Wheat Trade and the Adoption of ENSO-Based Forecasts: Different Scenarios

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The El Niño / Southern Oscillation (ENSO) phenomenon has been shown to affect climate patterns and agricultural production around the world. Though agricultural producers cannot control the climate, early forecasts of seasonal conditions may allow producers to make more efficient input decisions (Easterling and Stern; Hill et al 1998). Scientific understanding of the coupled atmospheric / oceanic system and associated ENSO phenomenon now allows forecasts to be issued with lead times of up to 13 months (Mason et al; O'Lenic). Moreover, studies have shown the quality of these forecasts is improving (Livesey; Wilks).

Most previous studies of climate information have used static models to show society would benefit if agricultural producers used climate forecasts in making production decisions (see Hill and Mjelde for a review of this literature). Climate information, however, can be viewed as a type of technology (Agrawala and Broad), which is generally adopted over time. When the transition from no adoption to full adoption is not considered, the changing magnitude and distribution of benefits as more producers adopt climate forecasts is ignored. To predict how benefits to adoption may be distributed, it is important to know who is adopting, in what order, and at what rate.

Ex ante examination of adoption allows society to make better decisions. For individual producers, the risks associated with adoption are reduced due to added information about possible benefits and costs. For change agents, information on the distribution of benefits allows efforts to be better focused. In addition, better understanding of adoption linkages increases awareness of indirect benefits and losses and allows us to see how adoption in one area is likely to affect welfare in other areas.

The static models used in most previous studies of climate information do not consider welfare distributions during the transition from no adoption to full adoption. Studies of technology adoption have considered economic effects during this transition period, but most have been done *ex post*, after the distribution of benefits has already taken place. This study combines the *ex ante* nature of climate studies with the dynamic nature of studies on technology adoption to examine potential welfare effects over time as increasing numbers of producers adopt climate forecasts for use in production decisions.

An international wheat trade model incorporating climate variability is used to simulate different scenarios when wheat producers in the U.S., Canada, and Australia adopt ENSO-based forecasts for use in production decisions. The model links forecast use to input usage, expected and actual yields, planted hectares, price, production, stocks, and trade through a system of economic equations. Baseline welfare measures are obtained under the assumption no producers use climate forecasts. These baseline measures are compared to welfare measures when producers in the U.S., Australia, and / or Canada adopt climate forecasts either all at once or over time. Adoption timing and rates are varied across countries in different scenarios.

Literature

Agrawala and Broad (p. 7) argue, "Seasonal forecasts, while not a piece of hardware, are certainly a knowledge product, and therefore they do fall within the purview of 'technology.'" In addition, information can be used or ignored by a producer, much as a technology can be adopted or not adopted. Therefore, literature on technology adoption supplements studies of climate forecast use to provide the basis for understanding how ENSO-based forecasts may be adopted by decision-makers.

The S-shaped Adoption Curve

The most consistent result in the technology adoption literature is that the adoption path follows a sigmoid (s-shaped) curve over time (Feder, Just, and Zilberman; Stoneman; Rogers and Stanfield). When first released, only a few agents adopt the technology. As information spreads, more agents become aware of the technology (Mansfield) and its net benefits (Hoppe). In addition, increased knowledge decreases the risk of adoption (Jovanovic and Lach), and widespread use often decreases the cost of adoption (Knudson). Thus, more agents adopt, increasing the rate of adoption. As time passes, the number of potential adopters decreases, eventually causing the rate of adoption to decrease. Ultimately, an adoption ceiling, or long-run equilibrium, is reached (Griliches). In many cases, the ceiling is reached before all agents have adopted the technology. For those who choose not to adopt, the technology may not be profitable, it may not be feasible, or a newer technology may have been adopted instead. Empirical studies support the s-shaped adoption pattern. Beginning with Grilches in his seminal study of hybrid corn and extended by Mansfield and Romeo, many empirical studies have used the logistic curve to examine adoption over time (see Rogers and Stanfield; Feder and Umali; Marra, Pannell, and Ghadim for reviews).

Adoption of Climate Forecast Information

As discussed, the literature on climate forecast use tends to ignore the idea that adoption takes place over time. One reason for ignoring time is that improved climate forecasts are relatively new. Only the earliest adopters are using the information. There has not been sufficient diffusion to estimate s-shaped adoption curves. Previous adoption literature and economic theory show that technology will only be used if it is profitable. Many studies, therefore, concentrate on calculating the economic value of climate forecast use (e.g. Bowman, McKeon, and White; Messina, Hansen, and Hall; Hammer, Holzworth, and Stone; Solow et al.; Hill et al. (2002); Costello, Adams, and Polasky). Though nearly all these studies report positive values, it is important to note benefits do not accrue to everyone (Hill and Mjelde; Peterson and Fraser; Lamb). This is not surprising since the effect of ENSO events varies by location.

Several studies examine how climate forecast use affects world trade. Sumner, Hallstrom, and Lee show welfare effects vary depending on a country's trade policies and size, responses by other countries, and demand. Chen and McCarl find welfare increases when ENSO forecasts are used in regional world agricultural production. They find U.S. consumers and foreign trading countries gain while U.S. producers lose. Hill et al. (2002) find the use of climate forecasts by wheat producers leads to a drop in the mean market price of wheat and an increase in consumer surplus. They also report producer surplus increases in exporting countries. Hill et al. (2002) note, however, there are non-trivial probabilities the market price will increase, and consumer or producer surplus will decrease.

Though climate information has been shown to have value, there are still impediments to adoption. Decision-makers may not know the information is available (Changnon, Sonka, and Hofing), the information may come too late (Washington and Downing), or it may not be in a usable form (Goddard et al.; Callahan, Miles, and Fluharty). Even if the information is received in a timely manner and understood, it is often difficult to integrate into production decisions, especially when complex corporate structures are involved (Changnon, Sonka, and Hofing; Goddard et al.; Pulwarty and Redmond; Changnon, Changnon, and Changnon). Furthermore, distrust, misunderstanding, and prior beliefs can hinder forecast use (Nicholls; Changnon, Sonka, and Hofing; Letson et al.; Nicholls; Agrawala and Broad), as can resource constraints (Agrawala and Broad).

