and then obtain their relative profit changes with labeling (see the Appendix). Assuming that the expected market share of GM will decrease in favor of non-GM ($Q_{0, g} \geq Q_{0, n}$), due to the expected hazard warning effect of GM labeling, we conclude that: $\Delta \Pi_{GM} \leq 0$ and that:

$$\Delta \Pi_{NGM} > 0 \Leftrightarrow c_{ml}Q_n + FC_{ml} < c'_g(Q_n)Q_n^2 - c'_n(Q_{0, n})Q_{0, n}^2,$$

(3)
Table 2 summarizes these results for five producer types. Domestic producers or exporters of GM products will oppose mandatory labeling. Domestic producers of non-GM products will support labeling if it does not result in substantial additional segregation costs. Exporters of non-GM, selling to countries with mandatory labeling, and that have already set up a segregation system (therefore $FC_{ml} = 0, c_{ml} = 0$) will benefit from a larger market share domestically. Domestic producers that are under political pressure or with low segregation costs may decide to switch to non-GM with labeling, but they will not necessarily be better off with mandatory labeling.

Using this framework, and with qualitative assumptions on the respective political weights and group homogeneities, we can compare the predictions of our model with the actual policies in major democratic countries. The EU confers power to three types of constituents, but the representation in Brussels tends to distort policies towards well-represented groups, so we can assume that $\alpha^p = \alpha^o \geq \alpha^c$. Producers are better organized than the other two groups, so the likely ranking of responsiveness will be $\phi^p \geq \phi^o \geq \phi^c$. Finally, as explained above, most EU producers are producing non-GM, most consumers are distrusting and hostile to GM, and civil groups are unanimously opposed to GM. Therefore, it is likely that $\sigma^o > \sigma^c > \sigma^p \geq 0$. Since all three groups are in favor of mandatory labeling, $\Sigma \alpha^i \phi^i \sigma^i \geq 0$, the model predicts that the EU will support mandatory labeling.

In the case of the United States, GM producer groups are largely represented and they will lobby against labeling regulations. US producers tend to play an important role in market regulations, more than civil groups or voters. As shown above, consumers will weakly oppose or be indifferent to labeling. Overall, it is reasonable to assume that: $\alpha^p \geq \alpha^o \geq \alpha^c$, $\sigma^o \geq \sigma^c = 0 \geq \sigma^p$ and $\phi^p \geq \phi^o \geq \phi^c$. Thus, mandatory labeling will be adopted only if $|\alpha^o \phi^o \sigma^o| > |\alpha^p \phi^p \sigma^p|$, which would only happen with a very large welfare effect $\sigma^o$. It is probable that the status quo will remain in place for as long as the agro-food industry favors it and the general public does not consider labeling a priority.\textsuperscript{12}

This model also shows how certain pressure groups can act to minimize the probability of adoption of GM crops. They can influence the allocation of political weights by monetary contributions or political representation and they can also try to affect the position of other groups. In the United States, green anti-GM groups coordinate their actions with organic producers (which tends to divide the producer lobbies), urge large food processors and retailers to take positions on GM food and labeling, and help conduct campaigns to obtain referendums on GM food labeling or GM production moratoriums. In the EU, anti-GM pressure groups maintain public support by publishing leaflets underlining the importance of the consumer right to know, and by coordinating their efforts with certain political parties and anti-corporate farm lobbies.

Table 2. Marginal Changes in Revenues, Costs, and Profit with Mandatory Labeling

<table>
<thead>
<tr>
<th>Producer categories</th>
<th>Revenues</th>
<th>Costs</th>
<th>Overall changes in profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>GM domestic producers</td>
<td>$\leq 0$</td>
<td>$\geq 0$</td>
<td>$\leq 0$</td>
</tr>
<tr>
<td>Non-GM domestic producers</td>
<td>$&gt; 0$</td>
<td>$\geq 0$</td>
<td>$\geq 0$ or $\leq 0$</td>
</tr>
<tr>
<td>GM exporters</td>
<td>$\leq 0$</td>
<td>$\geq 0$</td>
<td>$\leq 0$</td>
</tr>
<tr>
<td>Non-GM exporters</td>
<td>$\geq 0$</td>
<td>$\leq 0$ or $\geq 0$</td>
<td>$\geq 0$ or $\leq 0$</td>
</tr>
<tr>
<td>Switching domestic producers</td>
<td>$\geq 0$</td>
<td>$\geq 0$</td>
<td>$\geq 0$ or $\leq 0$</td>
</tr>
</tbody>
</table>

Source: Authors’ derivations; see the Appendix for details.

\[
\Delta \Pi^{SW} > 0 \iff c_{ml}Q_n + FC_{ml} < c'_{g}(Q_n)Q_n^2 - c'_{g}(Q_{0,g})Q_{0,g}^2. \tag{4}
\]
All three groups have some influence over the final decision, but it is likely that producer lobbies constitute the most politically powerful group in most countries. Consumers seem to be generally supportive of mandatory labeling in most countries surveyed, even if many surveys tend to ask for their opinion on labeling without providing any information on its potential costs. In contrast, producers may either support or oppose mandatory labeling depending on how it affects their profits (see Table 2 and discussion). If they support it, it is likely that their countries will adopt mandatory labeling. If they are opposed to mandatory labeling, then all will depend on the political weights of the three constituencies.

