EXPORTERS IN CROSS SECTION, STOCK MARKETS, AND
WILLINGNESS TO PAY FOR PESTICIDES’
ENVIRONMENTAL FEATURES

By
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To the Faculty of Washington State University:

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Last but not least, my gratitude goes to my parents and grandparents who always understand and support me to pursue my interests and career.
EXPORTERS IN CROSS SECTION, STOCK MARKETS, AND WILLINGNESS TO PAY FOR PESTICIDES’ ENVIRONMENTAL FEATURES

Abstract

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The dissertation consists of three studies that cover my fields of international economics, financial economics, and econometrics.

The first chapter studies how do producers that export their goods directly differ from those export through intermediaries? We take a standard model of trade with heterogeneous firms and add heterogeneity in quality to the usual heterogeneity in productivity. We model trade intermediaries as increasing marginal costs but decreasing fixed costs of exporting. We find that firms with the highest quality-adjusted productivity levels choose to export directly, while those with the lowest levels do not export at all; those in between use trade intermediaries. Quantitatively, we consider the effects of different distributions over quality and productivity draws and make comparisons with stylized facts in the literature.

Unlike other studies, we find that the two returns are related. In the sample of 1995-2009, a shock to the U.S. return significantly affects the volatilities of the Chinese return, but the effect is not the other way round. However, there is an interactive relationship between the two returns in the sample of 2006-2009. The estimation results further suggest that the Sharpe ratio for a 10-year holding period increases almost by one half when Chinese stocks are added. The relationship between the U.S. and Chinese returns appears to increase the share of Chinese stocks that maximizes the Sharpe ratio in a two-country portfolio.

The third chapter conducted a discrete-choice experiment using direct and indirect valuation to determine the values that environmental amenities represent to apple and pear growers when choosing a pesticide. We found no statistically significant differences across WTP obtained through either valuation, thus no evidence of social desirability bias. Because both apple and pear growers need to protect crops from damaging pests and are presented with varying degrees of production, financial, and marketing risks. In this situation stated choices show no evidence of departing from actual behavior due to social desirability sentiments.
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Dedication

This dissertation is dedicated to my parents and grandparents who unconditionally 
love and support me
CHAPTER ONE  INTRODUCTION

The interdependence of globalized economies has been crucial to the most of countries in the world; the study of the theory of international economics generates an understanding of many key events that shape our domestic and international environment. In my dissertation, the studies focus on two important perspectives of international economics: international trade and international financial market.

Exporters in Cross Section: Direct vs. Intermediated Trade

Some firms export their products directly, while others employ trade intermediaries. In the first study, we develop a model to analyze this tradeoff. We then consider the entire cross section of importers.

Bernard and Jensen (1995) and Bernard, Jensen, and Schott (2009) have found that only a fraction of firms directly export products to foreign markets using firm-level data, and this fact has been well-covered by a theoretical model in Melitz (2003) which features firm heterogeneity and fixed export cost. However, the role of intermediary firms has been ignored in these empirical and theoretical findings. A significant amount of trade occurs through intermediaries. For example, Ahn et al. (2011) find that Chinese export intermediaries contributed 22% of total exports. Blum et al. (2010) report that 35% of imports are handled by intermediaries. Bernard et al. (2010) find that intermediary exports account for 10 percent of total exports in the U.S..

Recently, the importance of intermediaries has been put on some papers in international trade. Akerman (2009) argue that the wholesaler technology exhibits economies of scope. Bernard et al. (2010) find that exporting firms in the US exhibit substantial heterogeneity as regards export mode, whether firms export directly or through intermediaries. Ahn et al. (2011)
predicts that firms will endogenously select their mode of export – either directly or indirectly through intermediary is determined by productivity.

In this paper, we develop a model to study how producers that export their goods directly differ from those that export through trade intermediaries. We model trade intermediary technology as increasing marginal costs because Ahn et al. (2011) report that exports through intermediaries incur an additional marginal cost, which captures re-labeling, packaging and other per-unit costs associated with taking the title of varieties from the manufactures, but decreasing fixed costs of exporting because Bernard et al. (2011) find fixed costs are positively associated with intermediary exports both in the aggregate and within firms.

The novelty of this paper is that we take a standard model of trade with heterogeneous firms and add heterogeneity in quality to the usual heterogeneity in productivity. We develop the model which allows consumers care about quality on the demand side and firms produce varieties of different quality on the supply side as in Baldwin and Harrigan (2011). The standard trade model with heterogeneous firms focus on differences in productivity, but it is increasingly common to also allow for differences in product quality. Feenstra and Hanson (2004) find higher mark-ups on re-exports of Chinese goods for differentiated goods and suggest a quality-sorting role for Hong Kong intermediaries. Whereas Khandelwal (2009), and Hallak and Schott (2006) report that the quality is unobserved, the approach to using price as a proxy of quality, while convenient, requires strong assumptions since prices could reflect not just quality, but also variations in manufacturing costs. Johnson (2011), and Hallak and Sivadasan (2008) uses the ratio of quality to cost as “capability” to develop a model and predict that, conditional on size, exporters sell products of higher quality and at higher prices. Crozet, Head, and Mayer (2009) use data of French wine exporters and observe that firms with higher measured quality are more
likely to export, export more, and charge higher prices. Selection into exporting can be driven by productivity sorting, quality sorting, or a quality-adjusted productivity.

The finding in Kugler and Verhoogen (2012) stress the point that we need add quality heterogeneity. They document that there is a robust positive correlation between plant size (measured by sales or employment) and output prices using Colombian manufacturing data, and show that the quality differences of both inputs and outputs are crucial in generating the price-plant size correlations by making a parsimonious extension of Melitz (2003) framework. Hallak and Sivadasan (2009) document a positive price-plant size relationship in Indian data as well. Whereas, in standard Melitz (2003) trade model, prices are negatively correlated with establishment size by considering productivity heterogeneity of heterogeneous firms.

To our knowledge, Dasgupta and Mondria (2012) is the only study that considers quality heterogeneity in the presence of intermediaries in standard trade model. They develop a model to study the role of intermediaries in alleviating quality uncertainly, they find the entry of intermediaries creates a positive externality for the direct exporters: in the presence of intermediaries, the low quality exporters choose to export through intermediaries, thereby raising the average quality of direct exporters. Whereas we consider both productivity and quality heterogeneity of heterogeneous firms in the presence of intermediation technology in standard trade model, and find that firms with the highest quality-adjusted productivity levels choose to export directly, while those with the lowest levels do not export at all; those in between use trade intermediaries. The size of one firm is determined by quality-adjusted productivity and export mode only. The primary role of quality heterogeneity is in altering the cross-sectional distribution over prices.
Quantitatively, we consider the effects of three different distributions over quality and productivity draws. The three examples have different implications for the distribution of over marginal cost. There is a positive correlation between establishment size and output prices in example of quality independent on productivity, and in example of quality dependent on productivity with some restrictions. However for bivariate joint distribution, whatever of positive or negative correlation of quality and productivity using bivariate Pareto or bivariate exponential distribution, we always find a negative correlation between price and establishment size.

In addition, we are concerning with capturing the facts in the data which are listed below, and in order to keep consistency, we use the facts of U.S. Linked/Longitudinal Firm Trade Transaction Database (LFTTD).

*Stylized fact #1*: The overall share of U.S. manufacturing firms that export is relatively small, at 18 percent (Bernard, Jensen, Redding, and Schott (2007));

*Stylized fact #2*: Indirect exporters account for 35 percent of total exporting firms (Bernard, Jensen, Redding and Schott (2010));

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Intermediaries export higher unit values than direct exporters. (e.g. Feenstra and Hanson (2004), Ahn, Khandelwal, and Wei (2011))

Antràs and Costinot (2010) develop a model that intermediaries work as a trader to match farmers and centralized markets, and show that intermediaries could raise or lower welfare depends on different types of integration. Ahn et al. (2011) find that the intermediaries play an important role in facilitating trade and realizing gains. Therefore, we did experiments to examine the importance of intermediaries by eliminating intermediaries in the model. We find that there is no big loss of welfare by eliminating intermediaries.

**The Co-Movement between Chinese and U.S. Aggregate Stock Returns**

The second study focuses on the co-movement between Chinese and U.S. aggregate stock returns. The Chinese economy is increasingly linked to other economies through international trade and capital flows. This suggests that the Chinese stock market may be integrated with international stock markets. The goal of this paper is to study how the Chinese stock market is linked to the U.S. stock market. Understanding this link will provide possible guidance for investors to diversify risks. For example, Longin and Solnik (1995) document that linkages between international asset returns are important for fund managers to diversify risks. In
addition, it will help us to understand the integration of international financial markets, which will eventually help to implement better international institutions or regulations.

Unlike Chen, H. et al. (2006), Li (2007) and Hu (2010), we find significant relation between the two markets. Especially, the Chinese market depends more strongly on the U.S. market. We further study the implication of our result on international portfolio allocation between the two markets using Sharpe ratio (Sharpe, 1966, 1994) analysis. In particular, we consider how the relation affects the investor’s problem to form a portfolio of Chinese and U.S. stocks. The Sharpe ratio is the expected excess return divided by the standard deviation. This is a relative measure of the expected return compared to the risk. In addition, an investor who prefers higher expected return and lower volatility (and nothing else) would choose a portfolio where the Sharpe ratio is maximized. We study how the Sharpe ratio is affected by a diversification between the U.S. and Chinese stock markets, given the estimated relation between Chinese and U.S. stock markets. The relation between the U.S. and Chinese returns appears to increase the share of Chinese stocks that maximizes the Sharpe ratio in the two-country portfolio.

**Willingness to Pay for Pesticides’ Environmental Features and Social Desirability Bias: The Case of Apple and Pear Growers**

In the third study, I make an application of my field of econometrics to study the willingness to pay for pesticide’s environmental features and social desirability bias: the case of apple and pear growers.

Agricultural producers, such as fruit growers, are committed to produce high quality fruits, in terms of wholesomeness, appealing appearance and sensory characteristics, and environmental and social sustainability. To assure obtaining high quality fruit, producers must select a bundle of mechanisms to protect their crops from pest damages. Given the benefits of
biological control and the proliferation of pesticides with unknown effects on natural enemies, one wonders if growers perceive a value for conserving natural enemies in the orchard and if these values are reflected in their choice of pesticides. One way to elicit growers’ values for environmental amenities when choosing pesticides is through hypothetical choice experiments. However these experiments have been long scrutinized, as they are believed to lack prediction accuracy of real choice behavior due to their hypothetical nature. One source of bias is the social desirability bias that happens when responses to hypothetical surveys are influenced by respondents’ desire to please the interviewer or to be consistent with societal norms (Legget et al. 2003).

We conducted a hypothetical discrete-choice experiment to determine the values that environmental amenities, represent to apple and pear growers when choosing a pesticide. To investigate for the potential presence of social desirability bias we used an indirect valuation approach. We found that different growing conditions faced by apple and pear growers dictate differences in their valuation for pesticides features. For both apple and pear growers we did not find evidence of social desirability bias when stating WTP for pesticide features. However, when predicting actual market shares for commercial pesticides, we found that the indirect valuation outperformed the direct valuation for pear growers, but not for apple growers.

To our knowledge, our study is the first one investigating fresh fruit growers’ perceptions for pesticides features affecting biological control systems. Fresh fruits are perennial crops that posit and interesting case as higher financial, production, and marketing risks are involved, compared to annual row crops. This is because perennial crops exhibit longer juvenility periods than annual crops and full production is not realized until the fifth year after establishment in apples and seventh year in pears (Gallardo, Taylor, and Hinman 2010; Galinato and Gallardo...
Hence, we wonder if the increased risks associated with fresh fruit production would have an impact on growers’ values for pesticides environmental related features.
References


CHAPTER TWO EXPORTERS IN CROSS-SECTION: DIRECT vs. INTERMEDIATED TRADE

Abstract

How do producers that export their goods directly differ from those that export through trade intermediaries? We take a standard model of trade with heterogeneous firms and add heterogeneity in quality to the usual heterogeneity in productivity. We model trade intermediaries as increasing marginal costs but decreasing fixed costs of exporting. We find that firms with the highest quality-adjusted productivity levels choose to export directly, while those with the lowest levels do not export at all; those in between use trade intermediaries. Quantitatively, we consider the effects of different distributions over quality and productivity draws and make comparisons with stylized facts in the literature.
1. Introduction

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The remaining paper is structured as follows. Section 2 lays out the basic model and propositions we will quantify in the data. Section 3 studies how firms’ size and price distributions depend on the distribution of draws. Section 4 provides quantitative analysis. Section 5 compares the model with the stylized facts in the data. Finally, Section 6 concludes.

2. Model

We develop a model economy with two symmetric countries. Since our focus is on the cross section of exporters, we omit from the model domestic production and consumption of goods. In each country, there is a continuum of monopolistically competitive exporting firms producing differentiated import goods. Labor is the only factor of production. Because the two countries are symmetric, the wages are equal and we normalize them to one. Each entering firm endogenously decides whether to export and, if so, whether to export directly or through an intermediary. Going through an intermediary lowers the fixed cost of exporting but increases the marginal cost.
2.1. Consumers

In each country there is a representative consumer and a continuum of differentiated import goods denoted by \( X \). The goods differ in both quantity and quality. Each consumer has the utility function

\[
C = \left( \int_X (\eta(x)c(x))^{\frac{\sigma-1}{\sigma}} \, dx \right)^{\frac{\sigma}{\sigma-1}},
\]

where \( c(x) \) is the quantity consumed of variety \( x \), \( \eta(x) \) is the quality of variety \( x \), and \( \sigma \), \( \sigma > 1 \), is the elasticity of substitution between any two varieties. The specification of quality is such that each consumer is indifferent between one unit of a good with a given level of quality and half of a unit of a good with twice the quality. Each consumer is endowed with \( \bar{T} \) units of labor, which are inelastically supplied to exporters. Each consumer maximizes (1) subject to the budget constraint

\[
\int_X p(x)c(x)dx = \bar{T},
\]

where \( p(x) \) is the price of variety \( x \). Demand for variety \( x \) is given by

\[
c(x) = \eta(x)^{\sigma-1} p(x)^{-\sigma} P^{\sigma-1} \bar{T},
\]

where

\[
P = \left( \int_X \eta(x)^{\sigma-1} p(x)^{-\sigma} \, dx \right)^{\frac{1}{1-\sigma}}
\]

is the aggregate price index.

2.2. Producers

In each country there is a continuum of monopolistically competitive export firms. Firms are heterogeneous in three dimensions: productivity, quality, and export mode. The first two
forms of heterogeneity are the result of a random draw from a joint probability distribution $G(\cdot, \cdot)$, while the third is endogenously chosen by each firm. A firm chooses whether to be a direct exporter (denoted by $D$) or an indirect exporter (denoted by $I$). The idea is that indirect exporters sell their products through trade intermediaries. Rather than explicitly modeling a trade intermediation sector, we set up a firm’s choice of export mode as a choice of technology. Relative to technology $D$, technology $I$ increases the marginal cost of exporting but decreases the fixed cost of exporting. Implicitly, there is a trade intermediation sector that charges a fixed cost per variety exported and a variable cost that is a percentage of the value of goods being exported.

The technologies are as follows. Output of a direct exporter with draw $(\eta, z)$ is given by

$$y_D(\eta, z) = \frac{z \delta_D(\eta, z)}{\eta^\alpha},$$

where $\delta_D(\eta, z)$ is the input of labor. Output of an indirect exporter with draw $(\eta, z)$ is given by

$$y_I(\eta, z) = \frac{z \delta_I(\eta, z)}{\gamma \eta^\alpha},$$

where $\delta_I(\eta, z)$ is the input of labor and $\gamma > 1$. Here $\gamma$ is the factor by which marginal cost is higher when exporting through a trade intermediary. Each firm takes the importing consumer’s demand function (3) as given, so output quantities also satisfy

$$y_j(\eta, z) = \eta^{\sigma-1} p_j(\eta, z)^{-\sigma} P^{\sigma-1},$$

where $p_j(\eta, z)$ is the price charged by an exporter with draw $(\eta, z)$ operating technology $j$. The fixed cost of operating technology $j$ is $f_j$ units of labor, where $f_D > f_I$ to reflect the role of trade intermediaries in reducing fixed costs of trade. Profits are then given by

$$\pi_j(\eta, z) = p_j(\eta, z)y_j(\eta, z) - \delta_j(\eta, z) - f_j.$$
A direct exporter chooses its product’s price to maximize (8) subject to (5) and (7). The profit-maximizing price is

\[ p_D(\eta, z) = \frac{\sigma \eta^\theta}{\sigma - 1} z. \]  

(9)

An indirect exporter chooses its product’s price to maximize (8) subject to (6) and (7). The profit-maximizing price is

\[ p_I(\eta, z) = \frac{\sigma \gamma^\theta}{\sigma - 1} z. \]  

(10)

Each price is a constant markup over marginal cost.