In addition, climate forecasts may have specificity issues (Hill and Mjelde). If a producer owns a very small plot of land, regional forecasts may not be accurate for the producer's plot. These impediments are especially problematic in developing countries. Though the scientific and economic aspects of climate forecasting are still emerging, and impediments to use remain, there is substantial evidence that climate forecast use in agricultural production decisions will affect global economic welfare.

International Wheat Trade Model

As mentioned, most technology adoption studies incorporate time but are done *ex post*. Most climate information studies, on the other hand, examine the issues *ex ante* but use static models. This study combines the ideas of both approaches by examining potential dynamics and distributions of benefits and losses associated with climate forecast adoption over time. An updated version of Hill et al.'s (2002) dynamic, stochastic wheat trade model provides the basis for this study. The model assumes a competitive trade environment and includes equations for production, consumption, stocks, and exports for the U.S., Canada, and Australia. Argentina, Europe, and China are modeled in less detail. Argentina represents a small percentage of world wheat trade, Europe is relatively unaffected by ENSO, and China is nearly impossible to model in a free trade environment. All other countries are aggregated into a Rest-of-World (ROW) category. For a complete description of the model, see Hill et al. (2002).

World wheat trade is simulated over a 20-year horizon. Technology, population, income, transportation costs, and input prices are fixed at 1997 levels to isolate potential effects of producers' use of seasonal climate forecasts. Country level, per-capita demand equations, estimated using the double log form, are functions of prices and per-capita incomes. Stock equations are estimated functions of the discounted expected price in year t for $t+1$, the actual price in t, and beginning stocks. Price in the U.S. is a function of stocks and expected price in year t for $t+1$. Prices in Canada, Australia, Argentina, and ROW are functions of the U.S. price, transportation costs, and exchange rates. Equilibrium prices, therefore, differ only by transportation costs and exchange rate differences. To ensure market clearing, the sum of each country's imports, supply, and beginning stocks equals the sum of its demand, ending stocks, and exports. To close the model, U.S. exports are set equal to ROW imports minus exports by Argentina, Australia, Canada, and Europe. Expected price in year t for $t+1$ is a function of expected production in $t+1$ and total exports in year *t*. Expected production is a function of the forecasted climate conditions and expected price.

Unique to this model is the use of ENSO-based climate forecasts by producers to alter their production decisions. The adoption of climate forecasts by producers is manifested in the trade model through the number of hectares planted and changes in input usage, which causes changes in yields per hectare. Both input usage and planted hectarage depend on the expected price, which is a function of the forecasted climate. Because ENSO-based seasonal forecasts have only recently become available, data regarding how producers integrate climate forecast information into their production management decisions are sparse. Consequently, standard econometric methods cannot be used to estimate supply responses. A proxy for producers' behavior must be used. Hill et al. (2001) provide details on the methodology used to obtain aggregate country-level production that incorporates climate forecast information. Biophysical simulation models combined with field-level decision models are used to obtain yields for representative fields throughout the U.S., Canada, and Australia under a range of management practices, site-specific characteristics, and climatic conditions. Producers respond to ENSO-based climate forecasts by changing planting dates and nitrogen application rates and, in the case of Australia, wheat variety. The five phases of the Southern Oscillation Index (SOI), a measure of the atmospheric pressure differences between the island of Tahiti and Darwin, Australia (Stone and Auliciems), are used to represent ENSO conditions.

Modeling Adoption

The literature on technology adoption suggests it is unlikely that all wheat producers would adopt climate forecast use in the same year. Producers may not have equal access to information, the benefits to adoption may be greater in some areas than others, and risk, costs, or other impediments may cause some producers to adopt later than others. In addition, adoption in one area impacts other areas through the price mechanism. While it may not initially be profitable for a region to adopt, it may become profitable as other regions adopt. Considering these factors, different scenarios are analyzed to examine potential linkages.

Hill et al.'s (2001) model is modified to allow some producers to adopt while others do not. The model is altered to allow producers in the U.S., Canada, and Australia to adopt at different rates. Modifications to the model involve changes to each country's aggregate production calculations based on the percentage of adopters and non-adopters. Because climate forecast use affects input usage (and thus yields), yield equations representing adopters and non-adopters are necessary:

$$(1) \qquad Y_{i,t}^{v,c} = E_{t-1}(P_{i,t})^{\beta_0^c} e^{\sum_{k=1}^{5} \beta_k^c \alpha_k} \varepsilon_{i,t}^{v,c}$$

where

$Y_{i,t}^{v,c}$ is the hectare-weighted yield, for country *i*, year *t*, and wheat class *v*,
$c = 1$ indicates adopters of climate forecasts and $c = 0$ indicates use of climatological (historical) climate information,
$E_{t-1}(P_{i,t})$ is the expected price in year *t-1* for production associated with year *t*,
e is the exponential operator,
α_k are binary variables for the five SOI phases, denoted by *k*,
β_k^c are estimated coefficients, and
$\varepsilon_{i,t}^{v,c}$ is a random error term.

For each country and wheat class, two yield equations are included in the model, one for producers using climate forecasts (*c=1*) and one for producers basing their production decisions on historical distributions of climate variables (*c=0*). The yield coefficients, β_k^c, associated with each ENSO phase vary between the two yield equations (Table 1). The majority of the estimated coefficients in Table 1 are statistically significantly related to yield. Hill et al. (2001) provide details on estimation of the yield equations.

The number of hectares planted to wheat is given by:

(2) $$H_{i,t}^{v} = \gamma_{v} E_{t-1}(P_{i,t})^{\eta}$$

where H is hectares, γ is a constant term, η represents the hectare price elasticity, and the expected price is the same value as used in the yield equation. To obtain aggregate production for each country and wheat class, yields are weighted by the corresponding percentage of adopters and non-adopters and then multiplied by wheat hectares:

(3) $$S_{i,t}^{v} = H_{i,t}^{v}(d_{i,t}Y_{i,t}^{v,1} + (1 - d_{i,t})Y_{i,t}^{v,0})$$

where S is aggregate production, and $d_{i,t}$ is the percentage of producers using ENSO-based climate forecasts. Of particular interest is that the percentage of adopters, $d_{i,t}$, can vary by country and year.

