

Journal of Applied Economics and Policy

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Published by the Department of Economics
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Journal of Applied Economics and Policy

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The *Journal of Applied Economics and Policy* accepts submissions from all JEL classifications; however, special attention is paid to manuscripts focusing on issues relating to Kentucky and the surrounding region.

Information and the online submission process can be found at kentuckyeconomicassociation.org/jaep/. The submission fee is \$20.00 and may be paid via Pay Pal using a credit card or by check made payable to the *Journal of Applied Economics and Policy*. Correspondence regarding articles submitted for publication in the *Journal*:

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The **Kentucky Economic Association** facilitates greater communication among state researchers from academia, government, and business, and promotes the sharing and discussion of research by economists and public policy analysts working on issues relevant to the Commonwealth. To these purposes the association holds an annual conference and publishes the *Journal of Applied Economics and Policy*. The Kentucky Economic Association's website is found at kentuckyeconomicassociation.org.

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Kentucky Economic Association Annual Conference
Friday, October 28, 2011—Capital Plaza Hotel, Frankfort, KY
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and KEA 2011 Distinguished Economist

PROGRAM:

Those interested in presenting or discussing papers, organizing a session or panel discussion, or serving as a session chair should submit their materials using our online submission form at kentuckyeconomicassociation.org or contact:

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The deadline for program submissions/abstracts is October 7, 2011. Completed manuscripts may be considered for publication in the *Journal of Applied Economics and Policy*. The JAEP is a publication of the Kentucky Economic Association. It is listed in Cabell's Directory of Publishing Opportunities and can be accessed online through EBSCOhost.

There will be a "Best Paper Award", as well as, undergraduate paper sessions and an award for "Best Undergraduate Paper." A completed paper must be submitted no later than October 7 to be considered for these awards.

A block of rooms has been reserved at the Capital Plaza Hotel in Frankfort. Ask for the KEA conference rate of \$84 plus tax. Please contact the hotel directly (502) 564-3093.

REGISTRATION FEES: \$75 early registration fee; \$95 (after October 20); \$20 student registration fee

To register for the conference, please use the online form at <http://kentuckyeconomicassociation.org> or mail the information form below with your materials to the KEA Program Chair above and your payment to:

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W IND E NERGY F EASIBILITY IN K ENTUCKY

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Abstract

Despite a strong political demand for non-carbon dioxide generating electrical sources, the low-cost of Kentucky electricity poses a challenge to incorporating wind power into the state. Nevertheless, there are sites in the state, such as Cumberland, Kentucky, where generating electricity from wind is already cost-competitive. Production of electricity through coal produces negative externalities in the form of pollution and greenhouse gases. As the price of energy from coal rises from increased regulation of greenhouse gases, other sites in Kentucky could quickly become competitive as well.

I. Introduction

There is a strong sentiment in Kentucky towards adopting alternative energy sources such as wind power. A survey conducted in Kentucky by Opinion Research Corporation in September of 2008 showed that citizens overwhelmingly desired a move to cleaner energy sources. The results showed that 43% of the respondents had a first priority of ‘transitioning to renewable energy sources, such as solar and wind’ (Kentucky Energy, 2008). Furthermore, a combined 73% claimed ‘more energy efficiency and less wasted energy’ as their first priority. In contrast, coal was viewed as a ‘power source of yesterday’ and wind was viewed as the ‘power source of tomorrow.’ More than three quarters of the respondents were in favor of a five-year suspension of new coal-fired power plants being built, as long as an increased investment was made in clean energy sources, like wind and solar (Kentucky Energy, 2008).

Development of a comprehensive national energy policy was found to be important to voters in Kentucky. According to the CLEAN survey, over 90% of the respondents in Kentucky listed energy-related issues as ‘important’ in how they would vote for elected officials. Of this majority, 64 percent rank the energy-related issues as ‘very important’ to how they will vote (Kentucky Energy, 2008). Only 16 percent of those surveyed responded that they would like to keep the incentives for nuclear power and coal-fired power the way they are today. Approximately 56% want the President’s first energy-related priority to be to promote wind and solar to achieve energy independence. Nevertheless, 50 percent of Kentuckians want to evenly split the incentives between nuclear and coal and renewable sources like wind or solar (Kentucky Energy, 2008).

