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Essays on agricultural, financial economics and education

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Essays on agricultural, financial economics and education

by

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DEDICATION

I would like to dedicate this thesis to my wife Analia and our daughter Julia.

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ABSTRACT

This dissertation is devoted to the study of three different topics under the advice of three different mayor professors. The only thing these topics have in common is the interest and curiosity of the author to explain real life events, using applied econometric techniques. Chapter 2 applies financial tools to assess whether stock values reacted across world markets to the announcement of indexes that synthesize the environmental performance of the world's largest publicly-traded companies. The environmental index selected for this purpose is the "Global 100 Ranking" (G100), a ranking of the 100 largest public companies by market capitalization. The results show that the market reacted to the "Global 100 Ranking" by changing the relative price of the stocks, but not the value of the portfolio. We also find that investors in US-traded stocks are more interested in past environmental performance than on managerial quality, while the opposite is true for investors in non-US-traded stocks. Chapter 3 estimates simultaneous equation models of barge and railroad rates for specific origin-destinations and grains (corn, wheat, and soybeans) in the US, using data from the Grain Transportation Report. Evidence of specific route competitiveness of various grains was found. Interestingly, it was possible to identify a railroad route with prices as complementary of barge rates, which may increase railroad market power. River levels affect barge rates, but there are differences for corn and wheat,

possibly due to production locations in the Mississippi basin. Ocean vessel rates affect barge rates directly and railroad rates indirectly. Real exchange rates affect barge rates more than railroad rates. Evidence suggests that distance between railroad origin and barge origin affects the impact of the later on the first one. Chapter 4 studies the effect on early education achievement of keeping the same classmates as in the previous year by utilizing the unique nature of the Tennessee Student Teacher Achievement Ratio (STAR). Results show that keeping all kindergarten classmates vs. losing all of them increases the probability of passing first grade by 7 to 10 percent. In addition, noncognitive skills are improved when more kindergarten classmates are kept as first grade classmates. If all classmates are kept together vs. staying alone in a new class, motivation and selfconfidence may increase by 0.5 of a standard deviation, while the number of absences may decrease by 2 to 3 days.

CHAPTER 1. GENERAL INTRODUCTION

Socially Responsible Investing has become a dynamic research area in recent years (Geczy et al. 2005; Kurtz 1997; Sauer 1997; Cummings 2000; Abramson and Chung 2000; Bauer et al. 2002; Mill 2006; Lobe and Walkshausl 2011). The popularity of Socially Responsible Investing has led to the development of indexes like the Dow Jones Sustainability Index (DJSI), in which environmental responsibility weights 9.2% (Fowler and Hope 2007). A specific environmental index created in 2009 targeting the Socially Responsible Investing audience is Newsweek's "Green Rankings." Its first edition included the "US 500 List," which comprises the 500 largest publicly-traded US companies. Its second edition, released online on October 18th, 2010 at 8 a.m. US East coast time, added the "Global 100 List," involving the 100 largest publicly traded companies worldwide.

These Newsweek rankings mostly use existing information regarding hundreds of environmental indicators and models. Nevertheless, they provide new information by presenting a clear unique measure of environmental performance for each company. This publicly available measure may help coordinate expectations about how the market weights all of the environmental data available. It also gives small investors access to costly environmental information, and increases public awareness about the largest companies' environmental performance. The first essay (Chapter 2) applies financial tools to assess whether stock values reacted across world markets to the announcement of the "Global 100 Ranking" (G100).

Most US grain production is located in the Midwest. Demand, however, is dispersed across the US and abroad, creating areas with large surpluses and deficits of grains, and requiring the transportation of more than 400 million tons of corn, soybean, and wheat each year (Marathon and Denicoff, 2011). As a consequence, an efficient intermodal transportation system of trucks, railroads, barges and vessels is fundamental in determining better prices for farmers, lower food and biofuel costs for consumers and more competitive export prices. While domestic transportation is covered mostly by truck, railroads and barges are the most important modal transportations for exports. Because grains are often transported in more than one mode, competition and complementarity exist among these modes. The second essay (Chapter 3) analyzes the competitive interactions between grain railroad rates and barge rates in the Mississippi waterway system.

The effect of peers on education and other social outcomes has attracted much attention in the economic literature. Effects have been documented on cognitive and non-cognitive skills including drug use, criminal behavior, and academic performance from early childhood to college. In general these studies benefit from experiments where the exogenous formation of groups addresses the endogeneity of peer selection. Many policies have been based on peer effects: schools for gifted children, tracking/sorting of students within schools, and desegregation policies are among them. Some of these policies have created debate among policy makers and scientists for their impact on inequality. Surprisingly little is known about the impact of the time duration of these peer connections on social outcomes. In the third essay (Chapter 4), I analyze the effects of a common elementary school practice of breaking classes apart and joining students from different groups at the beginning of the school year.

The first essay (Chapter 3) is titled “Investors’ Reaction to Environmental Performance: A Global Perspective of *Newsweek*’s “Green Rankings.”” Its contribution to the literature is twofold. First, it adds a world market dimension to environmental rankings and the response of investors. This is true because the G100 includes stocks traded in nine different exchanges (NYSE, London, Paris, Frankfurt, Switzerland, Hong Kong, Shanghai, South Korea, and Tokyo) from companies based on most of the continents (e.g., the US and Brazil in America; the United Kingdom, France, Italy, Germany, Spain, and Russia in Europe; and China, South Korea, and Japan in Asia). Second, the study quantifies the marginal effects of the ranking on stock prices. By employing cross-sectional models of abnormal returns against rankings, we are able to determine marginal effects that cannot be computed from the cumulative abnormal return statistics typically used in event studies. Third, we investigate the impact of rankings on returns by industry sectors. Finally and most importantly, to our knowledge it provides the first evidence of the existence of heterogeneity among investors in regard to their interest in past performance and managerial quality as predictors of future environmental performance.

The second essay (Chapter 3), "Competitive Interactions between Grain Railroad Rates and Barge Rates in the Mississippi Waterway System," analyzes the competitive interactions between grain railroad rates and barge rates in the Mississippi waterway system. US grain exports require large distance transportation from the Midwest to the ports in the Gulf and Pacific Northwest (PNW). For this reason, barge and rail transportation are preferred to trucks. Barges are able to carry one ton of cargo 576 miles per gallon of fuel, compared to 413 miles by rail and only 155 miles for a truck (Maritime Administration, 2010). Also, the capacity of a barge, 1,500 tons, is 15 times that of a rail car and 60 times that of a truck. Barge and rail transportation are also preferred from an environmental point of view. Trade transportation by barge releases 33 percent less pollutants than diesel trains and 373 percent less than diesel trucks (Maritime Administration, 2010).

In this chapter 3, by means of simultaneous equations models of barge rates and railroad rates, within the period 2002-2012, price-price elasticities were estimated for the three major grain crops: corn, soybeans, and wheat. Results differ by railroad lines, some show complementarity behavior with barges while others show competitive behavior. Water levels, real exchange rates, ocean rates, and diesel prices affect barge rates. Ocean rates complement the inland transportation services that reach their respective export ports. This chapter expands the scarce literature on rail-barge competition by concentrating for the first time on the effect of barge rates on railroad rates and analyzing the effect of distance between origin and the Mississippi waterway system on their competitive interactions.

The third essay (Chapter 4), “Oh, the More We Get Together: Peer effects in Early Elementary School,” considers the STAR program database to analyze the impact of keeping classmates (kindergarteners) on school performance. The Tennessee STAR (Student Teacher Achievement Ratio) program, a large scale class size experiment on elementary school, randomized the initial allocation of teachers and students in kindergarten within each school and randomly mixed up students of large classes at the beginning of first grade. The data collected in the STAR program has information on 4515 students that attended kindergarten and first grade in the 79 STAR participating schools. Measures of school performance include the probability of being recommended for grade promotion, cognitive and non-cognitive skills.

Regressions of recommendation for passing grade, and cognitive and noncognitive skills are estimated in this chapter for first, second and third grade. The cognitive variables include annual recommendation to pass a grade and test scores (math, reading, listening and word). Noncognitive skills include annual motivation scores, selfconfidence scores, and days absent. The explanatory variables include characteristics of the student and their classmates (measured at kindergarten to prevent endogeneity), the teachers, and the school that was presented in the data section. Besides the estimation of fixed and random effects models, this study encompasses modern microeconometric techniques by recognizing that individuals within schools come with a natural nesting and implements cluster sample techniques, like clustering errors and generalized estimation equation (GEE) models (Wooldridge, 2010).

This chapter is, to my knowledge the first to find evidence supporting the importance of time on peer effects. Specifically, the effect of peers does not depend only on their abilities and skills, but also on the time they have been peers. This is true even when there is not endogenous peer selection over time. These results have implications for educational policies like random mixing and sorting/tracking. For example, sorting/tracking policies may also affect students, not only by changing the level of the peers and allowing to adjust educational programs, but also by losing long time known peers. As a consequence, these policies may also have negative effects on the social capital of the student and the class that might be detrimental for child development.

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CHAPTER 2. INVESTORS' REACTION TO ENVIRONMENTAL PERFORMANCE: A GLOBAL PERSPECTIVE OF NEWSWEEK'S "GREEN RANKINGS"

Juan M. Murguia[1] and Sergio Lence

Abstract

We use event study analysis to determine whether the release of Newsweek's "Global 100 Ranking" is relevant for the market. We look at one- and two-day event windows to check two possible reactions of the market: changes in the value of an equal-weight portfolio, and changes in the relative price of the stocks. The results show that the market reacted to the "Global 100 Ranking" by changing the relative price of the stocks, but not the value of the portfolio. Specifically, getting one position closer to the top of Newsweek's "Global 100 Green Rankings" increases the value of an average firm in the list by eleven million dollars. There is also some evidence of a stronger reaction of non-US-traded stocks compared to US-traded ones. Non-heavy sector stocks display a more robust reaction to than heavy sector stocks. We find that investors in US-traded stocks are more interested on past environmental performance than on managerial quality, while the opposite is true for investors in non-US-traded stocks. Results are robust to alternative model specifications.

Keywords: Environmental ranking, event study, *Newsweek* magazine.

JEL Codes: M14, G02, G14, G24, Q51, Q56.

1. Introduction

Socially Responsible Investing, an investment strategy that favors corporate practices promoting environmental stewardship, consumer protection, human rights, and diversity, represents 12% of the $25.2 trillion in total world assets under professional management

[1] Primary researcher and author.

(Social Investment Forum 2010). Socially Responsible Investing has become a dynamic research area in recent years (Geczy *et al*. 2003; Kurtz 1997; Sauer 1997; Cummings 2000; Abramson and Chung 2000; Bauer *et al*. 2002; Mill 2006; Lobe, Roithmeier and Walkshausl 2009).[2] The popularity of Socially Responsible Investing has led to the development of indexes like the Dow Jones Sustainability Index (DJSI), in which environmental responsibility weights 9.2% (Fowler and Hope 2007).

A specific environmental index created in 2009 targeting the Socially Responsible Investing audience is *Newsweek*'s "Green Rankings." Its first edition included the "US 500 List," which comprises the 500 largest publicly-traded US companies. Its second edition, released online on October 18th, 2010 at 8 a.m. US East coast time, added the "Global 100 List," involving the 100 largest publicly traded companies worldwide. These *Newsweek's* rankings mostly use existing information about hundreds of environmental indicators and models. Nevertheless, they provide new information by presenting a clear unique measure of environmental performance for each company. This publicly available measure may help coordinate expectations about how the market weights all of the environmental data available. It also gives small investors access to costly environmental information, and increases public awareness about the largest companies' environmental performance.

The present study applies financial tools to assess whether stock values reacted across world markets to the announcement of indexes that synthesize the environmental performance of the world's largest publicly-traded companies. The environmental index selected for this purpose is the "Global 100 Ranking" (G100), a ranking of the 100 largest public companies by market capitalization. The G100 comprises stocks traded in nine

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[2] Kitzmueller and Shimshack (2012) provide an extensive review of this literature.

different exchanges across the world, which allows us to study whether there are differences in the reactions of investors operating within and outside the US stock market.[3] Specifically, we analyze (a) whether there are changes in the value of an equal-weight portfolio of the companies on the ranking; (b) whether a company's ranking position affects its stock value; (c) whether there are differences in the reactions to the ranking of US-traded companies compared to non-US-traded companies; and (d) whether the reactions to the ranking differ across industry sectors.

The present study contributes to the literature in four aspects. First, it adds a world market dimension to environmental rankings and the response of investors. This is true because the G100 includes stocks traded in nine different exchanges (NYSE, London, Paris, Frankfurt, Switzerland, Hong Kong, Shanghai, South Korea, and Tokyo) from companies based in most of the continents (e.g., the US and Brazil in America; the United Kingdom, France, Italy, Germany, Spain, and Russia in Europe; and China, South Korea, and Japan in Asia). Second, the study quantifies the marginal effects of the ranking on stock prices. By employing cross-sectional models of abnormal returns against rankings, we are able to determine marginal effects that cannot be computed from the cumulative abnormal return statistics typically used in event studies. Third, we investigate the impact of rankings on returns by industry sectors. Finally and most importantly, to our knowledge it provides the first evidence of the existence of heterogeneity among investors in regard to their interest in past performance and managerial quality as predictors of future environmental performance.

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[3] We use the G100 because, unlike the "US 500 List" and other environmental indexes, it includes both US- and non-US-traded firms. The "US 500 List" has been analyzed by Anderson-Weir (2010), Murguia (2010), Blumenshine and Wunnava (2010), van Iwaardenl *et al*. (2010), and Lyon and Shimshack (2011).

Previous studies have analyzed the impact of environmental news and rankings on stock markets, with results showing positive correlation between economic and environmental performance (Murphy 2002). Environmental news studies have included the Toxic Release Inventory of US firms (Khana, Quimio, and Bojilova 1998), pollution information of S&P 500 companies (Konar and Cohen 2001), explosions on chemical plants worldwide (Capelle-Blancard and Laguna 2010), and carbon disclosure (see Busch and Hoffmann 2011 for an extended literature review). Some of these studies found significant effects (Capelle-Blancard and Laguna 2010; Konar and Cohen 2001), whereas other studies uncovered significant effects only when repeated information was released (Khana, Quimio, and Bojilova 1998). Busch and Hoffmann (2011) report that, for companies in the Global 2500 Dow Jones, corporate environmental performance pays off when using carbon emissions as an outcome-based measurement. Margolis, Elfenbein and Walsh (2007) provide an extensive review of the literature linking corporate financial performance to corporate social performance.

Studies involving environmental news and rankings have been performed for Japan (Nagayama and Takeda 2007, Yamaguchi 2008, and Takeda and Tomozawa 2008) and the US. For the US, some studies used the KLD ranking (Plumlee *et al*. 2010; Walter 2009; Dawkins and Fraas 2011),[4] whereas others focused on *Newsweek's* ranking (Anderson-Weir 2010; Murguia 2010; Blumenshine and Wunnava 2010; van Iwaardenl *et al*. 2010; Lyon and Shimshack 2011). In the case of *Newsweek's* ranking, Anderson-Weir (2010), Murguia (2010) and van Iwaardenl *et al*. (2010) found no significant effects of *Newsweek*'s "Green

[4] In general, these papers find a positive relationship between environmental performance and voluntary climate change disclosure.

Ranking 2009" on the returns of S&P 500 stocks, whereas Lyon and Shimshack (2011) did.[5] Blumenshine and Wunnava (2010) found that companies with high environmental rankings have higher market capitalization values. They concluded that either investors include environmental factors when pricing stocks, or that a high environmental rank indicates other intangible variables that contribute to a company's value.

Succinctly, our results indicate that the market reacted to the G100 by changing the relative prices of the stocks included in it, but not the value of the equal-weight portfolio of such stocks. Specifically, increasing ten positions in the ranking improved the value of a stock by 0.1%, or 113 million dollars for the average company capitalization. There is also evidence of a stronger reaction for non-US-traded stocks compared to US-traded stocks, and a more robust one for stocks in the non-heavy sector compared to the ones in the heavy sector. Non-US- and US-traded stocks reacted different also with respect to past environmental performance and environmental managerial quality. In particular, US-traded stock returns appear to be affected only by past performance, whereas non-US-traded stock returns seem to respond only to managerial quality.

2. Theoretical Framework

Why should investors care about Corporate Social Responsability (CSR)? Chatterji, Levine, and Toffel (2009) propose four possible motivations for investors to desire transparency about both past social performance and current managerial decisions that influence future

[5] The differences in results may be due to the event windows selected, and the methods employed for estimating abnormal returns. Murguia (2010) analyses one and two days (the event day and the next one), Anderson-Weir (2010) three days (the day previous to the event plus the event day and the day after), van Iwaardenl *et al*. (2010) one year, and Lyon and Shimshack (2011) three and four days (starting the day of the event).

social performance. The first motivation is based on the idea that socially responsible companies may perform better financially by attracting socially responsible consumers, reducing the thread of regulation, and reducing concerns from activists and non-governmental organizations. The second motivation is the driving force underlying "deontological" investors, who do not want to profit from unethical behaviors. Deontological investors care about past performance because they want to ensure that current profits were not earned from previous unethical behavior, and they also care about current management to avoid future scandals which would taint future profits. The third motivation is associated with "consequentialist" investors, who are driven by a desire to reward good behavior and decrease the market share of environmental irresponsible firms. The fourth and final motivation corresponds to "expressive" investors, who want to show to themselves or others that they are socially responsible.

Kitzmueller and Shimshack (2012) discuss extensively the existing CSR theories and the supporting evidence. Regardless of the motives behind CSR, [6] there are investors who seek transparency in social rankings, in the sense of combining an accurate summary of past performance, and a careful evaluation of current managerial actions likely to influence future environmental performance (Chatterji, Levine, and Toffel 2009).

Chatterji, Levine, and Toffel (2009) suggest that future research should examine how the holding of socially responsible funds changes as stakeholders are provided with more transparency about corporate social performance; and argue that stakeholders might be

[6] Ditlev-Simonsen and Midttun (2011) provide a partial answer in this regard. In a survey of corporate leaders they find that branding, stakeholders, and value maximization are assumed to be key motivators of CSR by senior managers of the 20 largest Norwegian corporations. They also report that corporate leaders believe sustainability and branding should be the key motivators of CSR by senior managers of the 20 largest Norwegian corporations.

heterogeneous in their responses to higher-quality information. To the best of our knowledge, the present study is the first one to provide evidence of the latter, in the form of US-traded stocks reacting differently to the G100 announcement compared to non-US-traded stocks. We also provide evidence about what investors look for in practice, which might be beneficial for the construction of environmental indexes. We find that investors in US-traded stocks are more interested on past environmental performance than on managerial quality, while the opposite is true for investors in non-US-traded stocks. Our results for US-traded firms are consistent with Chatterji, Levine, and Toffel (2009), who found that KLD pollution prevention scores predicted pollution or regulation violations for companies regulated by the US Environmental Protection Agency.

According to Chatterji, Levine, and Toffel (2009), measures of (environmental) managerial quality are relevant when they contain little noise and have substantial incremental information about future environmental outcomes not contained in history alone. They present a theoretical model based on these ideas for the selection of the optimal weight in a social index. In our study, managerial quality is represented by its environmental policies and its reputation (the correlation between both is 0.51), which have a correlation with environmental performance of 0.35 and 0.03, respectively. It is possible then that managerial quality might be relevant for predicting future environmental performance, provided it is not too noisy.

Errors in CSR measures, and particularly in environmental rankings, may cause market inefficiencies and explain different results regarding their impact on stock performance (Chatterji, Levine, and Toffel 2009). Noisy measures may be the reason why some studies find little correlation between CSR metrics and financial performance.

Alternatively, if consumers or investors are misled by the errors, studies finding a positive correlation may overestimate the true relationship between actual CSR and financial performance. These limitations must be taken into account when evaluating the results of the present study, because measurement errors are likely to affect the indexes employed for the analysis.

3. Data

Data in the present study include the G100, stock returns, nine stock exchange indexes, and Fama-French indexes. A detailed explanation follows.

3.1 Newsweek's "Global 100 Ranking"

The G100 consists of a ranking of the world's 100 largest (by market capitalization) companies according to *Newsweek*'s "Green Score." The Green Score is a weighted sum of three component scores that are designed to complement each other, namely, the "Environmental Impact Score" (EIS) with 45% weight, the "Green Policies Score" (GPS) with 45% weight, and the "Reputation Survey Score" (RSS) with 10% weight. The raw component scores were first converted to standardized values called Z scores, which reflect how individual companies performed relative to the average. The Green Score, as well as each component score, is published on a scale from 1 (worst performing) to 100 (best performing) (*Newsweek* 2010).

The EIS is an index of past environmental performance based on data compiled by Trucost. It measures the total environmental impact of a corporation's global operations (90 %) and the disclosure of those impacts (10 %). The EIS incorporates more than 700 metrics, including emissions of nine key greenhouse gases, water use, solid-waste disposal, and emissions that contribute to acid rain and smog. When publicly disclosed environmental data are available, they are used to evaluate a company performance for each impact metric. An economic input-output model is used to calculate direct-company and supply-chain impacts in cases where data are unavailable (*Newsweek* 2010).

The companies are classified into 15 sectors according to the FTSE/Dow Jones Industry Classification Benchmark. Therefore, to fairly assess impacts for companies operating in more than one industry, a benchmarking system was used. To make it possible to compare companies of different size, this system calculates environmental impact in dollars per dollar of sales. This accounts for 90% of the raw EIS; the remaining 10 % measures the disclosure of usable data. In the case of investing firms, rankings are adjusted to take into account the impact of the equity under management (*Newsweek* 2010).

The GPS is a managerial performance index based on models provided by MSCI, and assesses how a company manages its environmental footprint. To estimate the GPS, MSCI created a model that measures the quality of each company's environmental reporting, policies, programs, and initiatives. More than 70 indicators are incorporated into the GPS, and categorized into five issues, namely, (a) climate-change policies and performance, (b) pollution policies and performance, (c) product impact, (d) environmental stewardship, and (e) management of environmental issues. They address, respectively, how well each company manages its carbon emissions; how well each company manages its non-carbon emissions to air, water, and land; the life-cycle impacts of each company's products and services; how well each company manages and uses its local resources; and the quality of each company's track record of managing environmental risks. Data on regulatory compliance, lawsuits, controversies, and community impacts are also among the indicators taken into account within each category (*Newsweek* 2010).

The RSS is another managerial index, but based on an opinion survey of CSR professionals, academics, and other environmental experts who subscribe to *CorporateRegister.com*. A total of 14,921 surveys were sent out asking each respondent to rate a random sample of 15 companies on a sliding scale (1 to 100) from “laggard” to “leader” in three key green areas: environmental performance, commitment, and communications. Of those surveyed, 2,480 were environmental sector specialists that were only asked to score companies in their sector of expertise. The survey’s response rate was 12 %, twice the rate for the 2009 reputation survey. Chief-executive scores, sector specialists, and other participants were given a weight of three, two, and one, respectively. Each company’s performance, commitment, and communications scores were then averaged to produce its raw RSS (*Newsweek* 2010).

Companies that appear on both the US and Global lists in the 2010 edition have different Green Scores and component scores because normalizations are different. Moreover, it is not possible to compare company scores over time due to the changes in the methods used to construct them (*Newsweek* 2010).

3.2 Stock Returns and Indexes

Values of stocks and market indexes adjusted by splits and dividends were obtained from Yahoo Finance.[7] When a company’s stock data were not available for the period under study, the company’s web site was used as the source of information. In three instances (Nissan

[7] Yahoo Finance web page for US and Asian stocks, and United Kingdom Yahoo Finance web pages for European stocks.

Motor, Toshiba, and Lukoil), pink-sheet data (i.e., over-the-counter transactions in the US) were used as a last resource.

Seventy one of the companies in the G100 are traded in the US. Out of the remaining 29 companies not traded in the US, 25 are traded in Europe and four are traded in Asia. For companies trading in more than one stock market and currency, the market selected was the one with the highest average daily volume. Since the companies in the ranking are traded in nine different stock markets, the indexes used include NYA (New York, 1,900 largest stocks), the SSE Composite Index (Shanghai, all stocks), the Hang Seng Index (Hong Kong, 50 largest stocks), the Nikkei 225 (Japan, 225 largest stocks), the Kospi Composite Index (Korea, all stocks), the CAC 40-Paris (France, 40 largest stocks), DAX (Germany, 30 largest stocks), SMI (Switzerland, 20 largest stocks), and the FTSE 100 (United Kingdom, 100 largest stocks).

For each stock in the G100 and the nine market indexes, daily excess returns were calculated by subtracting the risk-free rate (measured as the interest rate on the one-month Treasury bill, downloaded from French's web page (French 2011)) from the respective rate of return. Following the literature (Fama and French 1998; Griffin 2002; Hou, Karolyi, and Kho 2011; Fama and French 2012), rates of return for the 29 non-US-traded stocks and the market indexes other than NYA, were computed by first converting the values denominated in foreign currencies into US dollars.[8] For this purpose, the corresponding daily exchange rates from Oanda (2012) were used.

Fama-French factors for US-traded stocks were downloaded from French's web page (French 2011). The Fama-French factors are the small-minus-big factor (SMB_t), the high-minus-low factor (HML_t), and the factor consisting of the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios at time

[8] This procedure ignores exchange rate risk (Fama and French 1998; Griffin 2002; Hou, Karolyi, and Kho 2011; Fama and French 2012). It implies purchasing power parity, and that the stocks considered cannot be used to hedge exchange risk (Fama and French 2012).

t (MOM_t). SMB_t is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks at time t, whereas HML_t is the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks at time t. Unfortunately, to the best of our knowledge, local analogs of the SMB_t, HML_t, and MOM_t factors for non-US-traded stocks are not available on a daily basis (Ken French personal communication).[9]

4. Methods

Based on the previous discussion, it is hypothesized that the publication of the G100 may have impacted the listed firms in two ways, namely, (a) by affecting the overall value of the firms comprised in the G100 relative to firms not included in the index, and/or (b) by inducing changes in the relative prices of the G100 firms according to their respective rankings. A third testable hypothesis is whether investors were more interested in past environmental performance or present managerial skills.

The first hypothesis is tested by analyzing the significance of the abnormal return of the equal-weight portfolio of firms in the G100 when the index was released. The second and third ones are tested by regressing the companies' abnormal returns against their respective rankings (cross-section OLS models). Both methods are explained in detail in the following subsections. Finding out that the aforementioned cross-section OLS models are statistically significant would support the idea that the market reacted to the G100 announcement. These

[9] Fama and French (2012) constructed monthly factors for 23 different countries to study their effect on international stock returns. Kubota and Takehara (1997) also constructed monthly factors for Japan. Exeter University has factors calculated with a monthly frequency for the United Kingdom (http://xfi.exeter.ac.uk/researchandpublications/portfoliosandfactors/index.php). For Canada there are daily factors, but the series has been updated only until 2009 (http://expertise.hec.ca/professorship_information_financiere_strategique/fama-french-canadian-factors/).

findings cannot explain how the market used the information released,[10] but might provide evidence regarding whether investors care more about managerial practices or past performance, and whether there is homogeneity across stocks in this regard. In contrast, the statistical insignificance of these OLS models would indicate that there was no evidence of the G100 release affecting the market during the event window.

In this paper event studies methods are applied to assess whether the release of the G100 had an impact on the values of the firms included in it.[11] Event studies rely on the estimation of each firm's abnormal returns ($AR_{i,\tau}$) at date τ, which are a measure of the unexpected change in security holders' wealth associated with the event. Abnormal returns are calculated as

$$AR_{i,\tau} = R_{i,\tau} - E\left(R_{i,\tau} | \underline{\underline{X_\tau}}\right) \tag{1}$$

where $R_{i,\tau}$ denotes company i's excess return at time τ, and $E\left(R_{i,\tau} | \underline{\underline{X_\tau}}\right)$ is company i's expected excess return at time τ conditional on the value of the vector of variables $\underline{\underline{X_\tau}}$. Here, the conditional expected return $E\left(R_{i,\tau} | \underline{\underline{X_\tau}}\right)$ is estimated by means of two alternative models, namely, the market model (2), and an extended version of the Fama-French Four Factor Model (FFFM) (3)[12]

$$R_{i,t} = \alpha_i + \underline{\beta_i}\ \underline{\underline{\text{MARKETRF}_t}} + \eta_{i,t} \tag{2}$$

[10] Our tests do not distinguish among the possible theoretical motivations (presented earlier in section 2) underlying investors' reaction to the G100. For example, investors may react because the ranking contains new information. Alternatively, they may react because the release of the ranking helps coordinate how to interpret the large amount of information condensed in the G100, even though the basic information might not be new.

[11] Event studies in financial markets examine the behavior of firms' stock prices around a specific event (see MacKinlay (1997) for a detailed explanation of event study methods).

[12] FFFM is the result of the work of Fama and French (1993) and Jegadeesh and Timman (1993). FFFM extends the traditional single factor market model to explain abnormal returns that the latter model was unable to account for.

$$R_{i,t} = \alpha_i + \underline{\beta_i}\, \underline{\underline{\mathrm{MARKETRF}_t}} + s_i\, \mathrm{USSMB}_t + h_i\, \mathrm{USHML}_t + m_i\, \mathrm{USMOM}_t + \epsilon_{i,t} \tag{3}$$

where $\underline{\underline{\mathrm{MARKETRF}_t}}$ is a vector comprising the excess rates of return on the nine market indexes; USSMB_t, USHML_t, and USMOM_t are Fama-French factors for US-traded stocks; α_i, $\underline{\beta_i}$, s_i, h_i, and m_i are regression coefficients; and $\eta_{i,t}$ and $\epsilon_{i,t}$ are regression residuals.

The nine market returns comprised in $\underline{\underline{\mathrm{MARKETRF}_t}}$ are included as explanatory variables, because the existing literature on integrated international asset pricing indicates that it is more appropriate to use factors specific to the markets where stocks are listed than global factors (Karolyi and Stulz 2003, Griffin 2002, Fama and French 2012).[13] The estimation using nine market factors improves identification. Although it would be desirable for the market returns in regressions (2) and (3) to exclude the companies in the ranking, such data were not available. The second best option is to use a portfolio for each stock market that includes the companies of interest, but whose performance is not strongly affected by such companies. This is achieved by employing market portfolios that comprise a large number of other companies, causing a dilution effect.[14]

[13] We thank an anonymous referee for this suggestion. Fama and French (2012) examined local versions of the factor models in which the returns to be explained are from the same region, and found that global models perform poorly compared to local ones. Their results are in line with Griffin (2002), who found that country-specific factors explain returns better for portfolios and individual stocks in the cases of US, United Kingdom, Canada and Japan. Hybrid models including both local and global factors have been found to add no explanatory power compared to their purely local counterparts (Griffin 2002, Fama and French 2012). Interestingly, we find that local market factors from markets other than the one where the stock is traded are sometimes significant in explaining returns (e.g., asian markets affect Asian-based companies trading in the US).

[14] The dilution effect is important in all stock markets. For example, only 71 out of 1,900 firms in the NYA are included in the G100, representing 34% of the market capitalization of the New York Stock Exchange. Stocks in other markets have even lower relative market capitalizations.

Ideally, the set of explanatory variables in regression (3) should also include local Fama-French factors for the non-US-traded stocks (Fama and French 2012). That is not possible, however, because daily SMB, HML and MOM local factors are available only for US-traded stocks. Hence, rather than omitting the US Fama-French factors, they are included because they may help explain non-US-traded stock returns. Proceeding in this manner creates no estimation problems; in fact, it greatly facilitates the estimation from a computational point of view, as for the case of the companies it reduces a 100-equation SUR to an OLS estimation problem.[15]

Based on the length of the estimation periods typically employed in the previous literature (MacKinlay 1997), regressions (2) and (3) were estimated using data for dates t = 10/5/2009 through t = 10/4/2010. This period excluded the 10 trading days before the release of the information, to avoid biases from potential information leaks close to the event (MacKinlay 1997). The selected interval resulted in 250 observations for US-traded companies and some non-US-traded firms. For other non-US-traded companies the number of observations was slightly different from 250, due to differences in holidays and other non-trading days across countries over the fixed calendar period. Given the estimates of

[15] It seems unlikely that including local SBM, HML, and MOM factors would change the general results of the present study. This is true because the cross section models for the 71 US-traded stocks yield very similar results whether the Fama-French factors are included or not (see tables 8 and A4). The effect of not including local SMB, HML and MOM factors might be negligible especially due to the size of the firms. Fama and French (2012) find that SMB, HML and MOM vary with firm size, with the exception of Japan. While they do not find size premiums in any region studied, there are value premiums in all regions and momentum premiums in all but Japan. Previous studies have also reported the lack of momentum in Japan (Assness, Moskiwitz, and Pedersen 2009; Chui, Titman, and Wei 2010; Kubota and Takehara 1997). Interestingly, both value and momentum premiums are smaller for larger firms (Fama and French 2012).

regressions (2) and (3), abnormal returns for the date of interest τ are respectively computed from equations (4) and (5), respectively:

$$AR_{i,\tau} = R_{i,\tau} - \left(\underline{\hat{\alpha}_i} + \underline{\hat{\beta}_i}\ \underline{\underline{\mathrm{MARKETRF}_\tau}} \right) = \hat{\eta}_{i,\tau} \tag{4}$$

$$AR_{i,\tau} = R_{i,\tau} - \left(\underline{\hat{\alpha}_i} + \underline{\hat{\beta}_i}\ \underline{\underline{\mathrm{MARKETRF}_\tau}} + \hat{s}_i\ \mathrm{USSMB}_\tau + \hat{h}_i\ \mathrm{USHML}_\tau + \hat{m}\ \mathrm{USMOM}_\tau \right) = \hat{\epsilon}_{i,\tau}. \tag{5}$$

Using abnormal returns $AR_{i,\tau}$ resolves the potential problem of reverse causality (i.e., the G100 may be correlated with financial performance simply because more profitable firms in the past were able to invest more in CSR). That is, here correlation can be interpreted as the G100 impacting abnormal returns, because we control for past performance when estimating expected returns.

4.1 Equal-Weight Portfolio's Abnormal Return Test Statistic

To assess whether the release of the information increased the value of the entire set of companies on the list, the following test statistic was employed

$$J_1 \equiv \frac{\overline{AR}_\tau}{\sigma_{\overline{AR}_\tau}} \sim N(0,1) \tag{6}$$

where $\overline{AR}_\tau \equiv \sum_{i=1}^{i=100} AR_{i,\tau}/100$, $\sigma_{\overline{AR}_\tau}$ is the corresponding standard deviation, $N(0,1)$ is the standard normal distribution, and τ is the day of the online release of the G100, i.e., October

18th, 2010.[16] That is, the test statistic J_1 is the equally-weighted portfolio's abnormal return normalized by its standard deviation.

4.2 Cross Sectional Models

The test statistic J_1 is not recommended to test whether the G100 release affected relative stock prices according to their ranking performance. There are at least two reasons why this is the case. First, there is a loss in estimation efficiency, because the sample must be split into company groups according to ranking positions (e.g., high-, medium-, and low-ranked firms) to assess the effect of the ranking position using J_1. Second and more importantly, finding out statistically significantly different J_1s would only allow us to sign the marginal effect of the rankings. For these reasons, we apply a cross-sectional approach to analyze whether the market reacted by changing the relative price of the stocks comprised in the G100.

The advocated procedure consists of a cross-section OLS regression of each firm's abnormal returns ($AR_{i,\tau}$) based on equations (4) or (5), against the respective firm's ranking (GREENRANKING_i):

$$AR_\tau = \alpha_{GR,\tau} + \beta_{GR,\tau}\,\text{GREENRANKING} + \varphi_{GR,\tau} \tag{7}$$

where $\varphi_{GR,\tau}$ is a regression residual, and τ is October 18th, 2010 (i.e., the day of the online release of the G100). To further investigate the firm-specific impact of the G100, cross-sectional OLS regressions (8) through (10) were fitted, as well:

[16] The independence assumption of individual firms' abnormal returns is violated in the present application, because the event time is perfectly clustered due to the fact that information was released at the same time for all companies. A solution is to estimate the abnormal returns of a portfolio of companies (MacKinlay 1997).

$$AR_\tau = \alpha_{GS,\tau} + \beta_{GS,\tau}\,\text{GREENSCORE} + \varphi_{GS,\tau} \tag{8}$$

$$AR_\tau = \alpha_{EGR,\tau} + \beta_{EGR,\tau}\,\text{EIS} + \beta_{EGR,\tau}\,\text{GPS} + \beta_{EGR,\tau}\,\text{RSS} + \varphi_{EGR,\tau} \tag{9}$$

$$AR_\tau = \alpha_{ER,\tau} + \beta_{ER,\tau}\,\text{EISRSS} + \varphi_{ER,\tau} \tag{10}$$

where GREENSCORE, EIS, GPS, and RSS are respectively the firm-specific Green Score, EIS, GPS, and RSS, and EISRSS = EIS – RSS. Robust standard errors were computed for all regressions.[17]

To investigate the robustness of the findings, cross-sectional regressions analogous to (6)-(10) were also fit using each firm's cumulative abnormal returns over the two-day event window consisting of October 18th and 19th, 2010 (i.e., the day of the G100 release plus the following day, to account for time zone differences across countries). That is, the dependent variable in such regressions consists of

$$CAR_{i,(\tau_1:\tau_2)} \equiv \sum_{\tau=\tau_1}^{\tau=\tau_2} AR_{i,\tau} \tag{11}$$

where τ_1 and τ_2 are respectively October 18th and 19th, 2010. Further, cross-sectional regressions were also estimated separately for eight different sets of companies, namely, (a) all of the companies, (b) G100 top 50 companies, (c) G100 bottom 50 companies, (d) heavy sector companies,[18] (e) non-heavy sector companies, (f) US-traded companies, (g) non-US-

[17] Regression (10) corrects EIS by RSS, to control for previously available information.
[18] Industries are classified as belonging to the heavy sector if they are potentially highly pollutant. The heavy sector includes basic materials; consumer products and cars; general industrials, industrial goods, oil and gas; transport and aerospace; and utilities. The non-heavy sector consists of banks and insurance; food and beverage; media, travel, and leisure; pharmaceuticals; retail; and technology.

traded companies, and (h) non-heavy sector US-traded companies. A total of 128 cross-sectional models were estimated, 64 with $AR_{i,\tau}$ as the explanatory variable, and the other 64 with $CAR_{i,(\tau_1:\tau_2)}$ instead.

5. Results and Discussion

The next two subsections discuss the findings regarding the impact of the G100 on both the general and the relative value of the firms included in it.

5.1 The Impact of the G100 on the General Value of the Listed Firms

Result 1. The release of the ranking did not increase the price of the equal-weight portfolio of companies in the G100.

The test statistic J_1 is statistically non-significant for the equal-weight portfolio. Thus, the release of the ranking did not affect the price of the portfolio of companies in the G100, provided that there are no other confounding effects. One may argue that there is no reason for an improvement on the value of the portfolio, because the new information allows only for a comparison among the companies on the list. A change in the value of the portfolio would have implied that a comparison with companies not included in the G100 was possible.

Event studies analyzing one firm or a small number of firms often check for confounding effects, especially when testing the significance of the test statistic J_1. It may happen that other “new information” affects the performance of the company on the day the information of interest is released, leading to incorrect conclusions. On the day the G100 was released, the major news were related to higher-than-expected earnings from Citigroup, and an improvement in the housing sector that pushed prices up (cnn.money.com a). Companies in the banking sector were among that day's top performers, with average abnormal returns of 0.0081%, or 1.23 standard deviations higher than the average of all companies in the ranking (Table 1). This may have caused the price of the portfolio to go up, creating a positive bias on the estimation of the effect of being in the G100.

In some cross-sectional models the next-day information is also used. The stock market declined the day after the release of the G100, due to reports that a group of bondholders were trying to force Bank of America to repurchase bad mortgages. There was also a surprise rate hike by the Chinese government, and mixed data on the housing market and corporate results (cnn.money.com b).[19] Not analyzing these confounding effects might bias the estimates of the marginal effect of the G100 if the "new information" is correlated with the ranking. However, it is difficult to find plausible reasons for such kind of correlation to exist.