Adoption is examined under two assumptions. First, all producers in a given country either adopt or do not adopt climate forecasts at the beginning of the 20-year horizon. Once this decision is made, it is irreversible. For example, in one scenario all U.S. producers adopt, but no producers in Canada or Australia adopt. In this case, $d_{i,t}$ equals one for all U.S. producers and zero for producers in Canada and Australia for all years. With three countries, eight scenarios are possible under this adopt / don't adopt dichotomy. This simplifying assumption allows examination of what could be gained or lost by adopting or not adopting when producers in other countries act independently.

In the second set of scenarios, adoption within each country is assumed to take place over time. Because producers in different countries are likely to adopt climate forecasts at different rates, the rate of adoption varies by country. This time, instead of multiplying each part of the yield equation by zero or one, a logistic function is used to represent an s-shaped adoption path over time. The percentage of producers adopting climate forecasts in each scenario is given by:

(4) $$d_{it} = \frac{e^{(a_i + b_i t)}}{1 + (e^{a_i + b_i t})}$$

where a_i and b_i are country specific constants and t, which ranges from 1 to 20, represents the year since the beginning of the simulation. Because there is neither data to conduct an *ex post* analysis nor empirical studies that provide explicit values for a_i and b_i (Batz, Janssen, and Peters), arbitrary numbers are used. First, three different intercepts (*a*'s) are used. This allows producers in different countries to begin adopting in different years, though once adoption starts, the rate of adoption is the same in all countries. The three different adoption paths are shown in figure 1, panel a. Values for *a* are -5, -8, -11 with *b* held constant at one. Numbers closer to zero correspond to earlier adoption.

Second, producers in all three countries begin adopting in year one, but adoption occurs at different rates (figure 1, panel b). Here, *a* is held constant at –6, and *b* is allowed to vary. The *b*'s are set equal to 1.25, 0.75, and 0.5, where larger numbers indicate faster adoption. Of the infinite number of possible slope and intercept parameters, only three sets of cases are presented here. The results indicate that different parameters may alter the magnitude and time frame of benefits but not the ordering of who gains the most / least for a given adoption pattern. Because adoption is likely to occur over time, the results from the second set of scenarios provide the most insight into what will likely happen to welfare as climate forecast adoption occurs in the international wheat market.

Results and Discussion

The presented results and discussion are limited to producer surplus. First, most of the welfare change affects producers. Second, because of the number of scenarios, the focus on producer surplus keeps the presentation manageable. Readers interested in other economic measures are referred to Hill et al. (2002), which discusses changes in economic measures when all wheat producers simultaneously adopt climate forecasts in their planting decisions.

Adopt / Don't Adopt Dichotomy

There are eight possible scenarios under the assumption that all producers in each country make an irreversible decision in year one to adopt or not. The baseline scenario, when no producers adopt climate forecasts, is consistent with previous studies estimating the value of climate forecasts.

Discounted producer surplus is obtained for each country under each scenario for all 20 years of the simulation horizon. The average percentage changes in discounted producer surplus between the seven adoption scenarios and the (no adoption) baseline scenario are presented in Table 2.

When everybody adopts climate forecasts, producers in all three countries benefit. Australia's climate is affected more by ENSO than the U.S. or Canadian climates, so it is not surprising that Australian producers, with an average increase in surplus of 7.53%, gain the most by using ENSO-based forecasts. U.S. producers' welfare increases on average by 2.22%, while producers in Canada gain 1.33%. Averages, however, do provide the whole picture. Standard deviations associated with the changes in producer surplus are large. Calculated probability distributions show there will be losses associated with the use of ENSO-based forecasts in some years for all three countries. Graphs of the probability distributions and more detailed discussion of these results can be found in Hill et al. (2002).

Even if producers in one or more countries do not adopt climate forecasts, Australia has the most to gain by adopting. If Australian producers adopt, their minimum average change in producer surplus is 6.29%. When Canadian producers also adopt, Australia's producer surplus gains increase to 6.56% on average. When U.S. and Australian producers adopt, Australian producer surplus increases by 7.19%. Even if Australian producers do not adopt, they gain if either Canadian or U.S. producers adopt. Canadian adoption increases Australia's average producer surplus by 0.06%, while U.S. adoption leads to an average gain of 1.01% for Australia's producers. When Canada and the U.S. both adopt, Australia gains 1.13%. Australian gains are explained as follows: when U.S. producers use climate forecasts, U.S. production tends to decrease relative to production levels when forecasts are not used. The relative decrease in U.S. production is accompanied by an increase in the world price, which is not surprising given the magnitude of U.S. production relative to production in the rest of the world.

Producer surplus gains in Canada are driven by U.S. adoption. When Canadian producers adopt alone, they gain an average 0.59%. When only the U.S. adopts, producers in Canada gain an average 1.32%. This is raised to 1.37% if Canada also adopts. The reason for these gains is the same as discussed for Australia. U.S. adoption leads to an increase in the world price, which benefits Canadian producers. Australian adoption, on the other hand, hurts Canadian producers. Not only do the above Canadian percentages fall when Australian producers adopt, but when Australia adopts alone, Canadian producers lose an average 0.15%. This is because production in Australia tends increase with adoption, which exerts a slight downward pressure on the world price.

Given the above results, it is not surprising U.S. producer surplus decreases when either Canada or Australia adopts. U.S. producers gain the most when they alone adopt, (2.83%), and lose the most (-0.34%) when they alone do not adopt. It is interesting that despite declines in production, the U.S. can increase producer surplus by adopting, especially if others are adopting. Increases in producer surplus can accompany production declines because U.S. producers are more efficient when they adopt climate forecasts (Hill et al. 2002).

The above results indicate that adoption is the best choice for producers in all countries, especially if producers in other countries are adopting. However, these results are based on average percentage changes in producer surplus. It is unlikely that any given year will follow the above pattern. For this reason, probability distributions of the 20-year averages are given in figure 2 for selected scenarios. It is not surprising that Australia generally has the most variability, and the U.S. has the least. As mentioned, ENSO affects Australia more than the U.S. What is more interesting is that Australia's variability seems to increase with adoption. For example, when Australia adopts alone (figure 2, panel a), there is a 25% chance adoption will lead Australian producers to gain more than 11.15%, and another 25% chance adoption will cause them to gain less than 0.65% relative to if they had not adopted. On the other hand, when the U.S. adopts alone (figure 2, panel c), there is a

25% chance U.S. producers will gain more than 3.99%, and a 25% chance they will gain less than 1.49% relative to non-adoption. This is a much smaller range. One reason is that the model is based on profit maximization. Engaging in a risky activity may be the way to increase average profits. The above results also illustrate how actions in one country impact global welfare. If producers in one country begin using climate forecasts, producers are affected worldwide. Technology adoption does not happen in a vacuum.