Although wind energy has popular support, the history of energy in Kentucky indicates that a movement to wind energy could face some hurdles. Traditionally, coal has been king in Kentucky and has historically created a large number of well-paying jobs in the coal mining industry. Even today, coal plays a significant role in the Kentucky economy being the nation’s third largest producer of coal (E.I.A., KY, 2009). Currently, 93.5 percent of the total electricity for the Kentucky population of 4,300,000 is generated from coal-fired plants. Kentucky has 21 coal-fired power plant stations that produce over 16,000 megawatts, ranking sixth in the country. In addition, the power is relatively inexpensive with a cost of 7.04 cents per kWh, ranking among the lowest in the United States. Consistent with the emphasis on low-cost electricity, Kentucky is one of the few states in the country that does not have a renewable energy portfolio standard in place. Renewable forms of energy account for only a small percentage of the total electricity generated.

Nevertheless, production of electricity using coal has several negative externalities. Although the cost of electricity produced with coal is low, its current cost structure does not include negative externalities associated with high levels of pollution that is damaging the environment. Efforts to enact legislation like a carbon tax are attempts to recover these negative externalities and would change the trade-offs between coal and alternative energy sources. The Kentucky Energy survey shows that most citizens realize the harm that coal has caused and that new alternative methods of generating electricity should be brought to fruition. Kentucky emitted 143 million metric tons of carbon dioxide in 2003, which placed it

in the top 25% of states in the country (Chea et. al., 2007). Furthermore, the Environmental Protection Agency's list of the 44 most hazardous coal waste ponds in the country had six sites in Kentucky (Fact Sheet, 2009). Although the coal industry supplied a significant number of jobs in the past, now just one percent of the state's jobs are in the coal industry (The Economics of Coal, 2009). Using coal in the future may not be inexpensive because as old plants are torn down and new plants are constructed in their place, future coal plants will face increasingly harsh environmental requirements.

There is no longer a reason to combat the use of alternative energy due to a loss of jobs. In fact, more jobs would be created as alternative energy stations were developed. There is a significant amount of wind to sustain wind energy generation, especially in eastern Kentucky (Jafari, 2010). 2009 was a record year for wind turbines in the US. There were 10 GW of capacity added, which was 40% of 2008's capacity, bringing the total to 35 GW (Bolinger and Wiser, 2009). \$21 billion was spent on investment. \$2.2 billion of new Clean Renewable Energy Bonds were put forth.

II. Methodology and Analysis

A financial model is developed in this section to determine the economic feasibility of wind power at six locations in Kentucky. The wind velocity data for Kentucky were collected from the National Renewable Energy Laboratory Eastern Wind database. The analysis estimates the expected prices at which wind investors could deliver wind generated electricity to the grid, which are called the "busbar price". It does not include the transmission cost through the grid, which is included in the average price of electricity for the state, as given by the EIA (total cost is currently about 6.62 cents per kWh). Table 1 delineates the cost of electricity for residential, commercial, and industrial users in Kentucky and the United States. Once again, these costs include transmission and distribution costs.

The sites are located in the cities of Cumberland, Georgetown, Lexington (two sites), Middlesborough, and Wallins Creek and were tested using 50 meter wind assessments, in ten minute intervals (See Table 2). The data are from 2004 through 2006 (Eastern Wind Dataset, 2010), and the total sample size of observations equals approximately 158,000 for each location. The elevations of the sites varied from 264 to 1064 feet. Not surprisingly, the higher locations generate greater wind speeds. The greater wind speeds make the generation costs more economically feasible.

In our model, the busbar price varies inversely and nonlinearly with the average wind speed at each location. Given that investment is in fixed units, higher wind speeds generate more electricity per unit of capital investment. The power curve is a cubical function. The potential power function (Eskin et. al., 2008) is:

$$P = \frac{1}{2} \rho A v^3 \quad (1)$$

where ρ is the mean air density, v^3 is the mean value of wind speed raised to the third power, and A is the sweep area. Because of the cubic nature of the function, with regard to the velocity of the wind, small differences in wind speed generate relatively large differences in

power output. Because actual power generated is slightly less than the theoretical potential power function, we use actual power curves from the Gamesa G87 and G90 2.0 megawatt wind turbines to model potential electrical production from each site.