Our analytical framework highlights the importance of production-related factors, which may be the main drivers behind mandatory labeling policies, depending on the domestic use of GM crops and the export markets. However, this model simplifies the political process and it may not be able to predict the behavior of countries with very different political systems. As a result of these differences, certain countries may have chosen a strict policy with no observable advantage for producers or consumers. We will now turn to an empirical investigation of labeling policies to test these predictions.

3. The Data

We have gathered data on GM food labeling regulations for 108 selected countries presented in Table 3, as of 2004. The data come from various sources, including the US Department of Agriculture, Foreign Agricultural Service, Attaché Reports, and a number of other reports (Carter and Gruère, 2003; Richey, 2003; Haigh, 2004; Kochenderfer, 2004; Rao, 2004). We include countries with labeling policies, countries without labeling regulations but who are producing GM crops, and countries considering the introduction of a labeling policy. We treat the EU as a block of 15 countries (before May 2004), but exclude Germany and Spain, which are treated separately as the only two EU countries producing GM crops as of 2004.

We divide the countries into three categories depending on their labeling policies, and define the indicator variable $\text{TYP}$ as follows: $\text{TYP} = 0$ for countries with no labeling regulations or guidelines, $\text{TYP} = 1$ for countries with voluntary labeling, and $\text{TYP} = 2$ for countries with mandatory labeling. The regulatory variables include the threshold level for adventitious presence of GM ingredients ($\text{TOL}$, in percent), whether the regulation includes feed ($\text{FEED}$), meat ($\text{MEAT}$), additives ($\text{ADD}$), and flavoring ($\text{FLV}$), whether labeling is applied to restaurants ($\text{REST}$), and products derived from GM ingredients but without any detectable trace of the transgenic DNA ($\text{DER}$), and a dummy variable equal to 1 if the country has enforced its regulation as of April 2004 ($\text{ENF}$). We also construct a discrete variable representing the number of ingredients subject to the adventitious presence threshold ($\text{ING}$). This variable takes on the value 15 if all ingredients must be labeled, 0 if no ingredients are subject to the requirements, or the number of major ingredients subject to regulation.

On the production side, we use data from the Food and Agriculture Organization (FAO) database and International Service for the Acquisition of Agri-biotech Applications (ISAAA) publications on GM and total acreage of the four major GM crops (corn, soybeans, cotton, and canola) for 1999, 2000, 2001, and 2002. We use these data to compute the average share of transgenic crops among these four crops in each country and three aggregate measures of these shares: the total share of GM ($\text{SGM}$), the total share of all crops but cotton ($\text{SGMNT}$).

To represent trade variables, we collected import and export quantities for the four GM crops for 1999, 2000, and 2001, and bilateral trade quantities for corn between
### Table 3. Countries Included in the Study and their GM Labeling Policy Status as of April 2004

<table>
<thead>
<tr>
<th>Region</th>
<th>Countries with GM labeling (voluntary or mandatory)</th>
<th>Countries considering GM labeling</th>
<th>Countries with no labeling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Africa</td>
<td>Mauritius, <strong>South Africa</strong></td>
<td>Cameroon, Ethiopia, Ivory Coast,</td>
<td>Algeria, Angola, Benin, Botswana,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Namibia, Sudan, Zambia</td>
<td>Burkina-Faso, Central Africa, Chad, Congo, Congo DR, Egypt, Gambia, Ghana, Guinea, Kenya, Libya, Madagascar, Malawi, Mali, Morocco, Mozambique, Niger, Nigeria, Senegal, Syria, Tanzania, Togo, Tunisia, Uganda, Zimbabwe</td>
</tr>
<tr>
<td>Asia</td>
<td><strong>China</strong>, Japan, Hong Kong, Indonesia, <strong>Philippines</strong>, South Korea, Taiwan, Thailand, Vietnam</td>
<td><strong>India</strong>, Malaysia, Singapore</td>
<td>Bangladesh, Bhutan, Cambodia, Kazakhstan, Myanmar, Nepal, North Korea, Pakistan, Papua New Guinea, Sri Lanka, Uzbekistan</td>
</tr>
<tr>
<td>Europe</td>
<td><strong>European Union</strong>, Croatia, Czech Republic, <strong>Germany</strong>, Hungary, Norway, Poland, Russia, Serbia, <strong>Spain</strong>, Switzerland</td>
<td>Georgia</td>
<td>Albania, Belarus, Bulgaria, Iceland, Macedonia, <strong>Romania</strong>, Turkey, Ukraine</td>
</tr>
<tr>
<td>Middle East</td>
<td>Saudi Arabia</td>
<td>Israel, United Arab Emirates</td>
<td>Iran, Jordan, Oman, Yemen</td>
</tr>
<tr>
<td>North America</td>
<td><strong>Canada</strong>, <strong>United States</strong></td>
<td>Mexico</td>
<td>Colombia, Costa Rica, Cuba, El Salvador, Guatemala, Honduras, Panama, Paraguay, Peru, <strong>Uruguay</strong>, Venezuela</td>
</tr>
<tr>
<td>South America</td>
<td><strong>Argentina</strong>, <strong>Brazil</strong>, Chile</td>
<td>Bolivia, Ecuador</td>
<td></td>
</tr>
<tr>
<td>Oceania</td>
<td><strong>Australia</strong>, New Zealand</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Countries that produced one or more GM crops as of 2004 are in boldface.