Confounding effects can be ignored for the remainder of the study, because of the use of cross-sectional models and the methodology used to construct the G100. If on the day of the G100 release another event(s) affected returns across all firms, its impact would be controlled for by the constant in the cross-sectional models.[20] This would also be true for any event affecting a group of companies, provided the distribution of such group in the G100 is similar to the distribution of all the companies in the list. In particular, since the G100 is

[19] In particular, Bank of America reported a third-quarter net loss of $7.3 billion, Goldman Sachs disclosed a 40% plunge in profit for the third quarter, J&J stated a dip in sales, Yahoo reported less than expected sales, and Intel announced an up to $8 billion investment.

[20] For example, the news about improvement in the housing sector might have pushed prices up in general, which would affect the constant, but not the slope, of the cross sectional models.

constructed to make the ranking comparable across industries, any event affecting firms in a specific industry should only affect the constant of the estimated cross-sectional models.[21]

5.2 The Impact of the G100 Release on the Relative Prices of the Listed Firms

Key statistics for the cross-sectional models' first estimation step are presented in Table 2. Out of the 100 estimated FFFMs, the F-test indicates that 97 of them are statistically significant at the 95% confidence level, with a median explanatory power of 56%. For the 97 significant models, the market index in which the stock is traded is typically is significantly different from zero, whereas indexes for other markets are not. The coefficient corresponding to the NYA market index is significantly different from zero in 68 of the models (66 US-traded stocks and two European-traded stocks), and has a median value of 0.7975, a 95th percentile of 1.4525 and a 5th percentile of -0.1652.

Asian stock exchange indexes affected mostly Asian companies, independently of whether the stocks were traded in Asian or American markets. Some American and European stocks were also affected by Asian market indexes. The coefficients corresponding to Shanghai's SSE Composite Index and Hong Kong's Hang Seng Index are respectively significant in twelve and ten of the models.[22] Japanese and Korean stock exchange indexes affected US stocks. The coefficient corresponding to Japan's Nikkei 225 Index is significant

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[21] In the case of banks and insurance (the industry involving most of the news on the day of the G100 release), the ranking of the companies ranges from 9 to 89, covering almost all of the ranking range.

[22] The SSE Composite Index coefficient is significant for all three of the Chinese company stocks traded in Hong Kong, eight US-traded stocks, and one European stock. It has a median value of 0.0130, a 95th percentile of 0.2057, and a 5th percentile of -0.1183. The Hang Seng Index coefficient is significant for six US-traded companies, four European, and surprisingly none of the four Chinese companies traded in Hong Kong. It has a median value of -0.0117, a 95th percentile of 0.1153 and a 5th percentile of -0.1293.

in 22 of the models,[23] and the one corresponding to South Korea's Kospi Composite Index is significant at the 95% confidence level in 13 of the models, but significant only at the 10% level for the South Korean-traded stock of Samsung.[24]

European indexes are mostly significant in models of European stocks traded in the respective exchanges represented by the indexes. They are also significant, albeit at a lower level, in models of European stocks traded in other European exchanges, and US-traded stocks of European companies. The coefficient for France's CAC 40-Paris is significant in 29 of the models,[25] for Germany's DAX in 26,[26] for Switzerland's SMI in 22,[27] and for the United Kingdom's FTSE 100 Index coefficient in 17 of the models.[28]

The Fama-French factors SMB, HML and UMD are significantly different from zero in a considerable proportion of the US-traded stock models, whereas they are non-significant for most of non-US-traded stocks. SMB is significantly different from zero for 21 companies

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[23] The Nikkei 225 Index coefficient is significant for 14 US-traded stocks: eight of which are of Japanese companies (Hitachi, Honda Motor, Toyota Motor, Mitsubishi UFJ Financial Group, Sony, Toshiba, Panasonic, and Canon) and one of a Chinese company (China Mobile)–, five European, and three Hong Kong stocks of Chinese companies. It has a median value of 0.0132, a 95th percentile of 0.2831 and a 5th percentile of -0.1398.

[24] The Kospi Composite Index coefficient is significant for three stocks of Chinese companies traded in Hong Kong; seven US-traded stocks, and three European, and has a median value of 0.0221, a 95th percentile of 0.3636 and a 5th percentile of -0.1837.

[25] The CAC 40-Paris Index coefficient is significant for 14 European-traded stocks, 13 US-traded stocks –10 of European companies– and one Hong Kong stock of a Chinese company. It has a median value of 0.0433, a 95th percentile of 2.0105 and a 5th percentile of -0.3902.

[26] The DAX Index coefficient is significant for 14 European traded stocks, 10 US-traded stocks –seven of European companies– and two Hong Kong stocks of Chinese companies. It has a median value of 0.0093, a 95th percentile of 0.9366 and a 5th percentile of -0.7999.

[27] SMI Index coefficient is significant for 7 European traded stocks, and 15 US-traded stocks –eight of European companies. It has a median value of -0.0321, a 95th percentile of 0.4120, and a 5th percentile of -0.6274.

[28] The FTSE 100 Index coefficient is significant for four Europe-traded stocks, three of which correspond to companies based in the United Kingdom with stocks traded in London; 11 US-traded stocks, eight of which consist of European companies and one of a Taiwanese company; and two stocks of Chinese companies traded in Hong Kong. It has a median value of -0.0557, a 95th percentile of 0.8305, and a 5th percentile of -0.4678.

(20 US-traded, and one Europe-traded), HML is significant for 33 companies (30 US-traded, and three Europe-traded), and UMD is significant for 17 companies (13 US-traded, and four Europe-traded). The likely explanation for the lack of significance of the SMB, HML, and UMD daily factors in the models for non-US-traded stocks is that such factors are US-based. Ideally, the models should include exchange-specific SMB, HML, and UMD factors, but as explained earlier they were not available at a daily frequency for the period and stock exchanges of interest.

Given the similarity of the results obtained from the 128 cross-sectional models fitted in the second step, only the 64 models estimated using the FFFM abnormal returns are reported here. The other models are presented as Table 11 through Table **15** in the Appendix.[29] All tables in the paper have the same structure. Models numbered 1 to 4 have as independent variable the Green Score, Green ranking, green components (EIS, GPS, and RSS), and EIS minus RSS (EISRSS), respectively. Version (a) of the models denotes the case where abnormal returns are measured only on the day of the information release, whereas version (b) corresponds to the case where abnormal returns are evaluated over both the day of release and the next day.

Result 2: An eleven million dollar step: Getting one position closer to the top of Newsweek's G100 increases the value of an average firm in the list by 11.3 million dollars.[30]

[29] The table for non-heavy sector US-traded companies is not included in the appendix to save space.

[30] The average capitalization of a firm in the list was 115 billion dollars as of September 2010. As a consequence, moving up one position in the ranking, which increases the value of a stock by 0.00984%, represents 11.3 million dollars.

Ranking position and the Green Score affected stock prices on the day the information was released in the expected direction: negative for the ranking position, and positive for the Green Score (see Figure 1). Table 3 shows that at least 6.6% of the abnormal returns on the event day were explained in three different models by the Green Score (model 1-a), ranking position (model 2-a), and Green Score components (model 3-a), respectively. According to these results, moving ten positions closer to the top of the ranking increases the value of a company by 0.0984% with a 99% confidence level (model 2-a). By comparison, the absolute value of the daily return of the companies in the G100 during the estimation period (i.e., 10/5/2009 through 10/4/2010) was 0.014% on average.

Result 3: G100's top 50 performers reacted more strongly to the ranking than the bottom 50 performers.

We tested for the presence of non-linearities, and found that the top 50 performers reacted more strongly than the bottom 50 performers to the Green Score, the ranking position, and the components in both event windows.

Table 4 and Table 5 show respectively the results of the models for the top and bottom performers. There is a proportionally larger participation of heavy sector stocks in the bottom 50 performers (22 companies), which reacted more weakly to the ranking. To test for this confounding effect, we estimated regressions of the bottom 50 performers by sector. Results are omitted to save space, but they show that bottom 50 heavy sector stocks were not affected by being in the ranking (none of the models are significant). In contrast, non-heavy sector stocks in the bottom 50 did react to the EIS on the day the information was released (the coefficient estimate equals 1.731 and is significantly different from zero at the 5% level). The difference between the top and bottom companies may be explained in part by the weaker reaction of heavy sector stocks, presented later in the paper.

Result 4: Green Score components explain better the market reaction than the Green Score itself: EIS has a positive effect on stock prices, whereas RSS does not have a significant effect.

The explanatory power is higher using the components of the Green Score than employing the Green Score itself (model 3-a versus model 1-a). Out of the three components, the only one significantly different from zero is the EIS. The RSS coefficient is non-significant in either event window, which may be reasonable because it reflects the market expectations regarding the environmental performance of the firms. The non-significance may be explained by the efficient market hypothesis: the release provided information that had already been incorporated into the prices. The GPS is not significantly different from zero either, suggesting that neither the companies' reputation nor their policies were relevant new market information. Adding two non-significant components to the EIS to calculate the Green Score seems to distort the EIS signal, reducing the explanatory power of the Green Score model compared to the components' model.

Stocks in the non-heavy sector reacted fast to the G100, and took into account only the EIS (Table 6). In contrast, stocks in the heavy sector reacted in a slower and slightly, but non significantly, larger way with respect to the G100 ranking (|-1.764| > |-1.056|) and the Green Score (2.966 vs. 1.879). However, they were not significantly affected by any of the individual scores (Table 7). Ranking position and the Green Score impacted non-heavy stock prices on the day of the information release in the expected direction: negative for the ranking position and positive for the Green Score. According to the results, moving up ten positions in the ranking and improving the Green Score by ten points increased the expected value of a non-heavy sector company by 0.11% and 0.19%, respectively (Table 6, models 1-a and 2-a). Increasing the EIS by ten points raised a company's abnormal returns by 0.122%.

Result 5: Non-US traded stocks exhibit a stronger and "more prolonged" reaction compared to US-traded stocks.

The reaction to the release of G100 of non-US traded stocks in the two-day event window was significantly different from zero, and larger than the one- and two-day reactions of US-traded stocks (Table 8 and Table 9). The reaction of US-traded stocks was in most cases slightly smaller than, but not significantly different from, the reaction of non-US stocks for the one-day event window. According to these results, moving ten positions closer to the top of the ranking increases the expected value of a US traded company by 0.1007% with a 99% confidence level (model 2-a Table 8), for the one event window. For non-US traded companies, the corresponding expected increase is 0.33% (model 2-b Table 9, 90% confidence level), for the two-day event window. The apparently slower and more prolonged reaction for non-US traded stocks may be explained by differences in time zones, as 8am US Eastern Time Zone corresponds to 2pm in Europe and afterhours trading in Asian exchanges. In particular, US-traded stocks of non-heavy sector companies were the ones that reacted the most to the G100 (Table 10); moving ten positions closer to the top of the ranking increased the value of a US-traded company in the non-heavy sector by 0.133%.

One possible explanation for the different behavior of US- vs. non-US traded companies is the well-documented home bias puzzle.[31] European and Asian investors trade more non-US stocks due to the equity home bias (Sercu and Vanpee 2007). Also, European (French and German) consumers are more willing to support CSR than Americans (Maignan 2001). Another possible explanation for the higher reaction of non-US traded stocks is that more of the released information was relevant for the market, which is plausible because some of the US-traded companies had been assessed the previous year in the "US 500 List" (Table 9).

The Green Score components explain 25% and 41% of the non-US traded stocks abnormal returns in the one- and two-day event window models, respectively (models 3-a and 3-b in Table 8). Results are robust regarding the sign of the significant coefficients in both models. Interestingly, the RSS coefficient is negative, a sign of investors' adjusting for existing information.[32] Significant cross-sectional models using FFFM abnormal returns had lower explanatory power than the ones excluding the US Fama-French factors, e.g., 7.7% vs. 9.3% in model 1-a, and 6.6% vs. 8.4% in model 2-a in Table 3 and Table 11, respectively. The sign and magnitude of the coefficients of cross-sectional models based on the market factor model abnormal returns are consistent with the significant cross-sectional models

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[31] The equity home bias is the difference between the relative weight of domestic equity in the portfolio of country *j* and the relative weight of country *j* in the total world market. The equity home bias of the market portfolio in 2004 was 0.81 for the US, 0.77 for EMU members, and 0.79 non-EMU EU members (Schoenmaker and Bosch 2008); and in 2005 was 0.78 for Hong Kong, 0.79 for Japan, and 0.96 for Korea (Sercu and Vanpee 2007). An extended literature review of home bias puzzle is available in Karolyi and Stulz (2003), and a list of home bias by country is available in table 1 of Sercu and Vanpee (2007).

[32] The reaction of non-US traded stocks in the two-day window EISRSS model (model 4-b in Table 9) is also significant and positive as expected. For each ten point difference in EISRSS, the expected abnormal returns of a foreign traded company in the two-day event window increases by 0.2634%.

based on the FFFM abnormal returns. In this sense, the results presented here are the most conservative ones.

Why did the estimated market factor model abnormal returns outperform the FFFM ones in the cross-sectional models? We expected the opposite because the FFFMs have higher explanatory power, as they include the US Fama-French factors in addition to the market returns. However, in most instances the additional factors in the FFFM were non-significant (Table 2), and including them added noise to our estimation of expected returns. Therefore, the FFFM model is likely to incorporate unwarranted noise. This may end up being reflected in the predicted abnormal returns for the day of the event, thereby making the FFFM-based cross-sectional models lose explanatory power and even turn non-significant, especially in the two-day event window case.

Previous results support the idea that a new “green” process which affects a company's relative G100 performance will impact the firm's stock price. Consequently, the G100 becomes a tournament that (provided its information is correct) enhances the efficiency of investments in environmental performance by creating an extra incentive to improve environmental performance.[33] This occurs because firms that are able to improve their position in the G100 ranking at the lowest cost are the ones most likely to end up doing so. This result is independent of which mechanism is behind the investors’ reaction.

6. Conclusions

The present study adds a world market dimension to environmental rankings and the response of investors, quantifies the marginal effects of the G100 on stock prices, and

[33] It must be noted that the methodology framework applied in this paper cannot account for the dynamic dimension of green investments.

investigates the impact of rankings on returns by industry sectors. Further, to the best of our knowledge it is the first study providing evidence of the existence of heterogeneity among investors regarding their interest in past performance and managerial quality as predictors of future environmental performance, which has implications for the construction of optimal environmental indexes (Chatterji, Levine, and Toffel 2009).

Our results indicate that the market reacted to the G100 by changing the relative prices of the stocks included in it, but not the value of the equal-weight portfolio of such stocks. The magnitude of the effect was sizeable: moving one position closer to the top of Newsweek's G100 raised the value of an average firm in the list by 11.3 million dollars. This represents an increase in the stock price of 0.0984%, or seven times the average of the absolute daily rate of return of the companies in the G100 during the estimation period (i.e., 10/5/2009 through 10/4/2010). There is also evidence of a stronger reaction to the ranking position for top 50 companies in the G100 compared to bottom 50, for non-US-traded stocks compared to US-traded stocks, and of a more robust reaction for stocks in the non-heavy sector compared to the ones in the heavy sector.

The finding that the equal-weight portfolio return was not affected by the G100 release was expected, because the presence of the companies on the G100 list was only defined by their size. The use of a two-step procedure allowed us to identify a market effect that the standard event study method using only statistics of cumulative abnormal returns for the entire set might have ignored. The new information for the market was the performance of each company relative to the other ones in the set, and that is why the cross section in the second step was able to identify that effect in the firms' stock prices. The cross section also allowed us to estimate marginal effects.

The G100's top 50 performers reacted more strongly to the ranking release than the bottom 50 ones. The existence of this nonlinearity may be explained in part by a larger presence of heavy sector companies (which reacted less to the ranking) in the bottom 50.

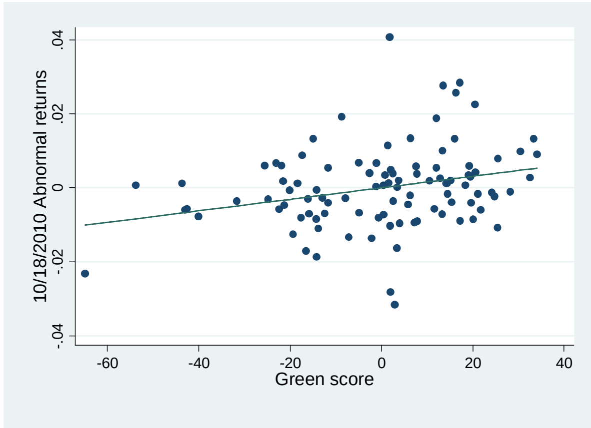
Stocks of companies in the non-heavy sector had a faster and more robust reaction to the G100 release than their heavy sector counterparts. Unlike heavy sector stocks, non-heavy sector stocks reacted significantly across all model specifications. One possible reason for this finding is that firms in the non-heavy sector might be closer to final consumers, and consequently pay more attention to consumers' reactions to environmental performance. Another plausible explanation is that heavy sector firms have an input matrix of raw materials and energy that has low elasticity of substitution, whereas companies in the non-heavy sector might have better more opportunities to improve their environmental performance at lower cost. For example, it might be easier to reduce energy consumption per unit of sales for a retail company (by replacing electric appliances with efficient ones, buying more locally, etc.) than for an iron company that basically consumes energy.

Across all model specifications, US-traded stocks had a stronger reaction for a one-day event window than non-US-traded stocks. However, in the case of a two-day event window, US-traded stocks had no significant reaction, whereas non-US-traded stocks exhibited a stronger reaction than with a one-day window. There are at least three possible explanations for this result. One explanation is that US-traded companies reacted as expected according to the efficient market hypothesis, and extending the event window only dilutes the effect making it non-significant. A second possible reason is that non-US-traded companies were included in a public environmental ranking for the first time, whereas some US-traded companies had already been in the "US 500 List" published in 2009. A third explanation is that most of the non-US-traded companies are European, for which GPS and RSS might provide better predictions about future performance. Given the different regulatory history and environment in Europe, expectations about future regulation might motivate investors' hedging behavior.

The use of stocks traded in international markets allowed us to find evidence of heterogeneity among investors with regard to their interest in past performance and managerial quality as predictors of future environmental performance. In particular, US-traded stock returns were affected only by past performance (EIS), contrasting with non-US-traded stock returns which responded only to managerial quality (GPS and RSS). These results have implications for the construction of optimal environmental rankings (Chatterji, Levine, and Toffel 2009), suggesting that the weight on past performance and managerial quality used to construct indexes environmental performance should differ across stock markets.

Provided the measurement errors in the G100 are relatively small, the robustness of the findings not only implies that the G100 had relevant information for the market, but also supports the idea that companies should account for the effect on stock prices when making decisions about environmental policies that might their position in the G100. Whether the reason for such reaction is branding (to build a positive reputation and brand image), stakeholding (to satisfy different stakeholders), sustainability (to contribute to long-term sustainable development), or ethics/morals (to do the ‘right thing’), among other possible theoretical explanations, is an issue to be addressed in future research.

Figures



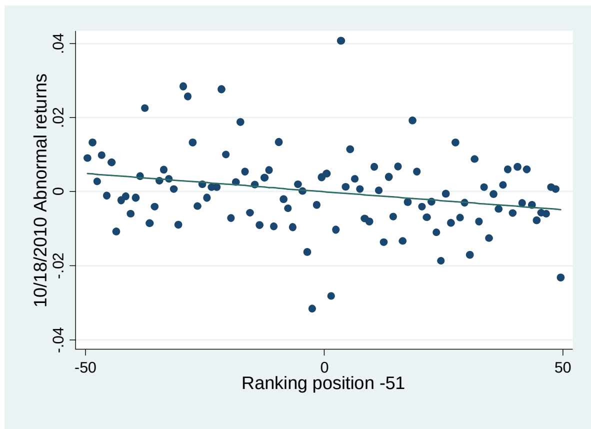


Figure 1. One-day window regressions for the 100 companies.

(Left: equation (8), Right equation (7)).

Tables

Table 1. Event day abnormal returns statistics for different company groups

	average	median	max	min	Std. dev.
All	-0.0056	-0.0002	0.0443	-0.0298	0.0111
US	0.0007	0.0006	0.0295	-0.0298	0.0095
Non-US	0.0047	0.0026	0.0426	-0.0213	0.0138
Heavy	-0.0013	0.0003	0.0117	-0.0298	0.0088
Non-Heavy	-0.0034	0.0025	0.0426	-0.0264	0.0117

Table 2. Summary statistics of the hundred estimated FFFMs by regression (3).

	R^2	NYA	000001_ss	His	n225	ks11	fchi	gdaxi	Ssmi	ftse	SMB	HML	UMD	constant
95 percentile	0.8012	1.4525	0.2057	0.1153	0.2831	0.3636	2.0105	0.9366	0.4120	0.8305	0.0036	0.0088	0.0051	0.0011
75 percentile	0.7012	1.0399	0.0568	0.0518	0.1092	0.1063	0.3813	0.2083	0.1004	0.1713	0.0005	0.0015	0.0014	0.0004
median	0.5656	0.7975	0.0130	-0.0117	0.0132	0.0221	0.0433	0.0093	-0.0321	-0.0557	-0.0006	-0.0011	-0.0003	-0.0001
mean	0.5479	0.6715	0.0150	-0.0160	0.0312	0.0622	0.2532	0.0468	-0.0708	0.0257	-0.0007	-0.0005	0.0000	0.0001
25 percentile	0.4578	0.1205	-0.0377	-0.0501	-0.0525	-0.0648	-0.1316	-0.1812	-0.2963	-0.1788	-0.0020	-0.0034	-0.0020	-0.0004
5 percentile	0.2189	-0.1652	-0.1183	-0.1293	-0.1398	-0.1837	-0.3902	-0.7999	-0.6274	-0.4678	-0.0046	-0.0066	-0.0059	-0.0011
Percentage of models 95% significant	97	68	12	10	22	13	29	26	22	17	21	33	17	2

Table 3. Robust OLS regressions using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.557	7.275						
	(0.442)***	(4.362)**						
Ranking			-0.984	-5.223				
			(0.309)***	(3.53)				
Environmental impact score					0.959	-2.48		
					(0.375)**	(4.523)		
Green policies and performance score					0.689	11.07		
					(0.586)	(9.796)		
Reputation survey score					-0.137	-1		
					(0.581)	(1.443)		
Env. Impact – Rep Survey							0.692	-1.373
							(0.311)**	(3.075)
Intercept	-84.386	-536.185	67.999	207.228	-62.971	-527.838	22.757	-65.422
	(29.469)***	(362.396)	(19.934)***	(106.374)**	(29.142)**	(409.286)	(11.43)**	(97.889)
R2	0.0769	0.0338	0.066	0.0374	0.0966	0.0609	0.047	0.0037
Significance (Prob >F)	0.0007***	0.0986**	0.0019***	0.1421	0.0062***	0.0417**	0.0286**	0.6562
AIC	-621.031	-225.8551	-619.8557	-226.2301	-619.1871	-224.7086	-617.8489	-222.7955
Observations	100	100	100	100	100	100	100	100

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000. 25 of the bottom 50 companies are in the heavy sector.

Table 4. Robust OLS regressions for top 50 performers in the G100 using estimated abnormal returns from FFFM for top 50 performers in the G100

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	3.409	1.895						
	(1.571)**	(2.313)						
Ranking			-1.91	-0.907				
			(0.998)**	(1.383)				
Environmental impact score					1.567	2.17		
					(0.763)**	(0.898)**		
Green policies and performance score					2.04	1.302		
					(1.026)**	(1.603)		
Reputation survey score					-0.339	-1.741		
					(0.973)	(1.531)		
Env. Impact – Rep Survey							1.072	1.979
							(0.553)**	(0.775)**
Intercept	-238.883	-93.967	87.072	83.257	-194.404	-68.538	35.684	55.167
	(132.379)**	(187.965)	(27.143)***	(42.635)**	(122.771)	(170.954)	(14.966)**	(19.441)***
R2	0.0698	0.0116	0.0638	0.0077	0.1501	0.1634	0.0822	0.1509
Significance	0.035**	0.4167	0.0617**	0.515	0.0972**	0.07**	0.0586**	0.0139**
(Prob >F)								
AIC	-309.4838	-275.5085	-309.1616	-275.3135	-309.9966	-279.8427	-310.157	-283.1033
Observations	50	50	50	50	50	50	50	50

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000. 25 of the bottom 50 companies are in the heavy sector.

Table 5. Robust OLS regressions for bottom 50 in the G100 using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.504	8.324						
	(1.107)	(4.826)**						
Ranking			-1.146	-12.878				
			(1.311)	(10.048)				
Environmental impact score					0.812	-6.681		
					(0.535)	(8.917)		
Green policies and performance score					-0.158	19.898		
					(1.273)	(18.757)		
Reputation survey score					0.455	-4.595		
					(0.788)	(5.531)		
Env. Impact – Rep Survey							0.28	-5.083
							(0.394)	(6.135)
Intercept	-77.771	-593.861	84.71	799.081	-44.822	-607.645	2.532	-251.668
	(51.127)	(387.772)	(107.698)	(611.053)	(38.814)	(487.355)	(17.572)	(245.682)
R2	0.0443	0.0137	0.0232	0.0296	0.035	0.0786	0.0093	0.0309
Significance	0.1806	0.091**	0.3865	0.2061	0.3651	0.6899	0.4798	0.4114
(Prob >F)								
AIC	-308.7799	-77.31148	-307.6929	-78.12518	-304.2997	-76.71407	-306.9846	-78.19054
Observations	50	50	50	50	50	50	50	50

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 6. Robust OLS regressions for non-heavy sector using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.879	14.933						
	(0.701)***	(12.774)						
Ranking			-1.056	-8.745				
			(0.461)**	(7.51)				
Environmental impact score					1.22	-2.015		
					(0.441)***	(3.972)		
Green policies and performance score					0.833	19.183		
					(0.773)	(17.383)		
Reputation survey score					0.0302	-1.318		
					(0.739)	(2.553)		
Env. Impact – Rep Survey							0.755	-1.956
							(0.352)**	(3.688)
Intercept	-99.462	-1127.892	80.337	316.589	-94.343	-1085.326	32.747	-60.068
	(51.332)**	(1021.203)	(24.744)***	(218.415)	(61.939)	(983.658)	(14.147)**	(111.324)
R2	0.0619	0.0593	0.0553	0.0575	0.105	0.1025	0.0515	0.0052
Significance (Prob >F)	0.0094***	0.2467	0.0252**	0.2486	0.0316**	0.1966	0.0357**	0.5976
AIC	-399.5811	-122.9094	-399.117	-122.7802	-398.6834	-122.0101	-398.852	-119.2195
Observations	66	66	66	66	66	66	66	66

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 7. Robust OLS regressions for heavy sector using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	0.8	2.966						
	(0.705)	(1.236)**						
Ranking			-0.44	-1.764				
			(0.466)	(0.922)**				
Environmental impact score					-0.366	1.365		
					(0.962)	(1.426)		
Green policies and performance score					0.597	1.269		
					(0.885)	(1.499)		
Reputation survey score					0.00273	0.0477		
					(0.963)	(1.865)		
Env. Impact – Rep Survey							-0.236	0.353
							(0.741)	(1.472)
Intercept	-57.388	-206.757	15.269	71.227	-31.691	-149.761	-18.325	-33.527
	(41.76)	(75.856)**	(34.407)	(59.673)	(30.919)	(59.88)**	(18.613)	(36.633)
R2	0.0422	0.1974	0.0211	0.1157	0.0184	0.0986	0.005	0.0038
Significance (Prob >F)	0.2649	0.0224**	0.3518	0.0648**	0.8672	0.2236	0.7526	0.8121
AIC	-222.7725	-192.1439	-222.0343	-188.8477	-217.9388	-184.1958	-221.4791	-184.7981
Observations	34	34	34	34	34	34	34	34

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 8. Robust OLS regressions for US traded stocks using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.532	10.342						
	(0.424)***	(7.787)						
Ranking			-1.007	-7.086				
			(0.278)***	(5.389)				
Environmental impact score					1.013	-6.742		
					(0.455)**	(7.707)		
Green policies and performance score					0.2	15.552		
					(0.639)	(13.751)		
Reputation survey score					0.446	0.357		
					(0.588)	(1.988)		
Env. Impact – Rep Survey							0.506	-4.562
							(0.338)	(5.36)
Intercept	-98.681	-820.029	53.484	220.386	-81.073	-751.101	10.523	-144.462
	(29.152)***	(640.143)	(18.261)***	(148.521)	(26.189)***	(576.917)	(12.044)	(148.853)
R2	0.0888	0.0439	0.094	0.0505	0.1242	0.1067	0.0276	0.0244
Significance (Prob >F)	0.0006***	0.1885	0.0006***	0.1929	0.0071***	0.4837	0.1388	0.3977
AIC	-462.4159	-137.8231	-462.8158	-138.3101	-461.2295	-138.6489	-457.7982	-136.3876
Observations	71	71	71	71	71	71	71	71

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 9. Robust OLS regressions for non-US traded stocks using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.47	5.355						
	(1.108)**	(1.723)***						
Ranking			-1.669	-3.3				
			(0.995)	(1.537)**				
Environmental impact score					-0.505	1.276		
					(0.817)	(1.137)		
Green policies and performance score					4.891	5.61		
					(1.873)**	(2.584)**		
Reputation survey score					-3.985	-5.645		
					(1.515)**	(2.261)**		
Env. Impact – Rep Survey							0.879	2.634
							(0.602)	(0.915)***
Intercept	-99.126	-243.903	147.404	271.336	38.482	25.033	49.838	81.475
	(62.112)	(100.853)**	(70.219)**	(99.933)**	(110.899)	(136.904)	(25.91)**	(32.275)**
R2	0.1404	0.3107	0.1021	0.188	0.253	0.4135	0.0714	0.3018
Significance (Prob >F)	0.0343**	0.0044***	0.1051	0.0409**	0.0237**	0.0128**	0.1557	0.0077***
AIC	-166.5924	-151.1669	-165.3288	-146.4154	-166.6638	-151.8474	-164.353	-150.7929
Observations	29	29	29	29	29	29	29	29

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 10. Robust OLS regressions for US traded stocks in non-Heady sectors using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.421	27.427						
	(0.743)***	(22.799)						
Ranking			-1.333	-15.226				
			(0.456)***	(12.669)				
Environmental impact score					1.595	-6.648		
					(0.442)***	(7.532)		
Green policies and performance score					0.289	34.735		
					(0.784)	(27.622)		
Reputation survey score					0.694	0.73		
					(0.777)	(4.467)		
Env. Impact – Rep Survey							0.849	-5.306
							(0.382)**	(6.677)
Intercept	-160.801	-2194.733	70.222	427.6	-137.916	-2133.17	19.006	-157.523
	(56.67)***	(1851.957)	(23.114)***	(330.821)	(52.73)**	(1647.713)	(14.711)	(175.49)
R2	0.1263	0.1208	0.1159	0.1127	0.2122	0.2259	0.0785	0.0228
Significance (Prob >F)	0.0022***	0.2357	0.0056***	0.2362	0.0027***	0.5766	0.0316**	0.4313
AIC	-282.9292	-67.07242	-282.4062	-66.6691	-283.4821	-68.67437	-280.5866	-62.42387
Observations	44	44	44	44	44	44	44	44

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

7. Appendix

Table 11. Robust OLS regressions using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.848	7.263						
	(0.528)***	(4.473)						
Ranking			-1.195	-5.329				
			(0.369)***	(3.61)				
Environmental impact score					1.149	-1.785		
					(0.441)**	(4.637)		
Green policies and performance score					0.952	10.94		
					(0.628)	(10.034)		
Reputation survey score					-0.558	-1.936		
					(0.55)	(1.459)		
Env. Impact – Rep Survey							0.955	-0.599
							(0.361)***	(3.134)
Intercept	-107.248	-540.395	74.968	207.596	-67.778	-506.906	20.774	-65.399
	(-33.243)***	(-370.213)	(24.782)***	(111.103)**	(30.024)**	(419.635)	(12.598)	(100.179)
R2	0.0929	0.0322	0.0835	0.0373	0.1246	0.0531	0.077	0.0007
Significance (Prob >F)	0.0007	0.1076	0.0017***	0.1431	0.0108**	0.0148**	0.0095***	0.8488
AIC		-221.4357	-606.4744	-221.9573	-607.0615	-219.6173	-605.7722	-218.2269
Observations	100	100	100	100	100	100	100	100

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 12. Robust OLS regressions for non-heavy sectors using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.581	15.981						
	(0.771)***	(12.974)						
Ranking			-1.511	-9.413				
			(0.504)***	(7.624)				
Environmental impact score					1.723	-0.667		
					(0.528)***	(4.065)		
Green policies and performance score					1.185	19.4		
					(0.815)	(17.765)		
Reputation survey score					-0.0476	-1.841		
					(0.703)	(2.647)		
Env. Impact – Rep Survey							1.096	-0.897
							(0.4)***	(3.757)
Intercept	-159.08	-1216.445	90.559	331.807	-152.251	-1164.054	22.431	-76.185
	(51.363)***	(1035.692)	(30.995)***	(224.222)	(59.241)**	(1004.636)	(15.251)	(114.002)
R2	0.0939	0.0651	0.091	0.0638	0.1685	0.0995	0.0872	0.0011
Significance (Prob >F)	0.0014***	0.2225	0.0039***	0.2215	0.0071***	0.0313**	0.008***	0.8121
AIC	-387.4357	-120.4593	-387.2226	-120.3683	-389.1057	-118.9383	-386.9454	-116.0877
Observations	66	66	66	66	66	66	66	66

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 13. Robust OLS regressions for heavy sectors using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.153	2.503						
	(0.84)	(1.408)**						
Ranking			-0.614	-1.44				
			(0.572)	(1.048)				
Environmental impact score					0.0464	1.798		
					(0.876)	(1.24)		
Green policies and performance score					1.061	1.327		
					(0.931)	(1.525)		
Reputation survey score					-0.786	-1.145		
					(0.992)	(1.656)		
Env. Impact – Rep Survey							0.334	1.226
							(0.782)	(1.314)
Intercept	-69.266	-168.667	34.192	62.782	-17.344	-89.502	2.614	-1.054
	(49.593)	(84.578)**	(40.35)	(69.233)	(32.15)	(64.335)	(18.602)	(34.536)
R2	0.0846	0.1495	0.0397	0.082	0.0497	0.111	0.0097	0.0492
Significance (Prob >F)	0.1794	0.0849**	0.2912	0.179	0.7218	0.3947	0.6722	0.3581
AIC	-223.108	-192.2746	-221.4825	-189.679	-217.8389	-186.7695	-220.4362	-188.4837
Observations	34	34	34	34	34	34	34	34

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 14. Robust OLS regressions for US-traded stocks using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.625	10.134						
	(0.523)***	(7.982)						
Ranking			-1.105	-7.081				
			(0.348)***	(5.508)				
Environmental impact score					1.188	-5.775		
					(0.599)**	(7.932)		
Green policies and performance score					0.513	15.455		
					(0.682)	(14.136)		
Reputation survey score					-0.177	-1.101		
					(0.558)	(2.071)		
Env. Impact – Rep Survey							0.836	-3.424
							(0.455)**	(5.489)
Intercept	-103.501	-809.33	59.578	216.549	-71.758	-713.26	14.627	-139.261
	(33.958)***	(654.78)	(23.897)**	(154.02)	(29.85)**	(592.969)	(15.312)	(152.866)
R2	0.0706	0.0404	0.0798	0.0483	0.1083	0.0893	0.0533	0.0132
Significance (Prob >F)	0.0028***	0.2085	0.0022***	0.2029	0.0446**	0.3592	0.0704**	0.5348
AIC	-436.3171	-134.5703	-437.0272	-135.1545	-435.2558	-134.2833	-435.006	-132.5817
Observations	71	71	71	71	71	71	71	71

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 15. Robust OLS regressions for non-US traded stocks using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.9	5.641						
	(1.225)**	(1.805)***						
Ranking			-2.001	-3.686				
			(1.143)**	(1.692)**				
Environmental impact score					0.233	2.173		
					(0.73)	(1.174)**		
Green policies and performance score					4.059	4.636		
					(1.904)**	(2.897)		
Reputation survey score					-2.955	-4.533		
					(1.306)**	(2.184)**		
Env. Impact – Rep Survey							1.087	2.927
							(0.619)**	(0.889)***
Intercept	-141.069	-269.202	150.855	286.174	-31.251	-42.074	34.01	74.064
	(66.938)**	(100.767)**	(80.015)**	(114.568)**	(107.469)	(147.389)	(24.332)	(33.967)**
R2	0.209	0.3069	0.1585	0.2088	0.2549	0.4066	0.1178	0.3318
Significance (Prob >F)	0.0253**	0.0042***	0.0915**	0.0383**	0.0629**	0.0117**	0.0906**	0.0028***
AIC	-171.2456	-147.6287	-169.4491	-143.7891	-168.977	-148.1316	-168.0797	-148.6895
Observations	29	29	29	29	29	29	29	29

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively. ** and *** represent 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

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CHAPTER 3. COMPETITIVE INTERACTIONS BETWEEN GRAIN RAILROAD RATES AND BARGE RATES IN THE MISSISSIPPI WATERWAY SYSTEM

Juan M. Murguia

Abstract

US grain is produced mostly in the Midwest and exported via the Pacific Northwest and the Gulf of Mexico. Barges on the Mississippi River and railroads play fundamental roles in export competitiveness. Railroads historically have caused concern about market power while barges have always been perceived as a competitive market because new transportation companies can share the river. Despite research on grain rail rates, little is known about the impact of barges on their market power. Using data from the Grain Transportation Report, this paper estimates simultaneous equation models of barge and railroad rates for specific origin-destinations and grains (corn, wheat, and soybeans). This study benefits from instrumental variables such as river levels and railroad cost indexes. Evidence of specific route competitiveness of various grains was found. Interestingly, it was possible to identify a railroad route with prices as complementary of barge rates, which may increase railroad market power. River levels affect barge rates, but there are differences for corn and wheat, possibly due to production locations in the Mississippi basin. Ocean vessel rates affect barge rates directly and railroad rates indirectly. Real exchange rates affect barge rates more than railroad rates. Evidence suggests that distance between railroad origin and barge origin affects the impact of the later on the first one. This study expands the

literature on the effect of barge rates on railroad rates by analyzing the effect of distance between origins and adding evidence of possible complementarities.

Keywords: transportation, barge rates, rail rates

JEL Codes: L9, L92, Q10, Q13, Q19, R41, L11, D22.

1. Introduction

Most of the US grain production is located in the Midwest. The states of Iowa, Illinois, Nebraska, Minnesota, and Indiana harvested 60% of the US corn and soybeans in 2007 (USDA NASS). Wheat production is also concentrated in the Midwest and some Western states[34]. Demand, however, is dispersed across the US and abroad creating areas with large surpluses and deficits of grains (Figure 2, Figure 3 and Figure 4), and requiring the transportation of more than 400 million tons of corn, soybean, and wheat each year (Marathon and Denicoff, 2011). As a consequence, an efficient intermodal transportation system of trucks, railroads (maps for BNSF and UP are presented in Figure 6 and Figure 7 respectively), barges and vessels is fundamental in determining better prices for farmers, lower food and biofuel costs for consumers and more competitive export prices. While domestic transportation is covered mostly by truck[35], railroads and barges are the most important modal transportations for exports. Rail and barge transportation represented

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[34] The top 10 state producers of wheat in 2007 accumulated 83 percent of the grain. All are in the western part of the Midwest: North Dakota, Kansas, Montana, South Dakota, Texas, Washington, Oklahoma, Colorado, Nebraska, and Idaho. (USDA NASS)

[35] In the period 2003-2007, of the total volume of corn, soybeans and wheat transported for the domestic market, 69% was by truck, 29% by rail, and only 2% by barge (Marathon and Denicoff 2011) (Table 1).

respectively 48 and 45% of the total volume of corn, soybeans and wheat exported in the period 2003-2007 (Marathon and Denicoff, 2011). Because grains are often transported in more than one mode, competition and complementarity exist among these modes. This paper analyzes the competitive interactions between grain railroad rates and barge rates in the Mississippi waterway system.

The total amount of grain transported almost doubled in the period 1978-2008 mostly due to an increase on corn production. Most of the increase in corn production was destined for the domestic market, causing exports rates to decrease over time. While in the early 80s almost 50% of US grains were exported, by 2007 exports were only 30%. Despite this, in absolute terms the exported volume has remained stable at between 50 and 60 million tons of corn, and 25 and 35 million tons of soybeans and wheat. The industrial use of corn, mostly by ethanol plants, explains this behavior[36]. Industrial use increased from 18% in 1990 to 34% in 2007. Given that most of the ethanol plants are located in the Midwest, truck transportation of corn increased its participation from 45 to 59% in the period 1995-2007 (Marathon and Denicoff, 2011).