The model uses the electric power produced at each site, together with capital costs, terms of financing, replacement costs, and operation and maintenance, to determine the threshold price at which the unit becomes financially feasible. This price is found where the NPV of the wind power projects is equal to zero after repaying all debt and equity investors.

Our object is to find the cost of energy (CE) of electricity from each wind site. Relevant factors include initial capital expenses and financial factors such as capital structure, terms of financing, return on equity, calculation of beta, calculation of WACC, and the capital recovery factor.

The approach involves the following related steps:

1. Determine a reasonable range for return on equity. In general, this is going to be approximately in the nine to ten percent range. We could use beta and the capital asset pricing model to calculate an optimal return on equity, however, this is really not necessary as there are more than adequate estimates of reasonable ROE from ongoing rate hearing cases held in front of public utility commissions. The vast majority of these are in the range of nine to ten percent (Gordon and Makholm, 2008).
2. Assess the ideal capital structure for an investment in wind energy. Assuming that an investment in wind energy is subject to the same financial constraints as other investments, we can again use the common capital structure assumptions that are used in various rate hearing cases (Gordon and Makholm, 2008).
3. Calculate the weighted average cost of capital (WACC) using 1 & 2 above.
4. Determine the optimal time period in which the capital should be recovered. In this paper we will use 20 years.
5. Calculate the capital recovery factor using the WACC.
6. Use the capital recovery factor to calculate the cost of energy.

Let us now examine the approach in a little more detail.

As stated above, the object of calculating the cost of energy is to find the price of power that makes the NPV of an investment in a windmill equal to zero. The initial investment, in our case, is \$3.3 million per windmill. This represents an investment in a Gamesa G90-2.0 MW system. This particular windmill is well-suited for Kentucky because it produces maximum output, at minimum cost per kWh, for low wind sites. This model has lighter blades made of fiberglass and carbon fiber. Noise emissions are minimized because of an aerodynamic design and the Gamesa NRS control system. The cost is complete with tower and balance of station items such as foundation, assembly and installation, and electrical interface connections. Construction time for the windmills is an important factor. Natural gas plants can take two years to build, coal plants can take four years, and nuclear plants can take

five years. Nevertheless, with favorable regulation, wind turbines can be installed between three months and one year (Dismukes, 2007, p.29; Tester, Drake, Driscoll, Golay, and Peters, 2005, p.633).

Feasibility analysis for electricity plants focuses mainly on recovery of capital costs. Unlike nuclear or fossil fuel plants, there is no cost in a wind plant for fuel. Consequently, the analysis can focus on the recovery of capital costs and ongoing operating costs. Using an equivalent annual annuity cost approach, we can treat recovery of capital costs as an annuity, using the WACC as the discount rate. This is a common approach and has been adopted by Malcolm and Hanson (2002), Drennen, Baker, and Kemery (2002), and Poore and Lettenmaier (2003).

Using this approach, the cost of energy is calculated by the following equation:

$$\dots\dots\dots \frac{\dots\dots\dots}{\dots\dots\dots} \dots\dots\dots$$

where:

- CE* is the average cost of energy;
- CEX* is the capital expense for the energy producing unit;
- CRF* is the capital recovery factor;
- AEP* is the net annual energy production;
- OPEX* is the average operating expense;
- SV_t* is the salvage value at time *t*;
- i* is the weighted average cost of capital; and,
- t* is the life of the project.