### 2.3. Selection of Export Mode

Each firm endogenously decides whether to export and, if so, which export mode to use.

The decision to export directly is given by the indicator function

\[ t_D(\eta, z) = \begin{cases} 1 & \text{if } \pi_D(\eta, z) \geq 0 \text{ and } \pi_D(\eta, z) \geq \pi_I(\eta, z) \\ 0 & \text{otherwise} \end{cases}. \]  

(11)

The decision to export indirectly is given by the indicator function

\[ t_I(\eta, z) = \begin{cases} 1 & \text{if } \pi_I(\eta, z) \geq 0 \text{ and } \pi_I(\eta, z) > \pi_D(\eta, z) \\ 0 & \text{otherwise} \end{cases}. \]  

(12)

We can alternatively characterize a firm’s choice of export mode in terms of cutoff rules based on a firm’s quality-adjusted productivity. To see why, notice that the profits of an indirect exporter with draw \((\eta, z)\) can be expressed as

\[ \pi_I(\eta, z) = \eta^{(\sigma-1)(1-\theta)} z^{\sigma-1} \gamma^{1-\sigma} \frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma} P^{\sigma-1} - f_I \]  

(13)

and the profits of a direct exporter with draw \((\eta, z)\) are
Defining a firm’s quality-adjusted productivity as
\[ q(\eta, z) = \eta^{(\sigma - 1)/(1 - \theta)} z^{1 - \sigma}, \]

We can specify simple cutoff rules for choice of export mode. We want the cutoffs to be binding, so we restrict our attention to the case where not all firms export and, among those that do export, not all use the same export mode. In this case we can define cutoffs in terms of quality-adjusted productivity as follows:

\[ \bar{q}_I = f_I / \left( \gamma^{1 - \sigma} P^{\sigma - 1} (\sigma - 1)^{\sigma - 1} \right) \]
\[ \bar{q}_D = \frac{f_D - f_I}{(1 - \gamma^{1 - \sigma}) P^{\sigma - 1} (\sigma - 1)^{\sigma - 1}}. \]

A firm with draw \((\eta, z)\) will not export if \(q(\eta, z) < \bar{q}_I\), will export through an intermediary if \(\bar{q}_I \leq q(\eta, z) < \bar{q}_D\), and will export directly if \(q(\eta, z) \geq \bar{q}_D\).

This is illustrated in Figure 1. The dotted line shows the profits of exporting by intermediaries as a function of quality-adjusted productivity. It intersects the vertical axis at \(-f_I\), the fixed cost of exporting through a trade intermediary. The solid line shows the profits of exporting directly as a function of quality-adjusted productivity. It intersects the vertical axis at \(-f_D\), the fixed cost of exporting directly. The solid line is steeper than the dotted line because of the higher marginal cost incurred by exporting through a trade intermediary. The figure shows that firms partition into different export modes by quality-adjusted productivity.

Another way of looking at a firm’s choice of export mode is through a two-dimensional plot of \(\eta\) and \(z\). We show this in Figure 2. The red cutoff line is given by
\[ \tilde{\eta}_I(z) = \left( \frac{f_I}{\gamma^{1-\sigma} P^\sigma z^{-\sigma-1} (\sigma - 1)^{\sigma-1}} \right)^{\frac{1}{(\sigma-1)(1-\sigma)}}, \quad (18) \]

while the blue cutoff line is given by

\[ \tilde{\eta}_D(z) = \left( \frac{f_D - f_I}{(1 - \gamma^{1-\sigma}) P^\sigma z^{-\sigma-1} (\sigma - 1)^{\sigma-1}} \right)^{\frac{1}{(\sigma-1)(1-\sigma)}}. \quad (19) \]

For each productivity level \( z \), there is a minimum quality \( \tilde{\eta}_I(z) \) such that firms exporting through intermediaries above this minimum earn non-negative profits. For each productivity level \( z \), there is a minimum quality \( \tilde{\eta}_D(z) \) such that firms exporting directly above this minimum earn non-negative profits. Firms within \( (\tilde{\eta}_I(z), \tilde{\eta}_D(z)) \) will export by intermediaries, and firms above \( \tilde{\eta}_D(z) \) will export directly.

**2.4. Aggregation, Free-Entry, and Market-Clearing Conditions**

Each entering firm must pay a fixed cost of \( f_e \) units of labor. After paying this cost, the entrant learns its productivity and product quality by taking a draw from a joint probability distribution \( G(\eta, z) \). Firms enter until the expected value of entry equals the cost of entry:

\[ \int \int (t_I(\eta, z)\pi_I(\eta, z) + t_D(\eta, z)\pi_D(\eta, z)) G(\eta, dz) = f_e. \quad (20) \]

Denoting the measure of entrants by \( M \), clearing in the labor market requires that

\[ M\left( \int \int (t_I(\eta, z)(1, \eta, z) + f_I) + t_D(\eta, z)(1, \eta, z) + f_D) G(\eta, dz) + f_e \right) = 1. \quad (21) \]

Finally, the aggregate price index must be consistent with the decisions of firms:

\[ P = \left( M\left( \int \int (t_I(\eta, z)\eta^{-\sigma-1} p_I(\eta, z)^{-\sigma} + t_D(\eta, z)\eta^{-\sigma-1} p_D(\eta, z)^{-\sigma}) G(\eta, dz) \right) \right)^{\frac{1}{1-\sigma}}. \quad (22) \]
2.5. Equilibrium

For two symmetric countries, an equilibrium of monopolistic competition consists of aggregates $\hat{P}$ and $\hat{M}$, consumption decisions $\hat{c}(x)$, goods prices $\hat{p}(x)$, and firm decision rules $\hat{p}_j(\eta, z)$, $\hat{y}_j(\eta, z)$, $\hat{\pi}_j(\eta, z)$ for $j = I, D$ such that:

Given $\hat{p}(x)$, the representative consumer in each country chooses $\hat{c}(x)$ to maximize utility (1) subject to the budget constraint (2).

A firm with draw $(\eta, z)$ operating technology $D$ chooses $\hat{p}_D(\eta, z)$, $\hat{y}_D(\eta, z)$, $\hat{\pi}_D(\eta, z)$ to maximize profits (8) subject to the technology constraint (5) and the demand constraint (7).

A firm with draw $(\eta, z)$ operating technology $I$ chooses $\hat{p}_I(\eta, z)$, $\hat{y}_I(\eta, z)$, $\hat{\pi}_I(\eta, z)$ to maximize profits (8) subject to the technology constraint (6) and the demand constraint (7).

If good $x$ is produced by a firm with draw $(\eta, z)$ operating technology $j$, then $\hat{c}(x) = \hat{y}_j(\eta, z)$ and $\hat{p}(x) = \hat{p}_j(\eta, z)$.

The aggregate price index $\hat{P}$ satisfies (22).

The free-entry condition (20) holds.

The labor market-clearing condition (21) holds.

Calculating the equilibrium involves finding the values of the aggregates $P$ and $M$ such that (20) and (22) hold. Then, by Walras’s Law, (21) must also hold.

2.6. Comparing Direct and Indirect Exporters by Size
Here we consider how direct and indirect exporters differ in terms of size and the prices of their goods. In the data, the two most common measures of firm size are revenue and employment (quantity data is typically not available). We consider these measures in the model. We can express the revenue of firms as

$$ r_f(\eta, z) = q(\eta, z)\gamma^{\sigma-1} \left( \frac{(\sigma-1)p}{\sigma} \right)^{\frac{\sigma-1}{\sigma}} T $$

(23)

$$ r_d(\eta, z) = q(\eta, z)\gamma^{\sigma-1} \left( \frac{(\sigma-1)p}{\sigma} \right)^{\frac{\sigma-1}{\sigma}} T $$

(24)

and the employment of firms as

$$ 1_f(\eta, z) = q(\eta, z)\gamma^{\sigma-1} \left( \frac{\sigma}{\sigma-1} \right)^{-\frac{\sigma}{\sigma-1}} p^{\sigma-1}T $$

(25)

$$ 1_d(\eta, z) = q(\eta, z)\gamma^{\sigma-1} \left( \frac{\sigma}{\sigma-1} \right)^{-\frac{\sigma}{\sigma-1}} p^{\sigma-1}T. $$

(26)

Here we see that a firm’s size, whether measured by revenue or employment, is proportional to its quality-adjusted productivity and that going through a trade intermediary reduces firm size by a factor of $\gamma^{\sigma-1}$. Since a firm’s choice of technology is determined by its quality-adjusted productivity, a firm’s size relative to others is, in a sense, entirely dependent on its quality-adjusted productivity. In the next section, we pay special attention to the distribution of quality-adjusted productivity.

We can also consider the role of intermediated trade from an aggregate perspective. Given a joint distribution of draws $G(\cdot, \cdot)$, let $H(\cdot)$ denote the implied distribution of quality-adjusted productivity. Then the ratio of revenue or employment from indirect exporters relative to direct exporters can be expressed as
As we would expect, this ratio is increasing in \( f_D \) and decreasing in \( f_I \) and \( \gamma \).

While the size distribution of firms depends on the distribution of quality-adjusted productivity, the distribution of prices charged by firms depends on the distribution of \( \eta^\theta / z \).

The primary role of quality heterogeneity is in altering the cross-sectional distribution over prices.

### 3. Examples of Distributions of Draws

Here we consider three examples of distributions of draws that are analytically tractable. We consider an example with no quality heterogeneity, an example in which a firm’s product quality is dependent on its draw of productivity, and an example in which the draws of quality and productivity come from two independent distributions. In each case, we use Pareto distributions because they are the most commonly used in the literature and give simple analytic solutions.

Given a particular joint distribution of draws \( G(\cdot, \cdot) \), we are particularly interested in the implied distributions over quality-adjusted productivity, \( \eta^{(\sigma-1)(1-\theta)} z^{-\sigma-1} \), and marginal cost, \( \eta^\theta / z \).

This is because the size distribution of exporters is closely tied to the distribution of quality-adjusted productivity and the price distribution of exporters’ goods is closely tied to the distribution of marginal cost. In particular, we examine the size of firms before taking into account the effect of trade intermediation, so firm size is entirely proportional to quality-adjusted productivity, and we examine the price distribution of firms before taking into account the effect of trade intermediation, so price is entirely proportional to marginal cost. We are further concerned with the correlation between the two quality-adjusted productivity and marginal cost.
3.1. No Quality Heterogeneity

In standard models of trade with heterogeneous firms, such as Melitz (2003), the only heterogeneity is in productivity. In this case we set $\eta = 1$ for all firms and let $z$ be drawn from a Pareto distribution. In this case, a firm’s quality-adjusted productivity is given by $z^{\sigma - 1}$. A firm’s marginal cost is $1/z$. There is a perfect negative correlation between a firm’s quality-adjusted productivity and its marginal cost. Suppose that the distribution over $z$ is Pareto with cumulative distribution function $G(z) = 1 - (z_0 / z)^k$, where $z_0$, $z_0 > 0$, is the lower bound and $k$, $k > 1$, is the shape parameter. Then the distribution over quality-adjusted productivity is Pareto with lower bound $z_0^{\sigma - 1}$ and shape parameter $k / (\sigma - 1)$. The distribution over the inverse of marginal cost is Pareto with lower bound $z_0$ and shape parameter $k$. The aggregate price and free entry condition as well as the relative price, employment, revenue, and measures of firms are reported in Appendix A.

3.2. Quality Dependent on Productivity

In this example we suppose that $z$ is drawn from a Pareto distribution with cumulative distribution function $G_z(z) = 1 - (z_0 / z)^k$, where $z_0 > 0$ and $k > (\sigma - 1)(1 + \alpha \theta - \alpha)$. We then set $\eta = \beta z^{-\alpha}$, where $\beta > 0$ and $\alpha > 0$. Here $\alpha$ indicates the extent to which higher marginal costs are related to higher quality. This parameterization of dependent draws is similar to that in Baldwin and Harrigan (2011). In this case, $q = \beta^{(\sigma - 1)(1 - \theta) - (\sigma - 1)(1 + \alpha \theta - \alpha)} z^{(\sigma - 1)(1 + \alpha \theta - \alpha)}$ and $\eta^\theta / z = \beta^\theta z^{-\alpha \theta - 1}$.

In this example, we have three different cases: $\alpha > 1 / (1 - \theta)$, $\alpha = 1 / (1 - \theta)$, and $\alpha < 1 / (1 - \theta)$. If $\alpha > 1 / (1 - \theta)$, there is a positive correlation between quality-adjusted
productivity and marginal cost. If $\alpha = 1/(1-\theta)$, then there is no heterogeneity in quality-adjusted productivity. If $\alpha < 1/(1-\theta)$, then there is a negative correlation between quality-adjusted productivity and marginal cost.

The distribution over quality-adjusted productivity is Pareto with lower bound $\beta^{(\sigma-1)(1-\theta)} z_0^{(\sigma-1)(1+\theta-\alpha)}$ and shape parameter $k / ((\sigma-1)(1+\alpha\theta-\alpha))$. The distribution over the inverse of marginal cost is Pareto with lower bound $\beta^{-\theta} z_0^{\alpha\theta+1}$ and shape parameter $k / (\alpha\theta+1)$. The aggregate price and free entry condition as well as the relative price, employment, revenue, and measures of firms are reported in Appendix B.

3.3. Independent Draws of Quality and Productivity

Firms take two draws $(\eta, z)$ independently. We assume that both $z$ and $\eta$ follow Pareto distributions. The cumulative distribution functions are $G_1(z) = 1 - (z_0 / z)^{k_1}$ and $G_2(\eta) = 1 - (\eta_0 / \eta)^{k_2}$. There is a perfect positive correlation between $q$ and $\eta^\theta / z$ in this case. The distribution over $q$ is Pareto with lower bound $\eta_0^{(\sigma-1)(1-\theta)} z_0^{\sigma-1}$ and shape parameter $(k_1 - k_2) / (\theta(\sigma-1))$. The distribution over marginal cost is with lower bound $\eta_0^{\theta} z_0^{-1}$ and shape parameter $(k_1 - k_2) / (1+\theta)$. The aggregate price and free entry condition as well as the relative price, employment, revenue, and measures of firms are reported in Appendix C.

3.4. Bivariate Joint Distribution

If firm draws quality $\eta$ and productivity $z$ from a bivariate joint distribution, the covariance between $\eta$ and $z$ governs the behavior of aggregate prices with respect to exporting.
thresholds, however, which does not yield a closed-form solution with common joint
distributions; we do a Monte-Carlo simulation of $10^5$ times using examples of bivariate
exponential and bivariate Pareto distribution to examine the correlation between quality-adjusted
productivity and marginal cost.

We adopt the first kind of bivariate exponential distribution in Gumbel (1960) in which
the coefficient of correlation is never positive, which is consistent with Baldwin and Harrigan
(2011) that firms choose the quality of the goods they produce subject to costs of upgrading
quality, hence, $\eta$ and $z$ follow the joint distribution

$$f(\eta, z) = e^{-\eta(1+\delta z) - z}[(1 + \delta \eta)(1 + \delta z) - \delta].$$

(28)

where $0 \leq \delta \leq 1$.

We simulate productivity $z$ from its marginal distribution,

$$f(z) = e^{-z}.$$  

(29)

and we simulate quality $\eta$ from its conditional distribution

$$f(\eta | z) = e^{-\eta(1+\delta z)}[(1 + \delta \eta)(1 + \delta z) - \delta].$$

(30)

Both quality-adjusted productivity and marginal cost are functions of $\eta$ and $z$, accordingly, we
find that the correlation between quality-adjusted productivity and marginal cost is negatively
correlated, which indicate that firms export through intermediaries charge a higher price.

On the contrary, the bivariate Pareto distribution always has a positive coefficient of
correlation, which reflect that higher productivity induces the firm to upgrade quality, which
raises marginal costs. However, we still find negative correlation between quality-adjusted
productivity and marginal cost.
3.5. Discussion of Size Distribution vs. Price Distribution

In each of the first three examples, we obtain a Pareto distribution over quality-adjusted productivity, which is proportional to firm size. But the three examples have different implications for the distribution over marginal cost. A negative correlation between quality-adjusted productivity and marginal cost is obvious when there is no quality heterogeneity, whereas, the importance of which has been shown in previous literature. As quality depends on productivity, the correlation tends to be negative when quality increases slowly with marginal cost, otherwise, the correlation would be positive. As draws are independent, there is always a positive correlation. By considering a bivariate joint distribution of quality and productivity draws, we find that there is a negative correlation between quality-adjusted productivity and marginal cost regardless of positive or negative correlation between productivity and quality.