US grain exports require large distance transportation from the Midwest to the ports in the Gulf and Pacific Northwest (PNW). For this reason, barge and rail transportation are preferred to trucks. Barges are able to carry one ton of cargo 576 miles per gallon of fuel compared to 413 miles by rail and only 155 miles for a truck (Maritime Administration. 2010). Also, the capacity of a barge, 1,500 tons, is 15 times that of a rail car and 60 times that

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[36] More than 90 percent of ethanol production capacity is located within a 50-mile radius of the corn producing areas (Marathon and Denicoff, 2011). Nevertheless, larger biofuel plans are capable of investing in railroad infrastructure and as a consequence the use of truck transportation may decline over time.

of a truck. Barge and rail transportation are also preferred from an environmental point of view. Trade transportation by barge releases 33 percent less pollutants than diesel trains and 373 percent less than diesel trucks (Maritime Administration. 2010). These advantages are, of course, limited because barges are available only in the Mississippi River system (figure 4) and the Columbia River. As a consequence, it is possible to send grains from the Midwest by barge or rail to the Gulf but only rail is available to the PNW.

Corn, soybeans, and wheat are produced in different areas with respect to the Mississippi waterway system. While corn (Figure 2) and soybeans (Figure 3) are produced close to the Mississippi waterway system (Figure 5) in the corn belt (north of Missouri and Ohio rivers), wheat production (Figure 4) is way west in the upper and lower plains. This situation affects the selected modal transportation of these grains for export. In the case of corn, the main mode of transportation for export is barge (55 to 58% in the period 1995-2007), followed by rail (33 to 35% in the same period). As a consequence of the high barge rate transportation, 63% of corn exports were through the Mississippi Gulf, 4% through Texas Gulf, and only 17% though the PNW in 2007 (Figure 2). Soybeans share a similar pattern with corn. Barge is the main mode of transportation for exports (46 to 69% in the period 1995-1997), followed by rail (23 to 46%). The Mississippi Gulf received 52% of the soybeans for export, while PNW received only 27%. Almost 45% of wheat is exported; however, since the main production areas are far away from the Mississippi river system, rail is the dominant mode of transportation (56 to 71% in the period 1995-2007). Barge transportation represents only 26 to 38% for the same period. Therefore the PNW is the main export port destination (37%), followed by Texas Gulf (27%) and Mississippi Gulf (19%) (Figure 4).

In recent years PNW has increased market participation as a grain export port. Until 2002 the Mississippi Gulf (composed of four major deep-draft ports: South Louisiana, New Orleans, Baton Rouge, and Plaquemines) was the leading port for grain exports, reaching more than 50% market share in the period 1995-2002. Starting in 2002, the PNW has gained market share (from an average of 20% in the 1990s to 25% in the period 2005-2009) at the expense of the Mississippi Gulf. Due to the complementarity of barges with Mississippi Gulf (while rail complements both export port regions), when the Mississippi Gulf share declines so does the barge share; and when the PNW or Texas Gulf share increases so does the rail share. Among the reasons for the recent PNW share increase are higher demand from Asia, lower ocean rates in PNW than in the Gulf, and lower rail rates compared to barges[37] due to the introduction of shuttle services at lower prices by the railroad companies and the reduction of the barge fleet since 2004. In this scenario, barge competition is relevant for the reduction of rail market power.

Improving understanding of various modal grain transportation rates is relevant for the determination of grain prices. Yu, Bessler and Fuller (2007) studied the spatial price linkages in US grain and transportation markets, and found that transportation rates (barge, rail, and ocean) explain a considerable proportion of the variation in corn prices in the long run (42–64%). Despite the extensive body of research analyzing grain rates in the railroad and barge sector, little is known about the extent to which they are complementary or

[37] While in the 1990's there was an ample supply of barges, starting in fall 2004, a decrease in the barge fleet size and an increase in the demand to transport non-grain commodities on the waterways occurred, created the beginning of the upward swing in barge rates. Since New Orleans receives about 90 percent of corn and soybeans by barge and, with the remaining 10 percent arriving by rail and truck, the increase in barge rate prices made the port less competitive compared to PNW (AMS-USDA Study of Rural Transportation Issues).

substitutive means of transportation. The aim of this paper is to determine the relationship between rail and barge transportation grain rates in the United States

Much effort has been made on the study of grain railroad prices and railroad market power. The Staggers Rail Act of 1980, which granted railroads greater freedom in setting shipping rates, caused a decrease in the rates (MacDonald 1987, Wilson, Wilson and Koo. 1988; Wilson and Wilson, 2001). Some evidence shows an increase in grain railroad rates after 2004, with increments even beyond cost inflation creating new concerns about railroad market power (Sparger and Pratter, 2012). Other studies have analyzed Ocean Freight Rates for Grain Shipments and found price changes by season and commodity (Park and Koo, 2004).

A few studies have jointly addressed the barge and railroad grain rates (Sorenson, 1973; Fuller and Shanmugbam, 1981; MacDonald, 1986; Hauser and Grove, 1986; Yu, Zhang, and Fuller, 2006; Yu, Bessler and Fuller, 2007). MacDonald (1986) found that barge competition measured as the mileage from the origin point to the nearest location of water transport, positively affecting railroad rates. More recently, Vachal et al. (2006) found price elasticity between barge and railroad of 0.0212 for the year 1981, which decreased during the period 1981 to 2000. Yu, Zhang, and Fuller (2006) estimated that short- and long-run grain barge transport demands were price inelastic in the upper Mississippi and Illinois Rivers for the period 1992 to 2001. Miljkovic et al. (2000) regressed a 3SLS railroad and barge supply and demand system for transportation of grain from Illinois to the Gulf for the period 1981-1995. They found that the barge rates responded positively to rail rates more than rail rates to barge rate, with the elasticity of 1.3544 and 0.114, respectively.

This paper estimates, within the period 2002-2012, simultaneous equations models of the barge rate and railroad rates for the three major grain crops: corn, soybeans, and wheat. Results differ by railroad lines. Some show complementarity behavior with barges while others show competitive behavior. Price-Price elasticities were estimated and various model specifications were regressed for robustness. The paper continues with some background on rail and barge markets, followed by the data and methodology section, and it ends with the results and conclusions section.

2. Background

The railroad industry has evolved since the Staggers Rail Act of 1980. Previously cars were priced individually and a complete train was assembled with cars form other origins (Sparger and Pratter, 2012). Unit trains (25 to 52 cars) were introduced at lower per-car rates (Sarmiento and Wilson, 2005), and later shuttle trains (75 to 120 cars) were able to order an entire train for one shipper (Sparger and Pratter, 2012). Shuttle trains, introduced in the market in the early 1990s, use the same engines and crew from source to origin; the train service is contracted over a long period of time (six to nine moths) with a specific origin-destination, and has time incentives to load and unload the cargo (Sarmiento and Wilson, 2005). To be able to use shuttle rates, elevators must make important investments[38] of 5 to 10 million dollars (Sarmiento and Wilson, 2005), to be able to load a large number of cars in a short period of time[39]. For these reasons shuttle rates are expected to be lower than unit rates.

[38] Only 6% of the elevators were capable of shuttle train shipping in 2001 (Sarmiento and Wilson 2005).
[39] Loading/Unloading of the entire unit train must not exceed 15 hours (BNSF 2012)

Railroad costs paid by shippers are composed of rates, fuel surcharges, and secondary market prices (in the case of purchasing in that market). Rail rates are determined in what is called a primary market, where shippers are able to secure rail cars for future shipments by auctioning to the railroad companies these contracts for single cars, unit, and shuttle trains. This practice was a consequence of the beginning of the Certificates of Transportation in 1988 (Wilson and Dahl, 2010). Before this cars were assigned on a first come first served system. The resulting rates are required by law to be published 20 days in advance, not allowing variation on a more frequent basis. To provide more flexibility, a secondary market was developed for shippers to exchange contracts[40]. The secondary market allows adjusting the rail rates on a weekly basis, with the difference between the published tariff and the second market price being collected by the shippers rather than by the railroads (Sparger and Pratter, 2012). In practice, most of the time there is no difference. In the period 2004-2010 90% of the primary actions were at nil premium (Wilson and Dahl, 2010). Fuel surcharges are part of the contracts and are charged per car by mile, while the tariff is fixed for a specific origin destination. The same fuel surcharge is applied for all the tariffs of a railroad company.

Barges are a slow mean of transportation compared to railroads and their rates are not regulated. To arrive to Baton Rouge, LA, a barge from Minneapolis takes 11 days, from Quad cities 9 days, and from St. Louis 5 days. The US Inland Waterway System uses a percent of tariff system to establish barge freight rates. Each city on the river has its own benchmark, with the northern most cities having the highest benchmarks since all have as destination Baton Rouge, NO. The tariffs were originally from the Bulk Grain and Grain

[40] No evidence of the participation of railroads in this market exists (Sparger and Pratter 2012).

Products Freight Tariff No. 7 issued by the Waterways Freight Bureau (WFB) of the Interstate Commerce Commission (ICC). In 1976, the United States Department of Justice entered into an agreement with the ICC: Tariff No. 7 became no longer applicable. Today, the WFB no longer exists and the ICC has become the Surface Transportation Board of the United States Department of Transportation. However, the barge industry continues to use the tariffs as benchmarks as rate units. (AMS-USDA).

3. Data and Methodology

3.1 Data

Two main sources of railroad and barge rate data exist: the Carload Waybill Sample of the Surface Transportation Board of the DOT, and the USDA'S Grain Transportation Report. The Carload Waybill Sample is a stratified sample of carload waybills for all U.S. rail traffic submitted by those rail carriers terminating 4,500 or more revenue carloads annually. Because the Waybill Sample contains sensitive shipping and revenue information, access to this information is restricted to federal institutions. The public version of this sample, the Public Use Waybill File, provides railroad monthly prices by commodity and origin-destination (Surface Transportation Board). This database has been used in previous papers; however, the reported rates of contracts are not the original ones, but are altered to prevent the identification of the companies' price strategies. Since approximately 60% of the transactions are under contract[41] the same proportion of the data has this problem.

[41] Personal Communication from the Surface Transportation Board.

The USDA's Grain Transportation Report (GTR) collects data from the railroad companies, the Carload Waybill Sample, the secondary market and information about the fuel surcharge. Since 2000, the GTR reports the secondary market unit grain train and shuttle grain train indexes (Figure 8) (2000=100%), which capture more than 20% of the total movements of wheat, corn, and soybeans across the country for both unit trains and shuttles in 38 major grain routes[42] (Sparger and Pratter, 2012). Three major events created abnormal picks in the indexes during 2002-2012 (Figure 8): the aftermath of Hurricane Katrina (August 2005 through January 2006), a record US export of corn, wheat, and soybeans (August through October 2007) and the Russian grain export ban (July through October 2010) (Sparger and Pratter, 2012). By adding each week's secondary railcar market average bid to the current month's average tariff rate with fuel surcharge, the AMS-USDA constructed the comprehensive rail rate indices using weekly data (AMS-USDA b).

The GTR database started in 2010 to include monthly rail tariffs for the most important grain corridors. These include rates for corn (Figure 9) in the corridors MN-OR, IL-LA, IN-TN, NE-TX, and Des Moines-Davenport; for soybeans (Figure 10) in the corridors ND-WA, SD-WA, MN-OR; and for wheat (Figure 11) in the corridors ND-OR, ND-TX, KS-TX. The graphs are quite flat in comparison to the unit and shuttle indexes because they include the tariff rates and fuel surcharges but not secondary market prices. These corridors have their own rates but they share the same fuel surcharge if they belong to

[42] These 38 origin-destination pairs include seven wheat, seven corn, and five soybean unit train routes and six wheat, seven corn, and six soybean shuttle routes. An unweight average of the 19 unit train tariff rates with accompanying fuel surcharges was calculated for each month to derive a monthly series of the average per car rate. The same procedure was applied to the 19 shuttle rates and fuel surcharges. The weekly frequency was obtaining by adding the secondary market data (Sparger and Pratter, 2012).

the same railroad company. The amount of money received by the railroad is the sum of the rate and the fuel surcharge (Figure 9 to Figure 11).

Whether or not to add the secondary market to the rate plus fuel surcharge is not a minor detail. The secondary market reflects changes in demand in the railroad system and adds the same variability to all grains and routes combinations. As a consequence, it may increase the amount of information in each series but may also introduce noise. Another point to take into account is that barges are slow to move, may take more than a week to be delivered, and their rates may not react to high frequency changes in the railroad prices but to their averages over a longer period of time. For this reason we estimated models using only the sum of rates and fuel surcharges and the sum of those plus the secondary market price.

The GTR is preferred to the Public Use Waybill File. The advantage of the GTR over the Public Use Waybill File is that it is constructed directly from the rail companies and from the private version of the Carload Waybill Sample[43], thus it contains true rates. It also has weekly data, Unit grain train, and shuttle train indexes (Figure 8) that take into account the secondary market. The GTR also reports secondary railcar market auction bids covering non-shuttle service (including unit trains) since 1997 and shuttle train service since 2006, which can be used to create new weekly indexes for specific grains and corridors.

Barge and vessel rates have also been reported in the GTR since 2000. The barge rates are for grains in general and for specific origin ports (Figure 12). All reported barge rates have the same destination, Baton Rouge, NO, since 95% of the grain transported by barge is for export. The origin ports are Minneapolis-St. Paul (Minneapolis, St. Paul, Red Wing, Shakopee, and Winona, MN), Mid-Mississippi (Albany, Keithsburg, New Boston, and

[43] The DOT informed the author that the Private version of the Carload Waybill Sample was available only to Federal institutions, and that it was not released for research purposes.

Rock Island, IL, Clinton; Davenport, and Muscatine, IA), Illinois River (Beardstown, Florence, Hardin, Havana, and Meredosia, IL), Upper Ohio (Cincinnati), Lower Ohio (Louisville, KY), and Cairo -Memphis (Birds Point, Linda, New Madrid, MO, Hickman, KY, and Cairo, IL).

Weekly Grain barge rates, measured as percent of 1976 tariff benchmark index (1976=100%), are reported for Illinois (Figure 13), Twin Cities, Lower Ohio (Figure 14), Middle Mississippi (Figure 15), St. Louis (Figure 16), Cincinnati (Figure 17), and Cairo-Memphis. All rates follow a similar pattern, with peak prices during the fall season and a tendency to increase over time similar to the one presented by unit and shuttle trains (for the period 2002-2012 the barge and railroad rates double their price). The big variability of barge rates compared to rail rates (Figure 18) may be reflecting the existing free market and competition in the industry. Figure 18 also shows that after 2004 barge rates became relatively more expensive than shuttle rates. The vessel rates are from the Gulf and from the Pacific Northwest to Japan (Figure 19) and present a similar pick in 2007 and abrupt decline in rates in 2009 as the diesel rate index (Figure 20) caused respectively by the oil pick of 2007 and US recession of 2009. Table 18 to Table 20 show high correlation among routes of the same transportation mode and less between modes. For the reasons previously exposed, the main data source in this paper is the GTR rather than the Public Use Waybill File.

The American Railroad Association (ARR) is the source of railroad costs. The ARR produces cost indexes for the railroad industry on a quarterly basis to construct the Railroad Cost Recovery Index (RCR). The RCR, available from 1977 to the present, is based on data from all Class I railroads in the United States, and is published for the Eastern District and the Western District railroads, as well as for the entire United States. The indexes include wage rates, wage supplements, fuel, materials and supplies, equipment rents, purchased services, depreciation, interest, taxes (other than income and payroll), and all other operating expenses. The fuel index represents the change in the average price per gallon of No. 2 diesel fuel paid by the four largest railroads Composite indexes are constructed from the basic ones, like the total excluding fuel (Figure 21) and the RCR. The weights used to calculate the RCR are based on freight operating expenses plus fixed charges for all Class I railroads. The base period of the RCR is 2003. (ARRb) [44]

Demand and supply shifters of grain transportation other than RCR components were also included in the data. The selected shifters are real exchange rates, diesel prices, Mississippi River levels, crop specific agricultural year dummy variables, and seasonal dummies. Monthly real exchange rates for corn, soybeans, and wheat (Figure 22) (from the US wrt the weighted average destinations[45]) were obtained from ERS-USDA. These real exchange rates behave in similar form and decrease over the available period indicating an improvement in the competitiveness of the US. Weekly Diesel price is reported by the GTR as Truck index (Figure 20). Mississippi river levels at Carlington, NO were obtained from the US Army Corps of Engineers (Figure 23) and other places along the river (Table 16 and Table 17). While in the upper sections of the Mississippi River there are docks and levies (Figure 24) that facilitate navigability by controlling water levels, in the lower sections water runs free. For this reason water level variation at Carlington, NO is more pronounced than in

[44] The RCR and its components have private information. We are grateful to the ARR for the release of this information for research purposes.

[45] Indexes are constructed so that an upward movement indicates a rise in the U.S. dollar's value (an appreciation) and a subsequent loss of price competitiveness for U.S. exports or a relative reduction in import prices.

any of the available points of the upper Mississippi River (Table 17)[46]. As a consequence, and also because the destination of all export barges is NO, the river level included in the models is the one at Carlington, NO.

Crop specific agricultural year dummies were included in the models to account for unobserved annual shifters like yearly grain production, export and ethanol demand changes. Corn and soybean agricultural year was defined as from October to October and wheat agricultural year was defined as August to August. The inclusion of these agricultural year dummies prevents joint movements of demand for transportation, which may move barge and railroad rates in the same direction, from creating any bias of the estimates. Due to the crop seasonality and the seasonal effect on water level, seasonal dummies were also included.

3.2 Stationarity

Unit root tests and stationarity tests were performed on the variables. The ADF tests (Table 21) rejected for most of the variables the presence of a unit root against a stationary process, and a stationary process with drift or trend in some cases. KPPS stationarity tests were also performed on all variables (Table 21). In all cases stationarity was rejected against a unitary root. Given the results of the tests, the type of data we are working on[47], and evidence of stationarity found in previous papers (Yu, Zhang, and Fuller, 2006; Yu, Bessler, and Fuller, 2007) we decided to treat the variables as stationary. In fact, no paper in the barge and

[46] Water levels at Carlington, NO varied for the available period from 1.24 to 17.04 feet.
[47] For example the unit root test reject Mississippi River levels to have a unit root but the KPSS test reject to be stationary. It seems unreasonable to consider that river levels are not stationary.

railroad literature has found railroad rates, barge rates, fuel prices and river levels to have unit roots.

3.3 Reduced form model

Following Wilson (1980), a reduced form model for grain transportation prices is as follows:

$$P_T = P_T(P, P^{t-1}, \overline{D}, \bar{S}, \overline{DT}, \overline{ST}, \varepsilon_{PT}) \quad (12)$$

Where P refers to the price of grain at the farm, P_T to the price of transportation to the destination, $\bar{S}$ and $\overline{D}$ to vectors of exogenous shifters, $\overline{DT}$ to exogenous demand shifters for transportation, $\overline{ST}$ to exogenous supply shifters for transportation, and ε_{PT} to an error term.

In the short run, if the determinants of equation 12 are exogenous, an OLS would provide unbiased estimations, given that the variables included in the model are stationary. Due to the existence of some competition between railroad and barges, the price of railroad grain rates might depend on barge rates and vice versa. A simultaneous equation model seems an appropriate approach to solve the possible bias estimates of an OLS. The proposed model is the following one:

$$P_{barge} = P_{barge}\left(P, P^{t-1}, \overline{D}, \bar{S}, \overline{DT}_{bage}, \overline{ST}_{barge}, \varepsilon_{P_{bage}}\right) \quad (13)$$

$$P_{rail} = P_{rail}\left(P, P^{t-1}, \overline{D}, \bar{S}, \overline{DT}_{rail}, \overline{ST}_{rail}, \varepsilon_{P_{rail}}\right) \quad (14)$$

Where P_{rail} and P_{barge} are specific rail tariff and barge rates for grains.

3.4 3SLS identification

A Durbin–Wu–Hausman test was performed and exogeneity of P_{barge} and P_{rail} in equations (13) and (14) respectively was rejected. This justifies the estimation of a three stage least square model. The presence of total-excluding-fuel, the rail cost index of all costs but fuel, only on equation (14) and a measure of water level in the river only on equation (14) allows the identification of the structural parameters in the 3-SLS. Equations (13) and (14) are estimated for different combination of barge and railroad rates.

3.5 Logs vs. levels

We estimate the model of equations (13) and (14) in levels and in logs. Previous studies have preferred log-log models for estimating grain rail demand and supply. MacDonald (1987) estimated a reduced form model of grain rail rates in logarithmic form to test the effect of the Staggers Rail Act of 1980. Fuller, Ruppel, and Bessler (1990) regressed a reduced form model of grain rail rates in logarithmic form to test the effect of contract disclosure on railroad grain rates. Miljkovic et al. (2000) used a log-log 3SLS to model the supply demand system for grain movement from the Midwest to the Mexican Gulf. Miljkovic (2001) estimated a log-log 3SLS for a system of demand and supply of grain railroad services for four states and two destinations. Yu and Fuller (2005) regressed a log-log 2SLS for the demand of grain barge transportation in the upper Mississippi River. Yu, Zahang and Fuller (2006) computed an SUR model in logs for the barge demand in the upper Mississippi and Illinois rivers.

4. Results and discussion

All models were estimated for railroad rates plus fuel surcharges, and for railroad rates plus fuel surcharges and secondary market. Results presented in this paper are the ones not including the secondary market[48], rather only railroad rates and fuel surcharges. The models were omitted from the paper because, with a few exceptions later mentioned, they were non significant. This may support the idea that the secondary market is adding more noise than information to each specific railroad route. Thus, the following results refer only to railroad rates plus fuel surcharges. Almost all models estimated in logs had better BICs than the corresponding level ones and consistent coefficient signs. Thus, results refer to models in logs while the models in levels are presented as tables in the annex of this paper.

4.1 Shuttle and unit rail rate indexes

To analyze the general relationship between barge and railroad rates for grains, 3SLS were estimated for a barge rate index (barge_illinois), a railroad shuttle rate index (Table 22), and unit rate index (Table 23). Table 22 shows six model specifications: the first table with variables in levels and the second in logs. Starting by including the rate of the other transportation mode and a specific explanatory variable (1); the models add seasonal and agricultural year dummy variables (2); real exchange rate of corn (3); ocean rates for the Gulf (ocean_gulf) and PNW (ocean_pnw) (4); a ratio of Gulf and PNW ocean rates (5); and fuel prices for barges (diesel) and railroads (fuel) (6). All other regression tables in this study have the same structure as Table 22.

[48] The exceptions are the shuttle and unit rate indexes.

Overall the unit models (Table 23) have more significant and robust results across the various model specifications than do the shuttle models (Table 22). A possible explanation is that since shuttle contracts are negotiated over a long period of time, they might be less reactive to short-term barge rates than unit rates. The shuttle and the unit rail indexes have a significant positive effect on the barge rate index (log_barge_illinois) in all models (Table 22 for shuttle and Table 23 for unit rail indexes), while barge rates have non-significant effects on shuttle and unit rates in most of the models. Barge rates have an elastic reaction to shuttle rates (1.2 to 1.6) and an inelastic reaction to unit rates (0.5 to 0.7). The higher elasticity of barge rate to shuttle compared to unit rates is logical given shuttles are more export oriented than are unit trains. What is surprising is how elastic the barge rate response is to shuttle rates, showing that the barge market may have more market power than previously expected. It is possible that the reduction of barges after 2004 made this possible. The elastic reaction of barges might be the cause of the amplified picks of barge rate compared to shuttle rate observed in Figure 18.

Water levels, real exchange rates, ocean rates, and diesel prices affect barge rates. The level in the Mississippi River (levelcarlington_no) has a negative impact on the barge rate index in all but one models independent of whether the rail rate index used is the shuttle or the unit one (Table 22 and Table 23). A lower level in the river may affect navigability, reducing the speed of transportation and the maximum cargo per barge. A one-foot decrease in the water level at Carlington, New Orleans increases the barge rates by 5-7% (Table 22 and Table 23). The real exchange rate of corn may be seen as a proxy for exports; when the real exchange rate increases the US becomes less competitive. The real exchange rate of corn, when significant, negatively affects shuttle and unit rates (Table 22 and Table 23).

Although unit rates may be slightly more related to domestic transportation than shuttle rates, both rates are for the use of the same limited amount of grain cars. This competition for cars may push the unit index up, despite an increase in the amount of grain destined for the domestic market. Another reason may be that unit trains may be used for transporting grain for export from elevators not invested in the facilities to charge a shuttle. In the case of barge rates, the real exchange rate of corn is significant only in the unit rate models[49] (Table 23) with an elasticity of 0.2 to 0.3.

Ocean rates are expected to complement the inland transportation services that reach their respective export ports. In the case of barge rates, the complementary service is the ocean rate from the Gulf (ocean_gulf), while the ocean rate from PNW (ocean_pnw) is a substitute. Given the fact that rail has no barge competition to PNW, an opposite reaction (compared to the barge rate one to ocean rates) is expected. Results confirm this assumption; the elasticity of barge rates to ocean rates from Gulf is -0.4 to -0.5; and 0.2 to 0.3 to ocean rates from PNW (model (4) in Table 22 and Table 23). The difference in the absolute magnitude of the elasticities (larger for the Gulf) may be partially explained by the more costly inland transportation to reach the PNW. As expected, rail rates reactions are in an opposite situation than barge rates with respect to ocean rates. Shuttle and unit rates are negatively affected by increments of ocean rates in the PNW (elasticities of -0.08 and -0.17 for shuttle and unit respectively) and positively by increments of ocean rates in the Gulf (0.20 for both). The lower reaction of unit rates to PNW(-0.08) compared to shuttle rates may be a reflection of shuttles being more oriented towards the long distance destination. Results using

[49] The different results in this case may be explained by the characteristic of long- term agreement of shuttle contracts.

the ratio of ocean Gulf to ocean PNW rates as repressor (model (5) in Table 22 and Table 23) also confirm the previous results.

Cost indexes have significant effects on barge and rail rate indexes. Diesel and railroad fuel prices (fuel) respectively increase the price of barge and shuttle and unit rate indexes as expected (model (6) Table 22 and Table 23). Barge rates have a stronger reaction to fuel prices (0.5-0.78) than rail rates (0.12 for shuttle and unit). The pricing system in both transportation modes may be a cause for that difference. The long term transportation contracts that rail companies offer to shippers may require them to manage fuel prices risk, allowing them to keep rates more stable to fuel price changes than barge companies. All rail costs but fuel (totalexclfuel) also significantly affect shuttle and unit rates in the expected direction across various model specifications (Table 22 and Table 23). The respective elasticities are in the order of 0.237 for shuttle rates and 0.4 to 0.9 for unit rates.

Yearly dummy variables (not reported in the tables) are significant, which indicates the existence of omitted shifters on demand and supply for transportation. In the case of barge rates, fall and winter seasons have higher rates than spring and summer when most exports occur. Shuttle rates are not affected by seasonality, possibly because they are negotiated over a long period of time that may cover up to three seasons.

4.2 Corn rail rates for specific origin-destinations

Corn, wheat and soybean rates for a variety of origins and destinations were analyzed to further investigate the relationship between barge and railroad rates. In the case of corn, the railroad routes include Des Moines, IA to Davenport, IA (Table 24 and Table 46); Urbana, IL to New Orleans, LA (Table 25 and Table 47); Indiana, IN to Knoxville, TN (Table 26 and Table 48 for Cincinnati barge rates and Table 27 and Table 49 for Lower Ohio barge rates); Nebraska to Houston, TX (Table 28 and Table 50 for St Louis barge rates and Table 29 and Table 51 for barge rate index), Minneapolis to Oregon (Table 30 and Table 52 for Twin Cities barge rate and Table 31 and Table 53 for barge rate index). Overall the results are less robust than the previous ones with the exception of the Des Moines, IA to Davenport, IA (Table 9 and Table 46).

Railroad rates from Des Moines, IA to Davenport, IA are expected to complement barge rates because the destination is an inland port on the Mississippi river. Results confirm that hypothesis (Table 24). Significant coefficients have the expected sign. The elasticity of railroad rates from Des Moines, IA to Davenport, IA with respect to the barge rate index is significant in different model specifications and at least equal to -0.093 (model (6) Table 24). However, rail rates from Des Moines to Davenport do not affect barge rates but in only one model (model (1) Table 24) where the sign is as expected. The effects of water level, ocean rates, and diesel prices are in the same direction and magnitude as in the previous models, while the real exchange rate of corn is the exception (either non significant or negative effect).

For the Urbana, IL to New Orleans, LA corn railroad rates results are less significant for most of the variables (Table 25), with signs in the expected direction with the exception of price-price elasticities that are negative for barge-rail and non significant for the inverse case. No clear explanation for this negative sign exists since it was expected that the two modal transports where competing with each other. It also is interesting to note that the instruments (levelcarlington_no and log_totalexclfuel) appear not to be good for these models: they are non significant in the majority of models.

In the case of transportation from Indiana to Tennessee, a destination area of big consumption of corn by the poultry industry, only model (4) has a significant positive effect of Cincinnati barge rates on railroad corn rates and vice versa (table 11). Table 12 presents results using the Lower Ohio River barge rates (loh) instead of Cincinnati barge rates. Results are almost identical to the previous ones. While the real exchange rate negatively affects barge rates (with an elasticity of -0.3 to -0.47 (Table 27 and Table 28 respectively)), it does not affect the railroad rate, probably because Tennessee is a domestic destination. An increase in the real exchange rate is expected to increase domestic consumption of corn creating a demand increment for transportation in this route, but the competition with export for grain railcars decrease pushes rail rates down. In this case the effects apparently offset each other. It appears that despite these barge rates not directly competing with rail rates to Tennessee they do affect them, possibly by changing the elevators' decision from selling in the domestic market to exporting the corm.

Corn railroad rates for Nebraska to Houston, TX models are presented in Table 28 and 29. Table 28 has as the other dependent variable, the St Louis barge rate, while Table 29 has the Illinois barge rate. Results are similar for both barge rates, with some significant effects of barge rates on railroad rates (positive as expected) and unexpected negative effects of barge rates on rail rates. Nevertheless, another expected result was confirmed. Given that the destination is on the Gulf, it was expected that Gulf vessel rates and PNW vessel rates affected respectively in a negative and positive form the railroad rate from Nebraska to

Houston, TX. The results confirm this hypothesis; the price-price elasticities are -0.42 and 0.21 respectively (Table 28 model (4)).

To account for the effect of rail rates to PNW on barge rates, corn rail rate models were estimated for Minneapolis to Oregon (Table 30 and Table 31). Table 30 presents results including as second dependent variable the Twin Cities barge rate (TWC)[50], while Table 31 includes the Illinois barge rate index, which is available all year around. Table 30 shows robust positive effects of barge rate on rail rates as expected[51]. It is interesting to note that when the barge_illinois rate is used (Table 31), instead of the TWC barge rate, the effect of barge rate on rail rate disappears. Considering that TWC is closer than the Illinois River to the origin (Minneapolis), this result provides supporting evidence that distance from the origin to the water system affects the completion between barges and railroads.

4.3 Wheat rail rates for specific origin-destinations

Wheat railroad rate models for the railroad routes of North Dakota to Oregon, North Dakota to Texas, and Kansas to Texas are presented on Table 32 to Table 37. For the route ND to Oregon, the effect of railroads on barge rate is significant and robust across various model specifications when using the TWC barge rate (Table 32). As in the case of corn transported to the PNW from Minneapolis, the effect disappears when using the Illinois instead of the TWC barge rate in the models (Table 33). This result further supports the importance, for rail barge competition, of the distance between the origin and the river transportation system.

[50] These barge rates are not available from the beginning of December to mid-March since the river is frozen and there is no barge service.
[51] The effect on the opposite direction has no robust results with coefficients changing signs across models.

Another similarity with corn transported from Minneapolis to the PNW (Table 30) is that the Mississippi water level has a positive effect on barge prices. This is the only origin where this happens. A possible explanation may be that even lower levels at New Orleans may affect barge navigability; higher levels may be even more problematic since they require closing levies to navigation. In other words, in the top upper part of the Mississippi River, high water levels are more problematic than lower levels. The effect of railroads on barge rates is also positive as in the case of corn to the PNW. The effect is significant in only two models (models (1) and (2) of Table 32), when the effect is positive as expected.

For the routes North Dakota to Texas (Table 34 and Table 35) and Kansas to Texas, results are similar to previous models from Minneapolis and North Dakota to PNW. TWC barge rates have robust significant positive impact on rail rates (Table 34) with a price-price elasticity of 0.3 to 0.6. On the contrary, Illinois barge rates (Table 35) do not have significant effects on rail rates from North Dakota to Texas. In the case of wheat from Kansas transported to Texas, the mid-Mississippi barge rate (Table 36) has a robust significant positive impact on rail rates (elasticity of 0.332) while there is no impact when the Illinois barge rate is the other dependent variable (Table 37). Water level in New Orleans has also in this case a robust positive impact on barge rates (Table 36).

4.4 Soybean rail rates for specific origin-destinations

Soybean models show similar results for the routes North Dakota and South Dakota to Washington State, and Minnesota to Oregon (Table 23 to Table 43). In most of the models there are no significant effects of barge rates on railroad rates, independent of whether the barge rate corresponds to the closest water route.

5. Conclusions

Every year more than 400 million tons of corn, soybeans and wheat are transported in the US from the Midwest to diverse destinations within the country (70%) and abroad (30%). Exports of corn, soybeans and wheat have been relatively stable over the last decade and account for an average of 55, 30, and 30 million tons respectively. The transportation of the grain is mostly intermodal by combining truck, train, barge and ocean-vessel. In some situations the modes of transportation compete and in others they complement each other. An efficient grain transportation system is fundamental in determining better prices for farmers, lower food and biofuel costs for consumers, and more competitive export prices. Yu, Bessler and Fuller (2007) studied the spatial price linkages in US grain and transportation markets, and found that transportation rates (barge, rail, and ocean) explain 42–64% of the variation in corn prices in the long run. Given the important role of competition on market efficiency (in this case between rail and barge) and the impact of transportation prices on grain price variation, this paper studies the competitive interactions between grain railroad rates and barge rates in the Mississippi Waterway System.

Corn and soybeans are produced closer to the Mississippi Waterway System than is wheat. For this reason more than 55% of corn and soybeans exported are moved by barges vs. 33% by rail; while only 30% of the wheat is moved by barge vs. 65% by rail. This geographical situation has an impact in the selection of the export port, with corn and soybeans highly concentrated in the Mississippi Gulf and wheat more in the PNW and Texas Gulf. Because the PNW cannot be reached by barge, grain rail rates may have more market power those farther from the Mississippi river. This study expands the scarce literature on rail-barge competition by concentrating for the first time on the effect of barge rates on railroad rates and analyzing the effect of distance between origin and the Mississippi waterway system on their competitive interactions.

Despite the existing research on grain rail rates, little is known about the impact of barges on their market power. By using data from the Grain Transportation Report this paper, estimates simultaneous equation models of barge and railroad rates (in logs and levels) for specific origins-destinations and grains (corn, wheat and soybeans). This study benefits from instrumental variables as river levels and railroad cost indexes.

Results show that barge rates have an elastic reaction to shuttle rates (1.2 to 1.6) and an inelastic reaction to unit rates (0.5 to 0.7) while they do not systematically respond to shuttle rates. The higher elasticity of barge rate to shuttle compared to unit rates is logical given shuttles are more export-oriented than are unit trains. What is surprising is how elastic the barge rate response is to shuttle rates, showing that the barge market might have more market power than previously expected. The instruments for the 3SLS models (Water level in the Mississippi River in the area of New Orleans and railroad-all-costs-but-fuel AAR index) where significant in most of the models showing that they were a good choice, especially considering water levels.

It was also possible to find results showing intermodal transportation that complement or compete with each other. Rails complement more than PNW barges do with the Gulf: the elasticity of barge rates to ocean rates from Gulf is -0.4 to -0.5, and 0.2 to 0.3 to ocean rates from PNW. The lower reaction of unit rates to PNW(-0.08) compared to shuttle rates may be a reflection of shuttles being more oriented towards that long distance destination. The paper also presents results for corn, wheat and soybeans.

In the case of corn it was possible to identify for the first time in the literature the existence of complementarity between rail and barges in the rail line from Des Moines, IA to Davenport, IA. Other covariates had similar effects as in the case of grain shuttle and unit rate models. For the line Minneapolis to PNW, TWC barge rates where found to have robust positive effects on rail rates as expected due to their competitive nature. The same model estimated with Illinois barge rate rather than TWC barge rate shows no effect of this rate on rail rates to PNW. This result provides supporting evidence that distance from the origin to the water system affects the completion between barges and railroads. Similar situations were found in wheat, which is produced farther from the Mississippi water system. As a consequence, the impact of barge rates on railroad rates is reduced when the origin of the grain is distant from the waterway.

The present study has some data limitations. In 2010, the USDA's Grain Transportation Report (GTR) started reporting the secondary market unit grain train and shuttle grain train indexes. At the same time, it also started reporting rail rates for corn, wheat, and soybeans for specific rail routes. Future research may provide extended data. One possible source used by the USDA to expand this data (over time and railroad routes) is the Private version of the Carload Waybill Sample, which is accessible only through federal institutions. Another limitation of the study is the use of only one water level at New Orleans. Given its effect for models of origin in Minnesota and Kansas that the sign is the opposite than expected, it might be beneficial to deeper study the effect of river levels at various points of the Mississippi River and its subsidiaries.

Figures

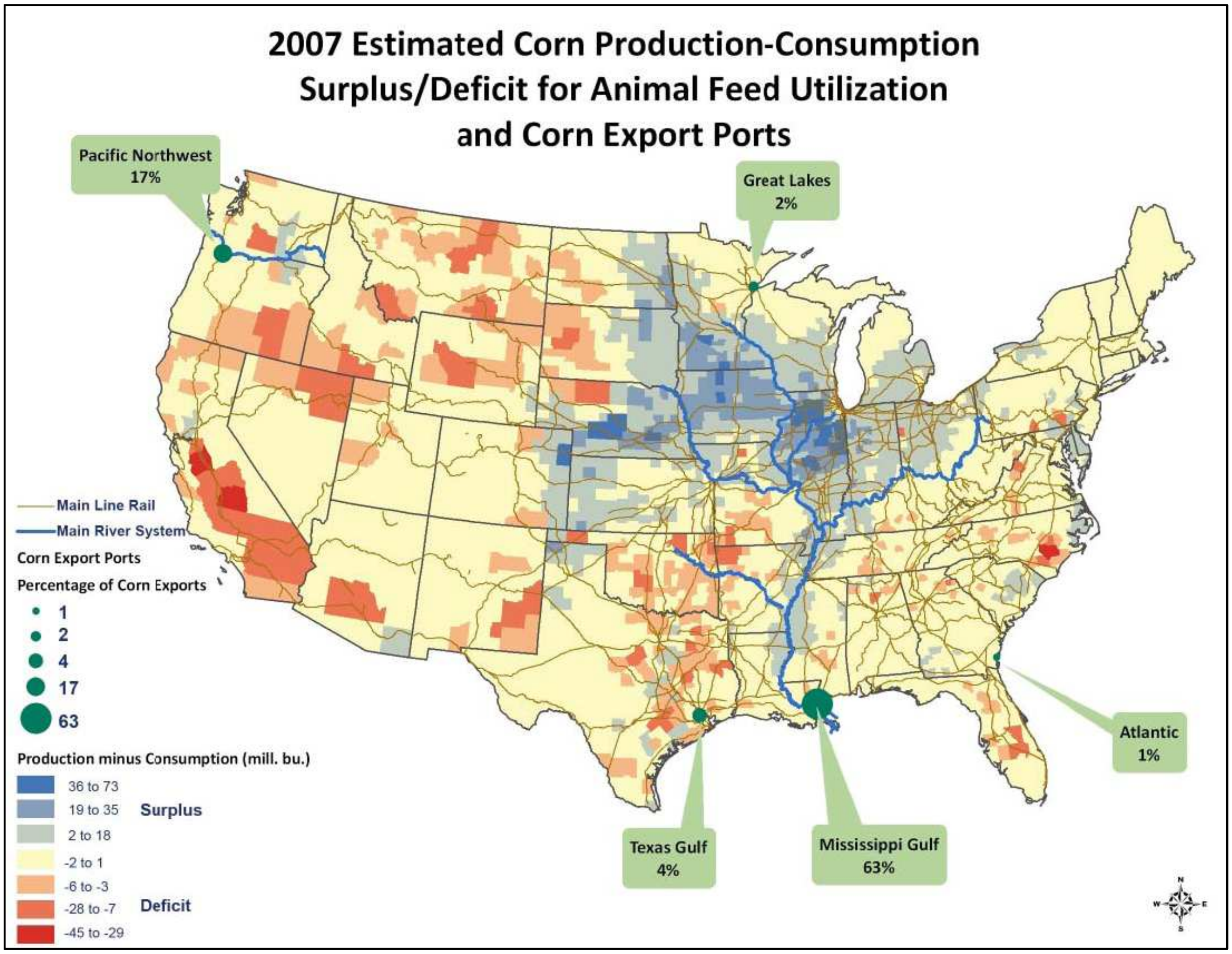

Figure 2. Origin and destination of corn.