**Sources:** US Department of Agriculture Foreign Agricultural Service Attaché Reports; other sources described in section 3.
these countries and Japan and the European Union (15 countries), from the United Nations FAOSTAT database. We also added data on the quantity of exports of soybeans, canola, and cotton (at the four-digit ITC level) from each country to the EU in 1999, 2000, and 2001, from the Eurostat database. We use these data to derive the average trade balances (from years 1999, 2000, and 2001) for cotton ($Tr^C$) and for the sum each of the other three crops ($Tr^{NT}$), both in billion metric tons. We also compute the share of corn exports from each country to Japan ($XJ^C$) and the average share of exports of the four crops to the EU ($XE^C, XE^S, XE^T, XE^{NT}$) for 1999, 2000, and 2001. The variable $XE^{NT}$ is the sum of export shares of the three food or feed crops to the EU. We use the US Department of Agriculture statistical database to determine the share of exports of corn, soybeans, and cotton from the United States to each importer ($MU^{CST}$).

In addition, we have data on the share of agricultural imports in total merchandise imports ($Agshimp$) and on the share of exports in total merchandise exports ($Agshexp$) for each country, published by the World Trade Organization (WTO) in 1999. We use average trade balances of agricultural chemicals—pesticides, insecticides, and herbicides in 1999, 2000, and 2001—from the FAO database (in $100 million). We add these three variables to obtain the total net trade balance of agricultural chemicals ($Chem$). We also include the usage of fertilizers ($Fert$, expressed as 10,000 kg/ha of arable land).

For political factors, we use qualitative data on the level of participation in the Cartagena Protocol on Biosafety (CPB)—not signed, signed, or ratified (CPB)—and the presence of the active environmental campaigns of Greenpeace and Friends of the Earth against transgenic crops, obtained from their websites in 2003 ($Green$). We also add the Human Development Index ($HDI$) developed by the United Nations Development Program. We set up a proxy variable for the consumer acceptance of GM food ($WTB$), using various international surveys published in the literature, by computing a weighted average share of the population’s willingness to buy GM food. Countries without consumer survey data are assigned the average value of all other countries in the sample. We add macroeconomic measurements of per capita GDP in 2003 ($pGDP$ in $10,000), annual percentage GDP growth from 2000 to 2002 (from the Economist Intelligent Unit and the IMF development indicators, noted $Grwth$), and the share of agriculture in total GDP ($AG$). Lastly, we use dummy variables to represent different regions in the world (e.g. $ASI$ for Asia, $SAM$ for South America, and $EUN$ for the EU).

4. Regression Analysis

Discrete Choice Approach: Type of Labeling Policy

We first model the labeling decision as a choice between three alternative regimes: no labeling, voluntary labeling, and mandatory labeling. We use a multinomial logit model, with the option of no labeling as default. Let $j$ be the index of labeling type, equal to one under no labeling, equal to two under mandatory labeling, and to three under voluntary labeling. Suppose $z_{ij}$ is a variable equal to one if country $i$ chooses policy $j$. The probability of country $i$ opting for alternative $j$ is defined as: $\pi_{ij} = \frac{e^{X_i\beta_j}}{\sum_j e^{X_i\beta_j}}$, where $X_i$ is the vector of regressors for individual $i$ and $\beta_j$ is the vector of coefficients under alternative $j$. The coefficient for alternative $j = 1$ (no labeling policy) is restricted to be equal to zero so that the probabilities for the three alternatives sum to one. The log-likelihood function, which is maximized, is defined as: $LL = \sum_i \sum_j z_{ij} \ln \pi_{ij}$. 

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We present the regression results on past and recent labeling decisions (dependent variable \( TYP \)) with all countries, and then run the regressions without the three potential outliers (the EU, the United States, and Japan). In each case, we present two alternative multinomial logit regressions, based on two different sets of independent variables. The results are shown in Table 4. Regression 1 includes variables on agricultural production and trade, economics, and political factors. Regression 2 combines other variables representing mainly political and economic factors.

First, the variables representing the share of GM crops (\( SGM \)), the trade balance in the four crops (\( Tr \)), and the trade balance in chemicals (\( Chem \)), increase the probability of opting for a voluntary labeling policy. At the same time, the variables \( Agshimp \), \( Grwth \), and \( XET \) are negatively correlated with this probability. We also observe a U-shaped relationship between the adoption of voluntary labeling and per capita income.

Secondly, the probability of implementing a mandatory labeling policy increases with the variables representing the share of exports of the three food and feed crops to the EU (\( XENT \)), the share of corn exports to Japan (\( XF \)), and the share of GM cotton production (\( SGMT \)). Moreover, the coefficient on \( WTB \) is negative and significant. Countries exporting GM food and feed crops to the EU and Japan, who produce GM cotton, and have a lower consumer acceptance, are more likely to have adopted mandatory labeling policies as opposed to voluntary labeling.