The literature primarily finds that there is a positive correlation between establishment size and output prices when there is no consideration of intermediated trade, though there is some evidence of a negative correlation. Using Colombian data, Kugler and Verhoogen (2012) found that, on average, there is a robust positive correlation between plant size (measured by sales or employment) and output prices: within narrow product categories, larger plants charge higher prices for the goods they produce. Using U.S. sectoral data, Johnson (2011) found a positive correlation between establishment size and prices in most sectors, but a negative correlation in some large sectors, including autos, electronics, and apparel/footwear. Using U.S. data, Baldwin and Harrigan (2011) find a positive correlation. With considering intermediaries, Feenstra and Hanson (2004) using Hong Kong exports, and Ahn, Khandelwal, and Wei (2011) using Chinese customs data both found intermediaries export higher unit values. Because export through intermediaries incur additional marginal cost, which captures re-labeling, packaging and
other per-unit costs associated with taking the title of varieties from the manufacturers. The price of indirectly exported varieties is therefore higher than the price of directly exported varieties by this factor.

4. Quantitative Analysis

We calibrate the model based on the distributions of draws. Then we use the model to examine the importance of intermediaries by making experiments and compare the model with the stylized facts in the data.

4.1. Calibration

First, we normalize some parameters that do not affect the quantitative findings. Then, we obtain some parameter values by setting up the same size distribution across three examples in that we can compare the other heterogeneous characteristics regarding to exporting behavior. Finally, we select the remaining parameter values to match the stylized facts in the data.

As normalizations, we set the labor endowment \( \bar{t} \); the lower bound on Pareto distribution, \( \eta_0 \) and \( z_0 \); and the cost of entry, \( f_e \), to 1. We set the elasticity of substitution, \( \sigma \), to 2.

Then we set the same size distribution across three examples. By doing that, be specific in draws, we obtain, under condition of no quality heterogeneity, \( \theta = 0 \), and shape parameter, \( k = 2.1 \). In example of quality depends on productivity, we obtain the parameter of elasticity of quality relates to marginal cost, \( \alpha = 0.5 \), and the coefficient of quality relates to marginal cost, \( \beta = 0.8 \). In addition, we get parameter that the elasticity of marginal cost with respect to quality, \( \theta = 0.5 \), and shape parameter, \( \bar{k} = 1.5 \). In example of quality independent on productivity, we
obtain shape parameters, \( k_1 = 3.4, k_2 = 1.1, \) minimum quality possible \( \eta_0 = 0.4. \) We also obtain \( z_0 = 0.5 \) which is common to draws.

With each distribution of draws, we can simultaneously choose the values of \( f_D, \) fixed cost of direct export, \( f_I, \) fixed cost of indirect export, and \( \gamma, \) the parameter which capture the higher marginal cost incurred by indirect export to match the facts: (i) the share of non-exports account for 80 percent, (ii) direct exports account for 13 percent, (iii) and the ratio of indirect to direct labor requirements is 60 percent. The calibration is summarized in Table 1.

The shape parameter of quality-adjusted productivity is 2.1. We draw the distribution over quality-adjusted productivity and price according to calibration, which are reported in Figure 3. The correlation of price and establishment size with bivariate joint distribution is reported in Table 3.

### 4.2. Results

Table 2 shows the extent to which the model captures the stylized facts listed in introduction.

The share of non-exporters, direct exporters, and indirect exporters; the share of indirect export revenue; relative price, employment, revenue, and measures of firms in three examples of distribution are reported in Appendixes A, B, and C.

In Table 2, non-exporters account for 78 percent, direct exporters account for 14 percent, and of indirect exporters is 8 percent. The share of indirect export revenue is 14 percent. The employment of indirect exporter is on average 60 percent of direct exporter; and relative revenue is 60 percent. The model quantitatively captures many important stylized facts of direct and
intermediated trade, only except the relative revenue because which is calibrated the same value with labor employment in the model.

4.3. Experiments

We use the calibration model to conduct the experiments: (i) eliminating intermediaries to see how welfare and trade volume would be affected if there were no intermediated trade; (ii) an increase of fixed cost to direct export; (iii) a reduction of fixed cost to indirect export; (iv) a reduction of marginal cost to indirect export. Report changes relative to the benchmark in the previous subsection. The results of calibration are pretty similar under each distribution assumption; therefore, we only report one group of results. This is summarized in Table 4.

To do so, we set $f_I = \infty$. We find that welfare and trade volume almost do not have any change. By eliminating intermediaries, the cutoff of direct exporters decrease by 44.4 percent, which is almost close to cutoff of indirect exporters when there are intermediaries, therefore, a large proportion, 7 percent of indirect exporters switch to export directly, only a very small proportion, 1 percent of indirect exporters become non-exporters.

Then, we examine the sensitivity of our model. By doing so, first, increase 1 percent of $f_D$, which make the cutoff of direct export increase 37.2 percent while the cutoff of indirect export does not change, as a result, 21.4 percent direct exporters switch to export through intermediaries, and indirect exporters increase 19.6 percent of their exports and direct exporters lose 19.6 percent of their exports, there is no change of welfare.

Second, decrease 1 percent of $f_I$, we find that the sensitivity of model to $f_I$ is similar to $f_D$, and indirect exporters increase 20 percent of their exports and direct exporters lose 19.6 percent of their exports, the welfare increases by 2 percent.
Finally, decrease 1 percent of $\gamma$, we find that the cutoff of direct export decrease 126 percent, which makes 32.1 percent of direct exporters switch to indirect export, and there is 1 percent non-exporters begin to export through intermediaries, and in total there is a 35.7 percent increase of indirect exporters. As a result, indirect exporters increase 35 percent of their exports and indirect exporters lose 34.8 percent their exports, and the welfare increases by 2 percent.

5. Conclusion

In this paper, we study how producers that export their goods directly differ from those that export through trade intermediaries considering heterogeneity of quality. To be specific, we investigate what kind of characteristics of firms determines their exporting choice. Furthermore, we provide quantitative analysis by making different experiments and comparing the model with the stylized facts in the existing literature.

The theoretical model predicts that firms with highest quality-adjusted productivity are more likely to export directly, while those with lowest do not export at all, those with in between export through intermediaries. Firm size, whether measured by revenue or employment, is determined by the distribution over quality-adjusted productivity. The primary role of quality heterogeneity is in altering the cross-sectional distribution over prices.

Quantitatively, we consider the effects of three different distributions over quality and productivity draws and bivariate joint distribution and match the model with stylized facts in the data. The three examples have different implications for the distribution over marginal cost. There is a positive correlation between establishment size and output prices in example of quality independent on productivity, and in example of quality dependent on productivity with some restrictions. However for bivariate joint distribution, whatever of positive or negative correlation
of quality and productivity using bivariate Pareto or bivariate exponential distribution, we always find a negative correlation between price and establishment size.

There is no evident welfare loss by eliminating intermediaries, which may be because the cutoff of direct export after eliminating intermediaries decreases almost close to cutoff of indirect exporters when there are intermediaries, and as a result, a large proportion of indirect exporters switch to export directly, only a very small proportion of indirect exporters become non-exporters.
References


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Economics, 86 (1).


Figure 2.1 Profit curves and quality-adjusted productivity

\[
\pi(\eta, z) = \eta^{(\sigma-1)(1-\theta)} z^{\sigma-1}
\]
Figure 2.2 Firm type by draws

- Cutoff of indirect exporter
- Cutoff of direct exporter
Figure 2.3 Size vs. Price distribution

(1a) size distribution of no quality

(1b) price distribution of no quality

(2a) size distribution of dependent draws

(2b) price distribution of dependent draws

(3a) size distribution of independent draws

(3b) price distribution of independent draws
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<td></td>
<td>Shape parameter of productivity draw</td>
</tr>
<tr>
<td>$k_2$</td>
<td>-</td>
<td>-</td>
<td>1.1</td>
<td></td>
<td>Shape parameter of quality draw</td>
</tr>
<tr>
<td>$f_D$</td>
<td>0.32</td>
<td>1.21</td>
<td>1.22</td>
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</tr>
<tr>
<td>$f_I$</td>
<td>0.30</td>
<td>1.15</td>
<td>1.13</td>
<td></td>
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</tr>
<tr>
<td>$\gamma$</td>
<td>1.05</td>
<td>1.04</td>
<td>1.05</td>
<td></td>
<td>Set to match the facts</td>
</tr>
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Table 2.2 Model vs. Data

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion of non-exporters</td>
<td>0.78</td>
<td>0.82</td>
</tr>
<tr>
<td>Proportion of direct exporters</td>
<td>0.14</td>
<td>0.12</td>
</tr>
<tr>
<td>Proportion of indirect exporters</td>
<td>0.08</td>
<td>0.06</td>
</tr>
<tr>
<td>Share of indirect exports</td>
<td>0.14</td>
<td>0.10</td>
</tr>
<tr>
<td>Relative labor employment of indirect to direct</td>
<td>0.60</td>
<td>0.60</td>
</tr>
<tr>
<td>Relative revenue of indirect to direct</td>
<td>0.60</td>
<td>0.11</td>
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</table>
### Table 2.3 Correlation of price and size

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<th>Distribution</th>
<th>$corr(\eta, z)$</th>
<th>$corr(\rho, \pi)$</th>
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<tr>
<td>Bivariate Exponential</td>
<td>-0.28</td>
<td>-0.09</td>
</tr>
<tr>
<td></td>
<td>-0.04</td>
<td>-0.11</td>
</tr>
<tr>
<td>Bivariate Pareto</td>
<td>0.45</td>
<td>-0.34</td>
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<td></td>
<td>0.06</td>
<td>-0.62</td>
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Table 2.4 Four Experiments

<table>
<thead>
<tr>
<th>Statistics (% change)</th>
<th>Eliminating Intermediaries</th>
<th>Fixed cost (DE) 1% reduction</th>
<th>Fixed cost (IE) 1% reduction</th>
<th>MC (IE) 1% Reduction</th>
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</thead>
<tbody>
<tr>
<td>Welfare</td>
<td>0.0</td>
<td>0.0</td>
<td>2.0</td>
<td>2.0</td>
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<tr>
<td>Trade Volume</td>
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<td>0.0</td>
<td>0.0</td>
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<tr>
<td>Cutoff of direct export</td>
<td>-12.0</td>
<td>-0.11</td>
<td>0.16</td>
<td>34.0</td>
</tr>
<tr>
<td>Cutoff of indirect export</td>
<td>N/A</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Direct exporters</td>
<td>7.0</td>
<td>21.4</td>
<td>-21.4</td>
<td>-32.1</td>
</tr>
<tr>
<td>Indirect exporters</td>
<td>N/A</td>
<td>-21.4</td>
<td>21.4</td>
<td>35.7</td>
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<tr>
<td>Non-exporters</td>
<td>1.0</td>
<td>0.0</td>
<td>0.0</td>
<td>-1.0</td>
</tr>
<tr>
<td>Share of direct exports</td>
<td>12.0</td>
<td>19.6</td>
<td>-19.6</td>
<td>-34.8</td>
</tr>
<tr>
<td>Share of indirect exports</td>
<td>-14.0</td>
<td>-19.6</td>
<td>20.0</td>
<td>3.1</td>
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CHAPTER THREE  THE CO-MOVEMENT OF CHINESE AND U.S. AGGREGATE STOCK RETURNS

Abstract

We study the co-movement of Chinese and U.S. aggregate stock returns in 1995-2009, based on the GARCH BEKK (Baba et al., 1989) method and GARCH CCC (constant conditional correlation) method. Unlike other studies, we find that the two returns are related. In the sample of 1995-2009, a shock to the U.S. return significantly affects the volatilities of the Chinese return, while the Chinese return does not significantly affect the volatilities of the U.S. return. However, there is an interactive relationship between the U.S. and Chinese returns in the sample of 2006-2009. The estimation results further suggest that the Sharpe ratio for a 10-year holding period increases almost by one half when Chinese stocks are added, compared to 11% when the portfolio consists of U.S. stocks only. The relationship between the U.S. and Chinese returns appears to increase the share of Chinese stocks that maximizes the Sharpe ratio in a two-country portfolio.

Key words: Chinese Stocks, U.S. Stocks, Portfolio Formation, Sharpe Ratio.

JEL Specifications: G11, G15, G17
1. Introduction

The Chinese economy is increasingly linked to other economies through international trade and capital flows. This suggests that the Chinese stock market may be integrated with international stock markets. The goal of this paper is to study how the Chinese stock market is linked to the U.S. stock market. Understanding this link will provide possible guidance for investors to diversify risks. For example, Longin and Solnik (1995) document that linkages between international asset returns are important for fund managers to diversify risks. In addition, it will help us to understand the integration of international financial markets, which will eventually help to implement better international institutions or regulations.

The Chinese stock market is relatively young. The Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) were opened in 1990. Initially, the stocks were divided into two types: “A” shares are bought and sold only by Chinese investors, while “B” shares are restricted to foreign investors. However, in 2002, an introduction of Qualified Foreign Institutional Investors (QFII) allowed licensed foreign investors to trade “A” shares. A considerable amount of state-owned shares have been sold to private investors since 2001. In short, the Chinese stock market has become more open and more market-based, representing a larger part of the Chinese economy. One can expect that this would increase the link between the Chinese and U.S. stock markets.

Indeed, we show that the correlation between Chinese and U.S. stock returns has substantially increased over time. We use monthly data from 1995-2009, where the Chinese observations include both SHSE and SZSE. To study this link more formally, we use the GARCH BEKK (Baba et al., 1989) method with a $t$ distribution so that return volatilities in the two markets, as well as the returns themselves, can co-move. In addition, we use the GARCH
CCC (constant conditional correlation) method with a $t$ distribution to estimate the correlation of residual returns between the two markets. We conclude that the two returns are related. In the sample of 1995-2009, a shock to the U.S. return significantly affects the volatilities of the Chinese return, while the Chinese return does not significantly affect the volatilities of the U.S. return. However, there is an interactive relationship between the U.S. and Chinese returns in the sample of 2006-2009.

Chen, D. H. et al. (2006) use weekly SHSE index from 1991 to 2004. However, SHSE does not represent the entire Chinese stock market. For example, Su (2003) documents that mean returns in SHSE have been higher than in SZSE. Chen, H. et al. (2006) use GARCH BEKK with a $t$ distribution and do not find any significant interdependence between Chinese and U.S. stock markets. Li (2007) uses daily SHSE and SZSE composite indices from 2001 to 2005 and employs a multivariate GARCH BEKK with a normal distribution to model volatility linkages between China, Hong Kong, and the U.S. However, the hypothesis of a normal distribution is rejected. He documents that the spillover effects between Chinese and U.S. stock markets do not seem to be significant. Hu (2010) uses daily SHSE index from 1991 to 2007 (not including SZSE in the analysis) and uses a Copula approach to find that the Chinese financial market is relatively separate from other financial markets.

The departure of this paper is as follows. This paper uses monthly SHSE and SZSE real returns from 1995 to 2009. Both SHSE and SZSE are used. We use real returns, accounting for inflation. We use returns, not just the price, to reflect dividend payments. In methods, we use GARCH BEKK with a $t$ distribution to capture the co-movement of volatilities and returns. We additionally use GARCH CCC with a $t$ distribution to reflect a possible correlation between residual returns. A comparison of this paper to other papers is summarized in Table 1.
Unlike Chen, H. et al. (2006), Li (2007) and Hu (2010), we find significant relation between the two markets. Especially, the Chinese market depends more strongly on the U.S. market. We further study the implication of our result on international portfolio allocation between the two markets using Sharpe ratio (Sharpe, 1966, 1994) analysis. In particular, we consider how the relation affects the investor’s problem to form a portfolio of Chinese and U.S. stocks. The Sharpe ratio is the expected excess return divided by the standard deviation. This is a relative measure of the expected return compared to the risk. In addition, an investor who prefers higher expected return and lower volatility (and nothing else) would choose a portfolio where the Sharpe ratio is maximized. We study how the Sharpe ratio is affected by a diversification between the U.S. and Chinese stock markets, given the estimated relation between Chinese and U.S. stock markets. The relation between the U.S. and Chinese returns appears to increase the share of Chinese stocks that maximizes the Sharpe ratio in the two-country portfolio.

The rest of this paper is organized as follows. Section 2 discusses data and preliminary analyses. Section 3 estimates the models of the evolutions of Chinese and U.S. stock returns using GARCH-BEKK and GARCH-CCC with a $t$ distribution. Section 4 studies how the Sharpe ratio changes according to the relative contribution of Chinese stocks. Section 5 concludes.

2. Data and Preliminary Analyses

Our data include monthly returns on Chinese and U.S. stocks from January 1995 to December 2009. The returns on Chinese stocks are obtained from Wind (www.wind.com.cn), which includes both A shares and B shares of SHSE and SZSE. These yuan-denominated returns are transformed into dollar-denominated returns using exchange rate data from the Board of Governors of the Federal Reserve System (http://research.stlouisfed.org/fred2/data/EXCHUS.txt).
The U.S. value-weighted returns are obtained from Kenneth French’s website. The real returns on Chinese and U.S. stocks are obtained using U.S. consumer-price-index data from the Bureau of Labor Statistics.