Source: Figure 8 in Marathon and Denicoff (2011). Based on Census of Agriculture, 2007 and Economic Research Service, USDA. Surplus-deficit estimate is based on county-level production, U.S. feed use, and county-level animal inventories (summed based on Grain Consuming Animal Unit factors). U.S. Waterborne Exports and Imports from the Port Import Export Reporting Service (PIERS).

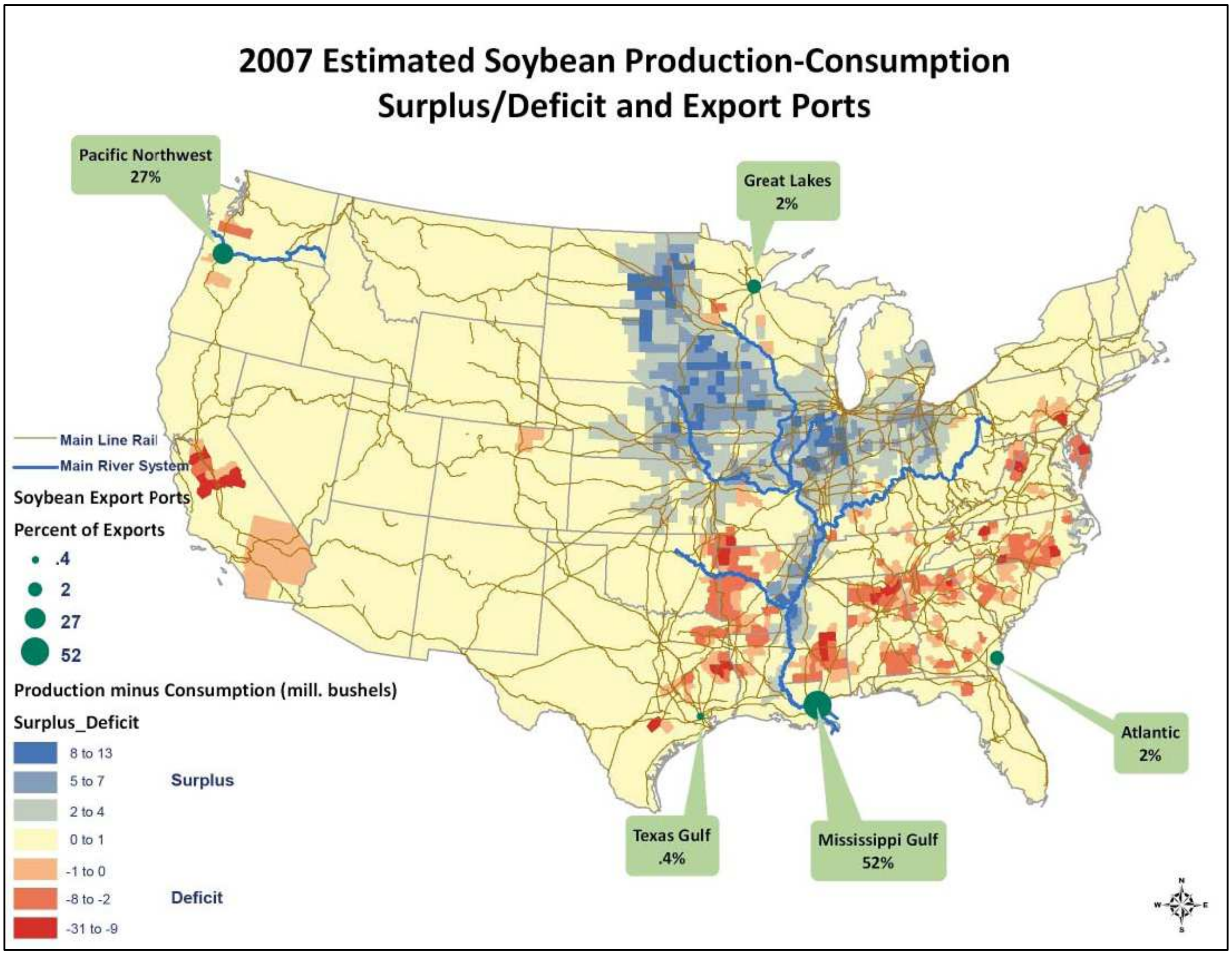

Figure 3. Origin and destination of soybean.

Source: Figure 14 in Marathon and Denicoff (2011). Based on Census of Agriculture, 2007 and Economic Research Service, USDA. Surplus-defi cit estimate is based on county-level production, U.S. soybean meal use (soybean equivalent), and county-level animal inventories (summed based on High Protein Animal Unit factors). U.S. Waterborne Exports and Imports from the Port Import Export Reporting Service (PIERS).

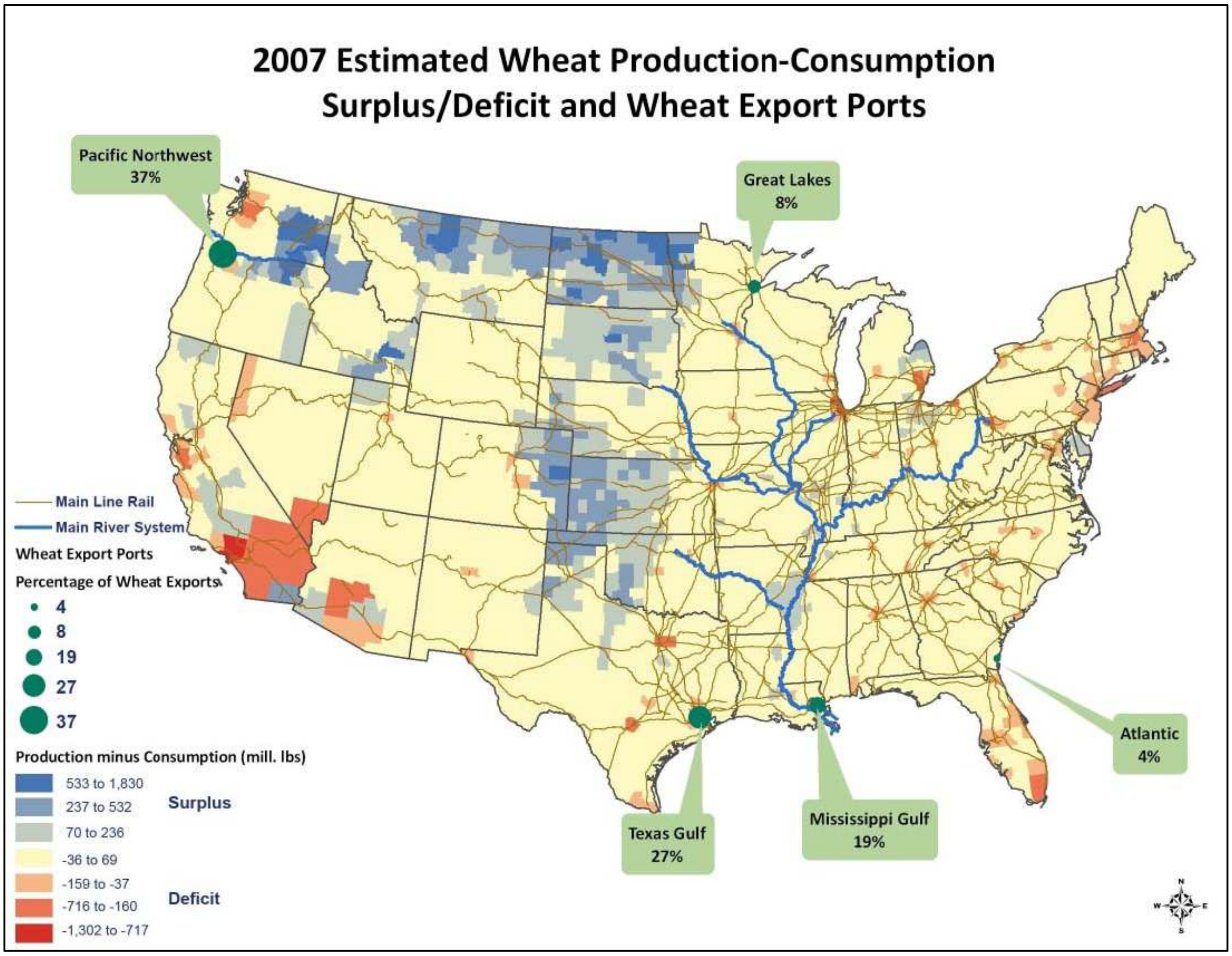

Figure 4. Origin and destination of wheat.

Source: Figure 11 in Marathon and Denicoff (2011). Based on Census of Agriculture, 2007 and Economic Research Service, USDA. Surplus-deficit estimate is based on county-level production and consumption (based on population and per capita fl our consumption). U.S. Waterborne

Exports and Imports from the Port Import Export Reporting Service (PIERS).

Figure 5. Inland navigation system

Source: Corps of Engineers.

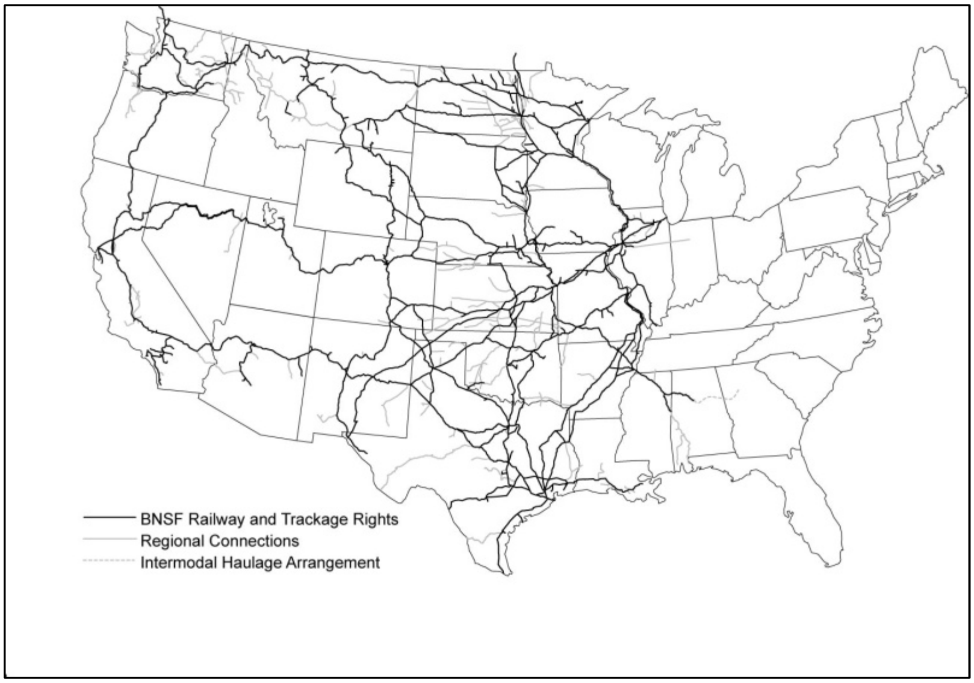

Figure 6. BNSF railroad map

Source: BNSF.

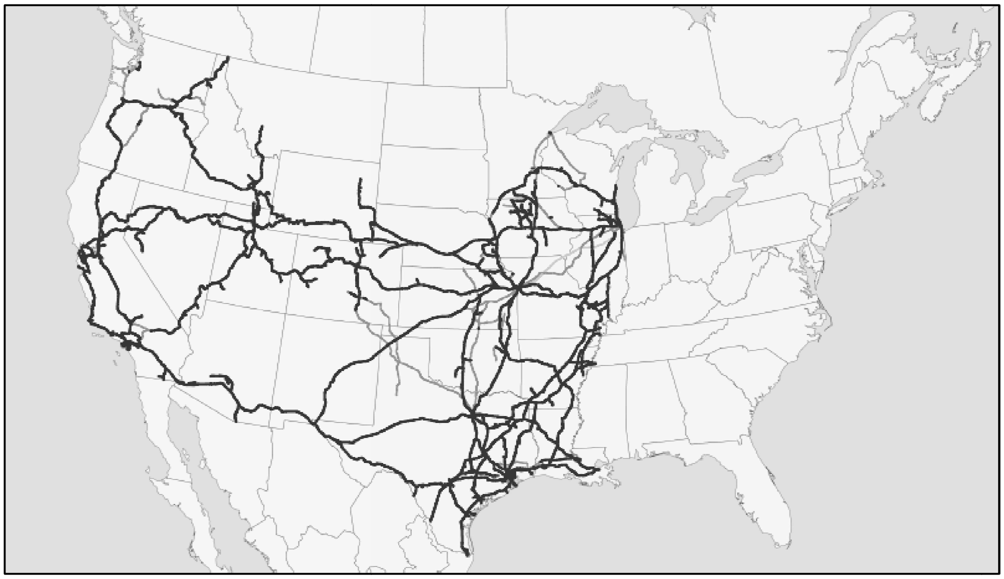

Figure 7. UP railroad map

Source: UP.

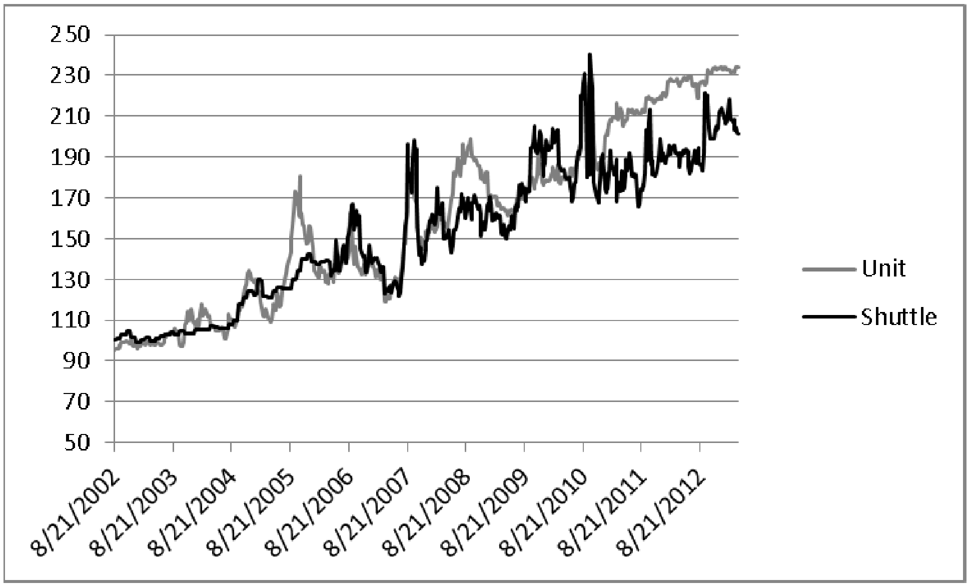

Figure 8. Unit and Shuttle grain railroad index rates

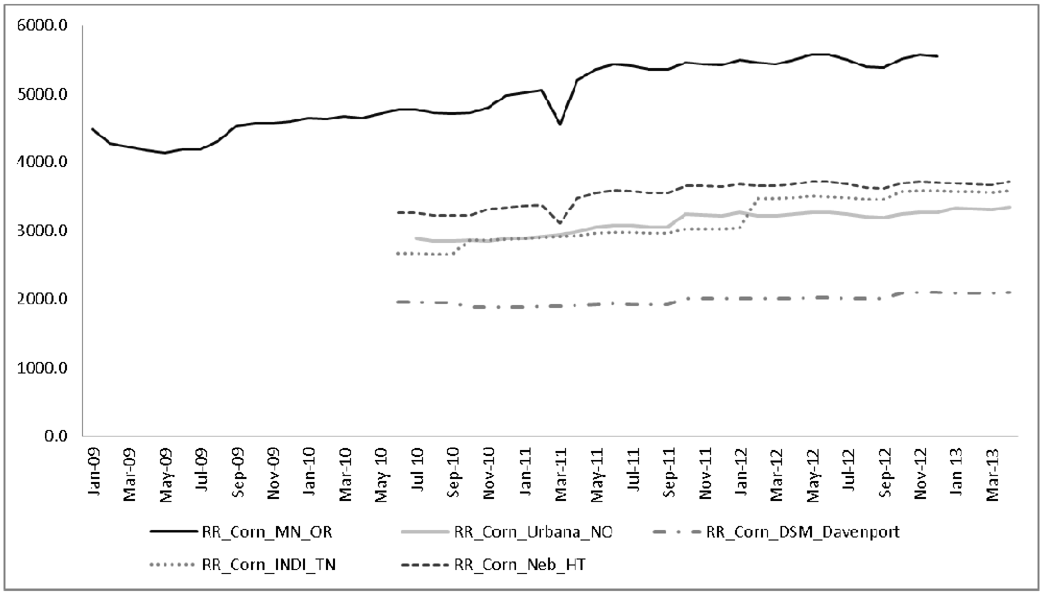

Figure 9. Railroad rate indexes for corn.

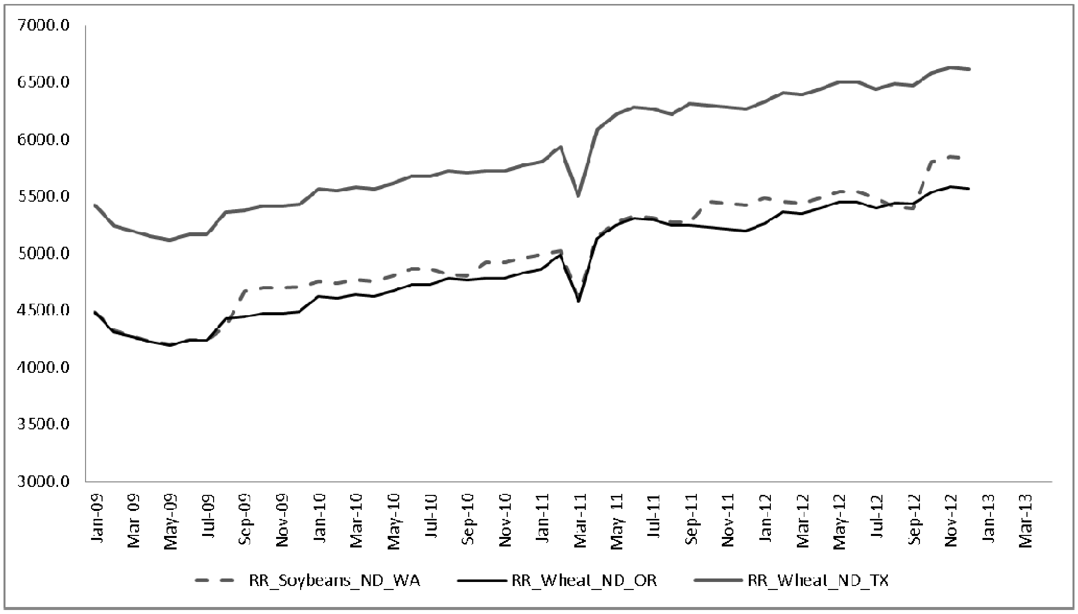

Figure 10. Railroad rate indexes for soybeans.

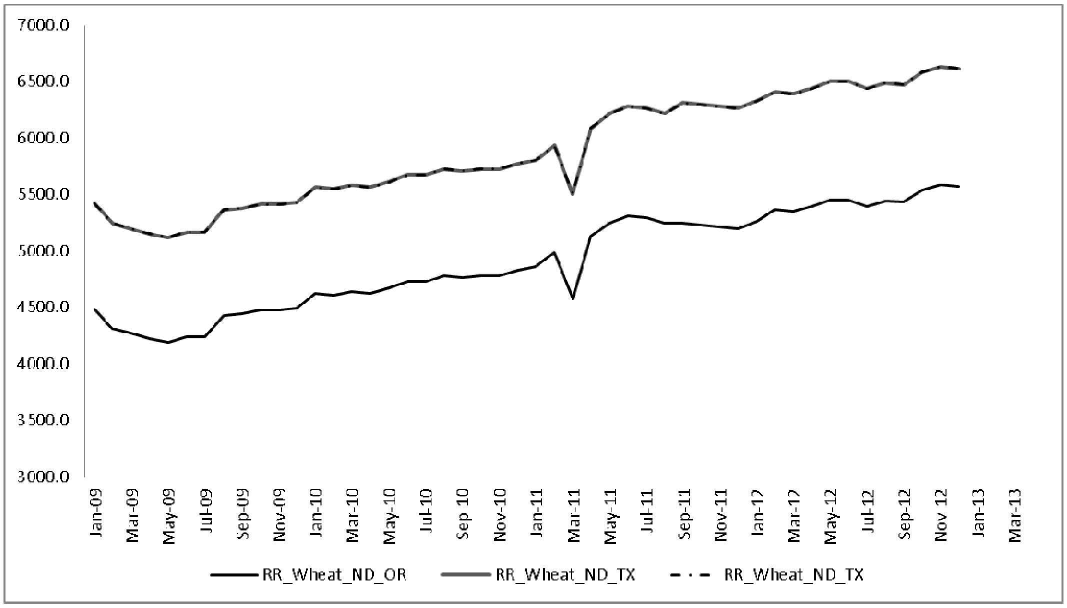

Figure 11. Railroad rate indexes for wheat.

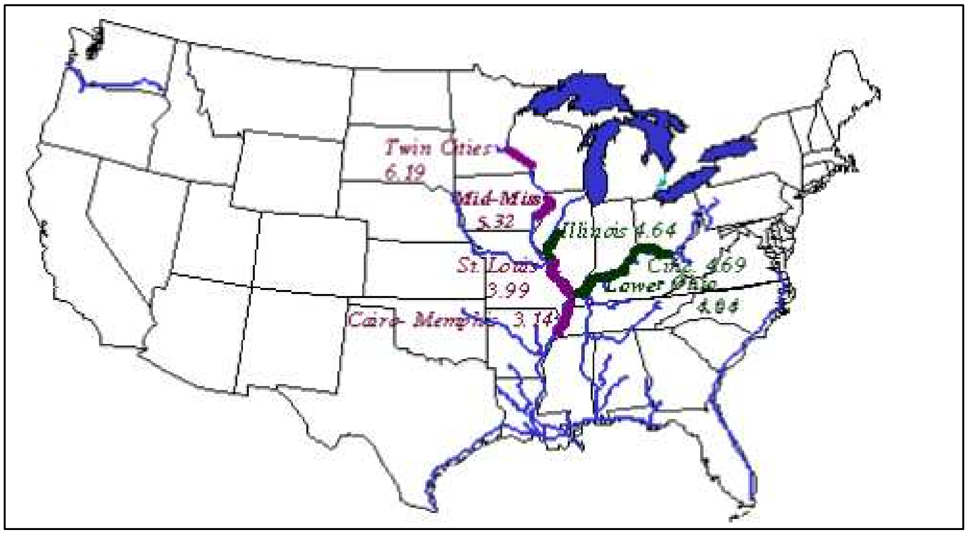

Figure 12. Barge routes and Barge rate origin locations.

Source: GTR.

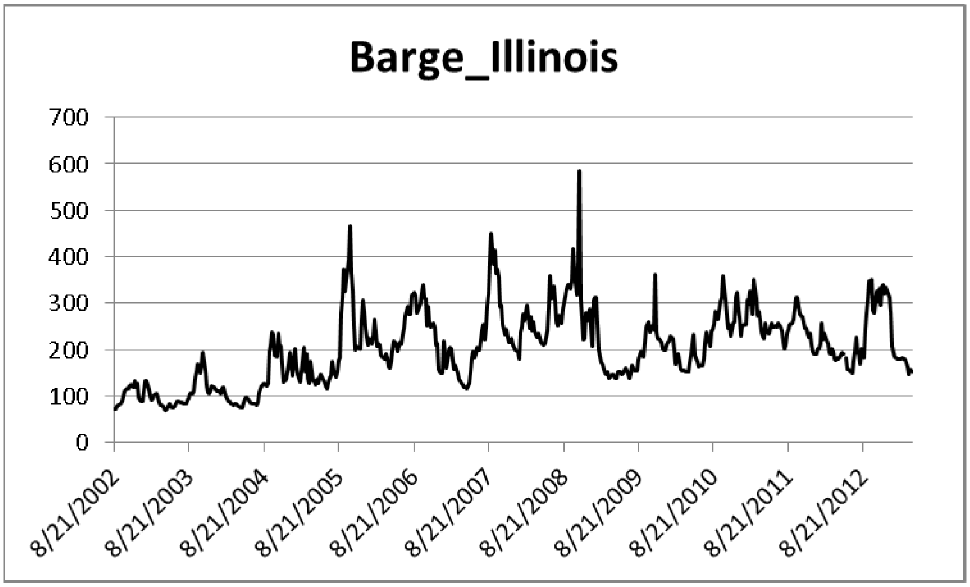

Figure 13. Barge Illinois river grain rates index.

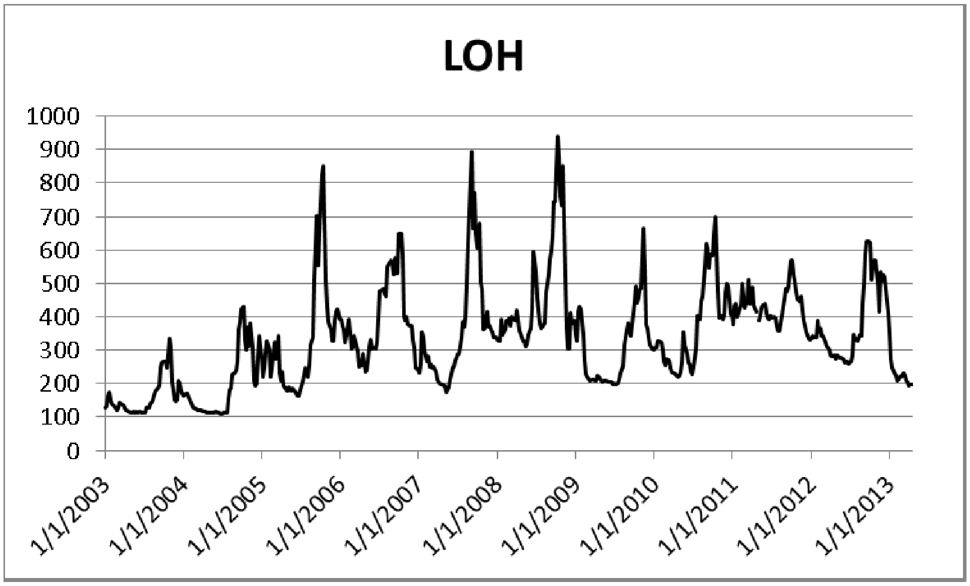

Figure 14. Barge Lower Ohio grain rates index.

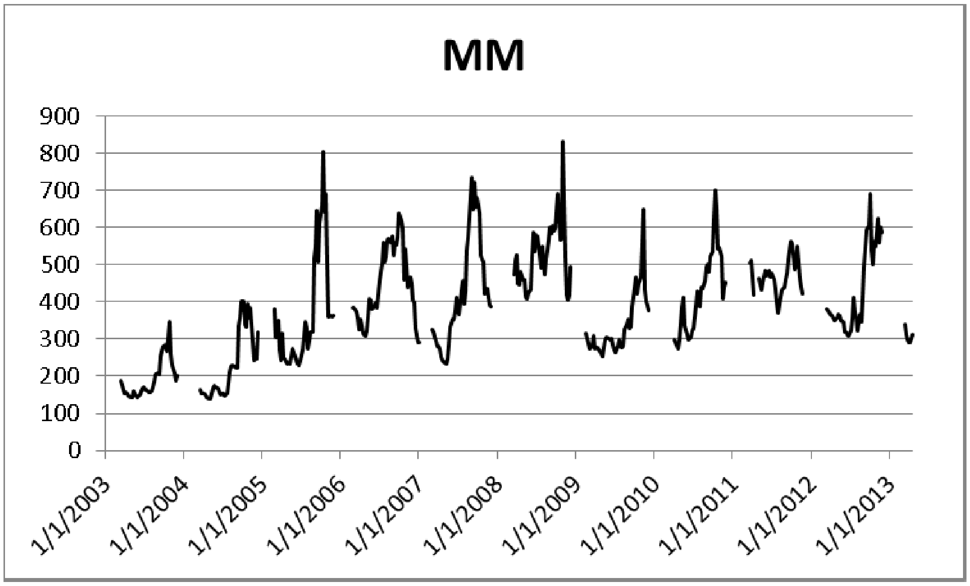

Figure 15. Barge Middle Mississippi grain rates index.

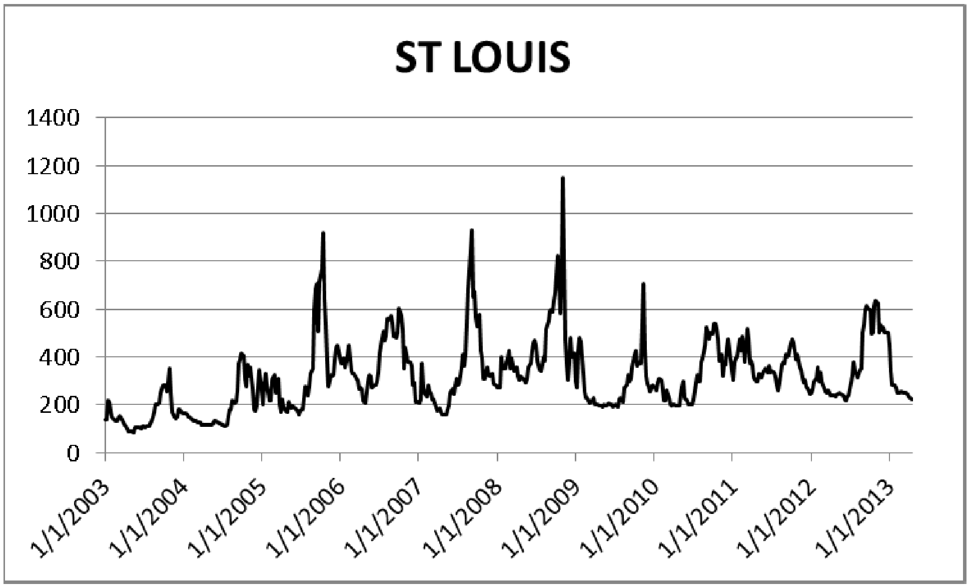

Figure 16. Barge St Louis grain rates index.

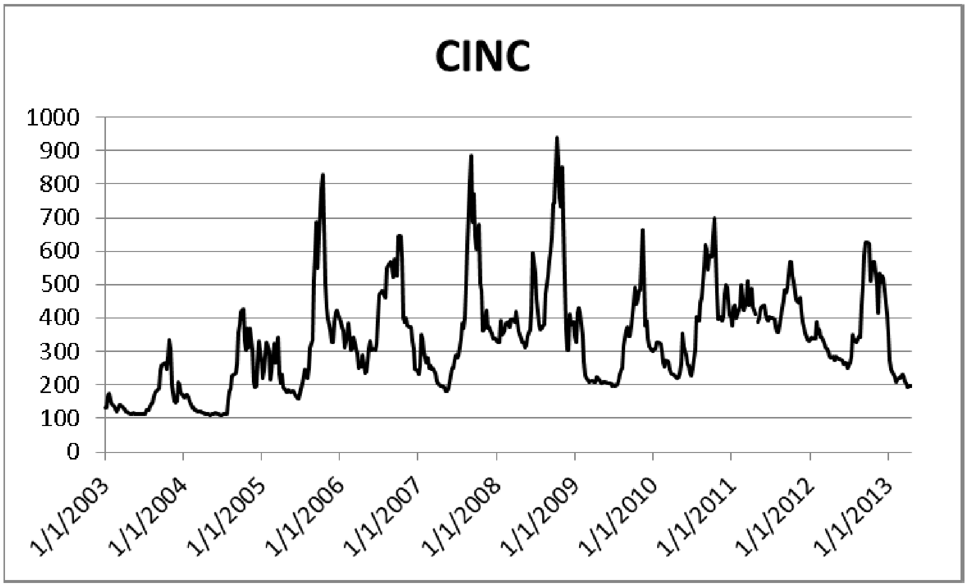

Figure 17. Barge Cincinatti grain rates index.

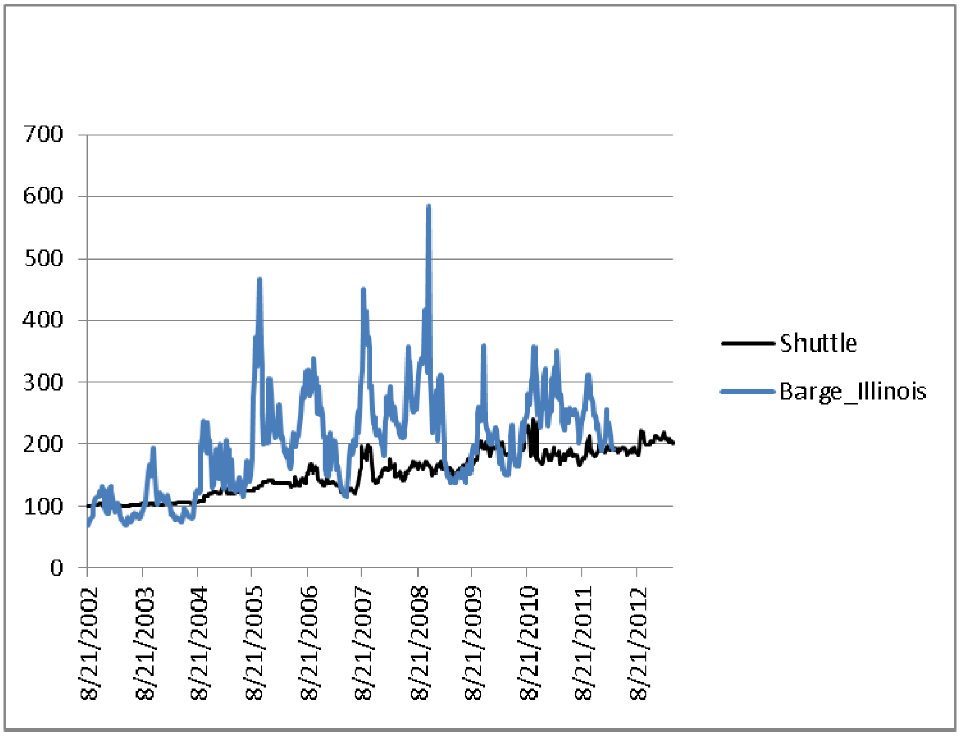

Figure 18. Barge Illinois and Shuttle train grain rates index.

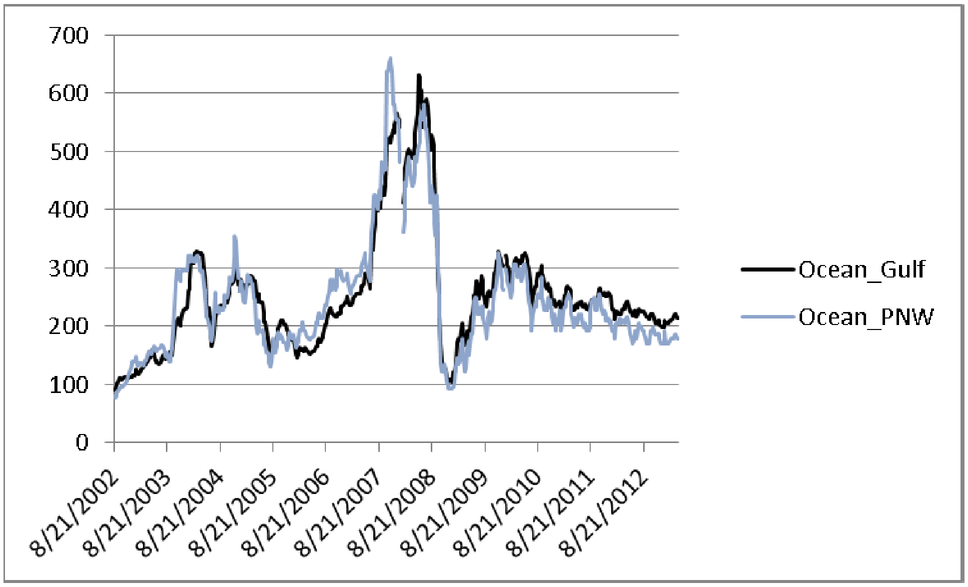

Figure 19. Ocean rate indexes.

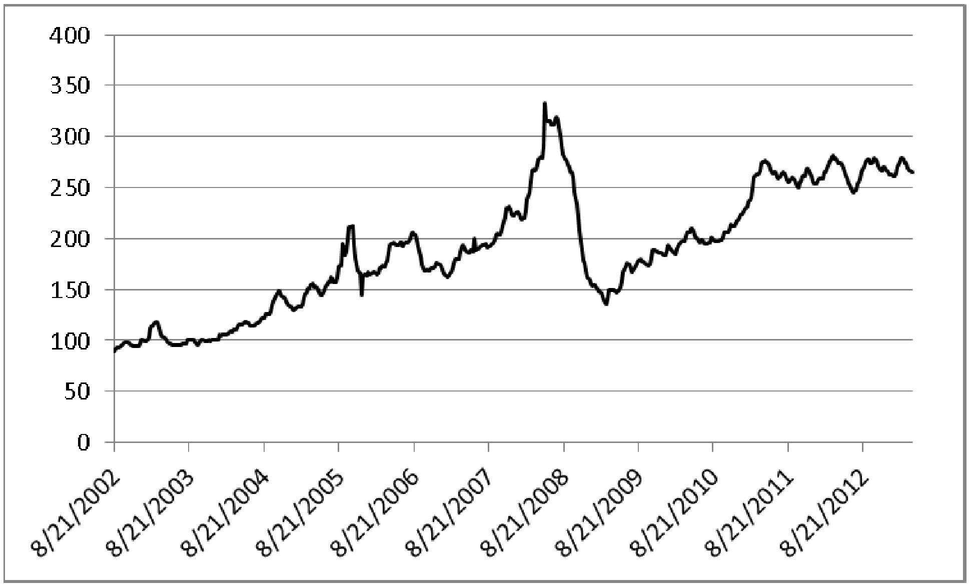

Figure 20. Diesel rate index.

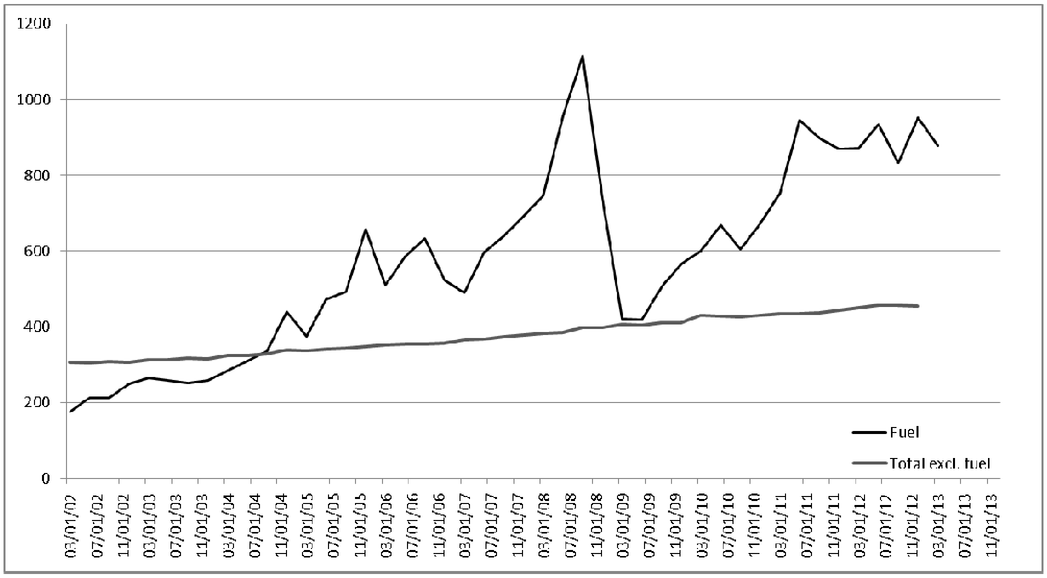

Figure 21. Railroad fuel and Total excluding fuel cost indexes.