Adoption Over Time

Next, adoption is allowed to take place over time, and the paths (figure 1) are allowed to vary by country. The graphs of producer surplus per hectare in figures 3-5 are yearly averages of 1000 simulations for the scenarios examined. The pattern of producer surplus given in each graph is shifted or elongated depending on the parameters used in the logit function, but the general shape is constant. The shape allows us to predict the likely pattern of gains and losses in any country. Each panel in figures 3-5 contains three paths for the producer surplus of the specified country: no adoption, adopters, and non-adopters. *No adoption* producer surplus is the baseline case, where no producer in any country ever adopts climate forecasts. Producer surplus for *adopters* and *non-adopters*, on the other hand, is determined by the adoption paths of all three countries. Gains and losses in the following discussion refer to producer surplus for adopters (non-adopters) relative to producer surplus for no adoption.

In all cases, the earliest adopters realize the largest gains, which decline quickly as more producers adopt. The decline begins in year 6-11 depending on the scenario. In addition, there is a point (usually between 70 and 90 percent adoption) when non-adopters begin to gain more than adopters. Non-adopter gains continue to increase until all agents have adopted, at which point there are no non-adopters. Though the model forces all producers to adopt eventually, full adoption may not occur by the end of the 20-year horizon.

As noted earlier, literature on technology adoption indicates that adoption ceilings generally occur below full adoption. In this case, the model forces all producers to eventually adopt climate forecasts, and non-adopters are allowed to gain more than adopters. When nearly everybody has adopted, the near zero gains to non-adoption go to one or two people as opposed to the gains to adoption, which are divided among the rest of the producers. This small number problem makes the gains to non-adoption in the last years misleadingly large. The same small number problem is present in the gains to adoption at the very beginning, so one should be wary of conclusions drawn from results on either end. In reality, the adoption ceiling would be close to the point where the gains to adoption equal the gains to non-adoption. This usually happens before full adoption.

In figure 3, the rate of adoption is the same for all countries, though the U.S. begins adopting first, followed by Canada and then Australia (see figure 1, panel a). Though from years one to three, benefits to adoption increase for U.S. producers, only 1.8% of U.S. producers adopt in year one, so the small number problem is present. By three, 12% of U.S. producers have adopted. Years three to five see rather level gains, which begin to decline in year six, at 73% adoption. In year seven, when adoption is at 88%, the benefits to non-adoption equal the benefits to adoption. If adoption continued, non-adopters would to gain until there were no more non-adopters. Adopter gains would fall to just above the baseline scenario of no adoption.

In Canada, the 5% who adopt before year five see the largest gains, though the small number problem is present to some extent. Between years 9 and 10, when approximately 80% of producers are using climate forecasts, the benefits to adoption equal the benefits to non-adoption. At this point, one would expect adoption to cease. In Australia, adoption happens more slowly, and the gains to adoption are more spread out. Gains are fairly steady until year 11, when 50% of the producers have adopted climate forecasts. Between years 12 and 13, when adoption reaches roughly 80%, benefits to adoption equal benefits to non-adoption.

For figure four, the adoption paths of the U.S. and Australia are switched, though the pattern still follows figure 1, panel a. Producers in Australia adopt first, followed by producers in Canada and then the U.S. The pattern for U.S. producers shifts to the right about six years. U.S. adoption peaks and levels from years 9-11, and the intersection of adopter and non-adopter gains occurs in year 13, at 88% adoption. Canada looks much the same as before, with the intersection of adopter and non-adopter producer surplus at 80% adoption. Australia's picture shifts to the left. Australia's major gains are compressed into the first five years, and benefits to adoption equal benefits to non-adoption between years six and seven, when 88% of producers are using climate forecasts.

In figure five, we see what happens when producers in all countries begin adoption in year one but adopt at different rates (see figure 1, panel b). Here, Australian producers have the highest rate of adoption, followed by Canadian producers and then U.S. producers. In the U.S., adoption begins very slowly, reaching 1% in year 3. Gains to adoption are fairly steady until year 12 and equal gains to non-adoption around year 14 when 74% of producers are using climate forecasts. The five percent of Canadian producers who adopt in the first four years gain the most, and gains to adoption intersect those of non-adoption just after year nine and 70% adoption. In Australia, gains remain high for five years, but in year six, at 82% adoption, the gains to adoption intersect the gains to non-adoption.

Conclusions

Though assumptions about the adoption rate compress or elongate the pattern of producer surplus over time, the shape remains fairly constant. In other words, the rate and timing of adoption affect the timing of benefits more than who benefits. In all cases, the first wheat producers to adopt ENSO-based climate forecasts receive the most benefits. As more producers adopt, the benefits level off and then fall. Between 70 and 90 percent adoption, the benefits to adoption intersect the benefits to non-adoption. At this point one would expect adoption to cease. Theory and previous studies indicate that adoption ceilings generally fall short of full adoption.

The results of this study indicate the best strategy from a county's perspective is for wheat producers to adopt ENSO-based forecasts in production decisions. Adoption is best for producers in all countries regardless of whether producers in other countries are adopting. The first producers to adopt can realize large gains. Later adopters can also gain, though the benefits to adoption decrease as more producers adopt. Failure to adopt when others are adopting, however, can lead to losses in producer surplus. Adoption does not happen in a vacuum. Economic linkages cause production decisions in one area to affect producers everywhere.

Though this study finds producers who adopt ENSO-based climate forecasts to gain on average, gains will not be realized every year. The distribution around the mean indicates that in some years gains will be large, while in other years producers will lose relative to if they had not used the forecast to make production decisions. Though the value of climate forecasts fluctuates by region, year, and the location and number of other producers using forecasts, adoption is the best strategy for most producers.