Figure 1 illustrates the real value-weighted monthly returns for U.S. stocks (solid line) and Chinese stocks (dotted line). Both returns are relatively volatile, so it is difficult to clearly observe the trends. Figure 2 is based on Figure 1, indicating the 3-year moving averages of those two returns. It also features the contribution of exchange rate movements to the return on Chinese stocks (dot-dash line). This contribution is obtained by dividing the exchange rate of the current period by the exchange rate of the previous period, and then subtracting the inflation rate of the U.S. The Chinese return follows the trend of the U.S. return from 1996 to 2005 with a one-year lag. There is an exceptional period from 2005 to 2006 in which Chinese returns are exceptionally high. This may be related to the decision of the Chinese government to sell state-owned shares in 2006. Alternatively, it may reflect international capital flows into China or China’s improved long-run economic prospects.

Figure 3 indicates 3-year moving volatilities (measured by standard deviations) of real value-weighted market returns. Compared with Figure 2, the volatility of U.S. stocks tends to move contrary to 3-year moving averages. The volatility of Chinese stocks initially runs contrary to the U.S. trend and moves the same direction as the average returns. We speculate that, because the Chinese market was small and immature in 1990s, the market return was more volatile then; as it became more mature, the volatility decreased.

Figure 4 indicates 3-year moving correlations of U.S. and Chinese stock returns (solid line, left scale), along with bilateral commodity trade as a share of China’s GDP (dotted line, right scale). Bilateral trade as a share of China’s GDP increased from 1996 to 2006. Bilateral
trade volume contributes more than 40% to China’s GDP in 2006. The greater relation between the Chinese and U.S. economies is reflected in the increased trade volume. It is also reflected in the increased correlation between the two stock returns. Since 2007, the correlation has been as high as 40%. As the relationship between the two economies becomes stronger, this correlation is expected to increase further.

The implications of the results so far on the econometric model that we will set up in the next section are as follows. First, the volatilities of the U.S. and Chinese stock returns, as well as the returns themselves, can co-move. This can be captured by the GARCH BEKK method, which we will introduce in the next section. Second, the correlation between two stock returns increased, and it is expected to increase further if the Chinese economy is linked more closely with the U.S. economy. This can be captured by the GARCH CCC method.

3. Econometric Results

Table 2 reports summary statistics for U.S. and Chinese (monthly real) stock returns. The U.S. returns have a mean of 0.6% lower than China’s 1.6%. The U.S. returns have a volatility (measured by standard deviation) of 4.8% which is also lower than China’s 9.7%. U.S. stock returns have negative skewness, while Chinese stock returns have positive skewness. This indicates that U.S. and Chinese stock returns are not symmetrically distributed. Both return series have kurtosis greater than three, which indicates that the return series of the U.S. and Chinese stock markets all have sharper peaks and longer, fatter tails. In the Jarque-Bera (Jarque and Bera, 1980) test, the null hypotheses of normality are rejected for both returns. These two observations imply that the normal distribution is not appropriate for describing the error term of the two returns. Hence, we use the \( t \) distribution.
3.1. GARCH BEKK Results

Based on Section 2, we consider a model that can capture the co-movement of the returns, as well as their volatilities, in the two markets. We use a vector autoregression model, assuming the error terms are heteroscedastic and correlated. Regarding the error terms, we use the generalized autoregressive conditional heteroscedasticity (GARCH), which was originally developed by Engle (1982) and Bollerslev (1986).

To be specific, we consider

\[ r_t = \alpha + \beta \sum_{k=1}^{T} r_{t-k} + \varepsilon_t \]  

(31)

where \( r_t = [r_{CHt}, r_{UST}] \) is a two-dimensional vector of the two monthly returns at time \( t \), \( k \) is the lag length (we consider one month lagged return \( k = 1 \) because returns have co-moved since 2006 and we do not observe the lagged co-movement of volatilities in Figure 3), \( \alpha \) is a \( 2 \times 1 \) vector of constants representing long-term drift coefficients, and \( \beta \) is a \( 2 \times 2 \) matrix of parameters associated with the lagged returns. The diagonal elements in matrix \( \beta \), \( \beta_{CH} \) and \( \beta_{US} \), measure the effect of past returns on current returns, while the off-diagonal elements, \( \beta_{CH \leftarrow US} \) and \( \beta_{CH \leftarrow US} \), capture the cross effects. The \( 2 \times 1 \) vector of error terms, \( \varepsilon_t \), reflects the innovations.

As we discussed, the Jarque-Bera test rejects the null hypotheses of normality. Hence, we assume each error term is \( t \) distributed with degree of freedom \( \nu \) and mean zero.

In order to measure the co-movement of volatilities, GARCH-BEKK (Baba, Engle, Kraft and Kroner, 1989) is employed. The variance-covariance matrix of returns, \( H_t \), depends on past
values of squared innovations, $\varepsilon_{t-k}e'_{t-k}$, as well as on its own past values, $H_{t-k}$. This allows for own-market and cross-market influences in the conditional variances. To be specific,

$$H_t = C'C + \sum_{k=1}^{n} A_k'\varepsilon_{t-k}e'_{t-k} + \sum_{k=1}^{n} G_k'H_{t-k}G_k,$$

where $C$ is an $n \times n$ symmetric matrix of constants. Here, $A$ is an $n \times n$ matrix, where the diagonal elements of $A$ measure the own past shock effect, while the off-diagonal elements of $A$ measure the degree of shocks cross stock market. In addition, $G$ is an $n \times n$ matrix, the diagonal elements of $G$ indicate the persistence of past own conditional volatility, the off-diagonal elements of $G$ indicate the persistence in conditional volatility cross market.

In particular, in this paper, we consider

$$H_t = \begin{bmatrix} c_{CH} & c_{CH,US} \\ c_{US,CH} & c_{US} \end{bmatrix} + \begin{bmatrix} a_{CH} & a_{CH-US} \\ a_{US-CH} & a_{US} \end{bmatrix}' \begin{bmatrix} \varepsilon_{CH,j-1}^2 & \varepsilon_{CH,j-1}\varepsilon_{US,j-1} \\ \varepsilon_{US,j-1}\varepsilon_{CH,j-1} & \varepsilon_{US,j-1}^2 \end{bmatrix} + \begin{bmatrix} g_{CH} & g_{CH-US} \\ g_{US-CH} & g_{US} \end{bmatrix}H_{t-1} \begin{bmatrix} g_{CH} & g_{CH-US} \\ g_{US-CH} & g_{US} \end{bmatrix}. \quad (33)$$

Since the probability density function for $\varepsilon_t$ is represented as

$$f(\varepsilon_t) = -\frac{\pi(v-2)}{\Gamma(v/2)} \left[ \frac{\varepsilon_t^2}{H_t^2} \right]^{\frac{v+1}{2}} \left[ 1 + \frac{\varepsilon_t^2}{H_t^2(v-2)} \right]^{-\frac{v+1}{2}}. \quad (34)$$

the parameters of GARCH BEKK can be estimated by applying the conditional log-likelihood function:

$$L_t(\theta) = -\frac{T}{2} \ln \left[ \frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma[(v+1)/2]^2} \right] - \frac{1}{2} \sum_{t=1}^{T} \ln H_t - \frac{v+1}{2} \sum_{t=1}^{T} \ln \left[ 1 + \frac{\varepsilon_t^2}{H_t^2(v-2)} \right]. \quad (35)$$
The log-likelihood function of the joint distribution is the sum of all the log-likelihood functions of the conditional distributions, i.e., the sum of the logs of the multivariate-$t$ distribution. Letting $L_t$ be the log likelihood of an observation at $t$ and letting $L$ be the joint log likelihood, we have

$$L = \sum_{i=1}^{T} L_t(\theta).$$

(36)

where $\theta$ is the vector of all parameters. Engle and Kroner (1995) and Kroner and Ng (1998) document that the above BEKK system can be estimated efficiently and consistently using the full information maximum-likelihood method.

Table 3 reports the estimates, standard errors, associated $t$ statistics and $p$-values. The parameters in the vector autogression model are asymptotically estimated using OLS, so we provide the $p$-values as well. Considering the returns are relatively volatile in Figure 1, they could be sufficiently small or sufficiently large, we adopted two-tailed $t$-test. The critical $t$ value with degree of freedom 11 is 1.80.

We report the results for two durations, one using the observations from 1995-2009, and the other from 2006-2009. This is because the volatilities of U.S. and Chinese stock returns, as well as the returns, have moved almost simultaneously since 2006, according to Figures 2 and 3.

According to Table 3, there is a considerable relationship between the two stock returns. We do not find any significant effect in estimates of parameter matrix $\beta$, which indicates no cross-market effect in the Chinese and U.S. stock returns with one lagged period.  

On the other hand, $c_{CH,US}$, $a_{CH-US}$, $a_{US-CH}$, $g_{CH-US}$ and $g_{US-CH}$ are constant for either 1995-2009 or 2005-2009. This implies that a shock in either market can affect the evolution of

---

1 We then use Granger-causality test to examine whether there is a relationship between the U.S. and Chinese stock returns. We find that 14 month earlier U.S. returns does Granger-cause current Chinese returns in a positive way, and the coefficient is 0.253, which indicates that if U.S. returns 14 months earlier increase, the current Chinese returns would increase 25.3%.
the return in the other market. In particular, $a_{CH\rightarrow US}$ and $a_{US\rightarrow CH}$ capture the effect of cross-market shock. Also, $g_{CH\rightarrow US}$ and $g_{US\rightarrow CH}$ capture the effect of cross-market volatility.

From 1995 to 2009, $a_{CH\rightarrow US}$ is significant, which indicates that past shocks from the U.S. market would affect the current volatility of Chinese stock returns, but this effect fades away since $g_{CH\rightarrow US}$ is negatively significant. The current volatility of U.S. stock returns would not be affected by the past shock of Chinese stock market since $a_{US\rightarrow CH}$ is not significant. However, it would be affected by the past volatility of Chinese stock market in a very subtle way, since $g_{US\rightarrow CH}$ is significant with a value of 0.007 only. In 2006-2009, $a_{CH\rightarrow US}$ and $a_{US\rightarrow CH}$ are positively significant, and the past shock would affect the current volatility mutually, but the effect from the Chinese to the U.S. stock market is stronger.

The parameters $a_{CH}$ and $a_{US}$ capture the effect of past shocks on current volatility. The parameters $g_{CH}$ and $g_{US}$ capture the effect of past volatility on current volatility. Here, $a_{US}$ is positively significant in both periods, which indicates that past shocks of the U.S. stock market would affect its current volatility. This effect will be persistent since $g_{US}$ is positively significant in both periods. In addition, $a_{CH}$ and $g_{CH}$ are only significant in 1995-2009, implying that deregulation and the reduction of state-owned shares of Chinese stock may result in the insignificance of $a_{CH}$ and $g_{CH}$ from 2006-2009.

The most important findings in Table 3 are about $a_{CH\rightarrow US}$ and $a_{US\rightarrow CH}$. In 1995-2009, $a_{CH\rightarrow US}$ is significant, implying that the shocks of U.S. returns significantly affect volatilities of Chinese stock returns. However, it is not the other way round as $a_{US\rightarrow CH}$ is not significant. On
the other hand, in the sample of 2006-2009, both \( a_{CH\rightarrow US} \) and \( a_{US\rightarrow CH} \) are significant, implying that the shocks significantly affect volatilities mutually.

### 3.2. GARCH CCC Results

We consider a model that captures a changing level of correlation between U.S. and Chinese stock returns. This is motivated by Figure 4’s finding that the correlation changes over time. We use GARCH CCC, which was first proposed by Bollerslev (1990). We still assume the vector of error terms is \( t \) distributed with degree of freedom \( \nu \) and mean zero, and it has a \( 2 \times 2 \) conditional variance-covariance matrix, \( H_t \). That is,

\[
Var(\varepsilon_t | \varphi_{t-1}) = H_t.
\]

where \( \varphi_{t-1} \) is the available information set at time \( t-1 \). Let \( h_{CH} \) and \( h_{US} \) be the diagonal elements in \( H_t \), then the conditional variances are:

\[
Var_t(\varepsilon_{CH} | \varphi_{t-1}) = h_{CH} = \omega_{CH} + a_{CH}^2 \varepsilon^2_{CH,t-1} + g_{CH} h_{CH,t-1}.
\]

\[
Var_t(\varepsilon_{US} | \varphi_{t-1}) = h_{US} = \omega_{US} + a_{US}^2 \varepsilon^2_{US,t-1} + g_{US} h_{US,t-1}.
\]

where \( \omega_{CH} \) and \( \omega_{US} \) are the constants, and \( a_{CH} \) and \( a_{US} \) capture the effect of past shocks of the Chinese and U.S. stocks respectively. Also, \( g_{CH} \) and \( g_{US} \) capture past volatility effects. The off-diagonal element in \( H_t \), denoted by \( h_{CH,US} \) is

\[
h_{CH,US} = \rho_{CH,US} (h_{CH} h_{US})^{1/2}.
\]

assuming the unconditional correlation between the U.S. and Chinese stock returns is \( \rho_{CH,US} \). Hence, the variance-covariance matrix \( H_t \) is:

\[
H_t = \begin{bmatrix} h_{CH} & h_{CH,US} \ h_{CH,US} & h_{US} \end{bmatrix}.
\]
The parameters are asymptotically estimated. Table 4 reports the estimates, standard errors, \( t \) statistics and \( p \)-values for two durations, 1995-2009 and 2006-2009. From 1995-2009, the constants \( \omega_{CH} \) and \( \omega_{US} \) are not significant and \( a_{CH} \) is positively significant, indicating that the past shock would affect the current volatility of Chinese stock returns. This effect is persistent since \( g_{CH} \) is significant as well. The persistence is also present for U.S. stock returns.

The most important result for our purpose in Table 4 is the parameter \( \rho_{CH,US} \). From 1995-2009, the estimate is 0.13 with a \( p \)-value of 0.125. While the estimate is not within 90% confidence interval, the \( p \)-value is fairly low. This can be because the correlation between the two markets changed with some trend (as in Figure 4), while our estimation assumes it is constant.

From 2006-2009, \( a_{US} \) is negatively significant, which indicates that a shock from the previous period decreases the volatility in the current period, and this effect is persistent since \( g_{US} \) is positively significant. This may be because the duration is too short. \( g_{CH} \) is positively significant. The interesting thing is \( \rho_{CH,US} \) significant. The estimate is 0.33 with a \( p \)-value of 0.034. This can be because of deregulation and the reduction in state-owned shares of Chinese stocks from 2006-2009.

4. Implications for the Sharpe Ratio

The Sharpe ratio is the expected excess return divided by the standard deviation for a defined period. That is,

\[
S_p = \frac{E(r_p - r_f)}{std_p}.
\]  

(41)
where $S_p$ is the Sharpe ratio for portfolio $p$, $r_p$ is the mean rate of return for a defined period, $r_f$ is the risk-free rate (we use one-month U.S. Treasury bills), and $std_p$ is the standard deviation of returns for portfolio $p$. The Sharpe ratio measures the reward to total volatility trade-off. In addition, it can be easily shown that, if an investor prefers higher expected return and lower volatility only, he will choose a portfolio that maximizes the Sharpe ratio. Hence, studying how portfolio composition between U.S. stocks and Chinese stocks affects the Sharpe ratio provides interesting implications for investment.

Consider a portfolio with a proportion $s$ invested in Chinese stocks and $(1 - s)$ invested in U.S. stocks. The expected return is

$$E(r_p) = sE(r_{CH}) + (1 - s)E(r_{US}).$$

(42)

while the standard deviation is

$$
\sigma_p = \sqrt{s^2 \sigma^2_{CH} + (1 - s)^2 \sigma^2_{US} + 2s(1 - s)\text{cov}_{\text{CH,US}}}.
$$

(43)

where $\text{cov}_{\text{CH,US}}$ is the covariance between the two returns. Equivalently,

$$
\sigma_p = \sqrt{s^2 \sigma^2_{CH} + (1 - s)^2 \sigma^2_{US} + 2s(1 - s)\text{corr}_{\text{CH,US}} \sigma_{CH} \sigma_{US}}.
$$

(44)

where $\text{corr}_{\text{CH,US}}$ is the correlation between the two returns, while $\sigma_{CH}$ and $\sigma_{US}$ are the standard deviations of the two returns, respectively. When $\text{corr}(r_{CH}, r_{US}) = 1.0$,

$$
\sigma_p = |s \sigma_{CH} + (1 - s) \sigma_{US}|.
$$

(45)

when $\text{corr}(r_{CH}, r_{US}) < 1.0$,

$$
\sigma_p < s \sigma_{CH} + (1 - s) \sigma_{US}.
$$

(46)

Finally, when $\text{corr}(r_{CH}, r_{US}) = -1.0$:
\[ \sigma_p = |s \sigma_{CH} - (1 - s) \sigma_{US}|. \quad (47) \]

Equation (42) indicates that the correlation between \( r_{CH} \) and \( r_{US} \) has no effect on \( E(r_p) \). However, (14) implies that it affects \( \sigma_p \). Given \( s, \sigma_{CH}, \) and \( \sigma_{US} \), the highest value of \( \sigma_p \) occurs when \( corr(r_{US}, r_{CH}) = 1.0 \), in which case diversification is ineffective. On the other hand, diversification is most effective when \( corr(r_{US}, r_{CH}) = -1.0 \).