Figure 22. Real exchange rates of corn, soybeans, and wheat.

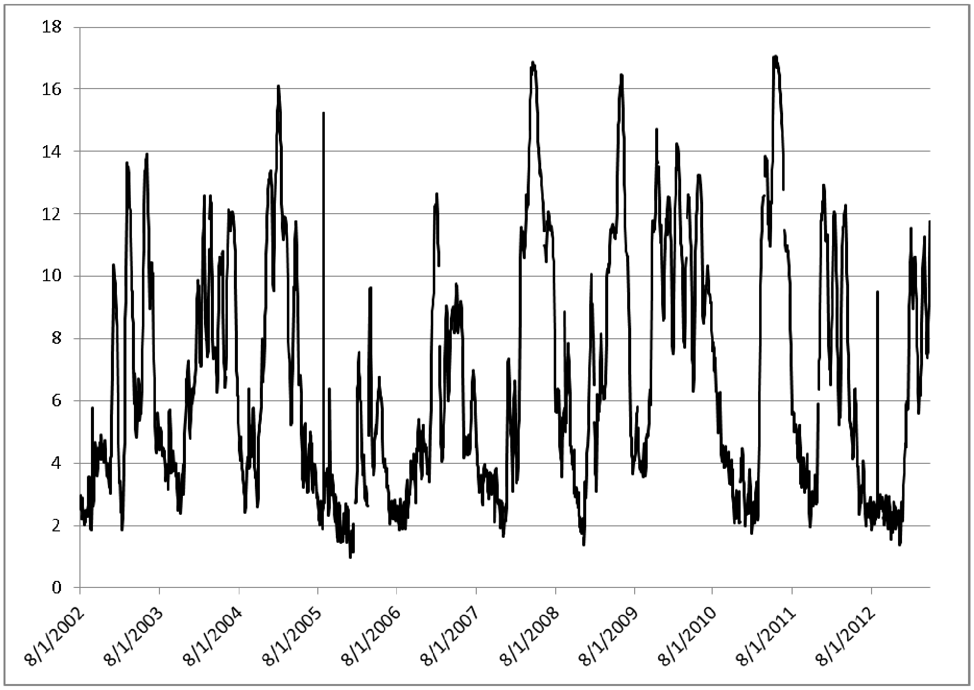

Figure 23. Level of the Mississipi river in Carlington, NO in feet.

Figure 24. Map of upper Mississippi and Illinois Rivers with locks and dams.

Source: Figure 1 in Yu, Bessler and Fuller (2006)

Tables

Table 16. Variables description.

Frequency	Variable	Start	End	Description
weekly	Level_Lock_15	8/21/2002	4/16/2013	Mississippi river level (ft) at Lock 15
	Level_Dub_IA	8/21/2002	4/16/2013	Mississippi river level (ft) at Dubuque, IA
	Level_NO	8/21/2002	4/16/2013	Mississippi river level (ft) at New Orleans, LA
	Level_Minn_MN	8/21/2002	4/16/2013	Mississippi river level (ft) at Minneapolis, MN
	Level_Lock_1	8/21/2002	4/16/2013	Mississippi river level (ft) at Lock 1, MN
	Level_Quincy	8/21/2002	4/16/2013	Mississippi river level (ft) at Quincy, IL
	diesel	8/21/2002	4/16/2013	Diesel rate index
	unit	8/21/2002	4/16/2013	Railroad unit grain index
	shuttle	8/21/2002	4/16/2013	Railroad shuttle grain index
	barge_illinois	8/21/2002	4/16/2013	Grain rate index in the Illinois river
	ocean_gulf	8/21/2002	4/16/2013	Ocean grain rate Gulf to Japan index
	ocean_pnw	8/21/2002	4/16/2013	Ocean grain rate PNW to Japan index
	twc	4/2/2003	4/16/2013	Grain rate index for Twin Cities
	mm	4/2/2003	4/16/2013	Grain rate index for Middle Mississipi
	ill	1/1/2003	4/16/2013	Grain rate index for Illinois river
	stlouis	1/1/2003	4/16/2013	Grain rate index for St. Louis
	cinc	1/1/2003	4/16/2013	Grain rate index for Cincinatti
	loh	1/1/2003	4/16/2013	Grain rate index for Lower Ohio
	carmem	1/1/2003	4/16/2013	Grain rate index for Cairo-Memphis
	memso	1/1/2003	4/16/2013	Grain rate index for Memphis-SO
monthly	rexch_corn	Jan-02	Mar-13	Real Exchange rate of Corn
	rexch_soybeans	Jan-02	Mar-13	Real Exchange rate of Soybeans
	rexch_wheat	Jan-02	Mar-13	Real Exchange rate of Wheat
	rrs_ndwa	Jan-09	Dec-12	Railroad soybean unit tariff from ND to WA
	rrs_mnor	Jan-09	Dec-12	Railroad soybean unit tariff from MN to OR
	rrw_kstx	Jan-09	Dec-12	Railroad wheat unit tariff from KS to TX
	rrw_ndor	Jan-09	Dec-12	Railroad wheat unit tariff from ND to OR
	rrw_ndtx	Jan-09	Dec-12	Railroad wheat unit tariff from ND to TX
	rrc_mnor	Jan-09	Dec-12	Railroad corn unit tariff from MN to OR
	rrs_sdwa	Jan-09	Dec-12	Railroad soybean unit tariff from SD to WA
	rrc_ilno	Jul-10	Apr-13	Railroad corn unit tariff from IL to NO
	rrc_dsmdvp	Jun-10	Apr-13	Railroad corn unit tariff from DSM to Davenport
	rrc_intn	Jun-10	Apr-13	Railroad corn unit tariff from IN to TN
	rrc_netx	Jun-10	Apr-13	Railroad corn unit tariff from NE to TX

Table 16. continued.

quarterly	fuel	Jan-02	Dec-12	American Railroad Association (ARR) Fuel index
	totalexclfuel	Jan-02	Dec-12	ARR Cost index of al inputs but fuel
	railroadcost	Jan-02	Dec-12	ARR Cost index of al inputs
	summer			Summer dummy variable
	fall			Fall dummy variable
	winter			Winter dummy variable

Table 17. Variable statistics

Frequency	Variable	Obs	Mean	Std. Dev	Min	Max
weekly	hoil	752	1.653965	.9099338	.2984	3.9435
	Level_Lock_15	750	7.338973	3.257307	2.67	22.29
	Level_Dub_IA	691	9.43741	2.633392	6.43	24.61
	Level_NO	740	6.530216	3.906012	1.24	17.04
	Level_Minn_MN	79	726.0089	1.382943	724.47	731.94
	Level_Lock_1	471	690.5071	3.620918	686.92	707.14
	Level_Quincy	748	12.66529	2.534144	8.71	29.76
	illrivr	751	316.6658	149.8966	115	1050
	diesel	558	189.5271	60.0172	89.46309	333.557
	unit	556	160.3496	43.35998	95.19223	234.2963
	shuttle	558	152.9056	34.99616	99.26523	240.342
	barge_illinois	556	203.529	78.97038	70	583.3333
	ocean_gulf	552	251.4452	105.2353	90.02683	630.5903
	ocean_pnw	552	244.4282	106.267	78.22695	659.5745
	twc	340	415.337	139.896	162	731.25
	mm	398	382.2276	141.9197	139	831
	ill	538	372.5618	140.1202	126	1050
	stlouis	539	316.1824	148.003	85	1150
	cinc	538	335.3301	152.7546	111	937.5
	loh	538	335.8902	153.3276	111	937.5
	carmem	537	288.8858	150.6934	88	1108.333
	memso	531	388.7893	197.6353	135	1422.526

Table 17. continued.

monthly	rexch_corn	519	94.28728	8.260909	76.2	113.3
	rexch_soybeans	519	85.34162	14.31317	56.2	106.8
	rexch_wheat	519	81.44644	15.98211	53	111.3
	rrs_ndwa	48	5009.438	463.4085	4201.5	5847.9
	rrs_mnor	48	5178.894	515.6183	4277.2	6088.9
	rrw_kstx	48	3261.585	338.786	2755.7	3914.9
	rrw_ndor	48	4910.538	434.8975	4193.4	5586.2
	rrw_ndtx	48	5889.296	481.1475	5121.3	6633
	rrc_mnor	48	4951.394	477.0677	4127.2	5558.9
	rrs_sdwa	48	5156.073	492.7511	4292.9	6035
	rrc_ilno	34	3117.433	169.6743	2848.02	3341.46
	rrc_dsmdvp	35	1983.576	71.1392	1879.21	2093.33
	rrc_intn	35	3159.319	331.4269	2652.91	3579.18
	rrc_netx	35	3534.253	185.906	3107.24	3715.08
quarterly	fuel	145	307.171	230.2819	95.1	1115
	totalexclfuel	144	259.7618	95.48318	96.8	456.8
	railroadcost	144	270.8882	113.8756	96.5	537.5

Table 18. Correlation between modal transportations

	diesel	shuttle	unit	barge_illinois	ocean_gulf	ocean_pnw
diesel	1					
shuttle	0.7781	1				
unit	0.8576	0.9362	1			
barge_illinois	0.6282	0.6026	0.5913	1		
ocean_gulf	0.4706	0.2343	0.1926	0.2882	1	
ocean_pnw	0.3326	0.0876	0.0288	0.2541	0.9435	1

Table 19. Correlation between different barge rates

	barge_illinois	twc	mm	ill	stlouis	cinc	loh	carmem
barge_illinois	1							
twc	0.9338	1						
mm	0.9848	0.9702	1					
ill	0.9999	0.9342	0.985	1				
stlouis	0.9617	0.8558	0.9347	0.9619	1			
cinc	0.9634	0.8807	0.9467	0.9637	0.9638	1		
loh	0.9628	0.879	0.9458	0.963	0.9647	0.9998	1	
carmem	0.9206	0.8015	0.888	0.9206	0.977	0.9526	0.9539	1

Table 20. Railroad rates correlation

	rrs_ndwa	rrs_mnor	rrw_kstx	rrw_ndor	rrw_ndtx	rrc_mnor	rrs_sdwa	rrc_ilno	rrc_dsmdvp	rrc_intn	rrc_netx
rrs_ndwa	1										
rrs_mnor	1.00	1									
rrw_kstx	0.84	0.83	1								
rrw_ndor	0.96	0.97	0.87	1							
rrw_ndtx	0.97	0.97	0.86	1.00	1						
rrc_mnor	0.94	0.95	0.75	0.96	0.96	1					
rrs_sdwa	1.00	1.00	0.83	0.96	0.97	0.95	1				
rrc_ilno	0.92	0.92	0.78	0.90	0.93	0.91	0.92	1			
rrc_dsmdvp	0.85	0.84	0.79	0.77	0.80	0.70	0.85	0.86	1		
rrc_intn	0.84	0.83	0.89	0.86	0.86	0.76	0.83	0.84	0.80	1	
rrc_netx	0.96	0.97	0.77	0.96	0.97	0.99	0.96	0.94	0.76	0.80	1

Table 21. ADF and KPPS tests

Frequency	Variable	ADF drift	ADF trend	ADF lags	ADF P value	KPSS P value
weekly	hoil	Yes		4	0.0842	<0.01
	Level_Lock_15			0	0.0000	<0.01
	Level_Dub_IA			0	0.0000	<0.01
	Level_NO			0	0.0000	<0.01
	Level_Minn_MN			0	0.0439	<0.01
	Level_Lock_1			0	0.0000	<0.01
	Level_Quincy			0	0.0000	<0.01
	illrivr			0	0.0003	<0.01
	diesel	Yes		4	0.0354	<0.01
	unit		Yes	4	0.0005	<0.01
	shuttle	Yes		0	0.0116	<0.01
	barge_illinois			0	0.0001	<0.01
	ocean_gulf	Yes		4	0.0054	<0.01
	ocean_pnw	Yes		4	0.0045	<0.01
	Twc			0	0.0274	<0.01
	Mm			0	0.0068	<0.01
	Ill			0	0.0001	<0.01
	Stlouis			0	0.0000	<0.01
	Cinc			0	0.0028	<0.01
	Loh			0	0.0023	<0.01
	Carmem			0	0.0000	<0.01
	Memso			0	0.0000	<0.01
monthly	Rer_corn	Yes		0	0.0076	<0.01
	Rer_soybeans	Yes		3	0.1093	<0.01
	Rer_wheat	Yes		3	0.1021	<0.01
	rrs_ndwa		Yes	0	0.0030	<0.01
	rrs_mnor		Yes	0	0.0018	<0.01
	rrw_kstx		Yes	0	0.062	<0.01
	rrw_ndor		Yes	0	0.0001	<0.01
	rrw_ndtx		Yes	0	0.0001	<0.01
	rrc_mnor		Yes	0	0.0144	<0.01
	rrs_sdwa		Yes	0	0.0020	<0.01
	rr_c_urbana_no	Yes		3	0.1060	<0.01
	rr_c_dsm_davenport		Yes	3	0.0014	<0.01
	rr_c_indi_tn	Yes		3	0.1174	<0.01
	rr_c_neb_ht	Yes		3	0.0456	<0.01
quarterly	Fuel	Yes		0	0.1807	<0.01
	Totalexclfuel	Yes		1	0.1190	<0.01
	Railroadcost		Yes	1	0.9966	<0.01

Table 22. 3SLS for Logs of Shuttle Railroad and Barge Rate Indexes of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_shuttle	0.660***	1.428***	1.325**	1.684***	1.634***	1.271***
levelcarlington_no	-0.232***	-0.053**	-0.058**	-0.037	-0.059**	-0.097***
summer		0.046	0.049	0.033	0.032	0.015
fall		0.296***	0.303***	0.259***	0.261***	0.296***
winter		0.130***	0.128***	0.089**	0.109***	0.197***
log_realexchangeratecorn			-0.138	-0.131	-0.080	-0.036
log_ocean_gulf				-0.492***		
log_ocean_pnw				0.234**		
log_gulf_pnw_ratio					-0.103***	-0.127***
log_diesel						0.788***
log_shuttle						
log_barge_illinois	0.167***	-0.009	0.102	0.239	0.099	-0.107
log_totalexclfuel	0.843***	0.493**	0.357**	0.228	0.325*	0.273**
summer		0.050	0.035	0.019	0.036	0.051***
fall		0.117	0.061	0.002	0.065	0.150***
winter		0.072	0.035	0.016	0.036	0.064***
log_realexchangeratecorn			-0.162*	-0.077	-0.163*	-0.237***
log_ocean_gulf				0.202***		
log_ocean_pnw				-0.086*		
log_gulf_pnw_ratio					0.032*	0.024
log_fuel						0.115**
bic	-1240.717	-1673.649	-1855.698	-2235.897	-1858.832	-1646.586
N	541	541	541	535	535	535

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23. 3SLS for Log of Unit Railroad and Barge Rate Indexes of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_unit	0.648***	0.681***	0.569***	0.724***	0.714***	0.743***
levelcarlington_no	-0.215***	-0.057**	-0.068***	-0.061***	-0.071***	-0.059***
summer		0.064**	0.069**	0.056*	0.055*	0.040
fall		0.362***	0.367***	0.338***	0.338***	0.357***
winter		0.162***	0.153***	0.126***	0.135***	0.195***
log_realexchangeratecorn			-0.315***	-0.333***	-0.306***	-0.194**
log_ocean_gulf				-0.385***		
log_ocean_pnw				0.269***		
log_gulf_pnw_ratio					-0.103***	-0.130***
log_diesel						0.537***
log_unit						
log_barge_illinois	0.265***	-0.158	-0.038	-0.002	-0.027	0.310***
log_totalexclfuel	0.800***	1.130***	0.985***	0.886***	0.903***	0.413***
summer		0.097**	0.080***	0.077***	0.080***	0.023*
fall		0.214	0.153*	0.141	0.152*	-0.028
winter		0.138**	0.099**	0.097**	0.101**	0.002
log_realexchangeratecorn			-0.170**	-0.138	-0.153*	-0.029
log_ocean_gulf				0.190***		
log_ocean_pnw				-0.173***		
log_gulf_pnw_ratio					0.060***	0.086***
log_fuel						0.127***
bic	-1362.746	-1580.448	-1673.549	-1696.510	-1679.716	-2119.094
N	539	539	539	533	533	533

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24. 3SLS for Log of Des Moines, IA to Davenport, IA Railroad and Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rr_c_dsm_davenport	-0.354***	1.138	1.315	2.399	1.294	-0.058
levelcarlington_no	-0.371***	-0.286*	-0.322**	-0.452**	-0.332**	-0.327***
summer		-0.315*	-0.361**	-0.456**	-0.368**	-0.254**
fall		0.370***	0.252***	0.183*	0.244**	0.251***
winter		0.121	0.038	0.072	0.042	0.041
log_realexchangeratecorn			-0.390***	-0.399***	-0.390***	-0.405***
log_ocean_gulf				0.291		
log_ocean_pnw				-0.119		
log_gulf_pnw_ratio					0.010	0.003
log_diesel						0.245
log_rr_c_dsm_davenport						
log_barge_illinois	-0.055	-0.487**	-0.425***	-0.418***	-0.423***	-0.093***
log_totalexclfuel	0.852***	0.170	0.173*	0.193**	0.186**	0.056***
summer		-0.048	-0.053	-0.038	-0.039	-0.082***
fall		0.211*	0.123	0.128*	0.132*	0.006
winter		0.025	-0.028	-0.004	-0.004	-0.052***
log_realexchangeratecorn			-0.215***	-0.206***	-0.206***	-0.070***
log_ocean_gulf				-0.060		
log_ocean_pnw				0.084		
log_gulf_pnw_ratio					-0.037	0.013
log_fuel						0.232***
bic	-793.969	-1084.961	-1107.534	-1017.152	-1096.425	-1364.230
N	142	142	142	141	141	141

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25. 10 3SLS for Log of Urbana, IL to New Orleans, LA Railroad and Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rr_c_urbana_no	-0.412***	0.629	0.857	2.077	0.811	-0.008
levelcarlington_no	-0.278***	-0.284	-0.372	-0.671	-0.377	-0.339***
Summer		-0.294	-0.383*	-0.607	-0.391*	-0.253***
Fall		0.381***	0.245**	0.079	0.234**	0.257***
winter		0.106	0.014	0.004	0.010	0.043
log_realexchangeratecorn			-0.361***	-0.432***	-0.364***	-0.333***
log_ocean_gulf				0.497		
log_ocean_pnw				-0.257		
log_gulf_pnw_ratio					0.024	0.007
log_diesel						0.217
log_rr_c_urbana_no						
log_barge_illinois	-0.430***	-1.339**	-1.076***	-1.033***	-1.075***	-0.241***
log_totalexclfuel	0.754***	0.283	0.292	0.418*	0.325	0.044
summer		-0.119	-0.121	-0.076	-0.090	-0.174***
fall		0.606	0.375*	0.359*	0.397*	0.053
winter		0.135	0.015	0.088	0.074	-0.056**
log_realexchangeratecorn			-0.356**	-0.338**	-0.338**	-0.082***
log_ocean_gulf				-0.008		
log_ocean_pnw				0.178		
log_gulf_pnw_ratio					-0.088	0.029
log_fuel						0.493***
bic	-744.703	-686.822	-685.983	-537.022	-684.065	-1026.079
N	137	137	137	136	136	136

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26. 3SLS for log of Indiana, IL to New Orleans, LA Railroad and Cincinnati Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_cinc						
log_rr_c_indi_tn	-0.430***	0.345	0.381	0.836**	0.394	0.033
levelcarlington_no	-0.400***	-0.112	-0.134*	-0.145*	-0.137*	-0.308***
summer		-0.096	-0.132	-0.074	-0.124	-0.144*
fall		0.615***	0.485***	0.500***	0.491***	0.409***
winter		0.114	0.017	0.141	0.037	0.014
log_realexchangeratecorn			-0.462***	-0.470***	-0.453***	-0.473***
log_ocean_gulf				0.399*		
log_ocean_pnw				0.005		
log_gulf_pnw_ratio					-0.024	0.017
log_diesel						0.348***
log_rr_c_indi_tn						
log_cinc	0.064	0.508	0.469	0.317*	0.457	-0.119
log_totalexclfuel	0.968***	0.520***	0.523***	0.399***	0.521***	0.744***
summer		-0.043	-0.040	-0.067	-0.045	-0.038
fall		-0.446*	-0.395**	-0.289***	-0.392**	-0.089*
winter		-0.161**	-0.137**	-0.168***	-0.145**	-0.109***
log_realexchangeratecorn			0.098	0.063	0.089	-0.198***
log_ocean_gulf				-0.232**		
log_ocean_pnw				0.008		
log_gulf_pnw_ratio					0.012	-0.032*
log_fuel						-0.156***
bic	-538.381	-698.869	-808.116	-825.008	-791.695	-729.643
N	142	142	142	141	141	141

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 27. 3SLS for Log of Indiana, IL to New Orleans, LA Railroad and Lower Ohio Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_loh						
log_rr_c_indi_tn	-0.431***	0.348	0.383	0.837**	0.396	0.035
levelcarlington_no	-0.400***	-0.112	-0.135*	-0.146*	-0.138*	-0.309***
summer		-0.098	-0.134	-0.077	-0.126	-0.147*
fall		0.613***	0.484***	0.498***	0.489***	0.406***
winter		0.113	0.015	0.139	0.034	0.011
log_realexchangeratecorn			-0.462***	-0.470***	-0.453***	-0.474***
log_ocean_gulf				0.399*		
log_ocean_pnw				0.004		
log_gulf_pnw_ratio					-0.024	0.018
log_diesel						0.348***
log_rr_c_indi_tn						
log_loh	0.064	0.505	0.467	0.316*	0.455	-0.118
log_totalexclfuel	0.968***	0.519***	0.523***	0.400***	0.521***	0.744***
summer		-0.042	-0.039	-0.066	-0.045	-0.038
fall		-0.443*	-0.393**	-0.288***	-0.390**	-0.089*
winter		-0.160**	-0.136**	-0.167***	-0.144**	-0.109***
log_realexchangeratecorn			0.097	0.062	0.088	-0.197***
log_ocean_gulf				-0.232**		
log_ocean_pnw				0.009		
log_gulf_pnw_ratio					0.012	-0.032*
log_fuel						-0.157***
bic	-538.347	-699.130	-808.897	-825.434	-792.380	-730.239
N	142	142	142	141	141	141

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 28. 3SLS for Log of Nebraska to Houston,TX Railroad and St Louis Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_stlouis						
log_rr_c_neb_ht	-0.187**	2.159	2.224	0.704***	2.120	-0.622
levelcarlington_no	-0.486***	-0.699**	-0.729**	-0.511***	-0.732***	-0.390***
summer		-0.697	-0.744	-0.304***	-0.753*	0.118
fall		0.172	0.067	0.096	0.053	0.419***
winter		-0.021	-0.098	-0.090	-0.114	0.136
log_realexchangeratecorn			-0.317*	-0.450***	-0.337**	-0.405***
log_ocean_gulf				0.345		
log_ocean_pnw				-0.100		
log_gulf_pnw_ratio					0.082	0.002
log_diesel						0.493**
log_rr_c_neb_ht						
log_stlouis	-0.188*	-0.755***	-0.684***	-0.741***	-0.687***	-0.053
log_totalexclfuel	0.806***	0.626***	0.607***	0.364*	0.633***	-0.029
summer		0.191**	0.167***	0.202***	0.192***	-0.003
fall		0.574***	0.432***	0.493***	0.450***	0.060
winter		0.236**	0.145*	0.141	0.188**	-0.015
log_realexchangeratecorn			-0.350***	-0.308***	-0.334***	-0.076
log_ocean_gulf				-0.425***		
log_ocean_pnw				0.210*		
log_gulf_pnw_ratio					-0.078	0.039
log_fuel						0.515***
bic	-562.110	-369.215	-408.290	-548.936	-406.048	-696.104
N	143	143	143	142	142	142

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 29. 3SLS for Log of Nebraska to Houston,TX Railroad and Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rr_c_neb_ht	-0.368***	0.513	0.595	8.948	0.583	-0.299
levelcarlington_no	-0.343***	-0.290	-0.328**	-2.453	-0.339**	-0.295***
summer		-0.384	-0.443*	-3.096	-0.450*	-0.134
fall		0.298**	0.166	-2.094	0.158	0.351**
winter		0.041	-0.057	-0.875	-0.051	0.130
log_realexchangeratecorn			-0.400***	-0.700	-0.401***	-0.396***
log_ocean_gulf				4.675		
log_ocean_pnw				-1.758		
log_gulf_pnw_ratio					0.013	0.001
log_diesel						0.426
log_rr_c_neb_ht						
log_barge_illinois	-0.251*	-1.128**	-0.989***	-1.104***	-0.995***	-0.116
log_totalexclfuel	0.758***	0.383	0.390*	0.281	0.422**	0.097
summer		0.016	0.007	0.014	0.038	-0.029
fall		0.626**	0.431**	0.531***	0.455**	0.109
winter		0.217	0.097	0.137	0.151	0.026
log_realexchangeratecorn			-0.480***	-0.464***	-0.463***	-0.103
log_ocean_gulf				-0.433**		
log_ocean_pnw				0.246		
log_gulf_pnw_ratio					-0.089	0.026
log_fuel						0.510***
bic	-646.151	-591.644	-613.130	-68.959	-602.602	-776.865
N	142	142	142	141	141	141

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 30. 3SLS for Log of Minneapolis to Oregon Railroad and Twin Cities Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_twc						
log_rrc_mnor	0.487^{***}	-0.292	-0.655^{**}	-0.778^{**}	-0.733^{**}	-0.166
levelcarlington_no	-0.077	0.177^{***}	0.265^{***}	0.298^{***}	0.297^{***}	0.274^{***}
summer		0.171^{***}	0.127^{**}	0.140^{**}	0.132^{**}	0.102^{*}
fall		0.517^{***}	0.419^{***}	0.438^{***}	0.431^{***}	0.386^{***}
o.winter		0.000	0.000	0.000	0.000	0.000
log_realexchangeratecorn			-0.764^{***}	-0.845^{***}	-0.798^{***}	-0.873^{***}
log_ocean_gulf				0.092		
log_ocean_pnw				-0.182		
log_gulf_pnw_ratio					0.082^{*}	0.043
log_diesel						-0.522^{**}
log_rrc_mnor						
log_twc	-0.827	0.655^{*}	0.614^{**}	0.530^{**}	0.534^{**}	-0.048
log_totalexclfuel	1.331^{*}	0.642^{***}	0.658^{***}	0.651^{***}	0.657^{***}	-0.117^{*}
summer		-0.017	-0.003	0.006	0.004	-0.076^{***}
fall		-0.227	-0.192^{**}	-0.164^{**}	-0.167^{**}	-0.029
o.winter		0.000	0.000	0.000	0.000	0.000
log_realexchangeratecorn			0.088	0.040	0.049	-0.096
log_ocean_gulf				-0.140		
log_ocean_pnw				0.159		
log_gulf_pnw_ratio					-0.053	0.016
log_fuel						0.805^{***}
bic	-458.286	-681.858	-661.079	-644.671	-657.307	-886.386
N	131	131	131	131	131	131

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 31. 3SLS for Logs of Minneapolis to Oregon Railroad and Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rrc_mnor	0.279***	0.243	-0.061	-0.204	-0.043	0.548**
levelcarlington_no	-0.270***	-0.072	-0.068	-0.049	-0.076	-0.077
summer		-0.009	-0.015	0.028	-0.018	-0.070
fall		0.462***	0.412***	0.452***	0.408***	0.464***
winter		0.289***	0.250***	0.229***	0.254***	0.305***
log_realexchangeratecorn			-0.358***	-0.426***	-0.351***	-0.140
log_ocean_gulf				-0.379**		
log_ocean_pnw				0.130		
log_gulf_pnw_ratio					-0.004	-0.001
log_diesel						0.264
log_rrc_mnor						
log_barge_illinois	-0.100	-2.450	-1.434	-1.525	-1.296	-0.022
log_totalexclfuel	0.943***	0.799	0.434*	0.305	0.453**	0.081
summer		0.195	0.096	0.140*	0.098	0.027
fall		1.371	0.713	0.790	0.656	0.029
winter		0.977	0.497	0.439	0.472*	-0.005
log_realexchangeratecorn			-0.566	-0.711	-0.510	-0.106
log_ocean_gulf				-0.703		
log_ocean_pnw				0.242		
log_gulf_pnw_ratio					-0.008	0.021
log_fuel						0.421***
bic	-731.306	-793.062	-1019.095	-1135.610	-982.656	-1036.710
N	203	203	203	201	201	201

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 32. 3SLS for Logs of North Dakota to Oregon Railroad and TWC Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
log_twc						
log_rrw_ndor	0.480***	0.620**	0.200	0.199	0.187	-0.259
levelcarlington_no	-0.063	0.215***	0.244***	0.243***	0.254***	0.185**
summer		0.131**	0.108*	0.114**	0.109*	0.115**
fall		0.656***	0.556***	0.564***	0.560***	0.579***
o.winter		0.000	0.000	0.000	0.000	0.000
log_realexchangeratewheat			-0.531***	-0.558***	-0.544***	-0.386***
log_ocean_gulf				-0.038		
log_ocean_pnw				0.000		
log_gulf_pnw_ratio					0.015	0.046
log_truck						0.652***
log_rrw_ndor						
log_twc	-0.314	0.505***	0.584***	0.573***	0.619***	0.301***
log_totalexclfuel	1.107***	0.296***	0.393***	0.395***	0.382***	0.225***
summer		-0.027	-0.009	0.002	-0.012	-0.049**
fall		-0.325***	-0.310***	-0.292***	-0.325***	-0.191***
o.winter		0.000	0.000	0.000	0.000	0.000
log_realexchangeratewheat			0.344***	0.297**	0.345***	0.214***
log_ocean_gulf				-0.074		
log_ocean_pnw				0.012		
log_gulf_pnw_ratio					0.019	0.017
log_fuel						0.372***
bic	-598.312	-950.751	-890.594	-890.078	-883.734	-909.922
N	131	131	131	131	131	131

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 33. 3SLS for Logs of North Dakota to Oregon Railroad and Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rrw_ndor	0.274***	-0.363	-0.452	-0.323	-0.321	0.722***
levelcarlington_no	-0.262***	0.070	0.069	0.064	0.028	-0.095*
summer		0.016	0.015	0.078	0.034	-0.021
fall		0.447***	0.433***	0.487***	0.444***	0.517***
winter		0.324***	0.308***	0.305***	0.335***	0.338***
log_realexchangeratewheat			-0.111	-0.079	-0.017	-0.035
log_ocean_gulf				-0.833***		
log_ocean_pnw				0.615***		
log_gulf_pnw_ratio					-0.132***	-0.141***
log_diesel						-0.064
log_rrw_ndor						
log_barge_illinois	0.012	3.616	8.061	6.831	0.362	-0.332
log_totalexclfuel	0.929***	0.994	2.147	1.505	0.526	0.153
summer		0.141	0.305	-0.137	0.061	-0.003
fall		-1.527	-3.238	-3.057	-0.157	0.125
winter		-0.962	-1.964	-1.785	-0.026	0.067
log_realexchangeratewheat			1.343	0.744	0.084	-0.041
log_ocean_gulf				4.628		
log_ocean_pnw				-3.713		
log_gulf_pnw_ratio					0.025	-0.020
log_fuel						0.476***
bic	-849.114	-752.618	-465.096	-667.440	-1016.286	-1041.978
N	203	203	203	201	201	201

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 34. 3SLS for Logs of North Dakota to Texas Railroad and TWC Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
log_twc						
log_rrw_ndtx	0.483***	0.608*	0.189	0.188	0.176	-0.224
levelcarlington_no	-0.055	0.220***	0.246***	0.246***	0.257***	0.178**
summer		0.134**	0.108*	0.115**	0.110*	0.114**
fall		0.646***	0.551***	0.560***	0.556***	0.586***
o.winter		0.000	0.000	0.000	0.000	0.000
log_realexchangeratewheat			-0.540***	-0.569***	-0.554***	-0.372***
log_ocean_gulf				-0.038		
log_ocean_pnw				-0.003		
log_gulf_pnw_ratio					0.017	0.043
log_diesel						0.647***
log_rrw_ndtx						
log_twc	-0.012	0.490***	0.579***	0.558***	0.600***	0.292***
log_totalexclfuel	0.963***	0.309***	0.418***	0.423***	0.412***	0.260***
summer		-0.028	-0.008	0.003	-0.010	-0.046**
fall		-0.298***	-0.281***	-0.260***	-0.290***	-0.160***
o.winter		0.000	0.000	0.000	0.000	0.000
log_realexchangeratewheat			0.388***	0.345***	0.389***	0.261***
log_ocean_gulf				-0.082		
log_ocean_pnw				0.030		
log_gulf_pnw_ratio					0.011	0.009
log_fuel						0.358***
bic	-654.418	-968.665	-915.024	-910.596	-905.801	-936.296
N	131	131	131	131	131	131

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 35. 3SLS for Log of North Dakota to Texas Railroad and Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rrw_ndtx	0.275***	-0.359	-0.438	-0.313	-0.311	0.704***
levelcarlington_no	-0.260***	0.071	0.069	0.064	0.028	-0.104*
summer		0.013	0.013	0.075	0.032	-0.024
fall		0.453***	0.441***	0.492***	0.450***	0.486***
winter		0.326***	0.312***	0.309***	0.338***	0.319***
log_realexchangeratewheat			-0.100	-0.069	-0.010	-0.069
log_ocean_gulf				-0.823***		
log_ocean_pnw				0.610***		
log_gulf_pnw_ratio					-0.132***	-0.146***
log_diesel						-0.124
log_rrw_ndtx						
log_barge_illinois	0.038	3.677	8.376	6.980	0.467	-0.406
log_totalexclfuel	0.920***	1.009	2.228	1.543	0.557	0.197
summer		0.137	0.311	-0.148	0.056	-0.002
fall		-1.536	-3.346	-3.106	-0.183	0.185
winter		-0.972	-2.032	-1.812	-0.046	0.113*
log_realexchangeratewheat			1.420	0.791	0.116	-0.008
log_ocean_gulf				4.761		
log_ocean_pnw				-3.806		
log_gulf_pnw_ratio					0.037	-0.032
log_fuel						0.461***
bic	-879.490	-803.852	-518.173	-721.387	-1057.815	-1076.718
N	203	203	203	201	201	201

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 36. 3SLS for Logs of Kansas to Texas Railroad and MM Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
log_mm						
log_rrw_kstx	0.408***	-0.075	-0.149	-0.136	-0.139	-0.201
levelcarlington_no	-0.091	0.255***	0.237***	0.220***	0.227***	0.175***
summer		0.082	0.076	0.082	0.075	0.097*
fall		0.630***	0.600***	0.601***	0.596***	0.651***
winter		0.094**	0.088**	0.087**	0.086**	0.104***
log_realexchangeratewheat			-0.192*	-0.197	-0.175	-0.060
log_ocean_gulf				-0.132		
log_ocean_pnw				0.108		
log_gulf_pnw_ratio					-0.021	-0.002
log_diesel						0.366***
log_rrw_kstx						
log_mm	0.661	0.135	0.235**	0.274**	0.323**	0.332**
log_totalexclfuel	0.684***	0.836***	0.916***	0.908***	0.909***	1.003***
summer		0.180***	0.198***	0.205***	0.191***	0.209***
fall		0.045	0.032	0.024	-0.014	-0.014
winter		0.055***	0.059***	0.058***	0.053***	0.075***
log_realexchangeratewheat			0.233***	0.168**	0.213***	0.218***
log_ocean_gulf				-0.044		
log_ocean_pnw				-0.039		
log_gulf_pnw_ratio					0.042*	0.039*
log_fuel						-0.140*
bic	-762.423	-931.519	-933.211	-934.924	-925.580	-928.306
N	148	148	148	148	148	148

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 37. 3SLS for Logs of Kansas to Texas Railroad and Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rrw_kstx	0.278***	-0.212	-0.274	-0.195	-0.194	-0.151
levelcarlington_no	-0.237***	0.034	0.021	0.026	-0.004**	-0.064
summer		0.023	0.024	0.079	0.041	0.055
fall		0.452***	0.437***	0.484***	0.447***	0.525***
winter		0.320***	0.299***	0.302***	0.329***	0.386***
log_realexchangeratewheat			-0.132	-0.086	-0.032	0.037
log_ocean_gulf				-0.774***		
log_ocean_pnw				0.591***		
log_gulf_pnw_ratio					-0.131***	-0.102**
log_diesel						0.441***
log_rrw_kstx						
log_barge_illinois	0.357***	0.479	1.536	1.562	-0.918	0.389
log_totalexclfuel	0.827***	0.811***	1.085	1.013	0.639**	0.747***
summer		0.187***	0.226	0.148	0.190	0.166***
fall		-0.115	-0.522	-0.591	0.495	-0.084
winter		-0.005	-0.243	-0.289	0.427	0.003
log_realexchangeratewheat			0.319	0.223	0.045	0.084
log_ocean_gulf				0.887		
log_ocean_pnw				-0.754		
log_gulf_pnw_ratio					-0.135	0.040
log_fuel						0.073
bic	-901.667	-1090.884	-983.384	-1054.118	-1198.685	-1108.055
N	203	203	203	201	201	201

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 38. 3SLS for Logs of North Dakota to Washington State Railroad and Barge Rates of Soybeans

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rrs_ndwa	0.279***	0.266	0.135	-0.000	0.148	0.731**
levelcarlington_no	-0.259***	-0.069	-0.105**	-0.099**	-0.110**	-0.102*
summer		-0.007	-0.032	0.000	-0.034	-0.065
fall		0.452***	0.414***	0.452***	0.411***	0.425***
winter		0.289***	0.267***	0.249***	0.271***	0.296***
log_realexchangeratesoybeans			-0.404*	-0.526**	-0.390*	-0.048
log_ocean_gulf				-0.333**		
log_ocean_pnw				0.102		
log_gulf_pnw_ratio					-0.004	-0.024
log_diesel						0.131
log_rrs_ndwa						
log_barge_illinois	0.052	-2.000	-0.521	-0.520*	-0.480	-0.117
log_totalexclfuel	0.903***	0.701	0.435***	0.369***	0.421***	0.161***
summer		0.163	0.069**	0.084***	0.064**	0.015
fall		1.170	0.346*	0.361**	0.322*	0.122
winter		0.814	0.265**	0.222**	0.247**	0.051
log_realexchangeratesoybeans			-0.575***	-0.657***	-0.563***	-0.329***
log_ocean_gulf				-0.239*		
log_ocean_pnw				0.016		
log_gulf_pnw_ratio					0.023	0.037**
log_fuel						0.326***
bic	-813.254	-895.029	-1068.225	-1105.497	-1046.231	-1111.822
N	203	203	203	201	201	201

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 39. 3SLS for Logs of South Dakota to Washington State Railroad and Barge Rates of Soybeans

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rrs_sdwa	0.279***	0.248	0.126	-0.000	0.139	0.684**
levelcarlington_no	-0.259***	-0.068	-0.104**	-0.099**	-0.110**	-0.102*
summer		-0.006	-0.032	0.000	-0.033	-0.064
fall		0.452***	0.414***	0.452***	0.411***	0.423***
winter		0.290***	0.267***	0.249***	0.272***	0.297***
log_realexchangeratesoybeans			-0.403*	-0.526**	-0.389*	-0.046
log_ocean_gulf				-0.333**		
log_ocean_pnw				0.102		
log_gulf_pnw_ratio					-0.004	-0.025
log_diesel						0.126
log_rrs_sdwa						
log_barge_illinois	0.051	-2.069	-0.513	-0.514	-0.472	-0.123
log_totalexclfuel	0.902***	0.744	0.464***	0.394***	0.448***	0.182***
summer		0.170	0.072**	0.087***	0.065**	0.014
fall		1.219	0.352*	0.368**	0.327*	0.134
winter		0.846	0.268**	0.223**	0.248**	0.055
log_realexchangeratesoybeans			-0.605***	-0.693***	-0.594***	-0.360***
log_ocean_gulf				-0.245*		
log_ocean_pnw				0.009		
log_gulf_pnw_ratio					0.026	0.041**
log_fuel						0.342***
bic	-794.692	-868.869	-1041.502	-1080.498	-1019.998	-1085.741
N	203	203	203	201	201	201