The total capital expenses (*CEX*) were estimated to be \$1.9 million per Megawatt. One station has an estimated cost of \$3.3 million per tower. Capital expenses for a windmill include the wind turbine itself and what is called the balance of station. The wind turbine consists of a rotor, drive train and nacelle, control and safety system and tower. The balance of station includes items such as foundations, electrical interface/connections, transportation, assembly and installation, and permits and engineering. The rotor consists of blades, hub and pitch mechanism, and bearings. The drive train and nacelle consists of a low speed shaft, bearings, gearbox, mechanical brake, yaw drive, main frame, generator, electrical connections, variable speed electronics, hydraulic system, and nacelle cover. Estimates of wind turbine components and their costs can be found in the report NREL/SR-500-32495 (Malcolm and Hansen, 2002).

years of project operations. The data indicate that the cost of maintenance and operations has been falling over the past three decades. The average operations and maintenance cost in the early 1980s was about three cents per kilowatt, but by the mid-1990s it had fallen to two cents per kilowatt. Costs continued to fall and were 1.5 cents per kilowatt for early 2000, and were as low as .9 cents per kilowatt for installations in 2008 (Bolinger and Wiser, 2009).

Maintenance costs are due to the wearing of parts such as blades and gears. Improvements in online monitoring, diagnostic, and control systems will lower the OPEX in the future. The combined L, R, and MT expense is assumed to be between one and two cents per kWh (Tester, Drake, Driscoll, Golay, and Peters, 2005, p.638). As a conservative estimate we used two cents per kWh for the OPEX (remember F is equal to zero, since wind is free). Nevertheless, current data from the US Department of Energy suggest that this is too high. Their annual report on wind shows that an appropriate estimate for this cost is closer to one cent per kWh for installed windmills since 2000 (Bolinger and Wiser, 2009). A study by Dismukes argues that the correct cost should be 1.39 cents per kWh, which includes insurance, leases and scheduled maintenance (Dismukes et. al., 2007). It should be noted that there is a rising cost with age and, consequently, one would expect the number to be higher than the .9 cents per kWh that was found in the government report. It needs to be remembered, however, that our analysis goes only through a 20-year period. After the 20-year period, the capital expenditures have been completely amortized by the capital recovery factor. Consequently, those annuity funds would be available for operations and maintenance after the twentieth year.

In general, we estimate that operation and maintenance costs are in the one cent to two cents per kilowatt range. This estimate of operations and maintenance costs is comparable to the cost estimates for other types of power. A great deal of data is available for the operation and maintenance costs of the nation's largest electrical utilities (See Table 3). In general, these costs are similar to our estimates. The average of nuclear power is about 1.6 cents per kilowatt, while the cost for gas turbine generation is about .6 cent per kilowatt. These data are reliable since they represent a significant portion of the nation's electrical generating capacity. In our results section, we will show the cost estimate with the high range, two cents per kilowatt, and the low range of one cent per kilowatt.

The annual energy production was calculated by measuring the wind speeds at the various sites and plugging them into the power curve, to yield a measure of electricity. The wind speeds were measured in ten minute intervals over a three-year period. The summation of each of these ten minute wind speed measures of electricity gave us the annual energy production.

There are three tax considerations that were used in this study. Modified Accelerated Cost-Recovery System (MACRS), the production tax credit, and the carry-forward tax rule all contributed to the cost equation. The rule that is specified by the IRS for companies that operate windmills is to use a five-year period under the MACRS depreciation schedule. The Renewable Electricity Production Tax Credit (PTC) helps to keep costs lower for the operator. The PTC is a per-kilowatt-hour tax credit for electricity that is generated by renewable energy sources, which includes wind. The credit that is granted is in the amount of

2.1 cents per kWh that is produced and sold for the first 10 years of the plant's operations (IRC Section 45). Carry-forward is a tax rule that allows firms to place losses to future income in one year. This can be done for up to 20 years.

III. Results

The results of our analysis show that wind potential in Kentucky has a strong seasonal pattern. As shown in Table 2, the average wind speed is greater in the winter months than in the summer months. This may cause some problems since residential peak loads tend to maximize in the summer months. In general, wind power has to be part of an integrated energy portfolio network. Typically, it is suggested that the network contain no more than 20 percent wind power because of the technical problems of incorporating a variable load power source in the network grid (U.S. Department of Energy, 2008). The seasonal pattern tends to exacerbate this problem.