The average return, volatility, and corresponding Sharpe ratio of U.S. stocks from 1950-2009 and 1995-2009, and of Chinese stocks from 1995-2009, are reported in Table 5.

The average and volatility of U.S. stock returns are 0.7% and 4.3% from 1950-2009 and 0.6% and 4.8% from 1995-2009. The average and volatility of Chinese stock returns are 1.6% and 9.7% from 1995-2009. The Sharpe ratios of U.S. and Chinese stocks are 0.11 and 0.15, respectively, from 1995-2009. The Sharpe ratio of Chinese stock returns is 36% higher than the U.S. counterpart.

What is the Sharpe ratio if we combine both stock markets into a single portfolio? Figure 5 indicates the historical average, volatility, and Sharpe ratio for a portfolio, where the horizontal axis indicates the share of Chinese stocks. The left figures use 1995-2009 observations while the right ones use 2005-09. In Part (C), volatility is minimized when the share of Chinese stocks is about 0.2. This is the gain from diversification. In Part (E), the Sharpe ratio is maximized at 0.18 when the share of Chinese stocks is about 0.45. Hence, if one holds U.S. stocks, it helps to hold Chinese stocks (or other stocks) for diversification. Considering there is a period from 2005 to 2006 during which Chinese returns were exceptionally high, we use observations from 2005-2009 in the right figures. Unlike the left figures, holding Chinese stocks only provides the highest Sharpe ratio.
While the historical Sharpe ratios are useful, we can also indirectly obtain Sharpe ratios using GARCH BEKK and GARCH CCC estimation results. Since the correlation between U.S. and Chinese stock returns increased, as in Figure 4, it is more useful to consider GARCH CCC, where we can assume an increased level of correlation.

4.1. GARCH BEKK

In order to obtain the Sharpe ratios based on the GARCH BEKK estimation results, we take the averages and volatilities of Chinese and U.S. stock returns from 1995-2009 as the initial values at “period 0.” That is, we write \( r_0 = [r_{CH0}, r_{US0}] = [0.016, 0.006]' \), \( \sigma_0 = [\sigma_{CH0}, \sigma_{US0}] = [0.097, 0.048]' \). The correlation coefficient of 0.13 between the two returns from 1995-2009 is consistent with \( H_0 = [0.0094 \, 0.0006; 0.0006 \, 0.0023] \).

The expected excess returns in period 1 can be computed using (31) and the estimation results reported in Table 3. That is,

\[
E(r_1) = \begin{bmatrix} 0.016 \\ 0.004 \end{bmatrix} + \begin{bmatrix} 0.084 & -0.076 \\ 0.042 & 0.140 \end{bmatrix} \begin{bmatrix} 0.016 \\ 0.006 \end{bmatrix} = \begin{bmatrix} 0.0172 \\ 0.0058 \end{bmatrix}.
\] (48)

Hence,

\[
E(r_1 - r_f) = 0.0172s + (1-s)0.0058 - 0.0008 = 0.0114s + 0.0050.
\] (49)

Then, \( H_1 \) is computed as

\[
H_1 = \begin{bmatrix} 0.038 & 0.002 \\ 0.002 & 0.007 \end{bmatrix} \begin{bmatrix} 0.038 & 0.002 \\ 0.002 & 0.007 \end{bmatrix} + \begin{bmatrix} 0.297 & 0.020 \\ -0.006 & 0.357 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0.297 & 0.020 \\ -0.006 & 0.357 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix}
\]

\[
+ \begin{bmatrix} 0.865 & -0.016 \\ 0.007 & 0.930 \end{bmatrix} \begin{bmatrix} 0.0094 & 0.0006 \\ 0.0006 & 0.0023 \end{bmatrix} + \begin{bmatrix} 0.865 & -0.016 \\ 0.007 & 0.930 \end{bmatrix} \begin{bmatrix} 0.007 \\ 0.930 \end{bmatrix} = \begin{bmatrix} 0.0085 & 0.0005 \\ 0.0005 & 0.0020 \end{bmatrix}.
\] (50)
Hence, the variance of the portfolio is given by

$$\sigma_p^2 = s^2 * 0.0085 + (1 - s)^2 * 0.0020 + 2s(1 - s) * 0.0005 = 0.0095s^2 - 0.003s + 0.0020.$$  \hspace{1cm} (51)

which is minimized when \( s = 0.16 \). Finally, the Sharpe ratio in period 1 becomes

$$S = \frac{0.0114s + 0.0050}{\sqrt{0.0095s^2 - 0.003s + 0.0020}}.$$  \hspace{1cm} (52)

which is illustrated in Figure 6. The Sharpe ratio is maximized when the share of Chinese stocks is 0.47.

In order to compute the Sharpe ratio with various lengths of the holding period, we apply a Monte Carlo simulation. From \( H_1 = \begin{bmatrix} 0.0085 & 0.0005; 0.0005 & 0.0020 \end{bmatrix} \), a \( 2 \times 1 \) vector of error terms, \( \epsilon_1 = \begin{bmatrix} \epsilon_{CH1}, \epsilon_{US1} \end{bmatrix} \), is drawn from a multivariate \( t \) distribution with variance-covariance matrix \( H_1 \) and degree of freedom of \( \nu \). This provides \( r_1 \) with (31) and the estimation results reported in Table (3). Further, we can obtain \( H_2 \), which provides \( r_2 \). We continue this for \( T = 12, 120, 240, 360 \) periods (which corresponds to one, 10, 20, and 30 years of holding periods). For each \( T \), we run 100,000 simulations to compute the Sharpe ratio. The results are illustrated in Figures 7 and 8. The simulated results indicate that the maximized Sharpe ratio is about 0.20 when the share of Chinese stocks is about 0.6, regardless of the holding period.

4.2. GARCH CCC

The correlation between U.S. and Chinese stock returns is 0.13 from 1995-2009. However, Figure 4 indicates that this correlation has been increasing. Hence, we assume that the correlation is 0.2 in order to see how the Sharpe ratios are affected. We use the initial values
from Subsection 4.1 and the estimation results of GARCH CCC in Table 4. Then, \( h_{CH1} \), \( h_{US1} \) and \( h_{CH,US1} \) can be computed as follows:

\[
\begin{align*}
    h_{CH1} &= 0.0003 + 0.1618 \times 0^2 + 0.9121 \times 0.0094 = 0.0089. \\
    h_{US1} &= 0.0001 + 0.0506 \times 0^2 + 0.8152 \times 0.0023 = 0.0020. \\
    h_{CH,US1} &= 0.2 \sqrt{h_{CH1} h_{US1}} = 0.0008.
\end{align*}
\] 

Then, the variance of the portfolio return becomes

\[
\sigma_p^2 = s^2 \times 0.0089 + (1-s)^2 \times 0.0020 + 2s(1-s) \times 0.0008 = 0.0093s^2 - 0.0024s + 0.002.
\] 

Hence, the Sharpe ratio becomes

\[
S = \frac{0.0114s + 0.0050}{\sqrt{0.0093s^2 - 0.0024s + 0.002}}.
\]

which is illustrated in Figure 9. The Sharpe ratio is maximized when \( s = 0.48 \). The maximized Sharpe ratio is 0.19.

For the Monte Carlo simulations, we use

\[
H_1 = \begin{bmatrix} h_{CH1} & h_{CH,US1} \\ h_{US1,CH1} & h_{US1} \end{bmatrix} = \begin{bmatrix} 0.0089 & 0.0008 \\ 0.0008 & 0.0020 \end{bmatrix}. \quad \text{A 2} \times 1 \text{ vector of error terms,}
\]

\[
\begin{bmatrix} \varepsilon_{CH1} \\ \varepsilon_{US1} \end{bmatrix}, \quad \text{is drawn from a multivariate } t \text{ distribution with variance-covariance matrix } H_1
\]

and degree of freedom \( \nu \). The returns are computed using the estimates reported in Table 4:

\[
\begin{bmatrix} r_1 \\ r_2 \end{bmatrix} = \begin{bmatrix} 0.016 & 0.004 \\ 0.042 & 0.140 \end{bmatrix} \times \begin{bmatrix} 0.016 \\ 0.006 \end{bmatrix} + \begin{bmatrix} \varepsilon_{CH1} \\ \varepsilon_{US1} \end{bmatrix}.
\]

This provides \( H_2 = \begin{bmatrix} h_{CH2} & h_{CH,US2} \\ h_{US,CH2} & h_{US2} \end{bmatrix} \). Following this procedure, \( \{ \varepsilon_t \} , \{ H_t \} , \{ r_t \} \), \( t = 1,2,\ldots,T \) are drawn 100,000 times, where \( T = 12, 120, 240, 360 \).
The resulting Sharpe ratios are reported in Figures 10 and 11. The maximized Sharpe ratio is 0.25, 0.13, 0.13, and 0.13, for one-year, 10-year, 20-year, and 30-year holding periods, respectively. These are maximized when the share of the Chinese stocks is about 0.50, 0.45, 0.45 and 0.45. Due to the positive correlation between two stock markets, volatility increases as the holding period increases. Hence, the Sharpe ratio tends to decrease. This explains the gap between the Sharpe ratios for one year and 10 years or more.

5. Concluding Remarks

We study the co-movement of Chinese and U.S. aggregate stock returns from 1995-2009, based on the GARCH BEKK method and the GARCH CCC method. Unlike other studies, we find that the two returns are related. The sample correlation between Chinese and U.S. stock returns is 0.13. This correlation is expected to increase in the future because the Chinese economy is increasingly linked to other economies through international trade and capital flows. The estimation results suggest that the Sharpe ratio for a 10-year holding period increases almost by one half when Chinese stocks are added, compared to 11% when the portfolio consists of the U.S. stocks only. The relation between the U.S. and Chinese returns appear to increase the share of Chinese stocks that maximizes the Sharpe ratio in the two-country portfolio.

The results imply that asset pricing should reflect the time-varying nature of conditional expected returns and their volatility. An extension of this study is to focus on how the degree of integration or segmentation in the Chinese and U.S. economies affects the results. Studying other emerging markets would be also useful in understanding increasingly globalized financial markets.
References


Table 3.1 Comparison of this paper to other papers

<table>
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<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>GARCH BEKK with ( t ) distribution</td>
<td>GARCH BEKK with normal distribution</td>
<td>Copula</td>
<td>GARCH BEKK and CCC with ( t ) distribution</td>
</tr>
<tr>
<td>Estimation Results</td>
<td>No significant dependence</td>
<td>No significant dependence</td>
<td>No significant dependence</td>
<td>Significant interdependence. Chinese market depends more strongly on the U.S. market.</td>
</tr>
<tr>
<td>Implications on portfolio allocation</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>Provided based on Sharpe ratio analysis</td>
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Table 3.2 Statistical Summary of the U.S. and Chinese Monthly Real Returns

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<tr>
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<th>U.S.</th>
<th>China</th>
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<tr>
<td>Mean</td>
<td>0.6%</td>
<td>1.6%</td>
</tr>
<tr>
<td>Volatility</td>
<td>4.8%</td>
<td>9.7%</td>
</tr>
<tr>
<td>Median</td>
<td>1.4%</td>
<td>1.1%</td>
</tr>
<tr>
<td>Maximum</td>
<td>10.8%</td>
<td>34.9%</td>
</tr>
<tr>
<td>Minimum</td>
<td>-17.4%</td>
<td>-22.0%</td>
</tr>
<tr>
<td>Skewness</td>
<td>-80.9%</td>
<td>53.3%</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>4.057</td>
<td>4.014</td>
</tr>
<tr>
<td>Jarque-Bera Statistic</td>
<td>27.990</td>
<td>16.23</td>
</tr>
<tr>
<td>P-value</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
### Table 3.3 GARCH BEKK Estimation Results

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Standard</td>
<td>T-stat</td>
<td>P-value</td>
<td>Estimate</td>
<td>Standard</td>
<td>T-stat</td>
<td>P-value</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Error</td>
<td></td>
<td></td>
<td></td>
<td>Error</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{CH}$</td>
<td>0.016*</td>
<td>0.007</td>
<td>2.322</td>
<td>0.020</td>
<td>0.033*</td>
<td>0.017</td>
<td>1.973</td>
<td>0.049</td>
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<tr>
<td>$\alpha_{US}$</td>
<td>0.004</td>
<td>0.004</td>
<td>1.148</td>
<td>0.251</td>
<td>-0.005</td>
<td>0.008</td>
<td>-0.568</td>
<td>0.570</td>
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<tr>
<td>$\beta_{CH}$</td>
<td>0.084</td>
<td>0.075</td>
<td>1.121</td>
<td>0.262</td>
<td>0.176</td>
<td>0.117</td>
<td>1.505</td>
<td>0.132</td>
<td></td>
</tr>
<tr>
<td>$\beta_{CH-US}$</td>
<td>-0.076</td>
<td>0.143</td>
<td>-0.536</td>
<td>0.592</td>
<td>-0.226</td>
<td>0.326</td>
<td>-0.695</td>
<td>0.487</td>
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<tr>
<td>$\beta_{US-CH}$</td>
<td>0.042</td>
<td>0.035</td>
<td>1.219</td>
<td>0.223</td>
<td>0.093</td>
<td>0.070</td>
<td>1.319</td>
<td>0.187</td>
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<tr>
<td>$\beta_{US}$</td>
<td>0.140</td>
<td>0.093</td>
<td>1.504</td>
<td>0.133</td>
<td>0.258</td>
<td>0.196</td>
<td>1.317</td>
<td>0.188</td>
<td></td>
</tr>
<tr>
<td>$c_{CH}$</td>
<td>0.038*</td>
<td>0.000</td>
<td>90.382</td>
<td>-</td>
<td>0.089*</td>
<td>0.012</td>
<td>7.646</td>
<td>-</td>
<td></td>
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<tr>
<td>$c_{CH-US}$</td>
<td>0.002*</td>
<td>0.000</td>
<td>79.268</td>
<td>-</td>
<td>0.007*</td>
<td>0.001</td>
<td>6.651</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>$c_{US}$</td>
<td>0.007*</td>
<td>0.000</td>
<td>208.63</td>
<td>-</td>
<td>-0.000*</td>
<td>0.000</td>
<td>18.816</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>$a_{CH}$</td>
<td>0.297*</td>
<td>0.018</td>
<td>16.221</td>
<td>-</td>
<td>0.134</td>
<td>0.108</td>
<td>1.244</td>
<td>-</td>
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<tr>
<td>$a_{CH-US}$</td>
<td>0.020*</td>
<td>0.004</td>
<td>4.806</td>
<td>-</td>
<td>0.032*</td>
<td>0.002</td>
<td>19.97</td>
<td>-</td>
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<tr>
<td>$a_{US-CH}$</td>
<td>-0.006</td>
<td>0.018</td>
<td>-0.332</td>
<td>-</td>
<td>0.719*</td>
<td>0.358</td>
<td>2.009</td>
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<tr>
<td>$a_{US}$</td>
<td>0.357*</td>
<td>0.003</td>
<td>117.21</td>
<td>-</td>
<td>0.439*</td>
<td>0.035</td>
<td>12.49</td>
<td>-</td>
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<tr>
<td>$g_{CH}$</td>
<td>0.865*</td>
<td>0.015</td>
<td>56.639</td>
<td>-</td>
<td>0.542</td>
<td>2.298</td>
<td>0.236</td>
<td>-</td>
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<tr>
<td>$g_{CH-US}$</td>
<td>-0.016*</td>
<td>0.001</td>
<td>11.525</td>
<td>-</td>
<td>0.011</td>
<td>0.037</td>
<td>0.305</td>
<td>-</td>
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<tr>
<td>$g_{US-CH}$</td>
<td>0.007*</td>
<td>0.003</td>
<td>2.586</td>
<td>-</td>
<td>-0.158</td>
<td>0.236</td>
<td>-0.669</td>
<td>-</td>
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<tr>
<td>$g_{US}$</td>
<td>0.930*</td>
<td>0.000</td>
<td>1630.7</td>
<td>-</td>
<td>0.875*</td>
<td>0.004</td>
<td>248.3</td>
<td>-</td>
<td></td>
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<tr>
<td>$T$</td>
<td>180</td>
<td>48</td>
<td></td>
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<td></td>
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Note: One asterisk (*) denotes values that are statistically significant at the 10% level.
### Table 3.4 GARCH CCC Estimation Results