Finally, this study found adoption of ENSO-based forecasts to benefit Australian wheat producers more than their Canadian or U.S. counterparts. It would thus be logical for widespread adoption to begin in Australia. At the policy level, forecast use is currently pushed most heavily in Australia. Globally, the first Australian adopters are likely to see the largest gains. Though wheat producers in the rest of the world will eventually use ENSO-based forecasts, the benefits will probably be somewhat lower.

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Table 1. Estimated Modified Log-Log Yield Equations for Winter and Spring Wheat Types in the U.S., Canada, Australia, and Argentina for the With and Without ENSO-Based Forecast Scenario (kilograms/hectare)[1]

	Wheat Class						
	U.S.				Canada	Australia	Argentina
Coefficient	Hard Red Winter	Soft Red Winter	Soft White Winter	Red Spring	Red Spring	Standard White	
			Without SOI-Based Climate Forecasts				
Price	0.0148	0.1894	0.2159	-0.0075	0.1795	0.0005	0.0206
	(0.17)	(1.53)	(857.1)*	(-0.01)	(3.45)*	(0.13)	(1.02)
Phase 1	7.6826	6.3829	-0.0114	7.7234	6.5409	6.9119	7.5333
	(18.60)*	(10.89)*	(-0.48)	(17.51)*	(25.55)*	(287.9)*	(75.33)*
Phase 2	7.6247	6.4693	0.0381	7.6412	6.7034	7.1365	7.3797
	(18.46)*	(11.06)*	(1.73)*	(17.33)*	(26.28)*	(339.8)*	(61.44)*
Phase 3	7.6945	6.7396	0.0513	7.7671	6.7025	6.8317	7.6588
	(18.54)*	(11.46)*	(1.39)	(17.61)*	(26.28)*	(284.6)*	(59.10)*
Phase 4	7.6044	6.8061	-0.0002	7.6282	6.3591	7.2205	7.4261
	(18.37)*	(11.59)*	(-0.07)	(17.30)*	(25.04)*	(361.0)*	(69.86)*
Phase 5	7.7701	6.3655	0.0070	7.6178	6.6525	6.9499	7.4264
	(18.81)*	(10.88)*	(0.33)	(17.27)*	(26.19)*	(330.9)*	(76.72)*
			With SOI-Based Climate Forecasts				
Price	0.0274	0.1708	1.7142	0.0454	0.1656	-0.0001	0.0206
	(0.33)	(1.43)	(857.1)*	(0.47)	(3.11)*	(-0.03)	(1.02)
Phase 1	7.6254	6.5265	0.0080	7.4697	6.6051	6.9197	7.5333
	(18.92)*	(11.45)*	(0.32)	(16.56)*	(25.50)*	(288.3)*	(75.26)*
Phase 2	7.5599	6.4916	0.0230	7.4207	6.8106	7.1687	7.3797
	(18.81)*	(11.39)*	(1.10)	(16.49)*	(26.40)*	(341.4)*	(61.45)*
Phase 3	7.6172	6.8649	0.0513	7.5680	6.8092	6.8581	7.6588
	(18.85)*	(12.00)*	(1.39)	(16.78)*	(26.29)*	(298.2)*	(59.10)*
Phase 4	7.5659	6.9509	-0.0002	7.4006	6.3989	7.2322	7.4261
	(18.77)*	(12.19)*	(-0.07)	(16.45)*	(24.80)*	(361.6)*	(69.85)*
Phase 5	7.7174	6.4025	0.0070	7.3829	6.7477	6.9185	7.4264
	(19.19)*	(11.23)*	(0.33)	(16.41)*	(26.15)*	(329.5)*	(76.71)*

[1] t-ratios are in parenthesis below the estimated coefficients.

* indicates significance at the 10% level.

Table 2. Mean Changes in Producer Surplus for Seven Scenarios

	(a) Australia Adopts			(b) Canada Adopts			(c) U.S. Adopts		
	Aus	Can	U.S.	Aus	Can	U.S.	Aus	Can	U.S.
Mean %	6.29	-0.15	0.06	0.06	0.59	-0.28	1.01	1.32	2.83
Std. Dev.	8.39	1.64	1.47	10.00	10.02	10.24	5.14	5.53	2.00
	(d) Canada and Aus Adopt			(e) U.S. and Australia Adopt			(f) U.S. and Canada Adopt		
	Aus	Can	U.S.	Aus	Can	U.S.	Aus	Can	U.S.
Mean %	6.56	0.52	-0.34	7.19	1.20	2.76	1.13	1.37	2.29
Std. Dev.	13.65	10.28	10.27	9.85	5.93	2.53	11.52	11.36	10.61
	(g) U.S., Canada, Australia Adopt								
	Aus	Can	U.S.						
Mean %	7.53	1.33	2.22						
Std. Dev.	14.80	11.66	10.66						