Thirdly, for these two regressions, the variables indicating the presence of a green campaign (\( Green \)) and a higher level of human development (\( HDI \)) are positively correlated with the adoption of some form of labeling. The variables representing the agricultural share of GDP (\( AG \)), CPB participation, and the share of agricultural exports in total merchandise exports (\( Agshexp \)), decrease the probability of introducing labeling. Less-developed countries, with no green campaign, but who are members of the CPB, with rural economies, and with a large agricultural share of exports in total merchandise exports, are less likely to have adopted any labeling policy.

In comparison, when we omit the three outlying countries (Regressions 3 and 4), we find just a few differences among significant factors. In the case of voluntary labeling, we find that the growth factor (\( Grwth \)) is no longer significant, whereas the coefficient on the share of GM cotton (\( SGMT \)) becomes negative and significant. For mandatory labeling, the coefficient on the share of exports of the food crops to the EU (\( XENT \)) is no longer significant, whereas the coefficient on the trade balance in chemicals (\( Chem \)) becomes negative and significant. These four variables are partially driven by the outliers in the comparison of the three types of labeling.

Characteristics of the Labeling Regulations

We define an index representing the degree of strictness of labeling policies:

\[
I^{LB}_{BL} = \left( TYP + \frac{LTR}{2} \right) \left( 1 + \frac{ENF}{2} \right) \left( 1 + \frac{FEED + MEAT + DER}{REST + ADD + FLV} \right) \left( 1 - \frac{TOL \times 100 \times \frac{ING}{15}}{2} \right).
\]

To avoid making China an outlier, we use a standardized version of \( I^{LB}_{BL} \), called \( LBL \).

With this index, we have set up three variables to represent the main characteristics of labeling policies: the number of ingredients that must be labeled (\( ING \)), the tolerance level (\( TOL \)), and the labeling index (\( LBL \)). Because many countries do not have
Table 4. Estimated Coefficients: Multinomial Logit Regressions on the Type of Labeling (TYP)

<table>
<thead>
<tr>
<th>Variables</th>
<th>All countries</th>
<th>Without EU, US, and Japan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Regression 1</td>
<td>Regression 2</td>
</tr>
<tr>
<td></td>
<td>Voluntary</td>
<td>Mandatory</td>
</tr>
<tr>
<td>SGM</td>
<td>17.62***</td>
<td>0.91</td>
</tr>
<tr>
<td>Tr</td>
<td>6.7***</td>
<td>0.16</td>
</tr>
<tr>
<td>$XE^{NT}$</td>
<td>0.95</td>
<td>1.07**</td>
</tr>
<tr>
<td>$XE^T$</td>
<td>−451.1***</td>
<td>−1.44</td>
</tr>
<tr>
<td>$XC^I$</td>
<td>−19.22</td>
<td>14.6**</td>
</tr>
<tr>
<td>Green</td>
<td>8.0***</td>
<td>2.74***</td>
</tr>
<tr>
<td>Agshexp</td>
<td>−32.26***</td>
<td>−6.11***</td>
</tr>
<tr>
<td>Chem</td>
<td>3.3**</td>
<td>−0.045</td>
</tr>
<tr>
<td>CPB</td>
<td>−9.38**</td>
<td>−1.07**</td>
</tr>
<tr>
<td>AG</td>
<td>−109.7**</td>
<td>−10.93**</td>
</tr>
<tr>
<td>Growth</td>
<td>−166.8*</td>
<td>5.83</td>
</tr>
<tr>
<td>Agshimp</td>
<td>−249.1***</td>
<td>−11.70</td>
</tr>
<tr>
<td>$MU^{CT}$</td>
<td>−0.45</td>
<td>0.41</td>
</tr>
<tr>
<td>HDI</td>
<td>236.9**</td>
<td>16.23***</td>
</tr>
<tr>
<td>WTB</td>
<td>33.58</td>
<td>−108.9***</td>
</tr>
<tr>
<td>pGDP</td>
<td>−38.0**</td>
<td>−4.2**</td>
</tr>
<tr>
<td>pGDP$^2$</td>
<td>7.7**</td>
<td>0.88</td>
</tr>
<tr>
<td>SGM$^T$</td>
<td>34.58</td>
<td>65.84***</td>
</tr>
<tr>
<td>Constant</td>
<td>−6.41***</td>
<td>−2.26***</td>
</tr>
<tr>
<td>Pseudo-$R^2$</td>
<td><strong>0.61</strong></td>
<td><strong>0.55</strong></td>
</tr>
</tbody>
</table>

Note: * 10%, ** 5%, *** 1% level of statistical significance.
labeling policies, their values for these three variables are set equal to a default value. These variables can be considered censored dependent variables, because it is only possible to observe the value of the tolerance level or the number of included ingredients for countries that have a labeling policy. In each case, the observed censored dependent variable \( y \) is equal to its default value or to a defined latent variable noted as \( y^* \). In the case of the number of ingredients, the default value is equal to zero, so \( y = \max\{0, y^*\} \). In this case, the density \( f(\cdot) \) of the observed variable can be written as
\[
f(y) = f^*(y)^b \cdot F^*(0)^{1-b}
\]
where \( f^*(\cdot) \) and \( F^*(\cdot) \) are the density function and the cumulative density function of \( y^* \), respectively, and \( b = 1 \) if and only if \( y > 0 \) , and \( b = 0 \) otherwise. The case of the labeling index uses its minimum as a default value, and the case of the tolerance level is symmetrical with a maximum default value. We use maximum likelihood to obtain the tobit estimations, assuming that the latent variables are normally distributed.