The results indicate that at least some locations in Kentucky can become commercially feasible, even without the effects of the Federal energy tax credit. The range of costs for generating power to the grid from wind using these sites was estimated to be between 2.81 and 5.13 cents per kWh (see Table 4), which includes a production tax credit (PTC) of two cents per kWh that is currently available. Even without the use of a PTC, however, the costs would range from 4.29 to 6.75 cents per kWh, which is still competitive. Recent utility rate hearing cases (Cross, 2009; Gordon and Makhholm, 2008) have resulted in a granted return on equity of between nine and ten percent, which indicates that the first two categories of capital costs, $d=5\%$ & $e=9\%$, and $d=6\%$ & $e=10\%$, in Table 4, are the most realistic at the present time.

Table 4 shows levelized costs with various capital structures, using one cent per kilowatt for the operations and maintenance expense, which has been argued by current research to be an appropriate approximation (Bolinger and Wiser, 2009). Table 5 shows a more conservative estimate and uses two cents per kWh for the maintenance expense. Although the prices are higher, sites can still be competitive in cost with state's electrical prices.

The wind site that looks to reap the greatest benefit is located in Cumberland, Kentucky. The cost savings of generating electricity from wind, with the benefit of a production tax credit is substantial. This ranges from 3.8 cents per kWh to 4.6 cents per kWh. Even without the PTC, the cost ranges from 5.3 to 6.2 cents per kWh, which is below the current state electrical prices of 6.62 cents per kWh. Similar cost savings are witnessed in the other cities that were used in the wind site studies. Middlesborough, KY, with the production tax credit, would have the cost of 4.3 to 5.2 cents per kWh. The Cumberland site has a competitive price per kilowatt even without the Federal energy Credit. With the Federal energy credit other sites become competitive. One problem with developing wind power in Kentucky is that the utilities have been good at controlling costs and consequently, the competitive bar is much higher. At 6.62 cents per kilowatt, Kentucky has extremely low-cost electricity. For example, compare that price with the cost in Pennsylvania of 10.40 cents per kilowatt. You can see that wind power, even with inferior wind resource sites in

Pennsylvania, is much more likely to develop in Pennsylvania, rather than as a result of market forces in Kentucky. On one hand, there are locations in Kentucky where wind power is competitive. With appropriate siting, there are probably a number of higher elevation locations as good as Cumberland. On the other hand, in some locations wind power appears to be about at parity with current production methods. In those locations, like at Lexington, it may be useful for the state to adopt a state portfolio energy standard. In essence we are saying if the cost is close to a tie, a state policy should favor wind power because of its relatively nonpolluting nature.

In the long run, solar and wind represent the best alternative to the next generation because they contribute relatively little greenhouse gases. It is important to begin the process in each state so that additional experience can be gained in the technology. Our analysis indicates that wind power is feasible in certain Kentucky locations and, with appropriate policy, such as Federal energy credits and a state portfolio standard favoring nonpolluting sources of electrical power, it is economically feasible in multiple locations.

IV. Conclusion

Since Kentucky has been provided with such low-cost electricity, it has been difficult to integrate wind power into the state, regardless of the fact that there is such a powerful political demand for renewable electrical sources. Nevertheless, sites such as Cumberland, Kentucky can produce electricity from wind farms that is, at the present time, cost-competitive with current electrical prices. As older power-generating sources of electricity, such as coal, become more expensive because of increased regulation of carbon dioxide and greenhouse gases, several other sites throughout Kentucky could rapidly become economically feasible and compete on price with current sources.

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Table 1. Average Kentucky and U.S. Energy Prices from the EIA (as of Aug. 2010)

Electricity	Costs (Cents per kWh) Including Distribution	
	Kentucky	US
Residential	8.99	12.02
Commercial	8.50	10.69
Industrial	5.56	7.21

Source: Energy Information Administration.