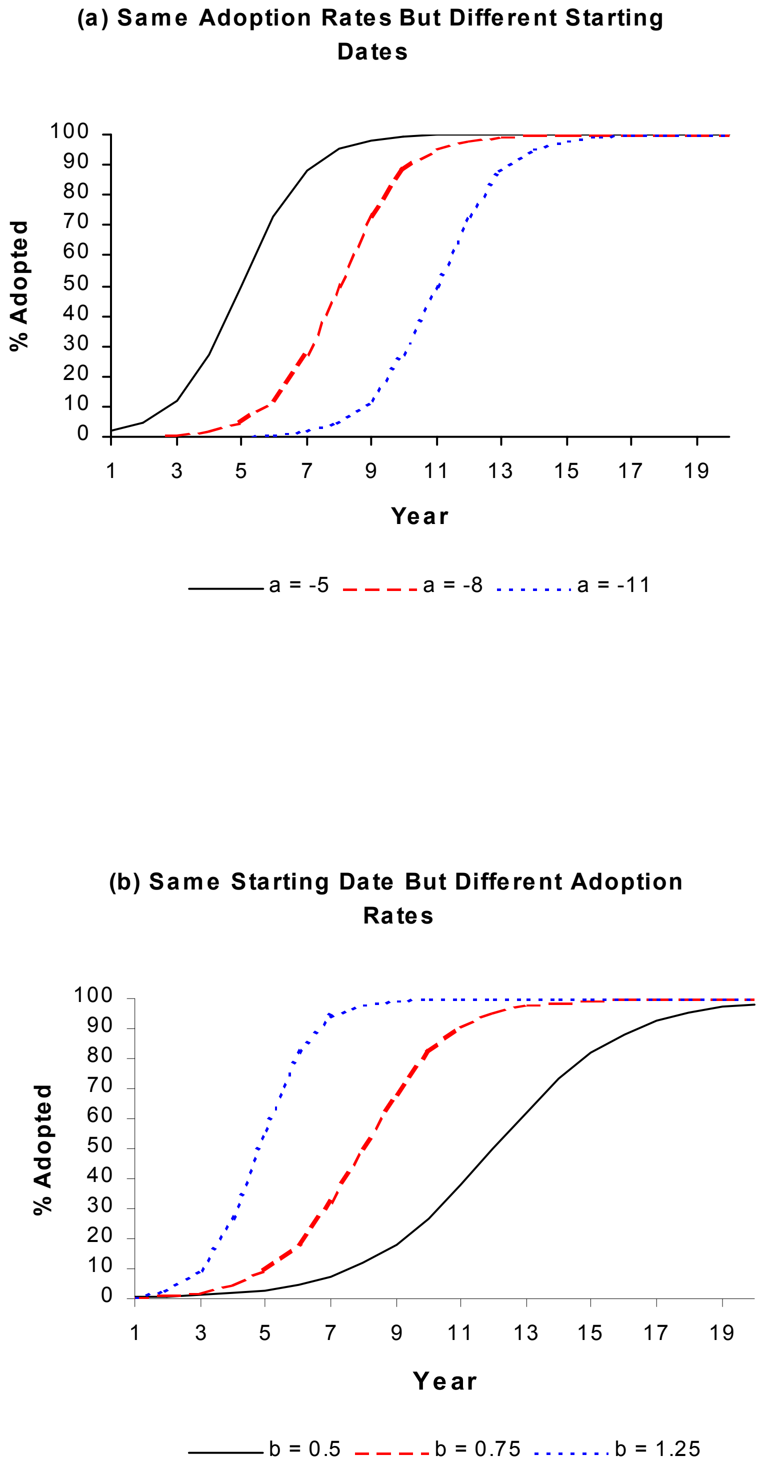

Figure 1. Assumed Adoption Paths

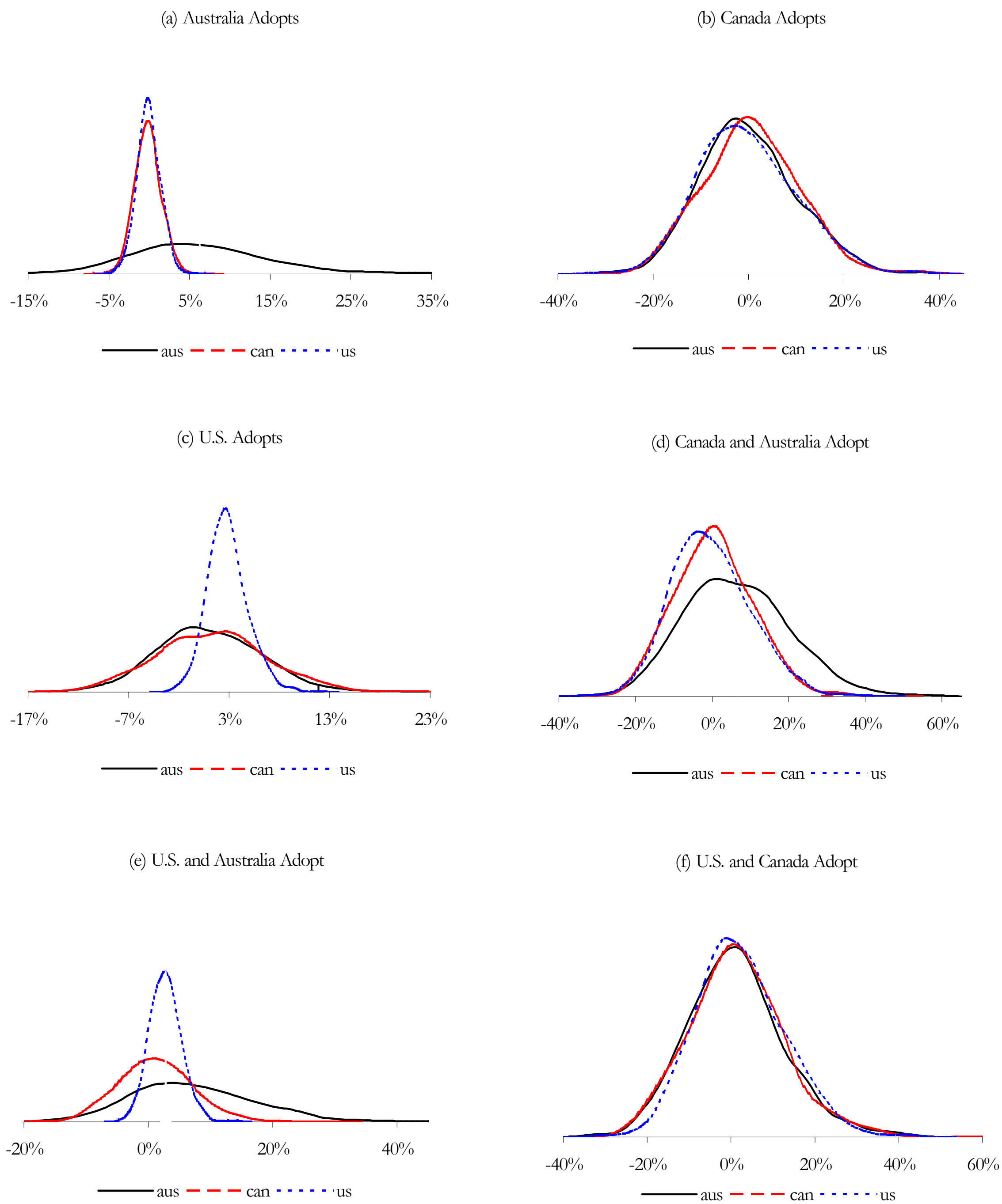

Figure 2. Probability Distributions of Average Changes in Producer Surplus Under Different Adoption Scenarios