We first run censored regressions on the number of ingredients that must be labeled. The results of the tobit estimations are shown in the second column (Regression 5) in Table 5. We find that the coefficients on the share of GM food crops \( SGM^N \), the trade balance in cotton \( Tr^T \), the share of exports of cotton to the EU \( XE^T \), CPB participation, and fertilizer use \( Fert \) are negative and significant. Thus, countries producing GM crops, cotton exporters, or countries with a large share of cotton exports to the EU, signatories of the CPB, or countries with intensive use of fertilizer, are more likely to

<table>
<thead>
<tr>
<th>Variables</th>
<th>Regression 5 on ING</th>
<th>Regression 6 on TOL</th>
<th>Regression 7 on LBL</th>
</tr>
</thead>
<tbody>
<tr>
<td>( SGM^N )</td>
<td>(-23.9*** (9.1))</td>
<td>(5.4* (3.2))</td>
<td>(-0.6*** (0.1))</td>
</tr>
<tr>
<td>( XE^S )</td>
<td>(-0.7 (7.0))</td>
<td>(-5.2 (3.6))</td>
<td>(0.3** (0.1))</td>
</tr>
<tr>
<td>( XE^C )</td>
<td>(-7.6 (8.0))</td>
<td>(1.0 (3.3))</td>
<td>(-0.3 (0.2))</td>
</tr>
<tr>
<td>( XE^LA )</td>
<td>(20.1*** (7.3))</td>
<td>(-5.3 (3.6))</td>
<td>(0.2 (0.2))</td>
</tr>
<tr>
<td>( XE^T )</td>
<td>(-13.2* (7.9))</td>
<td>(0.3 (3.1))</td>
<td>(-0.2 (0.2))</td>
</tr>
<tr>
<td>( XF^C )</td>
<td>(5.8 (19.6))</td>
<td>(-39.5*** (14))</td>
<td>(-0.1 (0.4))</td>
</tr>
<tr>
<td>( Tr^N )</td>
<td>(1.7 (1.3))</td>
<td>(-0.2 (0.7))</td>
<td>(0.034 (0.026))</td>
</tr>
<tr>
<td>( Tr^T )</td>
<td>(-31*** (10))</td>
<td>(14** (5.7))</td>
<td>(-0.66*** (0.2))</td>
</tr>
<tr>
<td>( Green )</td>
<td>(8.5** (3.6))</td>
<td>(-1.3 (1.5))</td>
<td>(0.3*** (0.06))</td>
</tr>
<tr>
<td>( pGDP )</td>
<td>(6.9 (8.3))</td>
<td>(-12.6** (4.9))</td>
<td>(0.91 (0.17))</td>
</tr>
<tr>
<td>( pGDP^2 )</td>
<td>(-1.1 (2.5))</td>
<td>(3.0** (1.4))</td>
<td>(0.03 (0.05))</td>
</tr>
<tr>
<td>( AG )</td>
<td>(-24.0 (22.6))</td>
<td>(-1.8 (7.9))</td>
<td>(-0.2 (0.3))</td>
</tr>
<tr>
<td>( CPB )</td>
<td>(-5.5** (2.7))</td>
<td>(1.0 (1.0))</td>
<td>(-0.1*** (0.04))</td>
</tr>
<tr>
<td>( Growth )</td>
<td>(274.3** (107.3))</td>
<td>(-46.9 (36.2))</td>
<td>(2.0 (1.3))</td>
</tr>
<tr>
<td>( Agshexp )</td>
<td>(-7.4 (12.8))</td>
<td>(-4.9 (3.7))</td>
<td>(0.04 (0.2))</td>
</tr>
<tr>
<td>( Agshimp )</td>
<td>(-33.8 (30.1))</td>
<td>(22.4* (12.7))</td>
<td>(-0.3 (0.5))</td>
</tr>
<tr>
<td>( Fert )</td>
<td>(-6.5* (3.3))</td>
<td>(12.3* (6.5))</td>
<td>(-0.2* (0.11))</td>
</tr>
<tr>
<td>( Chem )</td>
<td>(-140 (1100))</td>
<td>(276 (679))</td>
<td>(-18 (27))</td>
</tr>
<tr>
<td>( WTB )</td>
<td>(-6.0 (137.4))</td>
<td>(36.8 (79.4))</td>
<td>(4.1 (3.2))</td>
</tr>
<tr>
<td>( EUN )</td>
<td>(-1.3 (17.3))</td>
<td>(10.0 (9.7))</td>
<td>(3.8*** (0.4))</td>
</tr>
<tr>
<td>( SAM )</td>
<td>(-14.9** (7.0))</td>
<td>(2.1 (2.2))</td>
<td>(-0.07 (0.1))</td>
</tr>
<tr>
<td>( ASI )</td>
<td>(-15.1*** (5.5))</td>
<td>(9.5** (3.6))</td>
<td>(-0.3*** (0.1))</td>
</tr>
<tr>
<td>( China )</td>
<td>(10.5 (51.7))</td>
<td>(-29.9 (31.0))</td>
<td>(6.9*** (1.2))</td>
</tr>
<tr>
<td>Constant</td>
<td>(1.85 (59.3))</td>
<td>(-2.5 (33.7))</td>
<td>(-2.0 (1.4))</td>
</tr>
<tr>
<td>Pseudo-( R^2 )</td>
<td>(0.31)</td>
<td>(0.24)</td>
<td>(0.91)</td>
</tr>
</tbody>
</table>