<table>
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</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Standard Error</td>
<td>T-stat</td>
<td>P-value</td>
</tr>
<tr>
<td>( \omega_{CH} )</td>
<td>0.000</td>
<td>0.000</td>
<td>1.454</td>
<td>0.146</td>
</tr>
<tr>
<td>( \omega_{US} )</td>
<td>0.000</td>
<td>0.000</td>
<td>1.341</td>
<td>0.180</td>
</tr>
<tr>
<td>( a_{CH} )</td>
<td>0.162*</td>
<td>0.074</td>
<td>2.202</td>
<td>0.028</td>
</tr>
<tr>
<td>( a_{US} )</td>
<td>0.051</td>
<td>0.031</td>
<td>1.618</td>
<td>0.106</td>
</tr>
<tr>
<td>( g_{CH} )</td>
<td>0.912*</td>
<td>0.037</td>
<td>24.965</td>
<td>0.000</td>
</tr>
<tr>
<td>( g_{US} )</td>
<td>0.815*</td>
<td>0.077</td>
<td>10.660</td>
<td>0.000</td>
</tr>
<tr>
<td>( \rho_{CH,US} )</td>
<td>0.130</td>
<td>0.085</td>
<td>1.535</td>
<td>0.125</td>
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</tbody>
</table>

Note: One asterisk (*) denotes values that are statistically significant at the 10% level.
Table 3.5 Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>Average</td>
<td>0.7%</td>
<td>0.6%</td>
<td>1.6%</td>
</tr>
<tr>
<td>Volatility</td>
<td>4.3%</td>
<td>4.8%</td>
<td>9.7%</td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>0.13</td>
<td>0.11</td>
<td>0.15</td>
</tr>
</tbody>
</table>
Figure 3.1 U.S. and Chinese Real Value-Weighted Monthly Return (%)
Figure 3.2 Moving Averages of U.S. and Chinese Real Value-Weighted Monthly Return (%)

Moving Averages of Real VW Market Returns (%)

USA Real VW Return
CHN Real VW Return
CHN Real VW Return - Cont. from Exchange Rate movement
Figure 3.3 Moving Volatilities of Real Value-Weighted Market Returns (%)

Moving Volatilities of Real VW Market Returns (%)

- USA Real VW Return
- CHN Real VW Return (Dollar-Denominated)
Figure 3.4 Moving Correlations of Real Value Weighted Market Returns (%)
Figure 3.5 Historical Average, Volatility and Sharpe Ratio
(x-axis: Share of Chinese stocks (CHN) in the portfolio)
Figure 3.6 One-Period Average, Volatility and Sharpe Ratio Based on GARCH BEKK Estimation Result
(x-axis: Share of Chinese stocks (CHN) in the portfolio)
Figure 3.7 Average, Volatility and Sharpe Ratio Based on GARCH BEKK Estimation Result
(x-axis: Share of Chinese stocks (CHN) in the portfolio. Left figure: One-year holding period. Right figure: 10-year.)
Figure 3.8 Average, Volatility and Sharpe Ratio Based on GARCH BEKK Estimation Result
(x-axis: Share of Chinese stocks (CHN) in the portfolio. Left figure: 20-year holding period. Right figure: 30-year.)
Figure 3.9 One-Period Average, Volatility and Sharpe Ratio Based on GARCH CCC Estimation Result
(x-axis: Share of Chinese stocks (CHN) in the portfolio)
Figure 3.10 Average, Volatility and Sharpe Ratio Based on GARCH CCC Estimation Result
(x-axis: Share of Chinese stocks (CHN) in the portfolio. Left figure: One-year holding period. Right figure: 10-year.)
Figure 3.11 Average, Volatility and Sharpe Ratio Based on GARCH CCC Estimation Result
(x-axis: Share of Chinese stocks (CHN) in the portfolio. Left figure: 20-year holding period. Right figure: 30-year.)
CHAPTER FOUR  WILLINGNESS TO PAY FOR PESTICIDES’ ENVIRONMENTAL FEATURES AND SOCIAL DESIRABILITY BIAS: THE CASE OF APPLE AND PEAR GROWERS

Abstract

We conducted a hypothetical discrete-choice experiment to determine the values that environmental amenities, represent to apple and pear growers when choosing a pesticide. To investigate for the potential presence of social desirability bias we used an indirect valuation approach. We found that different growing conditions faced by apple and pear growers dictate differences in their valuation for pesticides features. For both apple and pear growers we did not find evidence of social desirability bias when stating WTP for pesticide features. However, when predicting actual market shares for commercial pesticides, we found that the indirect valuation outperformed the direct valuation for pear growers, but not for apple growers.

Keywords: Biological control, social desirability bias, hypothetical discrete choice.
1. Introduction

Agricultural producers, such as fruit growers, are committed to produce high quality fruits, in terms of wholesomeness, appealing appearance and sensory characteristics, and environmental and social sustainability. To assure obtaining high quality fruit, producers must select a bundle of mechanisms to protect their crops from pest damages. Typically, pest management systems rely on the use of pesticides. However, sole reliance on pesticides to control pests is economically and ecologically costly, affects worker safety, and is contrary to consumers’ concerns about food safety. Other environmental sustainable means of controlling pests, such as biological control, are gaining popularity. This system consists on keeping pests below damaging levels through the activities of living organisms known as predators and parasitoids (hereafter natural enemies) (Unruh 1993). There are three types of biological control, classical, conservation, and augmentation. Out of these, conservation is believed to be the most efficient because by applying pesticides that will not disrupt natural enemies already present in the orchard, there would be no need to apply additional pesticides to control for secondary pests (Jones et al. 2009).

Given the benefits of biological control and the proliferation of pesticides with unknown effects on natural enemies, one wonders if growers perceive a value for conserving natural enemies in the orchard and if these values are reflected in their choice of pesticides. One way to elicit growers’ values for environmental amenities when choosing pesticides is through hypothetical choice experiments. However these experiments have been long scrutinized, as they are believed to lack prediction accuracy of real choice behavior due to their hypothetical nature. One source of bias is the social desirability bias that happens when responses to
hypothetical surveys are influenced by respondents’ desire to please the interviewer or to be consistent with societal norms (Legget et al. 2003).

In this framework, the objectives of this study are threefold. The first one is to measure growers’ valuation for pesticides’ characteristics that would conserve natural enemies in the orchard. We conduct a hypothetical discrete-choice experiment to calculate apple and pear growers’ willingness to pay for pesticides’ environment related features, including not disrupting natural enemies. The second objective is to assess evidence of social desirability bias. We compare willingness-to-pay (WTP) estimates obtained via direct and indirect valuation (or indirect questioning). The hypothesis to test is that the WTP for pesticides’ features with a positive social connotation measured via an indirect valuation would be statistically significant higher than the WTP obtained via direct valuation. If this were true, then there would be evidence of social desirability bias. The third objective is to estimate the prediction accuracy of the estimates obtained by both the direct and indirect questioning formats. We test this accuracy by applying the prediction index that indicates the number of times the model predicted actual pesticides’ choices. Also, we test which approach can more accurately predict actual pesticides’ market shares by using the mean square error and the out-of-sample log likelihood function.

The indirect valuation in hypothetical choice experiments is believed to minimize the influence of social desirability biases. Several studies (Levitt and List 2007; Johansson-Stenman and Martinson 2006; Lusk and Norwood 2009a and 2009b, Norwood and Lusk 2011) have investigated social desirability bias assessing causes, triggering circumstances, and potential ways to mitigate this phenomenon. Levitt and List (2007) introduced the concept that utility could be additively separable into moral and wealth arguments. Johansson-Stenman and Martinson (2006) proposed a model in which utility, besides being a function of the good’s
characteristics, is a function of the individual’s perceived concern relative to the average perceived concern of others. Lusk and Norwood (2009a, 2009b) and Norwood and Lusk (2011) found that the indirect valuation has the potential to provide better predictions of field behavior if social concerns are the primary contributor to the bias; as such, the indirect valuation method may provide improved predictions of WTP and market shares. They proposed a model in which an individual’s utility is composed of two additively separable components: an ethical component and the traditional utility of wealth/consumption component. In this framework, the point at which the individual is indifferent between two different levels of the good’s attribute (or the WTP), is the tradeoff between the marginal utility of having an “upgraded” attribute, and the marginal utility of income, adjusted by a factor representing the marginal utility of giving a normative response. Olynk, Tonsor, and Wolf (2010) conducted an empirical application of the indirect valuation format to measure WTP for milk and pork chop production process attributes. They found that indirect valuation, compared to direct valuation, yielded more accurate representations of consumer values. Different from previous studies, in this study we present a pesticide choice case that, we believe, involves ethics and moral concerns related to worker health and the environment as well as the need to protect the crop from pest damages. To our knowledge, no study has investigated if pesticide choice would be associated with social desirability bias and if by using an indirect valuation this bias might decrease.

Scant research has been done in eliciting growers’ preferences for pesticides features that could affect the environment. Lohr, Park, and Higley (1999) estimated that growers in the Midwest (Illinois, Iowa, Nebraska, and Ohio) were willing to pay $8.25/acre to avoid moderate risks to the environment from pesticide applications. Cuyno, Norton, and Rola (2001) found that onion growers in the Philippines were willing to pay $17.00, $14.50, $14.43, $15.53, and $13.78
per crop season to reduce pesticide risks to human health, beneficial insects, birds, animals, and aquatic organisms, respectively. Hasing et al. (2010) determined that U.S. soybean farmers were willing to pay $27 to $38 per acre more to avoid the words “Warning” or “Danger” in the herbicide label, and $15 per acre more to avoid using herbicides with groundwater statements. All of these papers investigate annual row crop growers’ values for pesticides features related to the environment. To our knowledge, our study is the first one investigating fresh fruit growers’ perceptions for pesticides features affecting biological control systems. Fresh fruits are perennial crops that posit an interesting case as higher financial, production, and marketing risks are involved, compared to annual row crops. This is because perennial crops exhibit longer juvenility periods than annual crops and full production is not realized until the fifth year after establishment in apples and seventh year in pears (Gallardo, Taylor, and Hinman 2010; Galinato and Gallardo 2011). Hence, we wonder if the increased risks associated with fresh fruit production would have an impact on growers’ values for pesticides environmental related features.

2. Background

This study is centered on two popular fruit crops grown in the U.S. Pacific Northwest, apples and pears. Production practices for both crops are somewhat similar. Major cost centers include: soil preparation, planting trees, pruning, training, chemical and fertilizer application, pollination, irrigation and energy, harvest labor, and packing costs. Additional costs are the machinery maintenance and repairs, fixed costs such as depreciation, interest, taxes, insurance, and management. Overall, the cost of producing apples, on a full production year, is about $11,923 per acre (variety Gala) and pears $9,684 per acre (variety Anjou) (Gallardo, Taylor, and Hinman 2010; Galinato and Gallardo 2011). Perhaps the pivotal difference between these crops
is the existence of dwarf rootstocks for apples but not for pears. Dwarf rootstocks have led to improvements in various aspects of horticultural management. For example, dwarf rootstocks are associated with reduced tree size, increased planting density, and increased tree precocity (Robinson, Lakso, and Carpenter 1991; Hampson, Quamme, and Brownlee 2002). Also, having a less abundant tree canopy implies a more targeted pest control, reducing the need of multiple sprays. These improvements have not been realized in pears grown in the majority of U.S. regions and especially in the Pacific Northwest because there is no dwarf rootstock adaptable to the region’s climate conditions (Jacob 1998). As such, horticultural management, including pest control, is more costly and challenging for pear growers. In addition, to date, the mix of pests affecting these crops is different. For apples, the most damaging pest is the codling moth (*Cydia pomonella*); whereas in pears is the pear psylla (*Cacopsylla pyricola*) in addition to the codling moth (Brunner 2011). Our study provides cues that would assess if in fact these production condition differences affect apple and pear growers’ values and perceptions when making pesticide choices.

The organophosphate (OP) pesticide azinphos-methyl (AZM or Guthion™) is the most trusted product, in terms of effectiveness in controlling codling moth, in both apples and pears. However, this pesticide is suspicious of posing health risks to orchard workers and the environment. The Food Quality Protection Act passed by Congress in 1996 mandated reductions in the use of OP pesticides, including a complete phase out of AZM by September 2012 (U.S. Environmental Protection Agency 1996). There are OP-alternative pesticides available for controlling codling moth that are less toxic for workers and the environment. However, they require more precise application techniques, and integration with other pest management systems such as biological control. These OP-alternatives are more environmentally friendly however
they are perceived as less effective but more expensive than AZM. Being these new systems more complex and knowledge intensive, transitioning from AZM to OP-alternatives has presented challenges to the apple and pear industry (Goldberger, Lehrer, and Brunner 2010). Results from a 2010 survey show that WA state apple growers have begun eliminating AZM and adopting OP-alternatives, larger producers (in terms of acreage and income) and those more familiar with universities’ educational resources have reduced their AZM use. Same type of respondents (familiar with universities’ educational resources) are more likely to agree that the AZM phase-out will positively impact the environment, workers’ health, and marketing opportunities; and less likely to agree that the phase-out will increase pest damage risks and pest control costs (Goldberger, Lehrer, and Brunner 2010). In relation to the economic impacts of the AZM phase-out, Cassey, Galinato, and Taylor (2010) found that the AZM ban would have negligible impacts on the WA apple industry sales (-0.8%), apple prices (0.2%), and employment (0.1%). This situation underscores the timely significance of our study, as alternative to AZM pesticides are proliferating in the market, a question of interest is how decision makers perceive pesticide features that could be disruptive to ecological systems.

3. Data
Data were obtained from in-person interviews, at group meetings, with Washington apple growers during November – December 2010 and with Oregon pear growers during March 2011. The apple respondents’ sample consisted of 35 individuals, representing 26,864 acres or 16% of the entire apple bearing acreage in the state of Washington. Summary statistics describing the characteristics of the apple operations are presented in table 1. The pear respondents’ sample
included 26 individuals, representing 4,735 acres or 29% of the entire pear bearing acres in Oregon. Summary statistics describing pear operations are listed in table 2.

Before presenting the questionnaire, researchers explained to growers the purpose of the questionnaire, the methodology, and the assumptions made for each scenario. The questionnaire consisted of three sections. The first section included questions referring to characteristics of the orchard operation. The second asked about the pesticide that was used during the 2010 season to control codling moth, assuming the first generation application and a moderate initial pest pressure. This section also asked about perceptions of the pesticide used with respect to effectiveness, toxicity to natural enemies, wildlife, aquatic organisms, and re-entry intervals. The third section contained the choice experiment scenarios. Each respondent was randomly assigned one of two blocks (see subsequent paragraphs in this section for further detail) of sixteen scenarios each. Within each block, the scenarios presented were the same across respondents. Each scenario mimicked a situation in which respondents were presented three types of pesticides (option A, B, and C) assuming an existent moderate pest pressure. Pesticides option A and B presented a combination of different probabilities of pesticide effectiveness in controlling first generation codling moth, probabilities of pesticide toxicity to natural enemies, wildlife, and aquatic organisms, re-entry levels, and price. Respondents were presented with definitions for each pesticide feature. For example, a high probability of effectiveness was defined as 99% of all codling moth killed. A moderate and low probability of effectiveness was associated with a 90% to 95% and 80% to 90% of codling moth killed, respectively. A pesticide toxic for natural enemies, wildlife, and aquatic organisms was defined as a product that will decrease the presence of natural enemies, and negatively impact wildlife and aquatic organisms, respectively. Re-entry interval was defined as the period of time individuals must wait to enter
the orchard after a pesticide application, and was associated with the risk of a negative effect of pesticide residuals on worker’s health.

Option C in each scenario was the status quo and referenced the pesticide used during the 2010 season to control first generation codling moth, the same pesticide asked about in section two of the questionnaire. That is, we provided respondents with an option which levels represented each respondent’s recent experiences. The subsequent scenarios included the exact same questions as the first eight, with the sole difference that instead of asking what each respondent would choose, we asked what they believed the average grower would choose. This last set of questions provided choice information under the indirect valuation format. An example of the scenarios is presented in figure 1.