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 40. 3SLS for Logs of Minnesota to Oregon Railroad and Barge Rates of Soybeans

	(1)	(2)	(3)	(4)	(5)	(6)
log_barge_illinois						
log_rrs_mnor	0.279***	0.260	0.132	-0.000	0.145	0.705**
levelcarlington_no	-0.261***	-0.070	-0.105**	-0.099**	-0.111**	-0.107*
summer		-0.009	-0.033	0.000	-0.035	-0.072
fall		0.453***	0.414***	0.452***	0.411***	0.423***
winter		0.289***	0.267***	0.249***	0.271***	0.291***
log_realexchangeratesoybeans			-0.404*	-0.526**	-0.390*	-0.067
log_ocean_gulf				-0.333**		
log_ocean_pnw				0.102		
log_gulf_pnw_ratio					-0.004	-0.024
log_diesel						0.112
log_rrs_mnor						
log_barge_illinois	0.033	-2.112	-0.563	-0.563*	-0.518	-0.145
log_totalexclfuel	0.906***	0.726	0.447***	0.375***	0.433***	0.155**
summer		0.177	0.079**	0.096***	0.073**	0.020
fall		1.228	0.365*	0.383**	0.339*	0.133
winter		0.857	0.281**	0.236**	0.263**	0.057
log_realexchangeratesoybeans			-0.603***	-0.695***	-0.589***	-0.340***
log_ocean_gulf				-0.275*		
log_ocean_pnw				0.026		
log_gulf_pnw_ratio					0.023	0.039**
log_fuel						0.358***
bic	-767.533	-832.092	-1005.714	-1048.164	-984.111	-1046.715
N	203	203	203	201	201	201

Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 41. 3SLS for Logs of Minnesota to Oregon Railroad and TWC Barge Rates of Soybeans

	(1)	(2)	(3)	(4)	(5)	(6)
log_twc						
log_rrs_ndwa	0.492***	0.334***	1.224	1.082	1.170	-0.452
levelcarlington_no	-0.049	0.201	0.219**	0.249***	0.231**	0.155**
q1		-0.209**	-0.260***	-0.245**	-0.261***	-0.088
q2		-0.625***	-0.772***	-0.759***	-0.776***	-0.327***
q3		-0.321**	-0.471**	-0.448**	-0.479***	-0.118
log_realexchangeratesoybeans			0.236	0.186	0.182	-0.907***
log_ocean_gulf				0.252		
log_ocean_pnw				-0.223		
log_gulf_pnw_ratio					0.055	0.056
log_diesel						-0.564***
log_rrs_ndwa						
log_twc	0.235	0.043	-0.101	-0.024	-0.072	-0.240*
log_totalexclfuel	0.831***	-0.072	0.443***	0.381**	0.420***	0.122
q1		0.054*	-0.001	0.024	0.005	-0.031
q2		0.198**	-0.054	0.009	-0.035	-0.129
q3		0.246***	-0.079	-0.025	-0.067	-0.140*
log_realexchangeratesoybeans			-0.561***	-0.514***	-0.560***	-0.401***
log_ocean_gulf				0.107		
log_ocean_pnw				-0.088		
log_gulf_pnw_ratio					0.024	0.042**
log_fuel						0.429***
bic	-654.020	-785.185	-772.423	-783.951	-775.641	-917.825
N	131	131	131	131	131	131

Table 42. 3SLS for Logs of South Dakota to WA Railroad and St Louis Barge Rates of Soybeans

	(1)	(2)	(3)	(4)	(5)	(6)
log_stlouis						
log_rrs_sdwa	0.249***	1.106	1.269	1.250	1.547	0.247
levelcarlington_no	-0.382***	-0.144**	-0.135	-0.144	-0.134	-0.173**
q1		-0.213***	-0.219*	-0.231***	-0.218	-0.171***
q2		-0.571***	-0.595	-0.595	-0.628	-0.450***
q3		-0.238	-0.255	-0.257	-0.286	-0.122
log_realexchangeratesoybeans			0.091	0.070	0.214	-0.295
log_ocean_gulf				-0.192		
log_ocean_pnw				0.134		
log_gulf_pnw_ratio					-0.037	0.011
log_diesel						0.001
log_rrs_sdwa						
log_stlouis	0.035	-0.093	0.174	0.170	0.168	0.193
log_totalexclfuel	0.908***	-0.252***	-0.070	-0.039	-0.065	-0.088
q1		0.046	0.073*	0.047	0.074*	0.026
q2		0.161*	0.233***	0.213**	0.228***	0.197***
q3		0.271***	0.176***	0.148***	0.167***	0.103**
log_realexchangeratesoybeans			-0.280***	-0.340***	-0.305***	-0.233***
log_ocean_gulf				-0.016		
log_ocean_pnw				-0.070		
log_gulf_pnw_ratio					0.033	0.031
log_fuel						0.279***
bic	-698.640	-861.733	-1011.883	-1009.188	-1012.803	-965.317
N	204	204	204	202	202	202

Table 43. 3SLS for Logs of Minnesota to Oregon Railroad and TWC Barge Rates of Soybeans

	(1)	(2)	(3)	(4)	(5)	(6)
log_twc						
log_rrs_mnor	0.490***	-1.520	1.497	1.340	1.435	-0.468
levelcarlington_no	-0.054	0.235*	0.224**	0.251***	0.235**	0.155**
q1		-0.136	-0.287**	-0.271**	-0.287**	-0.084
q2		-0.338	-0.842***	-0.823***	-0.843***	-0.315***
q3		0.085	-0.534**	-0.507*	-0.539**	-0.108
log_realexchangeratesoybeans			0.359	0.299	0.303	-0.919***
log_ocean_gulf				0.228		
log_ocean_pnw				-0.205		
log_gulf_pnw_ratio					0.051	0.056
log_diesel						-0.568***
log_rrs_mnor						
log_twc	0.048	0.050	-0.101	-0.025	-0.072	-0.243*
log_totalexclfuel	0.921***	-0.106	0.371**	0.310**	0.349**	0.047
q1		0.065**	0.013	0.037	0.019	-0.019
q2		0.231***	-0.011	0.052	0.008	-0.092
q3		0.278***	-0.032	0.022	-0.020	-0.099
log_realexchangeratesoybeans			-0.547***	-0.501***	-0.547***	-0.381***
log_ocean_gulf				0.106		
log_ocean_pnw				-0.086		
log_gulf_pnw_ratio					0.023	0.042**
log_fuel						0.450***
bic	-602.564	-734.248	-740.313	-756.172	-744.932	-901.729
N	131	131	131	131	131	131

6. Appendix

Table 44. 3SLS for Shuttle Railroad and Barge Rate Indexes of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
barge_illinois						
shuttle	0.733***	-17.789	-1.909	-2.009	-1.890	2.894**
levelcarlington_no	-0.274***	-0.157	-0.104*	-0.125	-0.108*	-0.143***
summer		1.081	0.213	0.213	0.210	-0.083
fall		2.195	0.630***	0.650**	0.628**	0.160
winter		0.884	0.194**	0.220*	0.196**	0.152***
realexchangeratecorn			-0.982	-0.890	-0.974	0.468
ocean_gulf				0.389		
ocean_pnw				-0.157		
gulf_pnw_ratio					0.024	-0.161**
diesel						0.953***
shuttle						
barge_illinois	-0.110	0.088	0.190	0.278	0.180	-0.141*
totalexclfuel	0.615***	-0.013	-0.033	-0.036*	-0.033	0.012
summer		0.043	0.027	0.016	0.029	0.054***
fall		0.056	0.005	-0.029	0.015	0.161***
winter		0.026	0.001	-0.003	0.006	0.048**
realexchangeratecorn			-0.181*	-0.093	-0.183*	-0.283***
ocean_gulf				0.166***		
ocean_pnw				-0.055		
gulf_pnw_ratio					0.038**	0.029
fuel						0.119**
bic	11382.567	10929.817	10176.254	10224.813	10060.379	9980.149
N	548	548	545	539	539	539

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 45. 3SLS for Unit Railroad and Barge Rate Indexes of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
barge_illinois						
unit	0.730***	0.652*	-5.137	-5.230	-5.062	1.635***
levelcarlington_no	-0.250***	-0.062	-0.116	-0.149	-0.117	-0.033
summer		0.083	0.538	0.542	0.530	-0.005
fall		0.420	0.896	0.976	0.924	0.334***
winter		0.163	0.213	0.301	0.266	0.146***
realexchangeratecorn			-1.796	-1.440	-1.679	-0.015
ocean_gulf				1.340		
ocean_pnw				-1.170		
gulf_pnw_ratio					0.332	-0.159***
diesel						0.249
unit						
barge_illinois	0.011	-0.023	0.104	0.165	0.090	0.389***
totalexclfuel	0.568***	-0.004	-0.015	-0.018	-0.014	-0.002
summer		0.089**	0.069***	0.062***	0.071***	0.017
fall		0.102	0.039	0.024	0.053	-0.103***
winter		0.030	-0.001	0.005	0.012	-0.042***
realexchangeratecorn			-0.212***	-0.117	-0.199***	-0.048
ocean_gulf				0.242***		
ocean_pnw				-0.211***		
gulf_pnw_ratio					0.075***	0.085***
fuel						0.055
bic	11501.209	9838.987	10219.257	10306.356	10031.371	8340.641
N	546	546	543	537	537	537

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 46. 3SLS for Des Moines, IA to Davenport, IA Railroad and Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
barge_illinois						
rr_c_dsm_davenport	-1.178	6.610**	5.022	7.096	5.607	-0.079
levelcarlington_no	-0.516***	-0.707***	-0.601**	-0.846*	-0.664**	-0.331***
summer		-0.705**	-0.609**	-0.814*	-0.704**	-0.220**
fall		0.395***	0.305**	0.133	0.286**	0.260***
winter		0.360**	0.227	0.228	0.220	0.059
realexchangeratecorn			-0.269	-0.327*	-0.273	-0.445***
ocean_gulf				0.849		
ocean_pnw				-0.476		
gulf_pnw_ratio					0.111	0.007
diesel						0.198
rr_c_dsm_davenport						
barge_illinois	0.485	-0.349***	-0.313***	-0.322***	-0.303***	-0.057*
totalexclfuel	-0.220*	0.105***	0.066***	0.062**	0.062***	0.018**
summer		-0.009	-0.012	-0.009	-0.004	-0.071***
fall		0.109	0.050	0.064	0.049	-0.023
winter		-0.031	-0.068**	-0.054*	-0.058**	-0.068***
realexchangeratecorn			-0.164***	-0.158***	-0.156***	-0.060***
ocean_gulf				-0.070		
ocean_pnw				0.050		
gulf_pnw_ratio					-0.015	0.014*
fuel						0.213***
bic	3338.844	2913.903	2821.578	2881.282	2823.720	2404.819
N	146	146	146	145	145	145

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 47. 3SLS for Urbana, IL to New Orleans, LA Railroad and Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
barge_illinois						
rr_c_urbana_no	-2.506	22.017	9.177	-147.224	17.562	-0.107
levelcarlington_no	-0.335*	-4.270	-1.953	29.590	-3.627	-0.341***
summer		-3.642	-1.709	25.647	-3.416	-0.210**
fall		0.141	0.063	8.921	-0.293	0.259***
winter		0.977	0.285	-0.667	0.213	0.058
realexchangeratecorn			-0.605	6.201	-1.021	-0.392***
ocean_gulf				-27.204		
ocean_pnw				20.074		
gulf_pnw_ratio					0.822	0.011
diesel						0.191
rr_c_urbana_no						
barge_illinois	0.058	-0.981**	-0.832***	-0.800***	-0.804***	-0.206***
totalexclfuel	-0.080	0.223**	0.133**	0.122*	0.122*	-0.002
summer		-0.042	-0.045	-0.020	-0.026	-0.162***
fall		0.360*	0.215*	0.204*	0.210*	0.019
winter		0.014	-0.065	-0.037	-0.039	-0.071***
realexchangeratecorn			-0.273**	-0.254**	-0.254**	-0.083***
ocean_gulf				-0.058		
ocean_pnw				0.095		
gulf_pnw_ratio					-0.035	0.030*
fuel						0.456***
bic	3374.103	3805.317	3524.909	4238.654	3663.122	2736.282
N	141	141	141	140	140	140

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 48. 3SLS for Indiana, IN to New Orleans, LA Railroad and Cincinnati Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
cinc						
rr_c_indi_tn	-2.391	1.594**	1.049	1.411	1.033	0.904
levelcarlington_no	-0.821*	0.051	-0.031	-0.071	-0.040	-0.185
summer		-0.032	-0.087	-0.039	-0.091	-0.113
fall		1.033***	0.760***	0.695**	0.750***	0.703***
winter		0.475**	0.244	0.312	0.243	0.252
realexchangeratecorn			-0.332**	-0.389**	-0.333**	-0.331**
ocean_gulf				0.590*		
ocean_pnw				-0.082		
gulf_pnw_ratio					0.001	0.027
diesel						0.230
rr_c_indi_tn						
cinc	0.701*	0.850*	0.774**	0.459**	0.744**	0.391**
totalexclfuel	-0.235	-0.040	0.016	0.027	0.021	0.053
summer		0.048	0.054	-0.014	0.049	0.058
fall		-0.762**	-0.657***	-0.418***	-0.645***	-0.478***
winter		-0.300***	-0.249***	-0.251***	-0.258***	-0.271***
realexchangeratecorn			0.230	0.145	0.213	0.046
ocean_gulf				-0.351***		
ocean_pnw				0.033		
gulf_pnw_ratio					0.007	0.004
fuel						-0.085*
bic	4145.336	3198.228	2964.459	3117.983	3013.027	3310.100
N	146	146	146	145	145	145

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 49. 3SLS for Indiana, IL to New Orleans, LA Railroad and Lower Ohio Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
loh						
rr_c_indi_tn	-2.391	1.600**	1.056	1.419	1.040	0.912
levelcarlington_no	-0.821*	0.051	-0.031	-0.071	-0.040	-0.185
summer		-0.034	-0.089	-0.041	-0.093	-0.115
fall		1.032***	0.760***	0.695**	0.750***	0.703***
winter		0.474**	0.243	0.312	0.243	0.252
realexchangeratecorn			-0.331**	-0.388**	-0.332**	-0.330**
ocean_gulf				0.592*		
ocean_pnw				-0.083		
gulf_pnw_ratio					0.001	0.027
diesel						0.230
rr_c_indi_tn						
loh	0.702*	0.847*	0.772**	0.458**	0.742**	0.390**
totalexclfuel	-0.236	-0.041	0.016	0.026	0.021	0.053
summer		0.050	0.056	-0.012	0.050	0.059
fall		-0.759**	-0.655***	-0.417***	-0.642***	-0.476***
winter		-0.297***	-0.248***	-0.250***	-0.256***	-0.270***
realexchangeratecorn			0.229	0.144	0.212	0.046
ocean_gulf				-0.351***		
ocean_pnw				0.033		
gulf_pnw_ratio					0.006	0.004
fuel						-0.085*
bic	4145.784	3198.647	2959.253	3115.606	3008.522	3308.915
N	146	146	146	145	145	145

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 50. 3SLS for Nebraska to Houston, TX Railroad and St Louis Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
stlouis						
rr_c_neb_ht	-17.919	13.015	-5.274	-3.024	-4.264	-1.518***
levelcarlington_no	-1.855	-1.763	0.250	0.050	0.159	-0.290***
q1		0.607	-0.563	-0.549	-0.525	-0.400***
q2		-3.809	1.310	0.525	1.017	0.044
q3		-4.059	1.541	0.701	1.250	0.199
realexchangeratecorn			-1.071	-0.719***	-0.909	-0.585***
ocean_gulf				-0.745		
ocean_pnw				0.483		
gulf_pnw_ratio					-0.211	-0.039
diesel						0.482***
rr_c_neb_ht						
stlouis	0.164	-0.430***	-0.346***	-0.380***	-0.353***	-0.110
totalexclfuel	-0.031	0.099**	0.013	0.005	0.010	-0.055**
q1		-0.200**	-0.148**	-0.190***	-0.152***	-0.114***
q2		0.081	0.205***	0.165***	0.207***	0.203***
q3		0.253***	0.278***	0.233***	0.283***	0.120**
realexchangeratecorn			-0.270***	-0.260***	-0.263***	-0.199***
ocean_gulf				-0.237**		
ocean_pnw				0.164**		
gulf_pnw_ratio					-0.056*	-0.022
fuel						0.309***
bic	4123.846	3975.571	3335.820	2818.800	3177.900	3268.144
N	147	147	147	146	146	146

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 51. 3SLS for Nebraska to Houston, TX Railroad and Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
barge_illinois						
rr_c_neb_ht	-17.036	9.139	10.999	-7.353	29.307	-0.532
levelcarlington_no	-1.633	-1.892	-2.223	1.483	-5.704	-0.291***
summer		-2.950	-3.487	1.965	-9.500	-0.030
fall		-0.678	-0.820	1.876	-2.883	0.393***
winter		-0.261	-0.274	0.519	-1.196	0.179
realexchangeratecorn			0.228	-0.298	1.006	-0.428***
ocean_gulf				-3.404		
ocean_pnw				1.254		
gulf_pnw_ratio					1.408	0.004
diesel						0.472**
rr_c_neb_ht						
barge_illinois	0.233	-0.859***	-0.774***	-0.918***	-0.757***	-0.058
totalexclfuel	-0.048	0.202**	0.112*	0.105	0.102	-0.014
summer		0.098	0.091	0.059	0.111	-0.024
fall		0.401**	0.262**	0.394***	0.262**	0.044
winter		0.074	-0.014	0.034	0.010	-0.020
realexchangeratecorn			-0.389***	-0.386***	-0.371***	-0.097
ocean_gulf				-0.378**		
ocean_pnw				0.142		
gulf_pnw_ratio					-0.039	0.028
fuel						0.496***
bic	3968.268	3861.770	3863.717	3686.251	4104.239	3146.429
N	146	146	146	145	145	145

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 52. 3SLS for Minneapolis to Oregon Railroad and Twin Cities Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
twc						
rrc_mnor	0.428***	-0.431	-0.769**	-0.880**	-0.893**	-0.383
levelcarlington_no	-0.091	0.177***	0.258***	0.298***	0.303***	0.292***
summer		0.154**	0.114*	0.117*	0.121**	0.085
fall		0.500***	0.405***	0.422***	0.417***	0.384***
o.winter		0.000	0.000	0.000	0.000	0.000
realexchangeratecorn			-0.680***	-0.721***	-0.738***	-0.772***
ocean_gulf				0.192		
ocean_pnw				-0.271*		
gulf_pnw_ratio					0.105**	0.080*
diesel						-0.421*
rrc_mnor						
twc	-0.735	0.751	0.711*	0.567*	0.592**	-0.026
totalexclfuel	1.247**	0.669***	0.680***	0.637***	0.676***	-0.036
summer		-0.014	-0.002	0.017	0.006	-0.099***
fall		-0.274	-0.243**	-0.193**	-0.202**	-0.044
o.winter		0.000	0.000	0.000	0.000	0.000
realexchangeratecorn			0.076	-0.028	0.036	-0.133**
ocean_gulf				-0.258*		
ocean_pnw				0.251*		
gulf_pnw_ratio					-0.069	0.016
fuel						0.716***
bic	3373.178	3188.125	3211.495	3215.501	3212.627	2967.703
N	131	131	131	131	131	131

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 53. 3SLS for Minneapolis to Oregon Railroad and Barge Rates of Corn

	(1)	(2)	(3)	(4)	(5)	(6)
barge_illinois						
rrc_mnor	0.250***	0.327	0.090	-0.097	0.091	0.537*
levelcarlington_no	-0.290***	-0.091	-0.085	-0.065	-0.091	-0.115**
summer		-0.043	-0.048	-0.011	-0.051	-0.105
fall		0.440***	0.400***	0.432***	0.396***	0.374***
winter		0.257***	0.225***	0.216***	0.230***	0.206***
realexchangeratecorn			-0.275**	-0.349**	-0.273**	-0.247*
ocean_gulf				-0.279*		
ocean_pnw				0.063		
gulf_pnw_ratio					0.005	-0.010
diesel						-0.118
rrc_mnor						
barge_illinois	-0.110	-2.222	-1.512	-1.492	-1.362	-0.250
totalexclfuel	0.944***	0.822	0.514*	0.348	0.512*	0.131*
summer		0.141	0.075	0.103	0.076	-0.006
fall		1.219	0.746	0.757	0.679	0.136
winter		0.837	0.499	0.422	0.469	0.060
realexchangeratecorn			-0.484	-0.603	-0.438	-0.162**
ocean_gulf				-0.578*		
ocean_pnw				0.151		
gulf_pnw_ratio					0.005	0.025
fuel						0.481***
bic	4926.892	4897.905	4732.699	4564.491	4693.923	4610.742
N	203	203	203	201	201	201

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 54. 3SLS for North Dakota to Oregon Railroad and Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
barge_illinois						
rrw_ndor	0.246***	-0.222	-0.340	-0.221	-0.197	0.769***
levelcarlington_no	-0.282***	0.039	0.037	0.023	-0.021	-0.074
summer		-0.012	-0.013	0.044	-0.004	-0.069
fall		0.448***	0.429***	0.477***	0.432***	0.464***
winter		0.296***	0.274***	0.293***	0.297***	0.271***
realexchangeratewheat			-0.152	-0.115	-0.067	-0.107
ocean_gulf				-0.663***		
ocean_pnw				0.519***		
gulf_pnw_ratio					-0.117***	-0.140***
diesel						-0.321**
rrw_ndor						
barge_illinois	0.001	8.089	-25.078	-18.371	-0.322	-0.879*
totalexclfuel	0.934***	1.205	-3.476	-1.442	0.483	0.264
summer		0.333	-1.022	0.440	0.062	-0.033
fall		-3.524	10.364	8.512	0.150	0.427**
winter		-2.164	6.098	5.102	0.180	0.250**
realexchangeratewheat			-4.555	-2.298	0.071	-0.079
ocean_gulf				-11.176		
ocean_pnw				9.077		
gulf_pnw_ratio					-0.059	-0.076
fuel						0.594***
bic	4806.308	4991.221	5396.519	4941.314	4527.302	4675.784
N	203	203	203	201	201	201

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 55. 3SLS for North Dakota to Texas Railroad and Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
barge_illinois						
rrw_ndtx	0.247^{***}	-0.218	-0.327	-0.213	-0.190	0.718^{***}
levelcarlington_no	-0.280^{***}	0.039	0.037	0.023	-0.021	-0.073
summer		-0.014	-0.016	0.042	-0.005	-0.066
fall		0.452^{***}	0.436^{***}	0.481^{***}	0.436^{***}	0.443^{***}
winter		0.298^{***}	0.278^{***}	0.296^{***}	0.299^{***}	0.260^{***}
realexchangeratewheat			-0.144	-0.108	-0.062	-0.129
ocean_gulf				-0.655^{***}		
ocean_pnw				0.516^{***}		
gulf_pnw_ratio					-0.117^{***}	-0.140^{***}
diesel						-0.332^{**}
rrw_ndtx						
barge_illinois	0.027	8.132	-25.810	-18.630	-0.352	-1.007^{**}
totalexclfuel	0.926^{***}	1.217	-3.574	-1.451	0.499	0.309
summer		0.329	-1.057	0.439	0.058	-0.032
fall		-3.524	10.687	8.651	0.185	0.514^{**}
winter		-2.167	6.288	5.188	0.203	0.313^{***}
realexchangeratewheat			-4.661	-2.297	0.098	-0.050
ocean_gulf				-11.302		
ocean_pnw				9.192		
gulf_pnw_ratio					-0.063	-0.094^{*}
fuel						0.575^{**}
bic	4849.333	5007.736	5409.570	4949.477	4546.222	4705.856
N	203	203	203	201	201	201

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 56. 3SLS for North Dakota to Texas Railroad and TWC Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
twc						
rrw_ndtx	0.424***	0.597*	0.162	0.153	0.132	-0.294
levelcarlington_no	-0.070	0.194**	0.218***	0.226**	0.239***	0.125
summer		0.108*	0.076	0.081	0.080	0.098
fall		0.642***	0.540***	0.552***	0.549***	0.585***
o.winter		0.000	0.000	0.000	0.000	0.000
realexchangeratewheat			-0.576***	-0.621***	-0.605***	-0.440***
ocean_gulf				-0.012		
ocean_pnw				-0.043		
gulf_pnw_ratio					0.033	0.047
diesel						0.705***
rrw_ndtx						
twc	-0.051	0.543***	0.669***	0.633***	0.671***	0.314***
totalexclfuel	0.978***	0.299***	0.423***	0.432***	0.422***	0.315***
summer		-0.024	0.002	0.011	0.002	-0.050**
fall		-0.332***	-0.322***	-0.296***	-0.323***	-0.161***
o.winter		0.000	0.000	0.000	0.000	0.000
realexchangeratewheat			0.470***	0.421**	0.470***	0.289***
ocean_gulf				-0.091		
ocean_pnw				0.041		
gulf_pnw_ratio					0.001	0.001
fuel						0.355***
bic	3242.332	2926.886	2990.467	2993.370	3003.720	2955.204
N	131	131	131	131	131	131

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 57. 3SLS for Kansas to Texas Railroad and MM Barge Rates of Wheat

	(1)	(2)	(3)	(4)	(5)	(6)
mm						
rrw_kstx	0.362***	-0.027	-0.110	-0.109	-0.109	-0.123
levelcarlington_no	-0.114	0.234***	0.209***	0.207***	0.208***	0.178**
summer		0.064	0.054	0.056	0.054	0.079
fall		0.648***	0.611***	0.613***	0.611***	0.666***
winter		0.081**	0.074*	0.075*	0.074*	0.088**
realexchangeratewheat			-0.231*	-0.241*	-0.230*	-0.160
ocean_gulf				-0.030		
ocean_pnw				0.015		
gulf_pnw_ratio					-0.002	0.009
diesel						0.256**
rrw_kstx						
mm	0.607*	0.107	0.240*	0.266*	0.325**	0.269*
totalexclfuel	0.725***	0.865***	0.952***	0.946***	0.943***	0.982***
summer		0.184***	0.206***	0.213***	0.201***	0.212***
fall		0.067	0.038	0.037	-0.009	0.016
winter		0.061***	0.065***	0.068***	0.060***	0.074***
realexchangeratewheat			0.269***	0.194***	0.254***	0.240***
ocean_gulf				-0.077		
ocean_pnw				-0.021		
gulf_pnw_ratio					0.037	0.032
fuel						-0.088
bic	3464.085	3298.003	3293.127	3288.900	3301.077	3302.638
N	148	148	148	148	148	148

All models have agricultural year dummy variables. Standardized beta coefficients * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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CHAPTER 4. OH, THE MORE WE GET TOGETHER: PEER EFFECTS IN EARLY ELEMENTARY SCHOOL

Juan M. Murguia

Abstract

I study the effect on early educational achievement of keeping the same classmates as in the previous year by utilizing the unique nature of the Tennessee Student Teacher Achievement Ratio (STAR). I benefit from the randomized mixing up policy of the STAR program in the identification of effects of long time peers, peers that have been together for a long period of time, and estimate value-added models with and without school fixed and random effects. A novel microeconometric approach is also used: clustering errors by pooled models and by GEE. Specifically, I analyze the relationship between the chance of passing first grade and the proportion of kindergarten classmates kept as first grade classmates. I also study the relationship between noncognitive skills and the the proportion of kindergarten classmates kept as first grade classmates. Results show that keeping all kindergarten classmates vs. losing all of them increases the probability of passing first grade by 7 to 10 percent. In addition, noncognitive skills are improved when more kindergarten classmates are kept as first grade classmates. If all classmates are kept together vs. alone, motivation and selfconfidence may increase by 0.5 of a standard deviations while the number of days absent may decrease by 2 to 3. Interestingly, males show a stronger effect of long time peers than females on motivation and number of days absent. This paper presents evidence supporting the idea that the duration of peer connections is relevant in the estimation of peer effects, and

that mixing up classes in early education might be detrimental to the development of cognitive and noncognitive skills.

Key words: peer effects, noncognitive skills, early education, Social Capital, Education Policy.

JEL Codes: I210, I240, I250, Z13, O15.

1. Introduction

The effect of peers on education and other social outcomes has attracted much attention in the economic literature. Effects have been documented on cognitive and non-cognitive skills including drug use, criminal behavior, and academic performance from early childhood to college[52]. In general, these studies benefit from experiments where the exogenous formation of groups addresses the endogeneity of peer selection. Many policies have been based on peer effects: schools for gifted children, tracking/sorting of students within schools, and desegregation policies are among them. Some of these policies have created debate among policy makers and scientists for their impact on inequality. Surprisingly little is known about the impact of the time duration of these peer connections on social outcomes.

In this paper, I analyze the effects of a common elementary school practice of breaking classes apart and joining students from different groups at the beginning of the school year. This mixing up policy varies the time length students have been classmates, and

[52] There are documented peer effects on job search (Granovetter 1973 and 1995), youth criminal behavior and drug use (Case and Katz 1991), alcohol consumption and undergraduate academic performance (Kremer and Levy 2008), undergraduate academic performance (Betts and Morell 1999, Carrell, Fullerton and West 2008, Foster 2006), secondary school performance (Ding and Lehrer 2007, Lavy, Silva and Weinhardt 2009) and elementary school (Ammermuller and Pischke 2009, Iberman, Kugler and Sacerdote 2012, Fiesen and Krauth 2007, Lefgren 2004, Hanushek et al. 2003, McEwan 2003, Dills 2005, Neidell and Waldfogel 2010, Krueger 1999, Krueger and Whitmore 2001, Boozer and Cacciola 2001, Graham 2008).

as a consequence its impact on education and other social outcomes can be analyzed. Previous literature has ignored the impact of the length duration of the connections, and in particular the mixing up policies. One possible reason for the study of mixing up policies has been neglected is the difficulty to implement a large scale experiment that, at the beginning of the school year, randomly mixes up classes in different proportions. The Tennessee STAR (Student Teacher Achievement Ratio) program, a large scale class size experiment on elementary school, randomized the initial allocation of teachers and students in kindergarten within each school and randomly mixed up students of large classes at the beginning of first grade.

Schools cite many reasons for mixing up students. Among the reasons are to balance gender, ability levels and ethnicity ratios of a class, split cliques, encourage children to interact with others, learn to adapt to changes and facilitate/ease middle school transition (Mumsnet 2011). While meeting new classmates provides access to the benefits mentioned by schools it also exposes students to losing long time peers which can be detrimental to child development (Ladd 1990, Richardson and Schwartz 1998).

While there is little evidence regarding the impact of randomly mixing students, recent studies show that tracking/sorting may have positive benefits for high-scoring students, while benefits may be ambiguous for those who score low. Early tracking (tracking students into differing-ability classes) may increase educational inequality, according to a study that compared different countries (Hanushek and Wöbmann 2006). Sorting by home language and parental education may have an impact on the variance of test scores in schools in Canada (Frisen and Krauth 2007). Introducing schools for high ability students in a school district may have lowered the performance of low-scoring students in the same district (Dills

2005). Despite the previous evidence of the negative impact of sorting in low-scoring students, there is also evidence pointing toward a lack of harm in the case of secondary schools (Kim, Lee and Lee 2008). Even more so, evidence for elementary schools in Kenya shows that if sorting is combined with adjusting a teacher's program all students may benefit (Duflo, Dupas and Kremer 2008). Within the existing literature, Krueger (1999) is the only one who acknowledges the importance of mantaining classmates from previous year. When analyzing the effect of class size on academic test scores in the STAR program, in his paper he controlled for the proportion of actual classmates that were also classmates the previous year and found no significant effects.

Many studies have focused on elementary schools and the STAR program in particular. In the case of Europe, Ammermuller and Pischke (2009) using a sample of European countries found that a one-standard-deviation change in the background measure of peer composition leads to a 0.17-standard-deviation change in reading test scores of fourth graders. These studies found short and long term effects of peer characteristics on cognitive and noncognitive skills. In the US Iberman, Kugler and Sacerdote (2012) examined the effects of the absorption of evacuees from Hurricanes Katrina in Texas, and found evidence for monotonicity in peer effects: all students benefit from high-achieving peers. In the STAR program, peer effects on cognitive and non-cognitive skills during elementary school have been documented in the short and long term (Krueger 1999, Krueger and Whitmore 2001, Boozer and Cacciola 2001, Graham 2008). Class size and quality in the STAR program had a long term effect on test scores that fade out by grade eight; and a longer term effect on non-cognitive skills like: student's effort, initiative, non-participatory behavior, and value of the class (Krueger and Whitmore 2001). Even the effect of early education fades out on test scores it re-emerges in the job market, affecting earnings and college attendance (Chetty et al., 2010). The authors argue that this result might be explained by non-cognitive skills (Chetty et al., 2010). In the particular case of kindergarten students in the STAR program, Graham (2008) found that social interactions substantively contributed to the learning process in math and reading. As the previous studies show, the role of peers in developing skills, and in particular non-cognitive skills, has been extensively documented.

Gender differences in the creation and use of social networks have been documented during childhood. Evidence suggests that girls have smaller networks, enjoy fewer interactions with same sex peers than boys (Benenson, Morganstein, and Roy 1998) and are generally more cooperative in their peer relationships than are boys (Cole et al. 1990). Evolutionary psychology studies hypothesize that females should be less invested in peer relations than males because of more engagement in the raising of offspring during the evolution of the species (Krasnegor and Bridges 1990). Thus, I believe that it is possible that boys benefit more from girls' help in the learning process in the classroom than from other boys. Another important gender difference is the role that the social network plays for boys and girls. While the social network has been found to be important for boys’ development of academic and social skills (Belle, 1989; Belle et al. 1987, Feiring and Coates 1987), girls are reported to be important in regard to self-evaluation (Riley and Cochran 1987, Bryant 1985). I expect that keeping classmates might have different effects on self-esteem according to gender.

Non-cognitive skill formation has become an extremely active research topic because of its impact on labor markets. In particular a series of papers by Heckman and coauthors have greatly contributed to the field (Cunha and Heckman 2008; Cunha and Heckman 2007;

Cunha, Heckman, Lochner, and Masterov 2006; and Cunha, Heckman and Schennach 2010). Cunha and Heckman (2007) define non-cognitive skills as perseverance, motivation, time preference, risk aversion, self-esteem, self-control, and preference for leisure. They also point out the existence of evidence of the direct effects of non-cognitive skill on wages, schooling, crime, smoking, and test score performance, among others (a list of the existing literature supporting this evidence is presented in Cunha and Heckman (2007)). Surprisingly, non-cognitive skills are as important as cognitive skills in explaining a variety of aspects of social and economic life, including income (Heckman, Stixrud, and Urzua 2006).

I use the STAR program database to analyze the impact of keeping classmates (kindergarten ones) on school performance. Measures of school performance include the probability of being recommended for grade promotion, and cognitive and non-cognitive skills. I estimate a reduced form model of an education production function following Neidell and Waldfogel (2010). A probit model is regressed for the probability of being recommended to pass grade and robust standard error OLS models are estimated to explain cognitive and non-cognitive skills. There are two major findings in this paper. Keeping all kindergarten classmates vs. losing all of them may increase the probability of passing first grade by 7 to 10% in the students participating in the STAR program. The second most important finding is that non-cognitive skills might be improved when more kindergarten classmates are kept into first grade. If all classmates are kept together vs. staying alone in a new class, motivation may increase by 0.57 standard deviations and self-confidence by 0.47. The results found imply that if only short term benefits are considered, kindergarten students should not be randomly mixed when passing to first grade. These results may also apply for initial elementary school grades.

The rest of the paper is organized as follows. Section 2 presents information about the data and the methodological approach. It continues with the results in section 3 and concludes in section 4.

2. The STAR program

The STAR program was a large scale class size experiment initiated in the 1985-86 academic year, which targeted one cohort of students from kindergarten to third grade[53]. A total of 79 Tennessee schools, and 11,571 students participated in it[54]. Students entered the program when they joined a participating school and left it because of retention or transfer to a non-participating school. Given that kindergarten was not mandatory at that time in Tennessee, some students did not attend kindergarten. As a result of non-mandatory kindergarten and attrition, only 4,515 students attended kindergarten and first grade in a STAR participating school, and 4333 had data for all the variables used in this paper. The total number of classes was 325 in kindergarten (127 small, 99 regular without aid, and 99 regular with aid), and 339 in first grade (124 small, 115 regular without aid, and 100 regular with aid).

The experimental treatments consisted of two class sizes: small (13-17 students) and regular (22-26 students). In half of the regular classes there was a second teacher to help the principal one, a full time aide. Each participating school was required to have at least one class per type, and students and teachers were randomly assigned to initial classes within the school. In practice, the range of small classes was from 12 to 17 students, of regular classes

[53] For a more detailed description of the program, see Krueger (1999) and Nye, Hedges, and Konstantopoulos (2000)

[54] To span the State of Tennessee geographically, 79 schools in 42 districts were selected to participate. This included 17 inner-city schools and 16 suburban schools from metropolitan areas, plus 8 urban and 38 rural schools. (STAR user guide 2007)

with no aide 16 to 27, and regular classes with an aide was 15 to 28, as shown in Table 58. A battery of standardized tests at the end of the school year was administered from kindergarten to third grade. In addition, follow up tests were given in grade four and eight.

After the initial allocation to class size, students were expected to remain in the same class type until third grade. Parents with kids in kindergarten regular classes complained that their children were not assigned to smaller classes. Because there was no difference in kindergarten performance between the two types of regular classes[55], in response to the parents' complaints at the beginning of first grade large classes were randomly mixed up within their school. On the contrary, small classes were not mixed up. The STAR program's random design and random mixing of students between kindergarten and first grade is unique. These characteristics make it almost perfect to test peer effects and their evolution over time, given the duration is randomly interrupted. Random mixing provides an exogenous formation and breakup of groups which addresses the endogeneity of peer selection. Although random mixing is done only within schools and between large classes, it is possible to control for class treatment and school effects.

The random assignment was centralized at the STAR program, rather than being performed by the principals and teachers of the respective schools[56]. There is documented evidence that random assignment of students and teachers was followed in practice in the STAR program.

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[55] This result was probably caused because the large classes without full time aides had partial time aid.

[56] The randomization was conducted by members of the STAR Consortium and monitored at the school level by graduate students from the University of Tennessee, Tennessee State University, Vanderbilt University, and the University of Memphis. The samples were compared on gender, race, and free-lunch composition to look for any systematic bias that may have arisen; none was found. Teachers were assigned at random to the classes. Other than class size and teacher aides, no other experimental changes were implemented; the intent of the project was to maintain normal school policies and practices so that the effects of reduced class sizes could be shown clearly. (STAR user guide 2007)

Krueger (1999) found that 99.7% of students attended the kindergarten class that they were randomly assigned to. Krueger and Withmore (2001) modeled class-type assignment of students and teachers as a function of demographic characteristics and school of entry fixed effects, and found that these characteristics were not correlated to the class-type they were included. In addition, from kindergarten to first grade, 92% of small classes' students, 48.3% of regular and 44% of regular with aide stayed in their same type of class (Table 59), a sign that assignment of students to first grade treatments was close to the expected. These results imply that mixing up was also randomly made.

I concentrate this study on the early years of elementary school because the random mixing up took place at the beginning of first grade and sample attrition was high in the experiment (28.6% in kindergarten and 26.1% in first grade (Nye, Hedges, and Konstantopoulos, 2000)). There are two problems with sample attrition. It reduces the sample size and if it is non-random it may cause sample selection bias. Random attrition examples in the STAR program include families moving to another area (for a reason not related to the experiment) where the school was not participating in the program. Non-random attrition cases include retention and moving to another school after knowing the class type assignment (Krueger 1999). While it is not possible to know the reasons why parents moved at the beginning of the school year, there is evidence that grade retention was important, i.e. it reached 10% at first grade[57], which might cause attenuation bias.