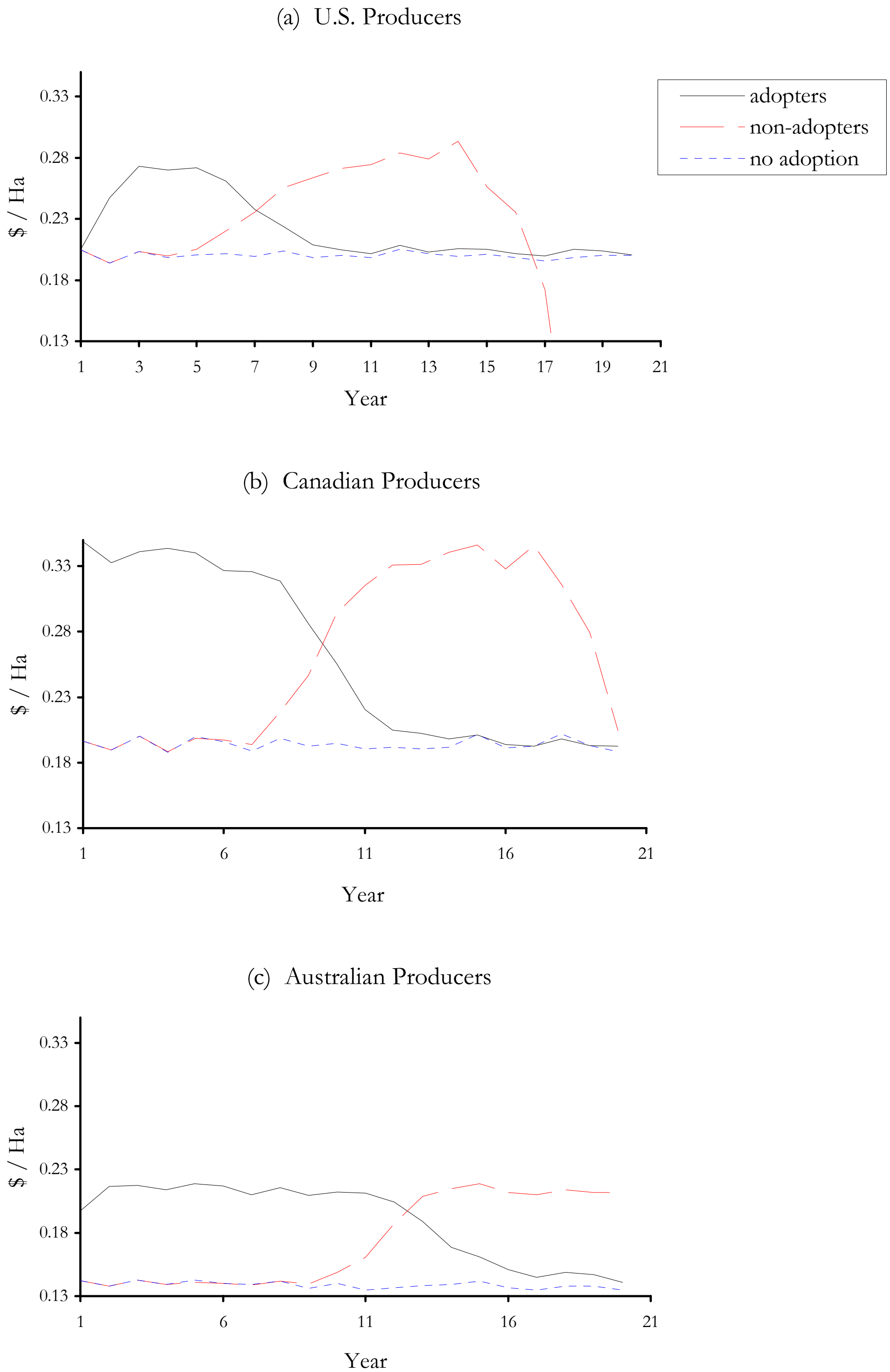

Figure 3. Producer Surplus Over Time When U.S. Starts Adopting First, Canada Starts Adopting Second, and Australia Starts Adopting Third (Figure 1, Panel a)