We used a factorial design to create random combinations of probabilities of effectiveness and levels of toxicity; and re-entry intervals, and prices. Re-entry intervals and prices were within the bounds of actual values for pesticides used in apples and pears to control for codling moth. The pesticide features levels used to create the random combinations of probabilities are reported in table 3. A full factorial design would have yielded 50,000 scenarios ($5^5 \times 4 \times 4$). Since this was impossible to accomplish, we used a main effects fractional factorial design. The SAS® procedure PLAN and OPTEX was used to create a design with random 16 choice scenarios that maximized the D-efficiency (94.3). Considering that individuals would have to respond to a total of 32 scenarios (16 for the direct and 16 for the indirect questions) leading to respondents’ fatigue, we randomly divided the 32 scenarios into two blocks of 16 scenarios each (8 for the direct and 8 for the indirect questions), creating two questionnaire versions. Each respondent randomly received either version of the questionnaire.
4. Methods

The data from questionnaires was analyzed using the random utility model. We used the random utility model because we are modeling choices in which growers consider environmental amenities when purchasing a pesticide. The random utility model is represented by,

\[ U_{ij} = V_{ij} + \epsilon_{ij} \]  

(1)

where \( U \) is the utility derived by grower \( i \) when choosing pesticide \( j \); \( V_{ij} \) is the non-stochastic component of the utility, typically assumed to be certain; and \( \epsilon_{ij} \) is the error component that captures the factors unobserved to the researcher. However, pesticide effectiveness and toxicity is uncertain; that is, one cannot know with certainty this outcome since they depend heavily on stochastic events, such as temperature, rainfall, relative humidity, pest recurrence, natural enemies’ ecology and behavior, among others. Hence, we follow the claim made by Roberts et al. (2008) that the probability of occurrence of an attribute (or feature) can be included as another attribute of choice, and this is consistent with the random utility theory.

The systematic portion of the utility is then given by:

\[ V_{ij} = \alpha_c + \beta_1 (\text{phigh})_{ij} + \beta_2 (\text{pmoderate})_{ij} + \beta_3 (\text{ptoxic natural enemies})_{ij} + \beta_4 (\text{ptoxic wildlife})_{ij} + \beta_5 (\text{ptoxic aquatic})_{ij} + \beta_6 (\text{reentry})_{ij} + \beta_7 (\text{price})_{ij} \]  

(2)

where \( \alpha_c \) is the alternative specific constant that represents the utility of choosing the status quo pesticide (option C), \( \text{phigh} \) is the probability that pesticide \( j \) has high effectiveness in controlling codling moth; \( \text{pmoderate} \) is the probability of moderate effectiveness; \( \text{ptoxic natural enemies} \) is the probability of toxicity for natural enemies; similarly \( \text{ptoxic wildlife} \), \( \text{ptoxic aquatic} \) is the probability of toxicity for wildlife and aquatic organisms, respectively; \( \text{reentry} \) is the period that the worker has to wait to re-enter the orchard once the pesticide has been applied; and \( \text{price} \) is the price of pesticide per acre (not considering the application costs, just the price for the
chemical). We had three levels of efficiency, high, moderate and low, each one associated with a probability level (0%, 10%, 50%, 90%, and 100%). We compare the probability of each efficiency level (high and moderate) against the probability of a low efficiency; thus, the probability for efficiency in all scenarios will always sum 100%. To control for the effect of respondents’ acreage, we interacted a weight factor for acres with each choice attribute and price, following,

\[ V_{ij} = \alpha + \beta_1 (\text{phigh x acres})_{ij} + \beta_2 (\text{pmoderate x acres})_{ij} + \beta_3 (\text{ptoxic natural enemies x acres})_{ij} + \beta_4 (\text{ptoxic wildlife x acres})_{ij} + \beta_5 (\text{ptoxic aquatic x acres})_{ij} + \beta_6 (\text{reentry x acres})_{ij} + \beta_7 (\text{price x acres})_{ij} \]

Note that equation (3) was estimated separately for the direct and the indirect valuation approaches. The probability that a consumer chooses alternative \( j \) is given by,

\[ \text{Prob}\{V_{ij} + \varepsilon_{ij} \geq V_{ik} + \varepsilon_{ik} \text{ for all } k \in C_i\} \]

where \( C_i \) is the choice set for individual \( i \). If \( \varepsilon_{ij} \) are independently and identically distributed across the \( j \) alternatives and \( N \) individuals with a type I extreme value distribution, then the probability is estimated via the conditional logit (CL) model, following,

\[ \text{prob}(j \text{ is chose}) = \frac{\exp^{V_{ij}}}{\sum_{k \in C} \exp^{V_{ik}}} \]

The CL approach suffers from the assumption of independence of irrelevant alternatives (IIA), and that model errors are independently and identically distributed across alternatives. Several other approaches relax the IIA assumption in different ways. One approach is the heteroscedastic extreme value (HEV) model where the error variance is allowed to differ across alternatives. In other words, the error terms are assumed to be independent but not identically distributed. Thus the probability of choice is given by:
\[
prob(j \text{ is chosen}) = \int_{-\infty}^{\infty} \prod_{k \in C, k \neq j} F \left[ \frac{V_j - V_k + \varepsilon_j}{\mu_k} \right] \times \frac{1}{\mu_j} f \left( \frac{\varepsilon_j}{\mu_j} \right) d\varepsilon_j
\]  

(6)

where \(F(\cdot)\) is the standard cumulative distribution of the extreme value distribution, \(f(\cdot)\) is the probability distribution of the extreme value distribution, and \(\mu_j\) is the scale parameter for alternative \(j\), inversely related to the standard deviation of the error component of alternative \(j\) (Louviere, Hensher, and Swait 2000).

To verify the IIA assumption, we conducted a Hausman test for both apple and pear grower datasets. Results show that one fails to reject the IIA assumption for the apple (Chisq=14.82, p-value=0.06), and pear dataset (Chisq=5.23, p-value=0.73). These results imply that both apple and pear growers are somewhat homogeneous in their pesticides’ choices. We also conducted a likelihood ratio test to analyze error variance heteroscedasticity. Results show that for the apple and pear dataset, error variances are heteroscedastic (apple: Chisq=7.72, p-value=0.005; pear: Chisq=33.83, p-value<0.05). Given these results, the econometric specification used was the HEV. All estimates were calculated using SAS®.

The willingness-to-pay (WTP) for an increase or decrease in the probability of pesticide effectiveness, probability of toxicity for natural enemies, wildlife, and aquatic organisms, and reentry interval levels is obtained by,

\[
WTP_m = -\frac{\beta_m}{\beta_{\text{price}}}
\]  

(7)

where \(WTP_m\) is the willingness to pay for pesticide feature \(m\), \((m= \text{probability of pesticide effectiveness, probability of toxicity for natural enemies, wildlife, and aquatic organisms, and reentry interval levels})\), \(\beta_m\) is the parameter estimate for pesticide feature \(m\), and \(\beta_{\text{price}}\) is the parameter estimate for price.
We estimated the WTP for direct and indirect valuation approaches. To assess evidence of social desirability bias when eliciting preferences for pesticides features, we compared WTP estimates obtained via direct and indirect valuation by applying the non-parametric combinatorial re-sampling approach developed by Poe, Loomis, and Giraud (2005). Here, we test the hypothesis that WTP obtained via the indirect valuation is higher than WTP obtained via the direct valuation, for variables that have a positive social consequence (non-toxicity for natural enemies, wildlife, aquatic organisms, and re-entry intervals).

To measure the prediction accuracy of the direct and indirect format we use four criteria: (1) Compare estimated and actual market shares for the commercial pesticides identified by respondents as the ones used in the 2010 season to control for first generation codling moth in both apples and pears, (2) prediction index; (3) mean square error (MSE); and (4) log likelihood function evaluated at out-of-sample observations (OSLLF).

For the market share comparison, we estimated the actual market share using responses to questions in section two in the questionnaire. The actual market share was calculated by obtaining the quotient between the number of times a pesticide was used divided by the total number of responses (35 in apples, 26 in pears). The predicted market shares were calculated by,

\[
\text{Market share}_j = \frac{V_j}{\sum_{l=1}^{L} V_l}
\]  

where Market share\(_j\) is the share for pesticide \(j\), and \(L\) denotes all pesticides used last season. \(V_j\) is depicted in expression (3), parameter estimates were obtained from the model, and the values for the probabilities of each choice attribute and price were the average of respondents’ perceived values (Option C) weighted by the number of acres of each respondent. This market share was estimated using parameters obtained via the direct and indirect valuation. Next, we compared
each predicted market share to the actual shares using the Poe, Loomis, and Giraud (2005) combinatorial re-sampling approach.

The prediction index indicates the percentage of times the model correctly predicted growers’ actual choices or option C. The MSE is the mean of the squared difference between the predicted and actual market share for each pesticide, for each valuation approach. The model with the smaller MSE sum across pesticides has better prediction. Norwood, Lusk, and Brorsen (2004) developed the OSLLF criterion. To apply it to our study, we multiplied the actual market share by the natural log of the predicted market share for each pesticide, and then sum this value across pesticides. We replicate this for each valuation approach. The model with the highest OSLLF has better prediction.

5. Results

Table 4 lists the parameter estimates for apple and pear growers’ pesticide choices. For the apple dataset, the alternative specific constant (ASC) for option C (the status quo option) is statistically significant and negative for the indirect valuation, implying that when asked about other growers’ choices, respondents favored less the status quo option. Controlling for apple operations’ acreage, the price coefficients are negative and statistically significant, meaning higher prices are associated with a lower probability of choosing a pesticide. The probability of high effectiveness was statistically significant for both direct and indirect valuation, but greater in magnitude for the indirect valuation, meaning that respondents considered that other growers would care more for pesticide effectiveness than themselves. Estimates for the probability of a moderate control are positive and statistically significant under both valuation methods. For the direct valuation, the parameter estimate for moderate effectiveness is higher than for high
effectiveness. This is not observed when using the indirect valuation. This result might imply that growers prefer a pesticide they have historically used (even if the effectiveness is moderate) over an unknown pesticide with a stated higher effectiveness. Estimates for the probability that the pesticide would be toxic to natural enemies are negative but statistically significant under the direct valuation only. This implies that the more toxic the pesticide is to natural enemies, the less likely growers would choose to buy it. Parameter estimates for the probability of toxicity for wildlife and aquatic organisms are negative but statistically significant only under the indirect valuation. This indicates that growers believe that other growers would be less likely to buy a pesticide toxic for wildlife and aquatic organisms. That growers stated for themselves a higher preference for moderate pesticide effectiveness (perceived as less effective but non-disruptive of the environment) might have rest significance to non-toxicity to environmental amenities. Estimates for re-entry interval are negative and statistically significant under both valuation approaches, indicating that longer re-entry intervals would negatively affect growers’ pesticide choice. The estimate for the scale or error variance is positive and statistically significant, indicating error variance variability across alternatives.

For the pear dataset, the alternative specific constant for option C is positive and statistically significant under the direct valuation, indicating that when asked about own pesticide choices respondents favored the status quo option over the other two presented. That pear growers showed a stronger preference for the status quo might be due to the high risks implied in pest control influencing growers’ choice of the pesticide option they know works the best for their own production conditions. Controlling for pear operations’ acreage, price coefficient is negative and statistically significant only under the direct valuation, implying that higher prices would lead to a lower probability of choosing a pesticide. Estimates for the probability of high
and moderate effectiveness in controlling codling moth are positive and statistically significant for both valuation methods (except the moderate effectiveness under direct valuation). This shows that for pear growers a high efficacy in controlling pests is crucial when selecting a pesticide. The magnitude of the indirect valuation coefficient for effectiveness is higher than the direct valuation, indicating that respondents believe that control efficacy would be more important for other growers than for themselves. The estimate for the probability of pesticide toxicity to natural enemies is negative and statistically significant only under the direct valuation, indicating that the more toxic a pesticide is for natural enemies the less likely growers would choose it. Parameter estimates for the probability of toxicity for wildlife and aquatic organisms are not statistically significant under either valuation method. Strict pesticide regulations in OR might lead pear growers to believe that pesticides in the market would not likely be toxic to wildlife and aquatic organisms. The estimates for re-entry interval are negative and statistically significant only under the indirect valuation, indicating that the longer the re-entry interval the less likely pear growers would choose it.

Table 5 presents the WTP to increase the probability of pesticide effectiveness, decrease the probability of toxicity for natural enemies, wildlife, and aquatic organisms, and increase the re-entry interval by one day. It also reports the standard deviations for each WTP that were calculated via parametric bootstrapping following the Krinsky and Robb procedure (Krinsky and Robb 1986). Table 5 also lists the combinatorial differences (p-values) between WTP obtained via direct and indirect valuation. A p-value less than 0.05 indicate that the WTP obtained via indirect valuation is greater than the WTP obtained via direct valuation.

We found that under the direct valuation, apple growers stated a WTP of $26.03/acre and under indirect valuation $26.60/acre to decrease the pesticides’ probability of being toxic to
natural enemies. In addition, we found that apple growers stated that other growers would have a higher WTP (compared to their own WTP), for high and moderate pesticide effectiveness in controlling codling moth. Also, higher WTP for other growers were estimated for decreasing the probability of toxicity for natural enemies, wildlife, aquatic organisms, and decreasing by one day the re-entry interval. However, there were no statistical significant differences between the WTP obtained via direct and indirect valuation for any of the variables presented. Thus, we reject the hypothesis that variables with a socially positive connotation exhibit indirect valuation WTP higher than direct valuation WTP.

For pear growers, the WTP to decrease the pesticides’ probability of toxicity for natural enemies under the direct valuation was estimated at $40.06/acre and under indirect valuation at $33.37/acre. The WTP obtained via indirect valuation was higher than the WTP obtained via direct valuation for the probability of high and moderate effectiveness in controlling codling moth, and for the probability of toxicity for wildlife, aquatic organisms, and re-entry interval. Same as for apples, there is no evidence of social desirability bias as there are no statistical significant differences across WTP obtained via the two approaches. That we did not find evidence of social desirability biases might signal that pesticide choice despite all the potential effects to worker health and environment, is a socially neutral phenomena, as growers are aware that they all face similar risk aversions to pest infestations, and that pesticide effectiveness is the main concern when choosing a pesticide. In addition, the strong regulations towards pesticide use and the phase-out of pesticides suspicious of having negative effects could have influenced growers’ perceptions.

Validation of results
Results listed in table 6 show actual and predicted market shares for seven commercial pesticides used in apples and pears. For apples, actual market share indicate a clear dominance of pesticides Altacor™, Delegate™, and Guthion™. Predicted market share results, obtained via the direct and indirect valuation, show a dominance of Intrepid™ and Assail™. For pears, actual market share shows dominance of Altacor™ and Delegate™. Predicted market shares obtained via the direct valuation are distributed across Calypso™ and Guthion™; and via the indirect valuation across Calypso™ and pheromones. Table 6 also lists results from the combinatorial differences across actual and predicted market shares. For pesticides used in apple orchards, there were no statistically significant differences between the actual and predicted market share obtained via the direct valuation for Assail™, Cyd-X™, Intrepid™, and Rimon™. For predicted market share obtained via indirect valuation, there were no statistically significant differences for Assail™ and Intrepid™. This result shows slight prediction superiority for market shares obtained via direct valuation. For pesticides used in pear orchards, there are no statistically significant differences between the actual and predicted market shares obtained via the direct valuation for Calypso™ and Cyd-X™. For market shares obtained via indirect valuation, there were no statistically significant differences for Calypso™, Guthion™, and pheromones. This result indicates slight prediction superiority for market shares obtained via the indirect valuation.

Results for the prediction index, MSE, and OSLLF are presented in table 7. For the apple dataset, the direct valuation has higher prediction accuracy when using all three criteria. For the pear dataset, the prediction index and the OSLLF favor the indirect valuation, but not the MSE. The MSE is affected by one large deviation in the predicted market share of pesticide Calypso™ that noticeably increased the MSE sum.
That the indirect valuation predicted slightly better in the pear dataset and not in the apple
dataset could be explained by the fact that apple and pear production conditions are different.
Recall that pear growers face greater challenges than apple growers in pest control, having to
invest more in pesticide applications. This could lead to different perceptions of how growers
themselves control pests and how they believe others control pests. It turns out that how pear
growers believe others would control is closer to actual practices. That pear growers stated that
others growers would care more for control effectiveness than themselves seems to have the
largest influence on the results favoring the prediction accuracy of the indirect valuation. This
also shows that pesticide effectiveness is the main concern for pear growers. A different
phenomenon is observed in the apple case. Apple growers stated for their own a higher value for
a moderate effectiveness than high effectiveness; thus favoring pesticides that will not be
disruptive to natural enemies or the environment (and that are perceived to be not as effective in
killing pests as broad spectrum disruptive pesticides). Yet, they stated lower values for pesticide
toxicity for natural enemies, wildlife, and aquatic organisms for their own compared to what was
stated for others.