Note: * 10% level, ** 5%, *** 1% level of statistical significance.
require labeling on fewer ingredients. In contrast, we find that the coefficients on the share of exports of canola to the EU ($X_{ELA}^L$), the presence of anti-GM green campaign ($Green$), and the average economic growth ($Growth$) are positive and significant. So countries that export canola mostly to the EU, countries with positive growth, or with green campaigns tend to have more comprehensive ingredient requirements.

These results confirm that cotton exporters tend to use less comprehensive labeling policies. As expected, producers of GM crops do not have stringent labeling policies, and green campaign groups are more present in countries with stringent labeling policies. Members of the CPB do not have stringent policies, probably because they use the Protocol as a safeguard regulation. As for economic growth and fertilizer use, transition countries tend to have stringent labeling policies, whereas countries with intensive agriculture may be more prone to have less stringent regulations on biotechnology. Lastly, the dummy variables on Asia ($AS$) and South America ($SAM$) are negative and significant, which shows that these two regions tend to have less comprehensive labeling regulations.

We use the tolerance level as a second characteristic of labeling policies. The results are reported in the third column of Table 5 (Regression 6). We find that the coefficients on the share of GM food crops ($SGMNT$), the cotton trade balance ($Tr^C$), the share of agriculture in total merchandise imports ($Agshimp$), and the use of fertilizer ($Fert$) are positive and significant. Producers of GM crops and exporters of cotton use more pragmatic tolerance levels. Countries that import a relatively large quantity of agricultural products may prefer to have a high tolerance level, to avoid increasing the consumer price of agricultural commodities. As mentioned before, countries with intensive agriculture may prefer less stringent policies on GM crops.

On the other hand, the coefficient on the share of exports of corn to Japan ($X_{Jc}^L$) is negative and significant. This result suggests that countries that export corn mainly to Japan will use low tolerance levels. Japan uses a relatively high tolerance level but most food processors are avoiding GM food ingredients in food products covered by the labeling requirements and many of them use GM-free claims as a marketing strategy. The use of low tolerance levels may be intended to support exporters to signal the existence of stringent segregation systems compatible with the countries of export.

The estimated coefficient on per capita income is negative and significant, but the coefficient on income squared is positive and significant, suggesting a U-shaped relationship between tolerance level and income level. High- and low-income countries tend to use relatively high tolerance levels, and intermediary countries may use low tolerance levels, but it is difficult to generalize this relationship without examining the boundaries of these three segments. The dummy on Asia is positive and significant, which confirms the regional homogeneity of labeling characteristics in Asia (mandatory labeling and high tolerance level).

As a third and last characteristic, we use the labeling index $LBL$ (Regression 7 in Table 5). We find that the coefficients on the share of exports of soybeans to the EU ($X_{E}^L$), and the presence of anti-GM green campaigns ($Green$) are positive and significant. Thus, countries with the highest index of strictness tend to be relatively large exporters of soybeans to the EU, or have a green campaign. Once again, the interpretation of these main results is the fact that exporters may think that they will benefit from more stringent labeling policies.

In contrast, the coefficients on the share of GM food crops ($SGMNT^L$), the trade balance of cotton ($Tr^C$), membership in the CPB, and the use of fertilizers ($Fert$) are negative and significant. Countries producing GM crops, exporting cotton, with inten-
sive agriculture or CPB members use less stringent and less costly labeling regulations. These results are parallel to those found for the number of ingredients.

5. Conclusions

Many countries have implemented labeling regimes for genetically modified (GM) food and the regulations vary considerably across countries. In this paper, we conducted a cross-national comparison of GM food labeling regulations, to explain why some countries choose to label, and why they opt for a specific labeling regime.

We introduced an analytical framework to explain the adoption of mandatory labeling policies. Our political-economic model accounts for three interest groups: producers, consumers/voters, and civil groups. Three types of parameters affect the adoption decision: the weight of each interest group in vote equivalents, the degree of support for labeling within each group, and the expected welfare change associated with mandatory labeling in each group. This model helps explain the opposite choice in labeling policies made by the United States and the European Union. It also predicts that production and trade factors are likely to have played an essential role in the decision to adopt labeling requirements in other countries.

In our empirical application, we considered three possible explanations for GM labeling policies: domestic political factors (consumer and producer preferences), international trade factors (trade dependency and trade relationships), and macroeconomic factors (income, importance of agriculture). Based on a cross-national dataset of 108 countries, we found that countries labeling GM food are usually more developed, and less dependent on agriculture. Furthermore, countries that did not adopt any labeling policy tend to be ratifying parties to the Cartagena Protocol on Biosafety, and do not have active green nongovernmental organizations (NGOs) sponsoring in-country anti-GM campaigns.