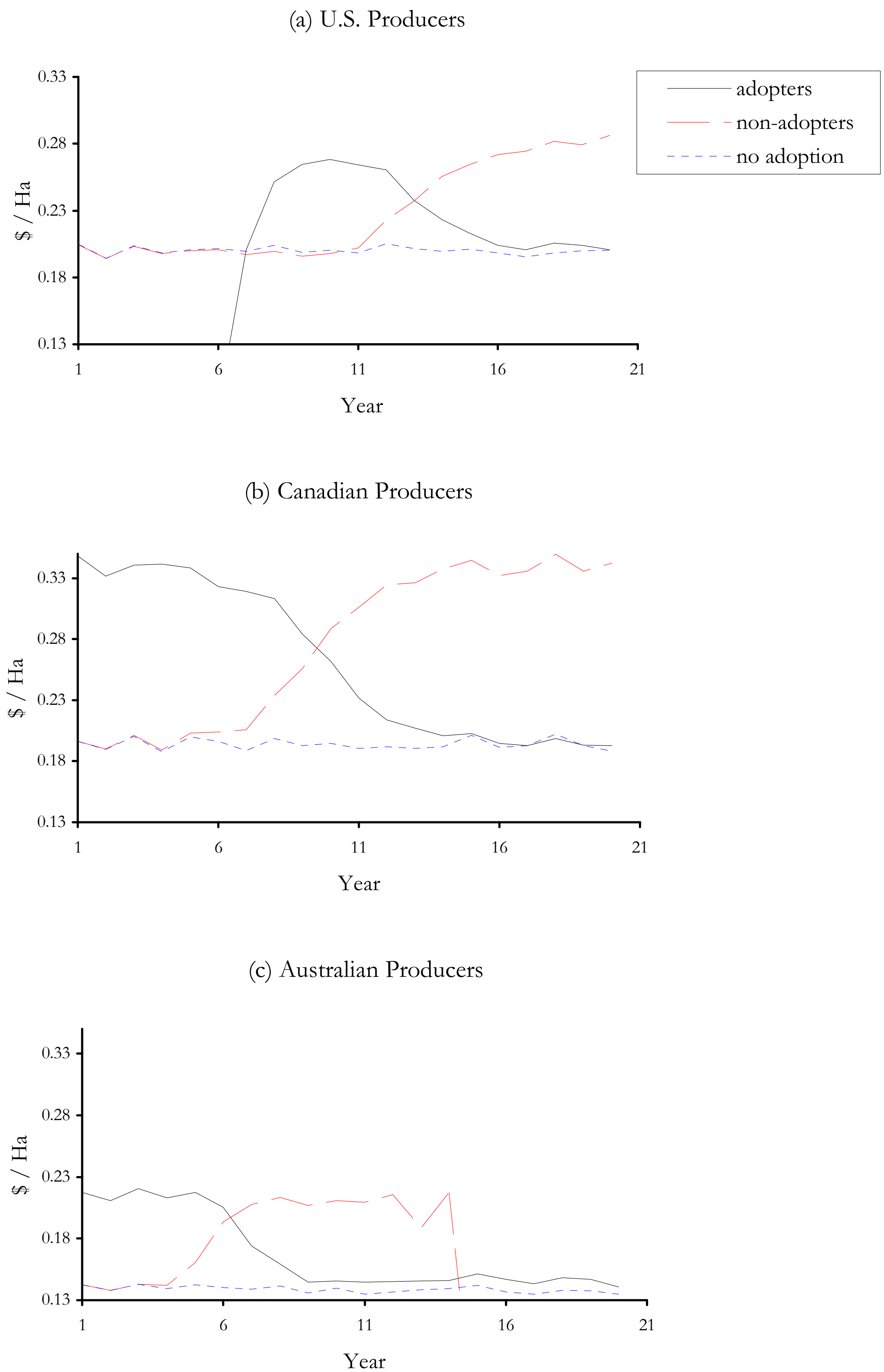

Figure 4. Producer Surplus Over Time When Australia Starts Adopting First, Canada Starts Adopting Second, and U.S. Starts Adopting Third (Figure 1, Panel a)

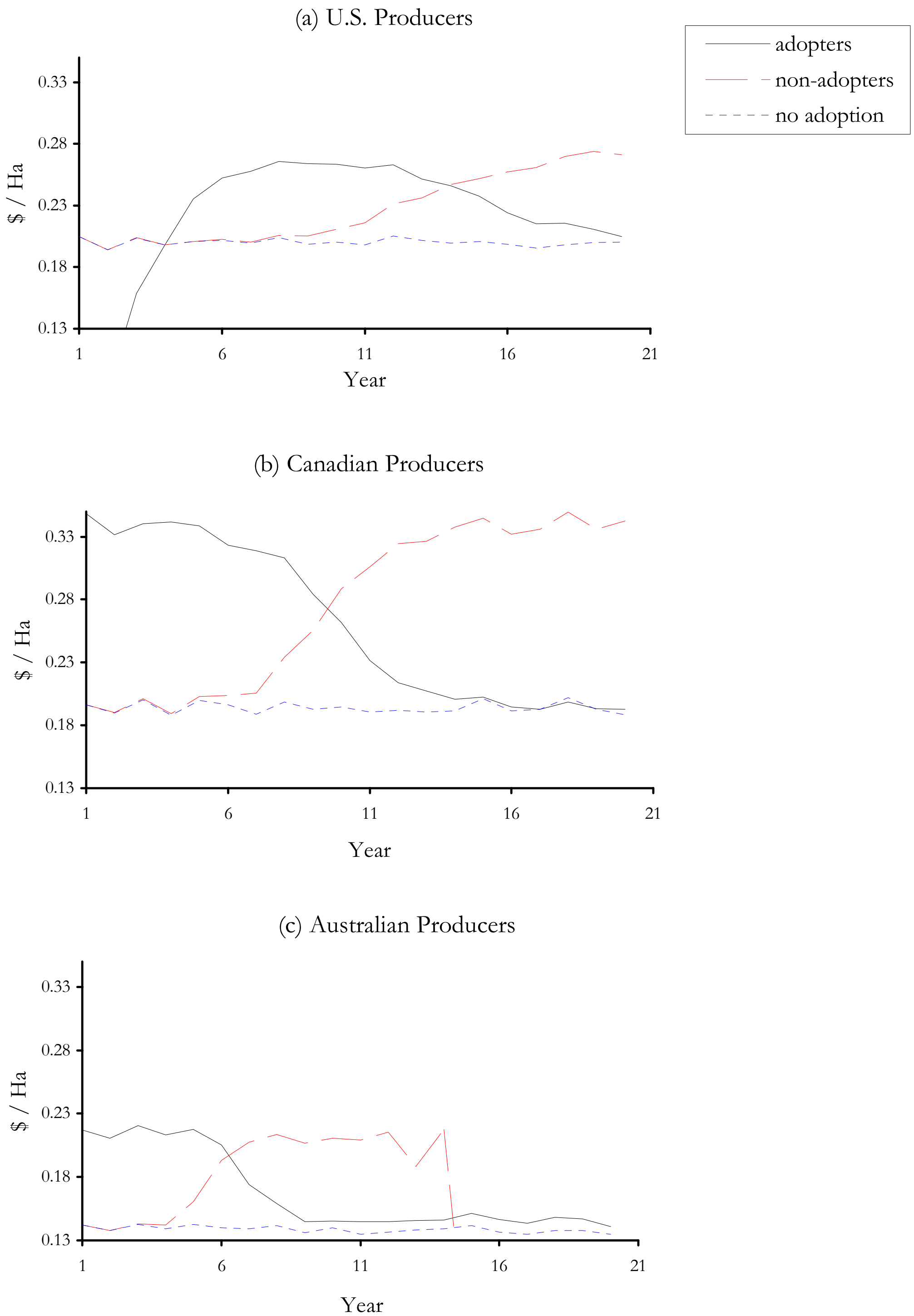

Figure 5. Producer Surplus Over Time When Australia Adopts Fastest, Canada Adopts Second Fastest, and the U.S. Adopts Slowest (Figure 1, Panel b)