Table 2. Mean Monthly and Annual Wind Speeds (m/s) for Kentucky*

Site ID	Jan.	Feb.	Mar.	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Year
4562	10.89	8.56	8.58	8.09	6.67	5.92	6.22	5.37	6.61	8.26	7.70	8.76	7.64
6273	9.42	7.45	8.01	7.54	6.31	5.70	5.76	5.17	6.29	7.50	7.03	7.67	6.99
6642	9.20	7.22	7.59	7.55	6.34	5.50	5.86	5.03	6.22	7.35	6.71	7.56	6.84
7544	8.56	6.87	6.77	7.03	6.06	5.42	5.49	5.17	6.04	7.00	6.03	7.48	6.49
7675	8.53	6.85	6.65	6.92	5.99	5.37	5.56	5.17	6.01	6.98	5.98	7.50	6.46
7800	8.44	6.67	6.68	6.77	5.85	5.28	5.39	5.11	5.90	6.81	5.88	7.45	6.35

*Note: Site 4562= Cumberland, 6273= Middleborough, 6642= Wallins Creek, 7544= Lexington (1), 7675= Lexington (2), 7800= Georgetown

Table 3. Average Power Plant Operating Expenses for Major U.S. Investor-Owned Electric Utilities, 2008. (Cents per kWh)

	Operation	Maintenance	Total
Nuclear	0.97	0.62	1.59
Fossil Steam	0.37	0.36	0.72
Hydroelectric	0.58	0.39	0.97
Gas Turbine and Small Scale	0.30	0.27	0.57

Source: Federal Energy Regulatory Commission, FERC Form 1, "Annual Report of Major Electric Utilities, Licensees and Others."

Table 4. Levelized Costs with Tax Considerations for Kentucky (Low Maintenance Costs)

Location	Levelized Costs (Cents per kWh)						State Electrical Prices
	<i>d=5%, e=9%</i>		<i>d=6%, e=10%</i>		<i>d=7%, e=11%</i>		
	With PTC	Without PTC	With PTC	Without PTC	With PTC	Without PTC	
Cumberland	2.81	4.29	3.19	4.74	3.59	5.19	
Middlesborough	3.30	4.78	3.75	5.29	4.21	5.82	
Wallins Creek	3.45	4.93	3.92	5.47	4.40	6.01	
Lexington (1)	3.86	5.33	4.37	5.77	4.91	6.53	
Lexington (2)	3.91	5.39	4.43	5.99	4.98	6.59	
Georgetown	4.03	5.51	4.57	6.13	5.13	6.75	
KY (Average)	3.56	5.04	4.04	5.57	4.54	6.15	6.62*

*Includes transmission and distribution costs

Table 5. Levelized Costs with Tax Considerations for Kentucky (Conservative Maintenance Costs)

Location	Levelized Costs (Cents per kWh)						State Electrical Prices
	<i>d=5%, e=9%</i>		<i>d=6%, e=10%</i>		<i>d=7%, e=11%</i>		
	With PTC	Without PTC	With PTC	Without PTC	With PTC	Without PTC	
Cumberland	3.81	5.29	4.19	5.74	4.59	6.19	
Middlesborough	4.30	5.78	4.75	6.29	5.21	6.82	
Wallins Creek	4.45	5.93	4.92	6.47	5.40	7.01	
Lexington (1)	4.86	6.33	5.37	6.77	5.91	7.53	
Lexington (2)	4.91	6.39	5.43	6.99	5.98	7.59	
Georgetown	5.03	6.51	5.57	7.13	6.13	7.75	
KY (Average)	4.56	6.04	5.04	6.57	5.54	7.15	6.62*

*Includes transmission and distribution costs

REPAYMENT CAPACITY OF FARMERS :
A BALANCED PANEL DATA APPROACH

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Abstract

Using a balanced panel of 184 unique Illinois farmers from 2000 to 2006, this study identifies the most pertinent factors that explain farmer repayment capacity. After correcting for endogeneity bias caused by farmer-specific effects by running a fixed effects regression model, we find that the one year lagged working capital ratio, the debt-to-asset ratio, and quarter age are significant variables in explaining the coverage ratio, at the 10 percent, 5 percent, and 1 percent significance levels, respectively. This study also finds that factors such as farm size, creditworthiness, screen borrowers, manage loan loss reserves, and price loans, thereby reducing the costs borne by the government and taxpayers.

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I. Introduction

The need to analyze loan quality remains an important issue given the large number of farmer loan defaults and bank failures (Turvey, 1991). Zech and Pederson (2003) argue that the lack of consensus concerning a unique set of variables to explain creditworthiness creates an environment where lenders develop different models “in search of specifications that best predict farm performance and repayment capacity of farmers”.