6. Conclusions
We used a hypothetical discrete choice model to measure apple and pear growers’
valuation for pesticide features that would conserve natural enemies in the orchard. We applied
the indirect valuation approach as a measure to remove potential wedges between growers’
stated values for a good in a hypothetical survey and actual values. The first objective of this
paper was to measure growers’ WTP for conserving natural enemies in the orchard. We found
that under direct valuation, apple growers stated a WTP of $26.03/acre and under indirect
valuation $26.60/acre to decrease the probability of toxicity to natural enemies. Pear growers under the direct valuation stated a WTP of $40.06/acre and under indirect valuation $33.37/acre.

A second objective of this paper was to assess evidence of social desirability bias when eliciting preferences for pesticides features. We found that for both apple and pear cases there was no evidence of social desirability biases as no statistically significant differences were found across WTP obtained via either valuation approach. These results contrast previous findings (Lusk and Norwood 2009a; Lusk and Norwood 2009b, Olynk, Tonsor, and Wolf 2010; Norwood and Lusk 2011) in that higher WTP estimates are expected for variables with a positive social influence. Our findings might be explained by List’s (2006) argument in that the potential to reduce social desirability biases when using an indirect valuation approach is dependent on the problem context. Pesticide choice in perennial crops (such as fresh fruits) might not be the context where to observe social desirability bias as pressures to respond according to social norms might not be the main reason behind a choice of pesticide, but the effectiveness in controlling for the pest.

To validate results we compared actual and estimated market shares for pesticides commonly used in apple and pear orchards to control first generation codling moth. We found mixed evidence, for the apple dataset it was the direct valuation that exhibited higher prediction accuracy whereas for the pear dataset it was the indirect valuation. Differences in the growing conditions for both fruits might have led to these results. Our findings emphasize the importance of the nature of the problem context when analyzing the potential of the indirect valuation to minimize the social desirability bias. We found that when growers face all similar conditions, in terms of production, financial, and marketing risks, the potential of the indirect valuation to reduce social desirability biases might be weak.
References

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Marsh, D., L. Mkwara, and R. Scarpa. “Do Respondents’ Perceptions of the Status Quo Matter in


Table 4.1 Summary Statistics Apple Grower Responses

<table>
<thead>
<tr>
<th>Definition</th>
<th>Value</th>
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<tbody>
<tr>
<td><strong>Average (median) number of acres</strong></td>
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<td>Owned</td>
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<tr>
<td>Rented</td>
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<td><strong>Location (=1 if respondent has orchards in any county listed below)</strong></td>
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<tr>
<td>Yakima</td>
<td>0.39</td>
</tr>
<tr>
<td><strong>2010 Annual Gross Income (=1 if respondent fall in any category listed below)</strong></td>
<td></td>
</tr>
<tr>
<td>$75,000 - $99,999</td>
<td>0.14</td>
</tr>
<tr>
<td>$100,000 - $249,999</td>
<td>0.17</td>
</tr>
<tr>
<td>$250,000 - $499,999</td>
<td>0.14</td>
</tr>
<tr>
<td>$500,000 - $1 million</td>
<td>0.11</td>
</tr>
<tr>
<td>More than $1 million</td>
<td>0.44</td>
</tr>
<tr>
<td><strong>Average number of years involved in apple production</strong></td>
<td>19.08</td>
</tr>
<tr>
<td><strong>Pesticide for first generation codling moth in 2010 (=1 if respondent fall into any pesticide listed below)</strong></td>
<td></td>
</tr>
<tr>
<td>Altacor™</td>
<td>0.43</td>
</tr>
<tr>
<td>Assail™</td>
<td>0.11</td>
</tr>
<tr>
<td>Cydxcem™</td>
<td>0.06</td>
</tr>
<tr>
<td>Delegate™</td>
<td>0.14</td>
</tr>
<tr>
<td>Guthion™</td>
<td>0.14</td>
</tr>
<tr>
<td>Intrepid™</td>
<td>0.06</td>
</tr>
<tr>
<td>Rimon™</td>
<td>0.06</td>
</tr>
</tbody>
</table>

*The numbers in between parenthesis indicates the median of the distribution.*
Table 4.2 Summary Statistics Pear Grower Responses

<table>
<thead>
<tr>
<th>Definition</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average (median) of the number of acres</td>
<td></td>
</tr>
<tr>
<td>Owned</td>
<td>149.04 (110.00)³</td>
</tr>
<tr>
<td>Rented</td>
<td>56.60 (21.00)</td>
</tr>
<tr>
<td>Managed/consulted but did not own/rent</td>
<td>98.00 (140.00)</td>
</tr>
<tr>
<td>Location (=1 if respondent has orchards in any county listed below)</td>
<td></td>
</tr>
<tr>
<td>Yakima</td>
<td>0.12</td>
</tr>
<tr>
<td>Hood River</td>
<td>0.88</td>
</tr>
<tr>
<td>2010 Annual Gross Income (=1 if respondent fall in any category listed below)</td>
<td></td>
</tr>
<tr>
<td>Less than $10,000</td>
<td>0.04</td>
</tr>
<tr>
<td>$25,000 - $49,999</td>
<td>0.04</td>
</tr>
<tr>
<td>$50,000 - $74,999</td>
<td>0.08</td>
</tr>
<tr>
<td>$100,000 - $249,999</td>
<td>0.11</td>
</tr>
<tr>
<td>$250,000 - $499,999</td>
<td>0.15</td>
</tr>
<tr>
<td>$500,000 - $1 million</td>
<td>0.27</td>
</tr>
<tr>
<td>More than $1 million</td>
<td>0.31</td>
</tr>
<tr>
<td>Average number of years involved in pear production</td>
<td>24.57</td>
</tr>
<tr>
<td>Pesticide for first generation codling moth in 2010 (=1 if respondent fall into any pesticide listed below)</td>
<td></td>
</tr>
<tr>
<td>Altacor™</td>
<td>0.38</td>
</tr>
<tr>
<td>Assail™</td>
<td>0.08</td>
</tr>
<tr>
<td>Calypso™</td>
<td>0.04</td>
</tr>
<tr>
<td>Cydxcem™</td>
<td>0.04</td>
</tr>
<tr>
<td>Delegate™</td>
<td>0.35</td>
</tr>
<tr>
<td>Guthion™</td>
<td>0.04</td>
</tr>
<tr>
<td>Pheromone</td>
<td>0.08</td>
</tr>
</tbody>
</table>

³ The numbers in between parenthesis indicates the median of the distribution.
<table>
<thead>
<tr>
<th>Pesticide features</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of high effectiveness in controlling codling</td>
<td>0</td>
</tr>
<tr>
<td>moth</td>
<td>10</td>
</tr>
<tr>
<td>Probability of moderate effectiveness in controlling codling</td>
<td>50</td>
</tr>
<tr>
<td>moth</td>
<td>90</td>
</tr>
<tr>
<td>Probability of toxicity for natural enemies (%)</td>
<td>100</td>
</tr>
<tr>
<td>Probability of toxicity for wildlife (%)</td>
<td>0</td>
</tr>
<tr>
<td>Probability of toxicity for aquatic organisms (%)</td>
<td>0</td>
</tr>
<tr>
<td>Re-entry interval (days)</td>
<td>0.17</td>
</tr>
<tr>
<td>Price(^a) ($/acre)</td>
<td>20</td>
</tr>
</tbody>
</table>

\(^a\) Price does not include application costs, only chemical costs per acre.
## Table 4.4 Heteroscedastic Extreme Value Models Estimates by Valuation Method for Pesticide Choice

<table>
<thead>
<tr>
<th></th>
<th>Apple Valuation</th>
<th></th>
<th>Pear Valuation</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct</td>
<td>Indirect</td>
<td>Direct</td>
<td>Indirect</td>
</tr>
<tr>
<td>ASC 3</td>
<td>0.26</td>
<td>-3.66**</td>
<td>15.21*</td>
<td>-4.14</td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
<td>(1.51)</td>
<td>(8.08)</td>
<td>(2.73)</td>
</tr>
<tr>
<td>Price*Acres</td>
<td>-0.07**</td>
<td>-0.07**</td>
<td>-0.51**</td>
<td>-0.28</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.04)</td>
<td>(0.25)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>High prob. of effectiveness in controlling c. moth*Acres</td>
<td>1.81*</td>
<td>10.28**</td>
<td>15.15**</td>
<td>89.58**</td>
</tr>
<tr>
<td></td>
<td>(1.02)</td>
<td>(2.94)</td>
<td>(7.71)</td>
<td>(45.10)</td>
</tr>
<tr>
<td>Moderate prob. of effectiveness in controlling c. moth*Acres</td>
<td>2.69**</td>
<td>7.51**</td>
<td>8.41</td>
<td>78.08**</td>
</tr>
<tr>
<td></td>
<td>(1.14)</td>
<td>(2.65)</td>
<td>(6.15)</td>
<td>(39.73)</td>
</tr>
<tr>
<td>Probability of toxicity for natural enemies*Acres</td>
<td>-1.95**</td>
<td>-1.99</td>
<td>-20.37*</td>
<td>-9.45</td>
</tr>
<tr>
<td></td>
<td>(0.89)</td>
<td>(1.64)</td>
<td>(10.29)</td>
<td>(6.44)</td>
</tr>
<tr>
<td>Probability of toxicity for wildlife*Acres</td>
<td>-1.25</td>
<td>-4.62**</td>
<td>-4.17</td>
<td>-7.16</td>
</tr>
<tr>
<td></td>
<td>(0.92)</td>
<td>(2.23)</td>
<td>(5.02)</td>
<td>(8.65)</td>
</tr>
<tr>
<td>Probability of toxicity for aquatic organisms*Acres</td>
<td>-0.93</td>
<td>-3.22**</td>
<td>-0.17</td>
<td>-5.57</td>
</tr>
<tr>
<td></td>
<td>(0.85)</td>
<td>(1.63)</td>
<td>(3.61)</td>
<td>(4.10)</td>
</tr>
<tr>
<td>Re-entry interval*Acres</td>
<td>-0.21**</td>
<td>-0.30*</td>
<td>-0.97</td>
<td>-2.45*</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.12)</td>
<td>(0.62)</td>
<td>(1.38)</td>
</tr>
<tr>
<td>Scale</td>
<td>0.97*</td>
<td>0.23**</td>
<td>0.04**</td>
<td>0.02*</td>
</tr>
<tr>
<td></td>
<td>(0.58)</td>
<td>(0.08)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-268.54</td>
<td>-279.81</td>
<td>-115.15</td>
<td>-99.07</td>
</tr>
<tr>
<td>Number of observations</td>
<td>280.00</td>
<td>280.00</td>
<td>208.00</td>
<td>208.00</td>
</tr>
</tbody>
</table>

*Numbers in parentheses are standard errors.

b One and two asterisks (**, *) denotes statistically significant at the 0.05 and 0.10 level, respectively.
### Table 4.5 Willingness to Pay (WTP) and Standard Deviations for Pesticides Features Used in Apples and Pears

<table>
<thead>
<tr>
<th>WTP for having a pesticide …</th>
<th>WTP apple growers</th>
<th>WTP pear growers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct ($/acre)</td>
<td>Indirect ($/acre)</td>
</tr>
<tr>
<td>Highly effective in controlling c. moth</td>
<td>24.14 (171.31)</td>
<td>137.43 (2219.59)</td>
</tr>
<tr>
<td>Moderately effective in controlling c. moth</td>
<td>35.96 (286.98)</td>
<td>100.39 (1675.64)</td>
</tr>
<tr>
<td>Non-toxic for natural enemies</td>
<td>26.03 (162.02)</td>
<td>26.60 (582.62)</td>
</tr>
<tr>
<td>Non-toxic for wildlife</td>
<td>16.62 (90.58)</td>
<td>61.83 (427.67)</td>
</tr>
<tr>
<td>Non-toxic for aquatic organisms</td>
<td>12.39 (31.53)</td>
<td>43.10 (918.66)</td>
</tr>
<tr>
<td>With one day less of re-entry interval</td>
<td>2.76 (9.53)</td>
<td>3.99 (84.04)</td>
</tr>
</tbody>
</table>

\(^a\) P-values represent the p-value of a one-sided test of indirect valuation WTP > direct valuation WTP. The one-sided p-value of direct valuation WTP > indirect valuation WTP is simply 1 – p-value reported in the table. A two-sided test for statistical differences is simply 2 * p-value in the table (Poe et al., 2005).

\(^b\) Numbers in parenthesis are standard deviations determined via parametric bootstrapping.
Table 4.6 Comparison between actual and predicted market share for seven commercial pesticides used in apples and pears

<table>
<thead>
<tr>
<th>Pesticide</th>
<th>Actual market share (%)</th>
<th>Predicted market share direct valuation (%)</th>
<th>Difference between the actual and predicted market share - direct valuation (p-value) (%)</th>
<th>Predicted market share indirect valuation (%)</th>
<th>Difference between the actual and predicted market share - indirect valuation (p-value) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Altacor™</td>
<td>42.86</td>
<td>1.63 (3.30)</td>
<td>0.00</td>
<td>0.01 (0.09)</td>
<td>0.01</td>
</tr>
<tr>
<td>Assail™</td>
<td>11.43</td>
<td>31.99 (36.80)</td>
<td>0.50</td>
<td>16.89 (32.17)</td>
<td>0.25</td>
</tr>
<tr>
<td>Cyd-X™</td>
<td>5.71</td>
<td>4.63 (12.93)</td>
<td>0.15</td>
<td>0.23 (3.49)</td>
<td>0.01</td>
</tr>
<tr>
<td>Delegate™</td>
<td>14.29</td>
<td>0.52 (4.99)</td>
<td>0.01</td>
<td>0.00 (0.03)</td>
<td>0.00</td>
</tr>
<tr>
<td>Guthion™</td>
<td>14.29</td>
<td>0.61 (7.43)</td>
<td>0.01</td>
<td>0.30 (5.35)</td>
<td>0.00</td>
</tr>
<tr>
<td>Intrepid™</td>
<td>5.71</td>
<td>58.04 (40.05)</td>
<td>0.79</td>
<td>82.24 (32.81)</td>
<td>0.93</td>
</tr>
<tr>
<td>Rimon™</td>
<td>5.71</td>
<td>2.58 (6.02)</td>
<td>0.13</td>
<td>0.32 (2.90)</td>
<td>0.01</td>
</tr>
<tr>
<td>Altacor™</td>
<td>38.46</td>
<td>0.88 (2.79)</td>
<td>0.00</td>
<td>2.09 (7.95)</td>
<td>0.01</td>
</tr>
<tr>
<td>Assail™</td>
<td>7.69</td>
<td>1.28 (9.68)</td>
<td>0.02</td>
<td>1.76 (11.20)</td>
<td>0.03</td>
</tr>
<tr>
<td>Calypso™</td>
<td>3.85</td>
<td>69.72 (39.01)</td>
<td>0.86</td>
<td>87.21 (26.68)</td>
<td>0.95</td>
</tr>
<tr>
<td>Cyd-X™</td>
<td>3.85</td>
<td>6.07 (19.91)</td>
<td>0.14</td>
<td>1.24 (10.20)</td>
<td>0.02</td>
</tr>
<tr>
<td>Delegate™</td>
<td>34.62</td>
<td>0.30 (3.16)</td>
<td>0.00</td>
<td>1.04 (6.98)</td>
<td>0.01</td>
</tr>
<tr>
<td>Guthion™</td>
<td>3.85</td>
<td>20.98 (35.28)</td>
<td>0.04</td>
<td>2.15 (12.49)</td>
<td>0.36</td>
</tr>
<tr>
<td>Pheromone</td>
<td>7.69</td>
<td>0.76 (3.10)</td>
<td>0.02</td>
<td>4.51 (11.00)</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Numbers in parentheses are standard deviations determined via parametric bootstrapping.
### Table 4.7 Prediction Accuracy for the Estimates Obtained via Direct and Indirect Valuation

<table>
<thead>
<tr>
<th></th>
<th>Direct Valuation</th>
<th>Indirect Valuation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prediction index</strong></td>
<td>91.43</td>
<td>10.00</td>
</tr>
<tr>
<td>MSE</td>
<td>0.525</td>
<td>0.818</td>
</tr>
<tr>
<td>OSLLF</td>
<td>-3.79</td>
<td>-7.32</td>
</tr>
</tbody>
</table>

**Apples**

<table>
<thead>
<tr>
<th></th>
<th>Direct Valuation</th>
<th>Indirect Valuation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prediction index</td>
<td>73.08</td>
<td>82.21</td>
</tr>
<tr>
<td>MSE</td>
<td>0.73</td>
<td>0.95</td>
</tr>
<tr>
<td>OSLLF</td>
<td>-4.72</td>
<td>-3.94</td>
</tr>
</tbody>
</table>

**Pears**

- Prediction index indicates the number of times the model predicted accurately actual pesticide choices; a higher number implies better prediction.
- MSE means mean square error between actual and predicted market share; a lower number implies better prediction.
- OSLLF means out-of-sample log likelihood function, considering actual and predicted market share; a higher number implies better prediction.