In addition, we found that some political and trade variables help explain labeling options. On the one hand, countries producing GM crops or exporting these crops in general tend to adopt more pragmatic and less costly labeling policies. On the other hand, countries with low consumer acceptance, exporting soybeans, corn, or canola mainly to the EU or corn mainly to Japan, are more likely to mandate the labeling of GM food. Moreover, trade relationships may encourage imitation; countries in Asia are more likely to have a relatively higher threshold level for the accidental presence of GM ingredients in non-GM products following Japan. Alternatively, countries located in Europe or exporting soybeans and canola mainly to the EU are more likely to have stringent labeling policies like the EU.

Interestingly, in the transatlantic comparison of opposite policy approaches, consumers and producers seem to find advantage in their own countries’ choice of labeling policy. This confirms the thesis of Caswell (2000) that each country will choose its own labeling regime to respond to its domestic economic and political interests. Our results also support the conclusions of Anderson and Jackson (2003), that production factors are determinants of transatlantic differences in biotechnology regulations. However, these results partially contradict the prediction of Fulton and Giannakas (2004), who concluded that consumers, producers, and seed companies never agree as to which labeling option to choose.

Apart from developed countries, which seem to have made choices according to their own national interest, we can also comment on labeling choices in developing countries. Regional influences and trade relationships are important factors in the determination of labeling policies in developing countries. Trade factors may in fact be
more important than the presence of consumer resistance or green anti-GM campaigns. In particular, large countries like Brazil, China, and Russia may have adopted mandatory labeling of GM food mainly for trade reasons.

### Appendix: Additional Computations

#### Changes in Consumer Welfare

**Welfare under no labeling** The indirect utility function of trusting consumers is $V^0_j = a - p_0$, and the one for distrusting consumers is $V^0_j = a - p_0 - \lambda$. Integrating these two expressions for $\theta_j$ between 0 and 1, and summing the two components with their proportional factors, we obtain:

$$U^0 = \beta_1 (a - p_0) + \beta_2 (a - p_0 - \lambda) = a - p_0 - \beta_2 \lambda. \quad (A1)$$

**Welfare under mandatory labeling** To derive $\theta^{GM}$, we equalize the indirect utility of consuming GM and non-GM for the two types of indifferent consumers. We obtain $\theta^{GM_t} = (p_n - p_0) / \lambda$ for trusting consumers and $\theta^{GM_d} = (p_n - p_0) / 2 \lambda$ for distrusting consumers. We can then derive the total utility of GM consumers:

$$U_{G_M}^{GM} = (a - p_g - T - \lambda + u_t) (\beta_1 \theta^{GM_t} + \beta_2 \theta^{GM_d})$$

$$= (a - p_g - T - \lambda + u_t) \left( \frac{p_n - p_g}{\lambda} \right) \left( \beta_1 + \frac{\beta_2}{2} \right). \quad (A2)$$

Similarly, we derive the total utility of non-GM consumers:

$$U_{G_M}^{NGM} = (a - p_n - T + u_t) \left( 1 - \left( \frac{\beta_1 + \frac{\beta_2}{2}}{\lambda} \right) \left( \frac{p_n - p_g}{\lambda} \right) \right) + \beta_2 \lambda \left( 1 - \frac{p_n - p_g}{2 \lambda} \right). \quad (A3)$$

**Change in consumer welfare** Let $\Theta = \beta_1 \theta^{GM_t} + \beta_2 \theta^{GM_d}$ be the total share of consumers purchasing GM. Then:

$$\Delta U = 2 \beta_2 \lambda + u_t - T - (p_n - p_0) - (1 - \Theta) (p_n - p_g).$$

Therefore:

$$\Delta U > 0 \Leftrightarrow 2 \beta_2 \lambda + u_t > T + (p_n - p_0) + (1 - \Theta) (p_n - p_g).$$

Marginal effects with respect to $\beta_2$:

$$\frac{\partial \Delta U}{\partial \beta_2} = 2 \lambda - \frac{(p_n - p_g)^2}{2 \lambda} = \frac{2 \lambda + p_n - p_g}{2 \lambda} \frac{(2 \lambda - p_n + p_g)}{2 \lambda}. \quad (A4)$$

As $\lambda \geq (p_n - p_g)$ by hypothesis, we find that $(\partial \Delta U / \partial \beta_2) \geq 0$.

In the case of $\lambda$,

$$\frac{\partial \Delta U}{\partial \lambda} = 2 \beta_2 - \left( \frac{\beta_1 + \frac{\beta_2}{2}}{\lambda} \right) \frac{(p_n - p_g)^2}{\lambda^2} = \frac{2 \beta_2 \lambda^2 - \left( \frac{\beta_1 + \frac{\beta_2}{2}}{\lambda} \right) (p_n - p_g)^2}{\lambda^2},$$

thus:

$$\frac{\partial \Delta U}{\partial \lambda} \geq 0 \Leftrightarrow \lambda \geq \frac{\sqrt{2}}{2 (1 - \beta_1)} \sqrt{1 + \frac{\beta_1}{\lambda (1 - \beta_1)}} \Leftrightarrow \lambda \geq \frac{1}{\beta_1} \sqrt{p_n - p_g} \frac{1 + \beta_1}{1 - \beta_1}. \quad (A5)$$
Because $\lambda \geq (p_n - p_g)$ and
\[
\left\{ \frac{1 + \beta_1}{1 - \beta_1} \leq 2 \Leftrightarrow \beta_1 \leq 0.6 \right\},
\]
we find that
\[
\left\{ \beta_2 \geq 0.4 \Rightarrow \frac{\partial \Delta U}{\partial \lambda} \geq 0 \right\}.
\]