The main objective of this study is therefore to statistically explore factors that explain a farmer’s repayment capacity (a measure of creditworthiness) using individual loan quality information.² Possible endogeneity bias caused by farmer-specific effects is accounted for by using panel data instead of cross-sectional data. The data used are obtained from the Illinois Farm Business Farm Management (FBFM) Association between 2000 and 2006. Results from the analysis will help lenders to isolate the most pertinent factors to consider when building credit scoring models in order to ensure accurate estimations of creditworthiness.

Credit scoring models aid in evaluating creditworthiness by monitoring loan quality within the Farm Credit System and other lending institutions. Because financial theory offers little specific guidance as to which explanatory financial variables should be used to assess creditworthiness, a variety of explanatory variables and estimation techniques have been explored for credit scoring models (Oltmans, 1994). For example, Lufburrow et al. (1984) use liquidity, leverage, collateral, and repayment history; Miller and LaDue (1989) use profitability, liquidity, solvency, efficiency, and farm size; Fischer and Moore (1986) use profitability, leverage, and efficiency; and Mortensen et al. (1988) use only leverage and efficiency to explain creditworthiness.

Additionally, the agricultural finance credit scoring literature includes linear probability models, discriminant analysis models, logit models, probit models, and regression models that use discrete dependent variables (Turvey, 1991; Splett et al., 1994; and Turvey and Brown, 1990). There are also recent studies that use linear regression models with continuous dependent variables (Novak and LaDue, 1997; and Oltmans, 1994).

One issue with credit scoring models is that there is no consensus on which structural model to use and which explanatory variables to include to explain variations in credit risk factors (Gustafson, 1989). With a well-defined set of explanatory variables, more accurate credit scoring can be achieved. Greater accuracy in credit scoring is more important to agricultural compared to non-agricultural lending institutions because the agricultural institutions cannot diversify their loan portfolio as well as non-agricultural institutions due to higher riskiness of loan portfolios in the agricultural sector (Turvey and Brown, 1990).

² Individual loan quality information is collected from farm-level business data.

A more accurate credit assessment model to evaluate loan applications and creditworthiness of borrowers results in more accurate loan pricing decisions, therefore, reducing the interest charged on loans issued to farmers (Lufburrow et al., 1984). Furthermore, improved credit scoring models enhance lenders' ability to screen potential borrowers and manage loan loss reserves, thereby decreasing the costs associated with defaulted loans. On the other hand, poor credit assessment methods may increase lending errors. For example, lenders may provide loans to very high risk borrowers (Type I error) or not provide loans to low risk borrowers (Type II error). In both cases, the lender loses profits.³ A high number of Type I and Type II errors might negatively affect the amount of credit available to the private sector by depleting banks' capital, increasing banks' deposit liabilities, reducing savings rates, and increasing loan losses. All these factors may result in an economic contraction (Fofack, 2005).

To reiterate, no consensus has been reached on a specific set of variables to explain creditworthiness and, even worse, the effect of endogeneity caused by farm-specific effects is often overlooked. Additionally, few existing studies on creditworthiness have used a continuous dependent variable.

This study addresses some of the important gaps in the literature. Most notably, this research uses a continuous dependent variable instead of a discrete dependent variable for creditworthiness for Illinois farms. This approach prevents loss of information. Furthermore, this research employs panel data techniques that allow time-invariant farmer-specific effects to be explored and corrected for. This is important because farmers might be inherently different from each other. For instance, one farmer might have low risk aversion, another farmer might have high risk aversion, and also each farmer might be different in their savings behavior. The existence of individual farmer-specific effects invariably leads to endogeneity bias. After addressing the issues of endogeneity and using a continuous dependent variable, this study employs a more reliable model for assessing creditworthiness, ultimately improving agricultural lenders' ability to accurately evaluate potential borrowers and maximize loan profitability.