[57] Retention in kindergarten was not registered in the STAR program. Nevertheless, whether a student in the first year of STAR (1985-1986) had also attended kindergarten the previous year was recorded, and only 4.12% were retained in kindergarten the previous year. (STAR user guide 2007)

3. Data

The data analyzed in this paper was obtained from the STAR program. In this study I focus on the 4,515 students that attended kindergarten and first grade in the 79 STAR participating schools. The total number of classes was 325 in kindergarten (127 small, 99 regular without aid, and 99 regular with aid) and 339 in first grade (124 small, 115 regular without aid, and 100 regular with aid). Table 58 shows the class size distribution according to class size type. The average class size in a small kindergarten class was 14.96, in a regular class was 22.16, and in a regular with aid class was, 22.54 students. The corresponding averages for first grade are 15.52, 22.47, and 23.2 students. Despite the differences in averages there was variation in the number of children, with overlapping of the distribution of the size treatments (Table 58).

School, class, teacher, classmates and student characteristics where measured during the STAR program. The variables used in this paper are the original STAR variables or variables constructed from them. The program had identification numbers for schools, teachers and students, allowing tracking students, class composition and school composition.

3.1 Student data

Student demographic characteristics (Table 60)[58] include gender (male), race (black), and the receipt of free lunch (gkfreelunch10 and g1freelunch10). Other student variables include days absent at kindergarten (gkabsent) and first grade (g1absent), SAT[59] tests on reading, math, listening, and word skills (respectively gktreadss, gktmathss, gktlistss, and

[58] When corresponding, the first two letters of the student variables indicate whether they were measured in kindergarten (gk) or first grade (g1).
[59] The SATs' (Stanford Achievement Tests) are norm-referenced achievement tests developed by the Psychological Corporation.

gkwordskillss_stddev), SCAMIN[60] motivation and selfconfidence measures (respectively gkmotivraw, and gkselfconcraw). Table 60 presents statistics for these variables.

Most of the students in the experiment were either white (69%) or black (29%) (Table 60). Close to half of the students (45%) were receiving free lunch in kindergarten and first grade (46%). More than 11% of the students failed to pass first grade. Students had an average of 10 absent days in kindergarten and 7 in first grade. SAT, and motivation and selfconfidence scores have large variability.

3.2 Classmates data

Classmates' characteristics are represented by the mean of the classmates' individual characteristics. Because of the randomized allocation of students in large classes (and large classes with an aide) at the beginning of first grade, the classmates variables have large random variation (Table 61).They were constructed by the author using the student characteristics and the student and teacher identification system of the STAR program, which helped to determine not only the class and teacher a student was placed in each academic year, but also who their classmates where. Table 61 presents the variables and summary statistics. Variable names start with either meangkclassmates, when referring to the average of classmates the student had in kindergarten (excluding himself), or meang1classmates, when referring to all classmates the student had in first grade followed by the name of the

[60] "The SCAMIN (Milchus, Farrah, and Reitz 1968) asks students to indicate pictorially their response to 24 situations. For example, what 'face' (happy, sad, indifferent) would the student wear if s/he "had to tell his/her parents they lost their coat?" The SCAMIN is group administered, with one form for prekindergarten and kindergarten students, and another for students in grades 1—3. The database contains total self-concept and motivation scores for each student in each grade." (STAR guideline 2007)

student level variable. All classmates' variables are measured at the time the students where in kindergarten to prevent endogeneity.

There are a set of variables that measure changes in the class network from kindergarten to first grade. The "long time peer" effect, the effect of peers that have been together for a long period of time, was measured by the variable propGKmateskept, the proportion of classmates in kindergarten that stayed with the student in first grade (Table 61). This also represents the proportion of direct connections of a complete social network maintained and the average time that peers have been together. A complete network assumes that all classmates are peers, which is not necessarily the case as Richardson and Schartz (1998) argue. Nevertheless, the proportion of classmates kept is an unbiased proxy for the expected proportion of peers kept, given randomization of the mixing up was followed in practice in the STAR program.

Students' performance may be affected by interactions among other students within the classroom. For example, when one student explains something to another student, a third one listen to what happens. Similarly, when one student disrupts a second student, this may affect a third one. This idea of important interactions occurring inside the classroom is a common assumption in the peer effect on early education literature. For that reason, a second measure of "long time peer" effect, and the proportion of all kindergarten connections that were kept in first grade – propGKnetworkkept – is calculated to account for the non-linearity of social networks (Table 61). The variable is constructed as the product of the number of classmates times the number of classmates minus one.

Another network variable was also included in this paper. The variable propg1matesnoattendedgk (Table 61) measures the proportion of classmates in first grade that either did not attend kindergarten, or attended but have no achievement data available in kindergarten. As later explained in the identification section, this variable is required to obtain unbiased estimates.

3.3 Teacher data

Demographic and experience variables for teachers in kindergarten and first grade are included in the data, together with class type and class size (Table 62). Among the teacher variables are gender (gktmale and g1tmale), race (gktblack and g1tblack), postgraduate education (gktpostgrade and g1tpostgrade), and years of teaching experience (gktyears and g1tyears). The class type variables refer to the class size in the STAR experimental design (gklarge_noaid, gklarge_aid in kindergarten and g1large_noaid,g1large_aid for first grade). Statistics show that due to the experimental design approximately one third of the classes in the sample are in each class size treatment. The class sizes vary in kindergarten from 12 to 28 students (gkclasssize) and in first grade from 12 to 30 (g1classsize).

3.4 School data

School data (Table 63) includes information regarding the type of neighborhood where the school is located: inner city (19%), urban (9%), suburban (19%) and rural (52%)[61]. The dummy variables gkInner_city, gksuburban, gkrural and g1Inner_city, g1suburban, and g1rural represent the respective neighborhood type the student attended in kindergarten and first grade respectively. School average variables were also constructed (these variables start

[61] Inner-city and suburban schools were all located in metropolitan areas (Nashville, Memphis, Knoxville, or Chattanooga). Schools with more than half of their students on free or reduced price lunch were defined as inner-city. Schools in the outlying areas of metropolitan cities were classified as suburban. Schools in non-metropolitan areas were classified as urban or rural depending on location. Urban schools were located in towns of over 2,500 persons, serving primarily an urban population according to the definition provided by the U.S. Census. All other schools were classified as rural. (STAR’s user guide 2007)

their names with sch_av followed by the variable name averaged at the school level) from all student, teacher, class type, and classmates' variables. For dummy variables, the averages represent the proportion of students with that characteristic in the school (Table 63)

There is large variation between school averages. The average number of absent days varies between 5 and 21 in kindergarten, and 4 and 11 in first grade. The variation on the proportion of students in a school who received free lunch is extreme, from o to 1. A similar situation occurs with race, where some schools are comprised of all black students and some are all-white students.

4. Methodology

Regressions of recommendation for passing grade, and cognitive and noncognitive skills are estimated in this research for first, second and third grade. The cognitive variables include annual recommendation to pass a grade and test scores (math, reading, listening and word). Noncognitive skills include annual motivation scores, selfconfidence scores, and days absent. The explanatory variables include characteristics of the student and their classmates (measured at kindergarten to prevent endogeneity), the teachers, and the school that was presented in the data section. For robustness clustering errors, random effects and fixed effects models where estimated and Hausman tests performed in this study.

Clarke et al. (2010), discuss the decision to use fixed effect (FE) or random effect (RE) specifically in the context of Educational Research. They conclude that an FE approach will be preferable in scenarios where the primary interest is in policy-relevant inference of the effects of individual characteristics, but the process through which pupils are selected into schools is poorly understood or the data are too limited to adjust for the effects of selection.

In the case of well understood selection mechanism and the existence of rich data, they recommend that the use of RE should be preferred because: (1) it can produce policy-relevant estimates; and (2) RE estimators of regression coefficients and shrinkage estimators of school effects are more statistically efficient than those for fixed effects.

The rest of this section covers peer effects identification, and different estimation approaches for linear and nonlinear models. These estimation approaches deal with the issue of nested sampling, which arises from students being assigned to a specific school according to their place of residency, rather than a random assignment. The next subsections present three different approaches: Clustering errors (CE), Random Effects (RE) (a more restrictive case of clustering errors) and the commonly used Fixed Effects (FE) models. These subsections (4.2 to 4.7) follow Wooldridge (2010), section 20.30.1, “Inference with large number of clusters and small cluster sizes,” Wooldridge (2006) and Wooldrige (2003).

4.1 Peer effects identification and the random mixing within school problem

Identification of peer effects has been solved using different strategies depending on whether the assignment of peers is random. All of the strategies are based on variation within schools (Ammermueller and Pischke 2009), i.e. FE models. In the case of random assignment of peers, the background characteristics are uncorrelated (Sacerdote 2001). In the STAR program random assignment was done within schools, so it is possible that there is correlation within schools that reflect neighborhood characteristics. Also in the STAR program, students were randomly mixed within schools. If random mixing would have done across all schools instead of only within, then the experiment would have been non stratified and pooled regression models would have been adequate. The proportion of kindergarten classmates kept as first grade classmates cannot be correlated with unobserved school level characteristics due to the fact that students are randomly assigned to specific classes within the school. Nevertheless, it it is possible that some control variables might be correlated with unobserved school level characteristics. For example, the average number of days a student is absent in a school may be correlated with the amount of support parents direct towards their child's education and the value of education that they teach to their kids.

4.2 Clustering errors for linear models

The STAR program samples individuals within schools, making a cluster sampling approach relevant since observations come with a natural nesting. Wooldridge (2010) addresses the issue of cluster sampling, where individual units are sampled in groups or clusters. The problem with cluster sampling is similar to that of panel data, where instead of having a time and individual dimension, there is respectively an individual (of students within the school) and a school dimension. The similarity is strong in this paper since there is a large number of cluster (79 schools), each relatively small, drawn from a large population of clusters (Wooldridge 2010 p. 863).

For each group or cluster g (school in this case), let $\{(y_{gm}, \mathbf{x}_g, \mathbf{z}_{gm}: m = 1, .., M_g)\}$ be the observable data, where M_g is the number of students (units) in school (cluster) g, y_{gm} is a scalar response, $\mathbf{x}_g$ is a vector of explanatory variables that vary only at the cluster level (e.g. school neighborhood type, school size), and $\mathbf{z}_{gm}$ is a vector of covariates that vary within and across schools (clusters) (i.e. student variables and classmates variables). It is assumed that the sampling scheme used in the STAR program generated observations that are independent across g.

The theory with $G \rightarrow \infty$ and the group sizes (the number of students in the school), M_g, fixed is well developed, for example White (1984) and Arellano (1987). In this study, given that it is possible to keep increasing the number of schools sampled while the number of students in a school stay fixed, the asymptotic theory is suitable for this framework. Assume the following standard linear model with additive error (Wooldridge 2003):

$$y_{gm} = \alpha + \mathbf{x}_g\boldsymbol{\beta} + \mathbf{z}_{gm}\boldsymbol{\gamma} + v_{gm},\ m = 1,..,M_g; g = 1,..,G. \tag{15}$$

The estimation approach may be driven by several factors. Among these factors are whether we are interested in the effect of aggregate variables ($\boldsymbol{\beta}$) or individual specific variables ($\boldsymbol{\gamma}$), and how much we care about efficiency vs. bias. Assumptions about the error term are necessary. One of these assumptions is whether v_{gm} has an additive unobserved cluster (group) effect and an idiosyncratic error:

$$v_{gm} = c_g + u_{gm},\ m = 1, \ldots M_g. \tag{16}$$

If the explanatory variables are assumed to be exogenous (for this reason student and classmates characteristics are measured at the time of kindergarten) and they satisfy:

$$E\left(v_{gm}|\mathbf{x}_g, \mathbf{z}_{gm}\right) = 0,\ m = 1, \ldots, M; g = 1, \ldots, G, \tag{17}$$

or even a zero correlation version, the pooled OLS (POLS) estimator is consistent as $G \rightarrow \infty$ with M_g fixed, and the pooled OLS estimator is $\sqrt{G}$-asymptotically normal. A robust variance matrix is needed to account for correlation within clusters and/or heteroskedasticity in $Var\left(v_{gm}|\mathbf{x}_g, \mathbf{z}_{gm}\right)$. Otherwise, OLS standard errors can be misleading. The following sandwich variance matrix estimator is computed in this paper where the cluster unit is the school, $\mathbf{W}_g$ is the matrix of all regressors on group g, and $\hat{\mathbf{v}}_g$ is the vector of POLS residuals for group g:

$$\widehat{Avar}(\hat{\theta}_{POLS}) = \left(\sum_{g=1}^{G} \mathbf{W}_{g}{}' \mathbf{W}_{g}\right)^{-1} \left(\sum_{g=1}^{G} \mathbf{W}_{g}{}' \hat{\mathbf{v}}_{g} \hat{\mathbf{v}}_{g}{}' \mathbf{W}_{g}\right) \left(\sum_{g=1}^{G} \mathbf{W}_{g}{}' \mathbf{W}_{g}\right)^{-1}. \quad (18)$$

4.3 Random effects for linear models

With further assumptions about the within cluster correlation of v_{gm}, which is not exploited in the POLS estimation, it is possible to obtain more efficient estimates by Generalized Least Squares (GLS). The extra assumption is that:

$$E\left(v_{gm} | \mathbf{x}_{g}, \mathbf{z}_{g}\right) = 0,\ m = 1, \dots, M; g = 1, \dots, G. \quad (19)$$

This assumption rules out covariates from one student (member) of the school (cluster) affecting the outcomes of another, holding own covariates fixed. These assumption also appears to rule out "peer effects", which is the aim of this paper. These effects can be allowed by including measures of peers in $\mathbf{z}_{gm}$.

The standard random effects approach adds extra assumptions such that the variance covariance matrix has the form:

$$Var\left(v_{gm}\right) = \sigma_{c}^{2} \mathbf{j}'_{M_g} \mathbf{j}_{M_g} + \sigma_{u}^{2} \mathbf{I}_{M_g}, \quad (20)$$

where $\mathbf{j}'_{M_g}$ is a vector of ones, and $\mathbf{I}_{M_g}$ is an identity matrix. Another assumption is the following homoscedasticity one (which does not restrict $Var(v_{gm})$):

$$Var\left(v_{g} | \mathbf{x}_{g}, \mathbf{z}_{g}\right) = Var\left(v_{gm}\right). \quad (21)$$

Under the previous two assumptions the resulting GLS estimator is the common random effect estimator (RE). The random effect estimator, $\hat{\theta}_{RE}$, is asymptotically more efficient than POLS (Pooled OLS), under assumptions (19), (20), and (21) as $G \rightarrow \infty$ with the M_g fixed.

Inference in RE should be made completely robust to an unknown form of $Var(v_g|\mathbf{x}_g, \mathbf{z}_g)$, by using a fully robust variance matrix. Even if $Var(v_g|\mathbf{x}_g, \mathbf{z}_g)$ has not the RE form, the estimators are still consistent, asymptotically normal and likely to be more efficient than POLS estimators. Even there is not the problem of serial correlation as in panel data that invalidate assumption (20), heteroskedasticity in $Var(c_g|\mathbf{x}_g, \mathbf{z}_g)$ or $Var(u_{gm}|\mathbf{x}_g, \mathbf{z}_g)$ is possible and justifies robust inference.

4.4 Fixed effects for linear models

If the interest of the researcher is $\boldsymbol{\gamma}$**,** like in this paper, the fixed effect (FE) or within estimator is an interesting and commonly used option. The within transformation subtracts within-group averages (school averages) from the dependent variable and explanatory variables:

$$y_{gm} - \bar{y}_g = (\mathbf{z}_{gm} - \bar{\mathbf{z}}_g)\boldsymbol{\gamma} + u_{gm} - \bar{u}_g,\ m = 1, .., M_g; g = 1, .., G, \tag{22}$$

and the equation (22) is estimated by pooled OLS. As in the panel data case, FE assumptions allow arbitrary correlation between c_g and $\mathbf{z}_{gm}$. Nevertheless, as in the RE case it is advisable to allow $Var(u_g|\ \mathbf{z}_g)$ to have an arbitrary form which may include within-group correlation and heteroskedasticity. A fully robust variance matrix estimator is:

$$\widehat{Avar}(\hat{\gamma}_{FE}) = \left(\sum_{g=1}^{G} \ddot{\mathbf{Z}}_g{}' \ddot{\mathbf{Z}}_g\right)^{-1} \left(\sum_{g=1}^{G} \ddot{\mathbf{Z}}_g{}' \widehat{\ddot{\mathbf{u}}_g} \widehat{\ddot{\mathbf{u}}_g}{}' \ddot{\mathbf{Z}}_g\right) \left(\sum_{g=1}^{G} \ddot{\mathbf{Z}}_g{}' \ddot{\mathbf{Z}}_g\right)^{-1}, \tag{23}$$

where $\ddot{\mathbf{Z}}_g$is the matrix of within-group deviations from means and $\widehat{\ddot{\mathbf{u}}_g}$ is the vector of FE residuals.

4.5 Alternative to FE

Woodridge (2010) proposes a model that adds group averages to the RE estimator. This model also leads to a simple Hausman test to compare FE and RE. The model is:

$$y_{gm} = \alpha + \mathbf{x}_g\boldsymbol{\beta} + \mathbf{z}_{gm}\boldsymbol{\gamma} + \bar{\mathbf{z}}_g\boldsymbol{\xi} + a_g + v_{gm},\ m = 1,..,M_g; g = 1,..,G, \tag{24}$$

where $c_g = \bar{\mathbf{z}}_g\boldsymbol{\xi} + a_g$. The RE estimation of (24) allows to test $H_0: \boldsymbol{\xi} = 0$ in a fully robust way, which tests the null that the RE estimator is consistent. Even if the panel is not balanced, the estimate of $\boldsymbol{\gamma}$ is the FE estimate (POLS also delivers the FE estimate of $\boldsymbol{\gamma}$).

4.6 Clustering errors and Random effects for non linear models

Many of the issues for nonlinear models are the same as for linear models (Wooldridge 2006). In the case of binary response models, a probit model can be defined as:

$$y_{gm} = 1[\alpha + \mathbf{x}_g\boldsymbol{\beta} + \mathbf{z}_{gm}\boldsymbol{\gamma} + c_g + u_{gm} \geq 0],\ m = 1,..,M_g; g = 1,..,G \tag{25}$$

$$u_{gm}|\mathbf{x}_g, \mathbf{Z}_g, c_g \sim N(0,1); \tag{26}$$

implying:

$$\begin{aligned} P(y_{gm} = 1|\mathbf{x}_g, \mathbf{z}_{gm}, c_g) &= P(y_{gm} = 1|\mathbf{x}_g, \mathbf{Z}_g, c_g) \\ &= \Phi(\alpha + \mathbf{x}_g\boldsymbol{\beta} + \mathbf{z}_{gm}\boldsymbol{\gamma} + c_g + u_{gm}), \end{aligned} \tag{27}$$

where $\Phi(.)$ is the standard normal distribution. If u_{gm} follows a logistic distribution, then $\Phi(.)$ is replaced by $\Lambda(.)$. The presence of $c_g$in (27) makes the marginal effects depend on it. If the first element of $\mathbf{x}_g$ is continuous,

$$\frac{\partial P(y_{gm}=1|\mathbf{x}_g,\mathbf{z}_{gm},c_g)}{\partial \mathbf{x}_{g1}} = \beta_1\phi(\alpha + \mathbf{x}_g\boldsymbol{\beta} + \mathbf{z}_{gm}\boldsymbol{\gamma} + c_g + u_{gm}), \tag{28}$$

where $\phi(.)$ is the standard normal density function.

To obtain the change in the response probability given a change in a regressor as in (28), the following assumption is required:

$$c_g|\mathbf{x}_g, \mathbf{Z}_g \sim N(0, \sigma_c^2). \quad (29)$$

To account for the presence of c_g in (28), two possible estimation methods are proposed by Wooldridge (2012), a pooled probit and a generalized estimation equation (GEE) approach. The GEE approach is a multivariate weighted nonlinear least squares estimator that accounts for misspecified variance matrix (see Wooldridge 2006 for an extended explanation), requiring a "sandwich" estimator to be used for inference. The GEE exploits the within-group correlation to obtain a more efficient estimator than the pooled probit. Both methods are simple and do not require specification of a joint distribution within clusters. As in the case of linear models, it is possible, with large number of clusters, to make the standard errors robust to arbitrary within group correlation. If an extra assumption is imposed (independence of idiosyncratic errors within a school (cluster)):

$$\{u_{g1}, .., u_{gM_g}\} \text{ are independent conditional on } (\mathbf{x}_g, \mathbf{Z}_g, c_g) \quad (30)$$

the RE probit model is obtained. The assumption of independence of individual outcomes after conditioning on a common cluster (school) is more believable than in the case of panel data. It is challenging to model correlation between the unobserved heterogeneity c_g and $\mathbf{z}_{gm}$ when the clusters have different sizes. Wooldrige (2012) proposes several approaches to deal with it, some requiring strong assumptions and others requiring a reduction on the cluster size of all clusters to the smallest cluster by sampling within each cluster. This last approach requires the assumption that the cluster sizes are exogenous. In this paper, when estimating the RE probit model,the limitation is acknowledged that no correction for cluster size is made.

4.7 Fixed effects for non linear models

Fixed effects probit procedure treats c_g as parameters to estimate:

$$P(y_{gm} = 1|, \mathbf{Z}_g, c_g) = P(y_{gm} = 1|\mathbf{z}_{gm}, c_g) = \Phi(\mathbf{z}_{gm}\boldsymbol{\gamma} + c_g + u_{gm}). \tag{31}$$

Due to the incidental parameters problem, with small group sizes M_g, the estimator of $\boldsymbol{\gamma}$ can be severely biased. For this reason a logit response function for FE is preferred, since under (29) the conditional maximum likelihood eliminates c_g, leading to consistent estimation of $\boldsymbol{\gamma}$**.**

To prevent this problem, we control for school characteristics like school attrition, proportion of students with free lunch, type of neighborhood (inner city, suburban, rural), average school SAT and non cognitive scores, and other characteristics like number of days absent and school fixed effects.

4.8 The model

I use a reduced education production function following the Clustering error, FE, and RE models previously presented. In this paper y_{gm} represents the variable of interest to be explained (the probability of passing grade, the academic scores of math, reading, and word skills, motivation, selfconfidence and days absent in first grade); $\bar{y}_g$ represents the mean in the school for that variable, $\mathbf{z}_{gm}$ represents the student, classmates, class and teacher characteristics; $\bar{\mathbf{z}}_g$is the average of the variables in the school; and $\mathbf{x}_g$ is a vector of school characteristics presented in the data section. As previously explained, $\mathbf{z}_{gm}$ is measured at the time the students where in kindergarten to avoid endogeneity. Since contemporaneous performances are omitted from these equations, the estimate reflects the reduced form of peer effects: the direct effect of students' performance plus the indirect effect on performance through its impact on class performance (Neidell and Waldfogel (2010)).

4.9 Identification strategy under sample selection

Ideally, a reduced form specification of an education production function should be estimated using all the classmates. This is not possible in this case because not all students attended kindergarten, and in such cases there is no information about ability tests. Neidell and Waldfogel(2010) studied the impact of the proportion of classmates that attended preschool on cognitive and noncognitive skills at the end of kindergarten in the Early STAR program. They controlled for entrance skill levels and found that the mean enrollment of the class in prekindergarten has significant effects on math and reading on kindergarten and latter grades. Given the students took a battery of tests at the beginning of kindergarten, they were able to estimate peer effects driven by the mean of the classmates on these test scores, independent of whether or not students attended prekindergarten.

In the STAR program, tests were only performed at the end of the school year, so students who did not attend kindergarten lack test score data previous to the exposition to first grade peers. In this paper, we are able to identify peer effects by regressing against the mean of the classmates that attended kindergarten (and have recorded data for all the variables included in the model); and the proportion of classmates that entered into the school in first grade (or in kindergarten but have some variables missing). The identification approach is the following: let $\mathbf{z}_{gm1}$, the first variable of $\mathbf{z}_{gm}$, representing the classmates average variables during kindergarten, be in the proposed model:

$$\boldsymbol{\gamma}_1\mathbf{z}_{gm1}. \tag{32}$$

The variable $\mathbf{z}_{gm1}$ can be expressed as the weighted average of the students that have this variable in their kindergarten data (defined as $\boldsymbol{Z}_{gm1}{}^{\boldsymbol{kinder}}$**),** and the ones that do not have it ($\boldsymbol{Z}_{gm1}{}^{\boldsymbol{no\_kinder}}$):

$$\boldsymbol{\gamma}_1\mathbf{z}_{gm1} = \boldsymbol{\gamma}_1\big(\,(1-\delta_{gm})\boldsymbol{Z}_{gm1}{}^{\boldsymbol{kinder}} + \delta_{gm}\boldsymbol{Z}_{gm1}{}^{\boldsymbol{no\_kinder}}\big). \tag{33}$$

Where δ_{gm} is the proportion of classmates that did not attend kindergarten. From (33) the following result is obtained:

$$\boldsymbol{\gamma}_1\mathbf{z}_{gm1} = \boldsymbol{\gamma}_1\boldsymbol{Z}_{gm1}{}^{\boldsymbol{kinder}} + \boldsymbol{\gamma}_1\delta_{gm}\left(\boldsymbol{Z}_{gm1}{}^{\boldsymbol{no\_kinder}} - \boldsymbol{Z}_{gm1}{}^{\boldsymbol{kinder}}\right) = \qquad = \\ \boldsymbol{\gamma}_1\boldsymbol{Z}_{gm1}{}^{\boldsymbol{kinder}} + \boldsymbol{\gamma}_{10}\delta_{gm}\,, \tag{34}$$

where $\boldsymbol{\gamma}_{10} = \boldsymbol{\gamma}_1\big(\boldsymbol{Z}_{gm1}{}^{\boldsymbol{no\_kinder}} - \boldsymbol{Z}_{gm1}{}^{\boldsymbol{kinder}}\big)$. The inclusion of δ_{gm} is critical, otherwise the “old peer effect” would be account for having more classmates in later grades that attended kindergarten: the “kindergarten peer effect” (the effect of peers that attended kindergarten). Even it is not possible to estimate in this case the “kindergarten peer effect,” it is possible to estimate the existence of difference in average abilities at the age of kindergarten between these two types of classmates. The null hypothesis for no difference in ability between students that attended kindergarten and the ones who did not is, $H_0\colon \boldsymbol{\gamma}_{10} = 0$.

5. Results

5.1 Probability of passing first grade

To address the effect of keeping kindergarten classmates on the probability of being recommended to pass first grade, I estimate probit models. To test the robustness of the estimates eight different model specifications are regressed in each table: Probit, FE, RE, RE with school means, GEE, GEE with school means, Pooled (with clustering errors), and Pooled with school means (with clustering errors). The key dependent variables are the proportion of kindergarten classmates kept in first grade (propGKmateskept) (Table 64) and the proportion of all connections kept (propGKnetworkkept) (Table 66). Both dependent variables are presented in Table 65.

Other dependent variables include the proportion of classmates that did not attended kindergarten(propg1matesnoattendedgk) -or that there is no data from them at the time of kindergarten- student characteristics, class size treatment (in kindergarten and first grade), teacher characteristics (in kindergarten and first grade), classmate characteristics (measured at kindergarten), and school average characteristics (average of all the previous characteristics at the school level: proportion of classmates that did not attended kindergarten (schdelta), student (schstudent), class size treatments (schclasstreatment), teacher characteristics (schteacher), and classmate characteristics (schclassmates)). Tables present for each model average marginal effects and their respective p values for the network variables (propGKmateskept, propGKnetworkkept) and for the proportion of classmates that did not attended kindergarten (propg1matesnoattendedgk), they also indicate which of the control variable groups have been used in the regression (Yes ,if that group of variables was used in the regression). For the models that include the school means, the p values of the F test of these variables is also included (schmeans F test pvalue). No fully robust (traditional) Hausman test p value is also presented for the RE model, and the joint F test for both network variables is at the end of the table (F network test p value). All estimations have robust standard errors.

There is evidence of a significant positive effect for keeping kindergarten classmates together on the probability of being recommended to pass first grade. Keeping all kindergarten classmates vs. losing all of them increases the probability of passing first grade by 7 to 10%. Table 66 shows that effect clearly. All models show coefficients in the range of 7% to 10% and 6 out of 8 models have their standard errors small enough to make the coefficients significant. The exceptions are the FE (p value 0.15) and the RE with school means (0.15 p value). The Hausman test shows no benefit for using FE (p value 0.30), while the RE with school means shows that the school means are significant.

Given the Pooled Probit imposes fewer restrictions than the RE model, it provides robustness to the results that both the Pooled and the Pooled with schmeans are also significant. Table 65 also includes the proportion of kindergarten classmates kept (a linear approach to networks) together with the proportion of the network kept. Again, results are similar to the ones in Table 66. Because both variables are not independent of each other, the marginal effect of keeping all classmates is the sum of both estimates. Most of the estimates of propGKnetworkkept are between 0.21 and 0.23, and the ones for propGKmateskept between -0.8 and -0.1. According to their differences, keeping all kindergarten classmates, vs. losing all of them, increases the probability of passing first grade by 9 to 13%. When only linear measures for a network are used in the regressions, results are less significant and around 5% (Table 64). This result gives support to the main hypothesis of the paper: long lasting connections may be more influential than short term connections, even when there is no endogenous selection by the quality of the connections over time.

There is a limitation in the interpretation of the results because it is not possible to differenciate between the effect of keeping previous year classmates and the effect of average time as peers. Both are represented by the variable propgkkept. The identification would be possible if I had at least one more academic year (second grade) in which students were again randomly assigned to classes. Then it would be possible to have two different variables in the models; one being the average time classmates have been together and another the proportion of previous years classmates that are togheter that academic year. It is possible that the effect of time might be nonlinear, and present a threshold of time (maybe a year) after which connections are strong enough that the effect of average time being peers stops increasing.

5.2 Probability of passing later grades

The effect of losing previous classmates fades out after one year (Table 67 and Table **68**). Table 67 shows that the proportion of the kindergarten network kept in first grade has no effect on the probability of being recommended to pass second grade. Results are robust for all model specifications. Similar results are obtained for third grade (Table 68). These results imply that even it takes time to build new peer relations, the strength that is required to affect academic success may take no longer than one year.

5.3 Cognitive and noncognitive skills in first grade

Cognitive skills are mostly not affected by keeping previous year classmates, while on the contrary noncognitive skills are. Motivation, selfconfidence and days absent are affected by keeping kindergarten classmate together, while listening skills are not (Table 72). Motivation is increased by two raw points on average –0.4 to 0.5 standard deviations– if all kindergarten classmates are kept (Table 73). Results are highly significant and robust across different model specifications. Selfconfidence is also increased by 2 to 3 raw points –0.4 to 0.6 standard deviations– if all kindergarten classmates are kept (Table 74). A student that keeps all his classmates will have, on average, 2 to 3 fewer days absent in the school year. Models are robust to different model specifications. The effects on motivation, self-confidence and days absent reflect the idea that there is an important role for maintaining peer relationships on the continuation of social skill development (Richardson and Schwartz 1998 pp. 68-69).

Math skills are not affected in all models. Reading skills in first grade results are not robust, either negative (Table 69), not significant (Table 77) or positive (Table 76). Word skill results are not robust, they appear to increase when only propGKmateskept is measuring network effects (Table 78), not to have an effect when only propGKnetworkkept is used (Table 79); and to be significant when both measures are used together (Table 71), but with magnitudes that make the overall effect no different from zero.

5.4 Gender differences

The impact of kindergarten classmates kept in first grade on noncognitivive skills differs by gender. While the number of days absent among females are not affected by the proportion of classmates kept, males may have 3.4 to 5.2 more absent days (0.51 to 0.78 standard deviations) during the school year, if they keep all their classmates, vs. losing all of them. Results are robust across all model specifications (Table 82 and Table **83**). Boys' motivation is more greately affected than girls' (Table 84 and Table **85**). While marginal effects for females are in the range of 1.3 to 2.0 for the raw motivation index (0.35 to 0.53 standard deviations), the effects for males are from 2.21 to 2.5 (0.59 to 0.66 standard deviations). The difference in the marginal effect is almost constant at 1.4 raw points for each model specification, which is close to 0.37 standard deviations. There is no clear evidence of gender differences in the case of selfconfidence (Table 68 and Table 69). Despite results which are significant across more model specifications in the case of females (Table 69), the magnitude of the marginal effects is not larger than in the significant models for males (Table 68). Marginal results for females vary between 1.9 and 3.5 selfconfidence raw points (0.36 to 0.66 standard deviations), and for males between 3.17 and 3.26 (0.59 to 0.61 standard deviations) (Table 68). Listening skills are not significantly affected in both genders by the proportion of kindergarten classmates (Table 88 and Table 89).

Cognitive skill results are less robust. Results on the probability of passing first grade by gender are not as robust as results for the entire population. In the case of significant models, marginal impacts appear not to be different by gender (between 9 and 13%) (Table 80 and Table 81). Reading skills results are negative when both network variables are included in the model (Table 90 and Table 93), and no significant when only one of both are included in the models (Table 91 and Table **92** for boys and Table 94 and Table **95** for girls). The negative reaction is stronger in girls than boys: 7 raw points -0.12 standard deviations- (Table 90) vs. 7 to 18 raw points -0.12 to 0.32 standard deviations- (Table 93). In the case of boys, math skills are not affected by keeping classmates (Table 96),while they are negatively affected in the case of girls by 14 raw points -0.32 standard deviations- (Table 97). Boys' and girls' word skills are negatively affected when both network variables are included (Table 98 and Table 99), but not affected when only one is (Table 99-Table 100 and Table 102-Table 103 respectively). When both network variables are included, girls are more negatively affected than boys: 6 to 14 raw points, -0.11 to 0.27 standard deviations- (Table 101) vs. 6 raw points, -0.11 standard deviations- (Table 98).

6. Discussion and conclusions

Despite the extensive amount of literature on peer effects, little is known about the effect of time on peer relationships. This paper explores the idea that peer effects depend on the strength of peer connections which may increase over time. I use the STAR program to study this idea in the context of early education. My decision to work on early education is motivated by a desire to facilitate the identification of time effect, rather than peer selection effect over time which increases later in life. The STAR program has some special characteristics that facilitate the identification of time on peer effects: the andom assignment of students to classrooms and teachers (preventing the endogenous selection of peers, and the correlation of background characteristics of students within schools), and the random mixing of students between kindergarten and first grade.

I estimated value-added models that controlled for peer, teacher, class and school characteristics. The effect of time on peer relationships was estimated as the proportion of kindergarten classmates (a linear network measure) and kindergarten network connections (an almost quadratic network measure) that were kept in the same class in first grade. By including the proportion of all possible kindergarten network connections that where kept at first grade, the models where able also to capture the effect of indirect connections. Indirect connections matter because the interaction between two students in a classroom is observed by other students that may be affected. This paper is the first to present evidence supporting the idea that indirect connections matter in a classroom environment. In fact, the omission of the nonlinearity of the network makes the effect of time non-significant, which may partialy explain the results found in Krueger (1999)[62]. The importance of indirect connections points towards the uniqueness of classroom peer effects, and the significance of this variable in the estimated models is consistent with network theory.

The results show that the average amount of time that classmates have been peers (up to an academic year) may have a significant effect on academic success and noncognitive skills. Whether this effect continues to exist beyond a year is not possible to be answered with the existing data. It might be the case that only the proportion of previous year classmates kept matters and not the average amount of time classmates have been together. Fade out effects on second and third grade provide some evidence supporting that the effect of time might not be linear, but rather present a threshold (maybe a year) after which connections are strong enough that the effect of average time being peers stops increasing.

There are robust, significant effects for the proportion of the kindergarten classmates kept as classmates in first grade on the probability of passing that grade and on motivation, days absent, and selfconfidence. Cognitive test scores are not robustly affected. This is a surprising result, given that Graham (2008) found that social interactions substantively contributed to the learning process in math and reading in the STAR program. A possible reason for this difference is that we focus only on first grade impacts.

The impact of retaining all previous classmates is large: it increases the probability of passing first grade by 7 to 13% compared to having all new classmates. This result gives support to the main hypothesis of the paper: long lasting connections may be more influential

[62] There is another possible reason for the results of Krueger (1999). He used the proportion of first grade classmates that where classmates in kindergarten as the effect of time on peers. This variable is also affected by the proportion of students who did not attend kindergarten, which causes a measurement error and possible attenuation bias.

than short term connections, even when there is no endogenous selection by the quality of the connections over time. The effect on motivation, days absent and selfconfidence reflect the idea that peer relationships play an important role in the continuation of social skill development (Richardson and Schwartz 1998 pp. 68-69, Howes 1988, Feiring and Lewis 1989, Ladd 1990). Results on peer effects are similar to previous studies (Krueger 1999, Whitmore and Krueger 2001, Boozer and Cacciola 2001, Graham 2008): average classmates skills' in math and reading increase the chances of passing first grade and fade out by second grade[63].

The findings of this article add to the gender differences literature on child development. Previous studies found gender differences in network sizes (Benenson, Morganstein, and Roy 1998), uses (Belle 1989, Belle et al. 1987, Feiring and Coates 1987, Riley and Cochran 1987, Bryant 1985), cooperation (Benenson, Morganstein, and Roy 1998), and predisposition to search for help (Benenson, Morganstein, and Roy 1998, Cole et al. 1990). In this study, boys appear to be more affected by the loss of classmates on their days absent and motivation. These results are supported by the existing evidence on boys which suggest that may have larger networksand are more dependent on them; that they have more problems searching for help from teacher, and that they have grater enjoyment than girls interacting in their networks (Belle 1989, Belle et al. 1987, Feiring and Coates 1987, Riley and Cochran 1987, Bryant 1985, Benenson, Morganstein, and Roy 1998, Cole et al. 1990).

The findings also provide evidence for the mechanism by which time affects peer effects. The effect on academic performance is via noncognitive skills, like motivation and

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[63] Results are not resported.

selfconfidence, rather than cognitive skills like math and reading. There is not enough evidence in the literature to explain why this might be the case. An explanation is required for why keeping more classmates affects chances for passing first grade, while it does not affect cognitive skills. Nevertheless, it may be reasonable that even the effect is only on noncognitive skills, and these skills may affect the probability of passing first grade. When a child is on the edge of failing to pass first grade, teachers may evaluate other skills, which might be noncognitive, to make their final decision.

This study is, to my knowledge the first to find evidence that may support the importance of time on peer effects. Specifically, the effect of peers does not depend only on their abilities and skills, but also on the time length they have been peers. Despite this initial finding, more research is required to confirm this result with data that has the maximum average time of being peers larger than a year. The findings of this paper also support that the time length they have been peers affects the magnitude of peer effects, even when there is not endogenous peer selection over time. These results have implications for educational policies like random mixing and sorting/tracking. For example, sorting/tracking policies may also affect students, not only by changing the level of the peers and allowing adjustments in educational programs, but also by losing long time known peers. As a consequence these policies may also have negative effects on the social capital of the student and the class, which might be detrimental for child development.

Tables

Table 58. Distribution of Actual Class Sizes among Classes Assigned to Each Type

	Kindergarten			Fist Grade		
Actual	Type of class			Type of class		
class size	Small	Regular	Regular/aide	Small	Regular	Regular/aide
12	8			2		
13	19			14		
14	22			18		
15	23		1	31		
16	31	1	1	16	1	
17	24	4	2	33	1	
18		1	6	6	2	
19		7	6	3	4	3
20		6	12	1	10	6
21		14	20		18	18
22		20	21		27	15
23		16	14		19	20
24		19	6		16	11
25		60	3		7	9
26		4	6		5	9
27		1	1		2	4
28					1	2
29					1	2
30					1	1
Total	127	99	99	124	115	100
Average	14.96	22.16	22.54	15.52	22.47	23.2

Notes: This table presents information from Nye, Hedges, and Konstantopoulos (2000) Table 1, pg 128.

Table 59. Transition matrix

	Type of first grade class			
Type of Kindergarten class	N	Small class	Regular class	Regular/aid
Small	1400	92.30%	4.30%	3.40%
Regular	1526	8.30%	48.30%	43.40%
Regular/aid	1589	7.70%	47.90%	44.40%
Total	4515			

Notes: Percentages are of the students that attended both, kindergarten and first grade in the STAR program. Small refers to reduced size classes, Regular to regular size classes, and Regular/aid to regular size classes with a teacher aid (a second teacher helping in the class). This table presents information from Nye, Hedges, and Konstantopoulos (2000) Table 4, pg 133

Table 60. Student characteristics.