Changes in Producer Welfare

For GM producers

\[
\Pi^0 = c_g'(Q_{0,g}) \cdot Q_{0,g}^2 \quad \text{and} \quad \Pi^{GM} = c'_g(Q_g) \cdot Q_g^2 - FC_{ml},
\]

so
\[
\Delta \Pi^{GM} = c'_g(Q_g) \cdot Q_g^2 - c_g'(Q_{0,g}) \cdot Q_{0,g}^2 - FC_{ml}.
\]

Assuming $Q_{0,g} \geq Q_g$, and $c_g'(\cdot)$ non-decreasing, we find that $\Delta \Pi^{GM} \leq 0$.

For non-GM producers

Similarly we find that: $\Delta \Pi^{NGM} = c'_n(Q_n) \cdot Q_n^2 - c_n'(Q_{0,n}) \cdot Q_{0,n}^2 - c_{ml}Q_n - FC_{ml}$. Therefore: $\Delta \Pi^{NGM} > 0 \Leftrightarrow c_{ml}Q_n + FC_{ml} < c_n'(Q_n) \cdot Q_n^2 - c_n'(Q_{0,n}) \cdot Q_{0,n}^2$. Assuming $Q_{0,n} \leq Q_n$, the second term of this inequality is positive.

For switching producers

These producers will switch only if $\Pi^{NGM} > \Pi^{GM}$, which is equivalent to $c'_n(Q_n) \cdot Q_n^2 - c_g'(Q_{0,g}) \cdot Q_{0,g}^2 > c_{ml}Q_n$. Their profits are:

\[
\Pi_0 = c_g'(Q_{0,g}) \cdot Q_{0,g}^2 \quad \text{and} \quad \Pi^{SW} = c'_n(Q_n) \cdot Q_n^2 - c_{ml}Q_n - FC_{ml},
\]

so
\[
\Delta \Pi^{SW} = c'_n(Q_n) \cdot Q_n^2 - c'_g(Q_{0,g}) \cdot Q_{0,g}^2 - c_{ml}Q_n - FC_{ml}.
\]

Assuming that $Q_{0,g} \leq Q_n$, the two first terms are positive, thus:
\[
\Delta \Pi^{SW} > 0 \Leftrightarrow c_{ml}Q_n + FC_{ml} < c'_n(Q_n) \cdot Q_n^2 - c'_g(Q_{0,g}) \cdot Q_{0,g}^2.
\]

References


Notes

1. These draft voluntary guidelines were published in 2001 by the US Food and Drug Administration.
2. The model could also be applied to voluntary labeling, with different results expected.
3. Further disaggregation of the groups, while possible, would not change the general results.
4. If instead we chose a centered Normal distribution, we would find the same qualitative results.
5. In this paper, we assume that all products have been cleared by the food safety authority, to focus on the effects of labeling on consumers. This reflects national policies; countries employ labeling on the basis of consumer choice, not as a food safety policy. At the same time, we acknowledge the fact that some consumers may perceive a possible long-term consumption risk.
6. We focus on current GM products which are derived from input-related traits, i.e. that do not provide any visible consumer benefit.
7. Ex-ante, consumers will perceive that introducing labeling will increase the variety of products, even if it may not be the case ex-post. For more on this, see Scatasta et al. (2007).
8. The tax is perceived to finance enforcement. The cost of labeling may also include other costs that will be borne by the industry and partially or fully transmitted to consumers.
9. We assume that \( \lambda \) is at least equal to the price difference \((p_a - p_b)\), which guarantees that the share of GM consumers is in \([0, 1]\).
10. For example, in a referendum held in 2002 in the State of Oregon, over 70% of voters rejected a proposed mandatory labeling policy for GM food.
11. Here, we limit ourselves to the case of food producers overall rather than seed companies, but the overall conclusions for GM producers can apply to them as well.
12. If there was a GM food safety crisis, the public may become more supportive towards labeling, because of the welfare change associated with it, and a new consensus would be reached.
13. Several developed countries have a mixed labeling system, with mandatory GM labeling and voluntary guidelines for non-GM products. For simplicity, we included them in the category of countries with mandatory labeling \((TYP = 2)\).
14. Some countries have published labeling regulations, but have not enforced them effectively.
15. The role of these two export factors was confirmed by the results of simple logit regressions (not presented here, but available on request) on the adoption of mandatory labeling.
16. We set a minimum default value equal to 0 for the number of ingredients and a maximum default (arbitrary) value of 10% for the tolerance level.
17. In the case of the tolerance level, the density function \(g(\cdot)\) will be of the form \(g(y) = g^*(y)b'G^*(0)^{1-b'}\), where \(g^* \) and \(G^* \) are the density function and the cumulative density function of \(y^*\), respectively, and \(b' = 1\) if and only if \(y < 10\), and \(b' = 0\) otherwise.