Variable	Obs	Mean	Std. Dev.	Min	Max
gender	4333	0.497	0.500	0	1
black	4333	0.301	0.459	0	1
gkfreelunch	4315	0.444	0.496	0	1
gkabsent	4311	9.911	9.088	0	93
gktreadss	4032	440.7981	31.572	358	627
gktmathss	4075	492.146	46.027	354	626
gktlistss	4053	541.292	32.001	427	671
gkwordskillss	4056	438.525	37.268	331	593
gkmotivraw	3578	25.699	2.330	0	36
gkselfconcraw	3578	56.182	4.779	0	72
g1promote10	4253	0.901	0.297	0	1
g2promote	3234	0.963	0.186	0	1
g3promote10	2909	0.968	0.174	0	1
g1absent	4253	7.398	6.586	0	63
g1treadss	4161	528.158	56.130	412	651
g1tmathss	4250	535.661	43.523	404	676
g1tlistss	4229	571.153	34.363	477	708
g1wordskillss	3653	521.082	52.866	317	601
g1motivraw	3831	50.244	3.746	27	60
g1selfconcraw	3831	45.496	5.294	20	60

Table 61. Classmates' characteristics.

Variable	Obs	Mean	Std. Dev.	Min	Max
meangkclassmatestreadss	4331	440.750	18.715	384	500.5
meankgclassmatesgmathss	4331	492.016	28.924	384	590.7
meankgclassmatestlistss	4331	541.220	18.327	474	607.5
meankgclassmateswordskillss	4331	438.576	21.146	391	506.7
meankgclassmatesmotivraw	4016	25.694	0.907	21.8	30.7
meankgclassmatesselfconcraw	4016	56.172	2.055	48.8	64.2
meang1classmatestreadss	4261	528.107	33.526	440.5	623.9
meang1classmatesgmathss	4332	535.636	27.407	461.8	620.6
meang1classmatestlistss	4332	571.095	19.990	519.7	642
meang1classmateswordskillss	4324	520.555	30.664	425.3	601
meang1classmatesmotivraw	4332	27.278	2.774	15.1	32
meang1classmatesselfconcraw	4332	39.685	2.868	27.6	44
propGKmateskept	4333	0.259	0.172	0	0.882
propGKnetworkkept	4333	0.088	0.126	0	0.772
propg1matesnoattendedgk	3238	0.052	0.108	0	1

Note: in this table gk and g1 refers to when the students where classmates, in kindergarten or in first grade. All variables are measured at the time the respective students where in kindergarten.

Table 62. Teacher and class characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
gklargenoaid	4333	0.334	0.471	0	1
gklargeaid	4333	0.354	0.478	0	1
g1largenoaid	4333	0.343	0.475	0	1
g1largeaid	4333	0.313	0.464	0	1
gktrace_black	4333	0.852	0.354	0	1
kgtandch_same_race	4333	0.208	0.406	0	1
gktpostgrade	4313	0.351	0.477	0	1
gktyears	4313	9.343	5.804	0	27
g1tgen_male	4320	0.005	0.074	0	1
g1trace_black	4320	0.162	0.369	0	1
g1tandch_same_race	4320	0.807	0.394	0	1
g1tpostgrade	4320	0.345	0.475	0	1
g1tyears	4320	11.748	8.826	0	42

Table 63. School characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
gkInner_city	4515	0.191	0.393	0	1
gksuburban	4515	0.192	0.394	0	1
gkrural	4515	0.522	0.499	0	1
g1Inner_city	4515	0.189	0.392	0	1
g1suburban	4515	0.194	0.395	0	1
g1rural	4515	0.523	0.499	0	1
sch_av_propGKmateskept	4333	0.088	0.070	0.019	0.333
sch_av_propGKnetworkkept	3757	0.063	0.154	0	1
sch_av_propg1matesnoattendedgk	4333	0.497	0.060	0.318	0.682
sch_av_black	4333	0.301	0.400	0	1
sch_av_gkfreelunch	4333	0.444	0.280	0	0.985
sch_av_gkabsent	4333	9.913	2.701	4.969	21.666
sch_av_gktreadss	4333	440.731	14.401	409.034	482.931
sch_av_gktmathss	4333	492.045	22.051	441.240	555.581
sch_av_gktlistss	4333	541.169	14.286	511.727	575.950
sch_av_gkwordskillss	4333	438.524	16.474	404.965	485.550
sch_av_gkmotivraw	4110	25.712	0.455	24.656	28.074
sch_av_gkselfconcraw	4110	56.228	1.142	53.114	59.333
sch_av_g1freelunch	4333	0.460	0.280	0.023	1
sch_av_gklargenoaid	4333	0.334	0.091	0	0.554
sch_av_gklargeaid	4333	0.354	0.080	0.212	0.727
sch_av_g1largenoaid	4333	0.343	0.107	0.142	0.714
sch_av_g1largeaid	4333	0.313	0.105	0	0.557
sch_av_gktrace_black	4333	0.852	0.254	0	1
sch_av_kgtandch_same_race	4333	0.208	0.257	0	1
sch_av_gktpostgrade	4333	0.351	0.263	0	1
sch_av_gktyears	4333	9.359	2.711	3.328	15
sch_av_g1tgen_male	4333	0.005	0.031	0	0.243
sch_av_g1trace_black	4333	0.162	0.254	0	0.890
sch_av_g1tandch_same_race	4333	0.808	0.213	0.236	1
sch_av_g1tpostgrade	4333	0.345	0.251	0	1
sch_av_g1tyears	4333	11.744	4.394	0.682	27.551
sch_av_meang1classmatestreadss	4262	528.112	27.46	467.433	578.165
sch_av_meang1classmatesgmathss	4333	535.640	21.301	491.00	577.868
sch_av_meang1classmatestlistss	4333	571.098	15.577	535.750	604.887
sch_av_meang1classmateswordskill	4333	520.592	23.058	461.924	561.561
sch_av_meang1classmatesmotivraw	4333	27.279	1.863	22.681	30.580
sch_av_meang1classmatesselfconcr	4333	39.685	1.972	35.074	42.723
sch_av_meangkclassmatestreadss	4333	440.751	14.433	409.025	482.514
sch_av_meankgclassmatesgmathss	4333	492.007	22.058	440.578	555.813

Table 63. continued.

sch_av_meankgclassmatestlistss	4333	541.216	14.207	510.827	574.822
sch_av_meankgclassmateswordskill	4333	438.568	16.320	404.925	484.341
sch_av_meankgclassmatesmotivraw	4110	25.713	0.455	24.584	28.065
sch_av_meankgclassmatesselfconcr	4110	56.236	1.182	53.185	60.153

Table 64. Probability of passing first grade models

g1promote10	Probit		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	0.05	0.09	0.02	0.52	0.46	0.18	0.13	0.74	0.05	0.06	0.01	0.76	0.05	0.07	0.01	0.69
propGKnetworkkept																
propg1matesnoattendedgk	0.15	0.03	0.16	0.20	1.49	0.07	0.81	0.45	0.15	0.02	0.06	0.49	0.15	0.02	0.08	0.36
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.02				0.00				0.00	
Hausman test					0.28											
F network test p value	0.09		0.52		0.18		0.74		0.06		0.76		0.07		0.69	
n	2295		1971		2295		2295		2295		2295		2295		2295	

Table 65. Probability of passing first grade models

g1promote10	Probit		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	-0.08	0.25	-0.10	0.25	-0.84	0.29	-1.29	0.12	-0.08	0.23	-0.14	0.06	-0.08	0.23	-0.13	0.07
propGKnetworkkept	0.21	0.03	0.21	0.10	2.07	0.07	2.21	0.06	0.22	0.01	0.23	0.01	0.21	0.01	0.22	0.01
propg1matesnoattendedgk	0.15	0.02	0.15	0.22	1.53	0.06	0.81	0.45	0.15	0.02	0.05	0.53	0.15	0.02	0.08	0.38
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.02				0.00				0.00	
Hausman test					0.21											
F network test p value	0.02		0.15		0.09		0.18		0.00		0.04		0.00		0.03	
n	2295		1971		2295		2295		2295		2295		2295		2295	

Table 66. Probability of passing first grade models

g1promote10	Probit		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept																
propGKnetworkkept	0.11	0.01	0.09	0.15	1.00	0.04	0.70	0.15	1.02	0.00	0.08	0.06	0.11	0.00	0.07	0.08
propg1matesnoattendedgk	0.15	0.03	0.16	0.21	1.50	0.07	0.82	0.45	1.46	0.03	0.06	0.49	0.16	0.02	0.08	0.37
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.017				0.00				0.00	
Hausman test					0.30											
F network test p value	0.01		0.15		0.04		0.15		0.00		0.06				0.08	
n	2295		1971		2295		2295		2295		2295		2295		2295	

Table 67. Probability of passing second grade models

g2promote10	Probit		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	-0.01	0.82	-0.12	0.35	-0.21	0.85	-1.40	0.36	-0.01	0.79	-0.07	0.27	-0.01	0.81	-0.07	0.23
propGKnetworkkept	0.00	0.99	0.22	0.28	0.00	0.99	1.04	0.59	0.00	0.98	0.04	0.69	0.00	0.99	0.05	0.52
propg1matesnoattendedgk	0.03	0.48	0.01	0.51	0.51	0.50	1.35	0.46	0.03	0.46	0.07	0.38	0.03	0.43	0.07	0.38
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.1113				0.00				0.00	
Hausman test					0.96											
F network test p value	0.87		0.44		0.91		0.57		0.85		0.38		0.87		0.38	
n	1803		1126		1817		1817		1817		1817		1803		1803	

Table 68. Probability of passing third grade models

g3promote10	Probit		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	0.01	0.84	0.01	0.93	0.19	0.87	0.38	0.79	0.01	0.85	0.01	0.87	0.01	0.86	0.02	0.81
propGKnetworkkept	0.03	0.66	0.07	0.67	0.80	0.62	0.73	0.71	0.03	0.71	0.03	0.73	0.03	0.71	0.03	0.74
propg1matesnoattendedgk	-0.00	0.87	-0.26	0.27	-0.02	0.97	-2.28	0.23	-0.00	0.96	-0.10	0.12	-0.00	0.90	-0.10	0.09
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.20				0.00				0.00	
Hausman test					0.94											
F network test p value	0.24		0.58		0.35		0.48		0.29		0.49		0.31		0.44	
n	1649		749		1663		1663		1663		1663		1649		1615	

Table 69. Cognitive skills in first grade: reading

g1treadss	Probit		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	43.97	0.00	49.50	0.00	43.97	0.00	42.10	0.00	46.29	0.00	41.61	0.00	43.97	0.00	42.10	0.00
propGKnetworkkept	-57.95	0.00	-59.30	0.00	-57.95	0.00	-48.83	0.00	-59.65	0.00	-48.31	0.00	-57.95	0.00	-48.83	0.00
propg1matesnoattendedgk	0.26	0.97	25.73	0.12	0.265	0.97	25.24	0.13	0.930	0.86	25.09	0.02	0.26	0.96	25.24	0.03
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.01				0.00				0.00	
Hausman test			0.00													
F network test p value	0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00	
n	2272		2272		2272		2272		2272		2272		2272		2272	

Table 70. Cognitive skills in first grade: math

g1tmathss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	6.79	0.40	9.17	0.33	6.79	0.43	5.25	0.56	6.15	0.40	2.58	0.76	6.79	0.38	5.25	0.55
propGKnetworkkept	-13.78	0.17	-16.99	0.16	-13.78	0.20	-12.92	0.27	-12.79	0.12	-10.17	0.23	-13.78	0.10	-12.92	0.16
propg1matesnoattendedgk	1.23	0.76	28.02	0.02	1.23	0.81	25.44	0.03	0.95	0.84	23.75	0.01	1.23	0.80	25.44	0.01
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.20				0.00				0.00	
Hausman test					0.00											
F network test p value	0.26		0.34		0.32		0.43		0.11		0.16		0.09		0.17	
n	2274		2274		2274		2274		2274		2274		2274		2274	

Table 71. Cognitive skills in first grade: word skills

g1wordskillss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	48.80	0.00	56.99	0	48.80	0.00	51.32	0	52.35	0.00	47.30	0	48.80	0.00	51.32	0.00
propGKnetworkkept	-58.79	0.00	-65.69	0	-58.79	0.00	-57.12	0.01	-62.73	0.00	-53.62	0	-58.79	0.00	-57.12	0.00
propg1matesnoattendedgk	0.69	0.93	-0.93	0.96	0.69	0.93	5.68	0.76	-0.05	0.99	5.57	0.70	0.69	0.90	5.68	0.70
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.11				0.00				0.00	
Hausman test					0.15											
F network test p value	0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00	
n	1962		1962		1962		1962		1962		1962		1962		1962	

Table 72. Cognitive skills in first grade: listening

g1tlistss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	10.90	0.13	11.60	0.15	10.90	0.14	8.96	0.25	8.90	0.19	6.09	0.42	10.90	0.13	8.96	0.26
propGKnetworkkept	-11.65	0.18	-12.58	0.23	-11.65	0.21	-9.67	0.34	-10.39	0.21	-6.43	0.47	-11.65	0.17	-9.67	0.31
propg1matesnoattendedgk	2.03	0.64	28.83	0.00	2.03	0.65	22.42	0.03	1.45	0.69	20.0	0.01	2.03	0.61	22.42	0.01
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.84				0.00				0.00	
Hausman test					0.00											
F network test p value	0.32		0.36		0.33		0.51		0.43		0.72		0.32		0.52	
n	2263		2263		2263		2263		2263		2263		2263		2263	

Table 73. Noncognitive skills in first grade: motivation

g1motivraw	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	-0.91	0.46	-0.70	0.61	-0.87	0.50	-0.44	0.74	-0.84	0.52	-0.53	0.70	-0.91	0.49	-0.44	0.75
propGKnetworkkept	3.18	0.03	2.62	0.14	3.15	0.05	2.68	0.12	3.10	0.07	2.71	0.13	3.18	0.07	2.68	0.14
propg1matesnoattendedgk	1.05	0.07	4.06	0.02	1.20	0.14	4.04	0.02	1.29	0.03	4.07	0.01	1.05	0.06	4.04	0.02
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.27				0.00				0.00	
Hausman test					0.64											
F network test p value	0.00		0.10		0.00		0.04		0.01		0.10		0.01		0.11	
n	2093		2093		2093		2093		2093		2093		2093		2093	

Table 74. Noncognitive skills in first grade: selfconfidence

g1selfconcraw	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	2.29	0.19	1.53	0.42	2.12	0.24	2.99	0.10	2.07	0.28	2.94	0.15	2.29	0.24	2.99	0.16
propGKnetworkkept	-1.23	0.58	1.60	0.51	-0.38	0.86	-0.09	0.96	-0.15	0.95	-0.03	0.98	-1.23	0.64	-0.09	0.97
propg1matesnoattendedgk	-0.00	0.99	-3.00	0.22	-0.01	0.99	-4.07	0.10	-0.02	0.98	-4.05	0.25	-0.00	0.99	-4.07	0.26
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.23											
F network test p value	0.14		0.02		0.06		0.00		0.11		0.01		0.30		0.01	
n	2093		2093		2093		2093		2093		2093		2093		2093	

Table 75. Noncognitive skills in first grade: days absent

g1absent	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	1.52	0.36	2.46	0.16	1.74	0.30	3.11	0.07	1.84	0.33	2.78	0.15	1.52	0.42	3.11	0.13
propGKnetworkkept	-3.68	0.08	-4.62	0.04	-4.09	0.06	-6.06	0.00	-4.21	0.13	-5.56	0.05	-3.68	0.21	-6.06	0.04
propg1matesnoattendedgk	-0.23	0.84	-1.21	0.60	-0.50	0.66	-1.14	0.62	-0.58	0.43	-1.16	0.62	-0.23	0.74	-1.14	0.63
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.00											
F network test p value	0.07		0.10		0.06		0.01		0.23		0.12		0.41		0.10	
n	2298		2298		2298		2298		2298		2298		2298		2298	

7. Appendix

Table 76. Cognitive skills in first grade: reading

g1treadss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	2.66	0.58	9.93	0.13	2.66	0.60	9.86	0.13	4.30	0.46	9.61	0.08	2.66	0.60	9.86	0.08
propGKnetworkkept																
propg1matesnoattendedgk	2.36	0.75	29.47	0.08	2.36	0.74	28.39	0.09	3.39	0.50	27.85	0.01	2.36	0.61	28.39	0.01
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.00											
F network test p value	0.58		0.13		0.60		0.13		0.46		0.08		0.60		0.08	
n	2272		2272		2272		2272		2272		2272		2272		2272	

Table 77. Cognitive skills in first grade: reading

g1treadss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept																
propGKnetworkkept	-7.44	0.20	-4.66	0.58	-7.44	0.25	-3.06	0.65	4.30	0.41	-3.57	0.57	-7.44	0.24	-3.06	0.65
propg1matesnoattendedgk	2.38	0.75	29.28	0.08	2.38	0.74	28.18	0.09	3.39	0.5	27.55	0.01	2.38	0.61	28.18	0.02
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.00											
F network test p value	0.20		0.58		0.25		0.65		0.41		0.57		0.24		0.65	
n	2272		2272		2272		2272		2272		2272		2272		2272	

Table 78. Cognitive skills in first grade: word skills

g1wordskillss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	6.39	0.22	12.64	0.08	6.39	0.24	12.98	0.07	7.40	0.21	11.57	0.08	6.39	0.27	12.98	0.06
propGKnetworkkept																
propg1matesnoattendedgk	3.10	0.73	4.71	0.80	3.10	0.73	10.52	0.57	2.98	0.61	9.85	0.50	3.10	0.58	10.52	0.47
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.07				0.00				0.00	
Hausman test					0.00											
F network test p value																
n	1962		1962		1962		1962		1962		1962		1962		1962	

Table 79. Cognitive skills in first grade: word skills

g1wordskillss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept																
propGKnetworkkept	-3.30	0.61	-3.95	0.67	-3.30	0.63	3.01	0.68	-3.72	0.62	2.38	0.71	-3.30	0.65	3.01	0.70
propg1matesnoattendedgk	3.42	0.71	5.26	0.78	3.42	0.70	11.25	0.55	3.32	0.56	10.54	0.47	3.42	0.54	11.25	0.45
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.10				0.00				0.00	
Hausman test					0.00											
F network test p value																
n	1962		1962		1962		1962		1962		1962		1962		1962	

Table 80. Males probability of passing first grade

g1promote10	Probit		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	-0.17	0.14	-0.09	0.5	-1.40	0.17	-1.59	0.17	-0.17	0.19	-0.20	0.17	-0.17	0.19	-0.18	0.185
propGKnetworkkept	0.32	0.03	0.17	0.43	2.63	0.06	2.18	0.18	0.32	0.04	0.27	0.12	0.32	0.04	0.25	0.129
propg1matesnoattendedgk	0.18	0.16	0.23	0.27	1.47	0.19	1.44	0.32	0.17	0.07	0.15	0.18	0.18	0.06	0.17	0.13
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.38				0.00				0.00	
Hausman test					0.96											
F network test p value	0.06		0.72		0.14		0.37		0.02		0.31		0.03		0.3261	
n	1151		882		1151		1151		1151		1151		1151		1151	

Table 81.Females probability of passing first grade

g1promote10	Probit		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	-0.01	0.85	-0.13	0.32	-0.19	0.88	-0.82	0.56	-0.00	0.95	-0.03	0.71	-0.01	0.85	-0.06	0.53
propGKnetworkkept	0.11	0.35	0.29	0.17	1.37	0.48	2.05	0.33	0.09	0.42	0.11	0.40	0.11	0.32	0.15	0.26
propg1matesnoattendedgk	0.13	0.06	-0.03	0.80	1.58	0.19	0.06	0.97	0.14	0.07	0.00	0.99	0.13	0.07	0.00	0.97
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.23				0.00				0.00	
Hausman test					0.42											
F network test p value	0.23		0.08		0.43		0.56		0.11		0.57		0.08		0.38	
n	1137		864		1144		1144		1144		1144		1137		1113	

Table 82.Males noncognitive skills: absent days

g1absent	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	3.23	0.19	3.41	0.19	3.28	0.17	4.26	0.09	3.41	0.23	4.16	0.16	3.23	0.26	4.26	0.17
propGKnetworkkept	-6.62	0.02	-8.52	0.01	-6.76	0.02	-9.45	0.00	-7.28	0.06	-9.38	0.02	-6.62	0.09	-9.45	0.03
propg1matesnoattendedgk	3.14	0.08	2.84	0.40	3.10	0.05	3.48	0.30	3.00	0.00	3.42	0.23	3.14	0.00	3.48	0.25
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.01				0.00				0.00	
Hausman test					0.00											
F network test p value	0.02		0.00		0.02		0.00		0.10		0.03		0.18		0.04	
n	1156		1156		1156		1156		1156		1156		1156		1156	

Table 83.Females noncognitive skills: absent days

g1absent	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	-0.25	0.91	2.17	0.37	0.10	0.96	2.28	0.33	0.34	0.88	2.27	0.38	-0.25	0.91	2.28	0.39
propGKnetworkkept	-0.36	0.90	-1.11	0.72	-0.56	0.85	-2.46	0.42	-0.68	0.83	-2.46	0.46	-0.36	0.91	-2.46	0.47
propg1matesnoattendedgk	-2.79	0.06	-5.23	0.10	-3.02	0.03	-5.38	0.09	-3.17	0	-5.38	0.07	-2.79	0.00	-5.38	0.08
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.98											
F network test p value	0.87		0.49		0.94		0.62		0.97		0.67		0.91		0.69	
n	1142		1142		1142		1142		1142		1142		1142		1142	

Table 84.Males noncognitive skills: motivation

g1motivraw	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	-3.92	0.04	-3.87	0.07	-3.92	0.04	-3.53	0.08	-3.95	0.01	-3.49	0.04	-3.92	0.01	-3.53	0.05
propGKnetworkkept	6.41	0.00	6.08	0.02	6.41	0.00	5.97	0.02	6.43	0.00	5.86	0.00	6.41	0.00	5.97	0.00
propg1matesnoattendedgk	1.81	0.03	4.72	0.08	1.81	0.13	4.58	0.09	1.77	0.00	4.62	0.02	1.81	0.01	4.58	0.02
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.51				0.00				0.00	
Hausman test					0.10											
F network test p value	0.00		0.07		0.01		0.06		0.00		0.01		0.00		0.01	
n	1049		1049		1049		1049		1049		1049		1049		1049	

Table 85.Females noncognitive skills: motivation

g1motivraw	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	2.22	0.15	2.93	0.12	2.29	0.19	2.75	0.13	2.27	0.12	2.75	0.07	2.22	0.14	2.75	0.09
propGKnetworkkept	-0.36	0.85	-1.62	0.50	-0.38	0.86	-0.71	0.76	-0.36	0.85	-0.71	0.74	-0.36	0.85	-0.71	0.75
propg1matesnoattendedgk	0.67	0.39	4.22	0.08	0.82	0.44	4.08	0.09	0.80	0.29	4.08	0.11	0.67	0.37	4.08	0.13
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.69				0.00				0.01	
Hausman test					0.77											
F network test p value	0.02		0.14		0.03		0.05		0.01		0.05		0.02		0.08	
n	1044		1044		1044		1044		1044		1044		1044		1044	

Table 86.Males noncognitive skills: selfconfidence

g1selfconcraw	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	1.81	0.49	1.03	0.72	1.74	0.51	2.63	0.34	1.79	0.52	3.23	0.28	1.81	0.53	2.63	0.38
propGKnetworkkept	-0.88	0.79	1.94	0.59	-0.27	0.93	0.53	0.87	-0.59	0.87	0.02	0.99	-0.88	0.82	0.53	0.88
propg1matesnoattendedgk	0.02	0.98	-2.50	0.50	0.15	0.92	-5.07	0.17	0.09	0.94	-5.68	0.11	0.02	0.98	-5.07	0.17
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.10				0.00				0.00	
Hausman test					0.49											
F network test p value	0.57		0.23		0.42		0.10		0.56		0.03		0.65		0.07	
n	1049		1049		1049		1049		1049		1049		1049		1049	

Table 87.Females noncognitive skills: selfconfidence

g1selfconcraw	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	3.32	0.15	1.99	0.45	3.32	0.16	3.811	0.13	3.21	0.11	4.83	0.02	3.32	0.11	3.81	0.08
propGKnetworkkept	-2.16	0.47	1.55	0.65	-2.16	0.48	-1.31	0.68	-1.89	0.47	-2.86	0.34	-2.16	0.42	-1.31	0.67
propg1matesnoattendedgk	0.28	0.80	-1.62	0.64	0.28	0.83	-1.73	0.61	0.30	0.76	-1.81	0.69	0.28	0.77	-1.73	0.72
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes								Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.15				0.00				0.00	
Hausman test					0.02											
F network test p value	0.13		0.08		0.16		0.08		0.11		0.01		0.14		0.03	
n	1044		1044		1044		1044		1044		1044		1044		1044	

Table 88.Males noncognitive skills: listening

g1tlistss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	10.03	0.35	7.80	0.51	10.03	0.35	6.36	0.57	10.75	0.39	3.26	0.77	10.03	0.42	6.36	0.61
propGKnetworkkept	-8.62	0.5	-5.33	0.72	-8.62	0.52	-5.30	0.71	-9.00	0.56	-1.88	0.90	-8.62	0.57	-5.30	0.76
propg1matesnoattendedgk	-2.09	0.73	34.93	0.02	-2.09	0.76	27.70	0.07	-1.52	0.86	26.82	0.05	-2.09	0.81	27.70	0.06
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.05				0.00				0.00	
Hausman test					0.00											
F network test p value	0.60		0.74		0.58		0.83		0.59		0.93		0.64		0.85	
n	1136		1136		1136		1136		1136		1136		1136		1136	

Table 89.Females noncognitive skills: listening

g1tlistss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	11.21	0.27	11.30	0.32	11.21	0.27	10.75	0.32	10.92	0.22	9.75	0.33	11.21	0.23	10.75	0.30
propGKnetworkkept	-15.64	0.22	-15.61	0.29	-15.64	0.24	-11.76	0.41	-15.45	0.11	-8.85	0.36	-15.64	0.12	-11.76	0.26
propg1matesnoattendedgk	5.29	0.37	26.30	0.07	5.29	0.38	19.04	0.19	4.90	0.25	14.14	0.19	5.29	0.23	19.04	0.10
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.54				0.00				0.00	
Hausman test					0.12											
F network test p value	0.47		0.56		0.50		0.61		0.27		0.60		0.29		0.515	
n	1127		1127		1127		1127		1127		1127		1127		1127	

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Table 90.Males cognitive skills: reading

g1treadss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	50.83	0.00	41.63	0.02	50.83	0.00	41.01	0.02	50.45	0.00	40.74	0.01	50.83	0.00	41.02	0.02
propGKnetworkkept	-61.74	0.00	-48.11	0.04	-61.74	0.00	-48.73	0.03	-60.69	0.00	-48.55	0.02	-61.74	0.00	-48.73	0.04
propg1matesnoattendedgk	-2.38	0.84	37.42	0.11	-2.38	0.83	41.98	0.08	-1.65	0.88	42.06	0.04	-2.38	0.83	41.98	0.06
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.01				0.00				0.00	
Hausman test																
F network test p value	0.00		0.08		0.01		0.07		0.01		0.04		0.02		0.06	
n	1139		1139		1139		1139		1139		1139		1139		1139	

Table 91.Males cognitive skills: reading

g1treadss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	6.06	0.37	8.90	0.34	6.06	0.40	7.97	0.39	6.95	0.27	7.87	0.33	6.06	0.33	7.97	0.34
propGKnetworkkept																
propg1matesnoattendedgk	0.39	0.97	42.03	0.07	0.39	0.97	46.35	0.05	1.51	0.89	46.43	0.02	0.39	0.97	46.35	0.02
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.00											
F network test p value	0.36		0.34		0.40		0.39		0.27		0.33		0.33		0.34	
n	1139		1139		1139		1139		1139		1139		1139		1139	

Table 92.Males cognitive skills: reading

g1treadss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept																
propGKnetworkkept	-4.17	0.62	-2.51	0.83	-4.17	0.64	-5.30	0.58	6.95	0.27	-5.86	0.43	-4.17	0.55	-5.30	0.50
propg1matesnoattendedgk	0.429	0.97	41.84	0.08	0.42	0.96	45.60	0.05	1.51	0.89	45.62	0.02	0.42	0.96	45.60	0.03
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0											
F network test p value	0.62		0.83		0.64		0.58		0.27		0.43		0.55		0.50	
n	1139		1139		1139		1139		1139		1139		1139		1139	

Table 93.Females cognitive skills: reading

g1treadss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	37.95	0.01	50.67	0.00	37.95	0.02	41.84	0.01	40.94	0.00	38.76	0.00	37.95	0.00	41.84	0.00
propGKnetworkkept	-55.03	0.00	-66.05	0.00	-55.03	0.01	-49.37	0.03	-58.12	0.00	-45.02	0.00	-55.03	0.00	-49.37	0.00
propg1matesnoattendedgk	1.92	0.83	13.78	0.56	1.92	0.84	10.41	0.66	2.08	0.68	6.71	0.75	1.92	0.70	10.41	0.63
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.00											
F network test p value	0.01		0.01		0.04		0.05		0.00		0.00		0.003		0.00	
n	1133		1133		1133		1133		1133		1133		1133		1133	

Table 94.Females cognitive skills: reading

g1treadss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	-0.75	0.91	7.41	0.44	-0.75	0.91	9.40	0.32	0.34	0.96	9.03		-0.75	0.91	9.40	0.26
propGKnetworkkept																
propg1matesnoattendedgk	3.66	0.68	16.20	0.50	3.66	0.71	12.60	0.60	4.03	0.44	8.98		3.66	0.48	12.60	0.58
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.00											
F network test p value	0.91		0.44		0.91		0.32		0.96		0.27		0.91		0.26	
n	1133		1133		1133		1133		1133		1133		1133		1133	

Table 95.Females cognitive skills: reading

g1treadss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept																
propGKnetworkkept	-10.91	0.18	-9.96	0.43	-10.91	0.24	-1.97	0.84	0.34	0.96	-0.32	0.96	-10.91	0.22	-1.97	0.81
propg1matesnoattendedgk	3.62	0.69	16.01	0.50	3.62	0.71	12.57	0.60	4.03	0.44	8.99	0.68	3.62	0.48	12.57	0.58
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test			0.00													
F network test p value	0.18		0.43		0.24		0.84		0.96		0.96		0.22		0.81	
n	1133		1133		1133		1133		1133		1133		1133		1133	

Table 96.Males cognitive skills: math

g1tmathss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	-7.29	0.54	-8.75	0.53	-7.29	0.56	-10.21	0.45	-7.31	0.51	-11.18	0.32	-7.29	0.52	-10.21	0.39
propGKnetworkkept	4.75	0.75	4.19	0.81	4.75	0.76	5.34	0.75	4.76	0.67	6.15	0.63	4.75	0.67	5.34	0.69
propg1matesnoattendedgk	0.83	0.90	22.65	0.21	0.83	0.92	22.47	0.21	0.84	0.90	22.41	0.15	0.83	0.91	22.47	0.16
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.76				0.00				0.00	
Hausman test					0.16											
F network test p value	0.73		0.69		0.74		0.60		0.74		0.55		0.75		0.64	
n	1140		1140		1140		1140		1140		1140		1140		1140	

Table 97.Females cognitive skills: math

g1tmathss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	19.83	0.07	27.74	0.03	19.83	0.09	22.14	0.07	19.80	0.04	20.39	0.05	19.83	0.04	22.14	0.06
propGKnetworkkept	-34.16	0.01	-44.32	0.00	-34.16	0.02	-36.27	0.02	-34.10	0.00	-33.44	0.01	-34.16	0.00	-36.27	0.01
propg1matesnoattendedgk	-0.83	0.87	26.75	0.11	-0.83	0.90	23.611	0.16	-0.85	0.86	21.66	0.15	-0.83	0.86	23.61	0.13
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.10				0.00				0.00	
Hausman test					0.00											
F network test p value	0.02		0.03		0.05		0.07		0.00		0.03		0.01		0.03	
n	1134		1134		1134		1134		1134		1134		1134		1134	

Table 98.Males cognitive skills: g1wordskillss

g1wordskillss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	52.48	0.00	44.21	0.02	52.48	0.00	48.09	0.01	53.29	0.00	46.33	0.00	52.48	0.00	48.09	0.00
propGKnetworkkept	-58.75	0.00	-53.04	0.03	-58.75	0.00	-56.86	0.02	-60.36	0.00	-54.97	0.00	-58.75	0.01	-56.86	0.00
propg1matesnoattendedgk	9.95	0.41	18.79	0.48	9.95	0.47	22.57	0.39	10.30	0.27	23.12	0.27	9.95	0.31	22.57	0.31
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.09				0.00				0.00	
Hausman test					0.00											
F network test p value	0.00		0.08		0.01		0.04		0.01		0.01		0.02		0.0187	
n	981		981		981		981		981		981		981		981	

Table 99.Males cognitive skills: word

g1wordskillss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	9.25	0.21	7.78	0.45	9.25	0.22	9.03	0.37	9.19	0.19	9.65	0.26	9.25	0.19	9.03	0.31
propGKnetworkkept																
propg1matesnoattendedgk	13.86	0.26	26.54	0.32	13.86	0.31	29.9	0.26	14.47	0.10	30.01	0.15	13.86	0.14	29.98	0.16
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.06				0.00				0.00	
Hausman test					0.00											
F network test p value	0.21		0.45		0.22		0.37		0.19		0.26		0.19		0.31	
n	981		981		981		981		981		981		981		981	

Table 100.Males cognitive skills: word

g1wordskillss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept																
propGKnetworkkept	-0.06	0.99	-5.46	0.67	-0.06	0.99	-1.27	0.90	-0.94	0.91	-3.08	0.68	-0.06	0.99	-1.28	0.88
propg1matesnoattendedgk	14.21	0.25	26.45	0.32	14.21	0.30	30.06	0.25	14.86	0.09	30.04	0.15	14.21	0.12	30.06	0.17
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.04				0.00				0.00	
Hausman test					0.88											
F network test p value	0.99		0.67		0.99		0.90		0.91		0.68		0.99		0.8849	
n	981		981		981		981		981		981		981		981	

Table 101.Females cognitive skills: word

g1wordskillss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	49.19	0.00	58.18	0.00	49.19	0.00	53.68	0.00	52.05	0.00	52.30	0.00	49.19	0.00	53.68	0.00
propGKnetworkkept	-63.60	0.00	-72.68	0.00	-63.60	0.00	-60.26	0.01	-66.71	0.00	-57.63	0.01	-63.60	0.00	-60.26	0.01
propg1matesnoattendedgk	-6.65	0.58	-20.33	0.45	-6.65	0.58	-16.95	0.53	-8.43	0.48	-18.55	0.44	-6.65	0.56	-16.95	0.50
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.00											
F network test p value	0.01		0.01		0.02		0.02		0.01		0.01		0.02		0.03	
n	981		981		981		981		981		981		981		981	

Table 102.Females cognitive skills: word

g1wordskillss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept	4.10	0.59	9.80	0.37	4.10	0.60	12.79	0.23	5.17	0.52	12.87	0.19	4.10	0.60	12.79	0.22
propGKnetworkkept																
propg1matesnoattendedgk	-4.97	0.68	-17.45	0.52	-4.97	0.68	-13.95	0.60	-6.22	0.61	-15.35	0.53	-4.97	0.67	-13.95	0.58
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.00											
F network test p value	0.59		0.37		0.60		0.22		0.52		0.19		0.60		0.22	
n	981		981		981		981		981		981		981		981	

Table 103.Females cognitive skills: word

g1wordskillss	OLS		FE		RE		RE with schmeans		GEE		GEE with schmeans		Pooled		Pooled with schmeans	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
propGKmateskept																
propGKnetworkkept	-6.78	0.46	-9.59	0.49	-6.78	0.50	5.49	0.61	-7.21	0.45	8.55	0.29	-6.78	0.48	5.49	0.55
propg1matesnoattendedgk	-4.68	0.70	-17.43	0.52	-4.68	0.70	-13.18	0.62	-5.92	0.62	-14.21	0.56	-4.68	0.69	-13.18	0.60
student	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classtreatment	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
teacher	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
classmates	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
schnetwork							Yes				Yes				Yes	
schdelta							Yes				Yes				Yes	
schstudent							Yes				Yes				Yes	
schclasstreatment							Yes				Yes				Yes	
schteacher							Yes				Yes				Yes	
schclassmates							Yes				Yes				Yes	
Sschdummies			Yes													
schmeans F test pvalue							0.00				0.00				0.00	
Hausman test					0.00											
F network test p value	0.46		0.49		0.50		0.61		0.45		0.29		0.48		0.55	
n	981		981		981		981		981		981		981		981	

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CHAPTER 5. GENERAL CONCLUSIONS

This dissertation is devoted to the study of three different topics under the advice of three different major professors. The topics only have in common the interest and curiosity of the author to explain real life events using applied econometric techniques. Chapter 2 applies financial tools to assess whether stock values reacted across world markets to the announcement of indexes that synthesize the environmental performance of the world’s largest publicly-traded companies.

Our results indicate that the market reacted to the G100 by changing the relative prices of the stocks included in it, but not the value of the equal-weight portfolio of such stocks. The magnitude of the effect was sizeable: moving one position closer to the top of Newsweek’s G100 raised the value of an average firm in the list by 11.3 million dollars. The use of stocks traded in international markets allowed us to find evidence of heterogeneity among investors. They have different interests in past performance and managerial quality as predictors of future environmental performance. In particular, US-traded stock returns were affected only by past performance (EIS), contrasting with non-US-traded stock returns which responded only to managerial quality (GPS and RSS). These results have implications for the construction of optimal environmental rankings (Chatterji, Levine, and Toffel 2009), suggesting that the weight on past performance and managerial quality that are used to construct environmental performance indexes, should differ across stock markets.

In Chapter 3, we analyze the grain transportation market in the US. Every year more than 400 million tons of corn, soybeans and wheat are transported from the Midwest to diverse destinations within the US (70%) and abroad (30%). The transportation of grain is mostly intermodal by combining truck, train, barge and ocean-vessel and its rates explain 42–64% of the variation in corn prices in the long run. By using data from the Grain Transportation Report, this paper estimates simultaneous equation models of barge and railroad rates (in logs and levels) for specific origins-destinations and grains (corn, wheat and soybeans).

Results show that barge rates have an elastic reaction to shuttle rates (1.2 to 1.6) and an inelastic reaction to unit rates (0.5 to 0.7), while they do not systematically respond to shuttle rates. It was also possible to find results showing intermodal transportation that complement or compete with each other: rails complement more with the PNW than barges do with the Gulf. In the case of corn, it was possible to identify for the first time in the literature the existence of complementarity between rail and barges in the rail line from Des Moines, IA to Davenport, IA. Results also support that the impact of barge rates on railroad rates is reduced when the origin of the grain is distant from the waterway.

The forth chapter of the dissertation explores the idea that peer effects depend on the strength of peer connections, which may increase over time. It analyzes the effect on early education achievement of keeping the same classmates as in the previous year by utilizing the unique nature of the Tennessee Student Teacher Achievement Ratio (STAR). I study the relationship between the chance of passing first grade, as well as noncognitive skills and the proportion of kindergarten classmates that continue to be classmates in first grade. I benefit from the randomized mixing up policy of the STAR program in the identification of effects of long time peers, peers that have been together for a long period of time, and estimate value-added models with and without school fixed and random effects. A novel microeconometric approach is also used: clustering errors by pooled models and by GEE.

There are two major findings in this paper. Keeping all kindergarten classmates, vs. losing all of them, may increase the probability of passing first grade by 7 to 10% among students participating in the STAR program. This result gives partial support to the main hypothesis of the paper: that long lasting connections may be more influential than short term connections, even when there is no endogenous selection by the quality of the connections over time. Future research is required to address the possibility of non linearities in the effect of average time that peers have been together. To address that issue the maximum average amount of time that classmates have been peers is required to be larger than a year, while students need to be randomly assigned to each class every academic year. The second most important finding is that non-cognitive skills might be improved when more kindergarten classmates are kept in first grade. If all classmates are kept together vs. staying alone in a new class, motivation and selfconfidence may increase by 0.5 of a standard deviations while the number of absent days may decrease by 2 to 3 days.

This study is, to my knowledge, the first to find evidence partialy supporting the importance of time on peer effects. Specifically, the effect of peers does not depend only on their abilities and skills, but also on the time they have been peers. This is true even when there is not endogenous peer selection over time. These results have implications for educational policies like random mixing and sorting/tracking.

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