II. Literature Review

As mentioned in the introduction, there are competing approaches for relating financial variables to creditworthiness. Therefore, a variety of explanatory variables and estimation techniques have been used for credit scoring models (Oltmans, 1994). A study by Ellinger et al. (1992) also emphasizes the lack of a uniform model or models in evaluating creditworthiness for agricultural borrowers. Ellinger et al. (1992) specifically analyze the characteristics and consistency of 87 credit scoring models used by agricultural lenders in Illinois and Iowa areas, and find inconsistent credit scoring models among lenders. Additionally, in the literature, we see one set of studies that focus on

³ For Type I errors, the lost profit includes lost principal, lost interest on the principal, and additional costs incurred for administration, legal fees, and insurance coverage. For Type II errors, the lost profit is the difference in expected profit between a good borrower who is denied the loan and an alternative borrower who is issued the loan but may be a high or low credit risk borrower (Nayak and Turvey, 1997).

individual loan quality information, whereas some other studies examine aggregate loan quality information to build credit scoring models.⁴

Considering individual loan quality information, Miller and LaDue (1989) observe that financial measures of liquidity, profitability, and operating efficiency are good indicators of borrower quality.⁵ Mortensen et al. (1988) find that debt-to-asset, a solvency measure, and operating ratios are the most effective treatment variables in explaining loan performance of North Dakota farmers.⁶ Turvey and Brown (1990) conclude that measures of profitability, solvency, financial efficiency, liquidity, and debt repayment capacity should be combined in credit scoring models for Canada's Farm Credit Corporation.⁷ A study by Zech and Pederson (2003) applies both linear and logistic regression to Southwestern Minnesota farm data to predict borrower repayment capacity (which is proxied by coverage ratio).⁸ They discover that debt-to-asset ratio persistently exhibits a negative relation with farmer repayment capacity. Limsombunchai et al. (2005) determine a credit scoring model, to predict creditworthiness and default risk, for agricultural loans in Thailand. They find total asset value, capital turnover ratio, and duration of bank-borrower relation to be significant factors of creditworthiness. Featherstone et al. (2006) look at components that affect probability of default for agricultural loans and use loan data from the Seventh Farm Credit District's database. They find repayment capacity, owner equity, and working capital to be important determinants of probability of default.

In addition to these studies, some other studies directly focus on farm financial performance. For instance, Purdy et al. (1997) examine factors that influence the financial performance of a sample of Kansas farms. They discover that operator age, financial efficiency, farmland tenure position, and leverage negatively impact farm financial performance, while farm size has a positive impact on financial health.⁹ Gloy et al. (2002) examine farm profitability in a panel of 106 New York dairy farms over a seven-year period. They use fixed-effects regression models to test hypotheses regarding the effects of managerial factors on farm performance. They find that individual farm effects, such as initial endowments, resource constraints, and production and financial management factors impact farm profitability. Plumley and Hornbaker (1991) analyze the characteristics of successful Illinois farms, identified by net farm income per tillable acre. Their findings suggest that these successful farms have a balanced composition of assets, lower debt, and higher profitability.

⁴ The literature of credit scoring models is based mostly on individual rather than aggregate loan quality information. Aggregate loan quality information uses the macro and micro level, whereas individual loan quality information uses only the micro level indicators of loan quality.

⁵ Liquidity shows how quickly one can generate cash. Profitability reflects wealth and the ability of a farmer to generate profit. Operating efficiency measures the farm's efficiency of operating expense management.

⁶ Debt-to-asset ratio is a measure for expressing farm business risk exposure.

⁷ Leverage is measured by the debt-to-equity ratio, and expresses the farm business' risk exposure.

Financial efficiency represents how effectively a business uses its assets to generate gross revenues.

⁸ Coverage ratio relates asset returns to debt obligations for a period of time.

⁹ Farmland tenure position is the ratio of owned acres to total acres operated.

For aggregate loan quality models, Oltmans (1994) shows that aggregate models do not provide early warning signals for changes in loan quality; however, they still indicate key factors that should be analyzed for understanding loan quality. He finds that collateral, liquidity, government program payments, off-farm income, and debt-to-asset ratio should be analyzed to understand loan quality.¹⁰ On the other hand, Escalante et al. (2004) show that farm-specific factors, such as farm size, tenure, asset turnover, operator age, diversification index, soil productivity rating, and income risk have little explanatory power for the probability of credit risk transitions.¹¹ Instead, macroeconomic factors, such as money supply growth, farmland value growth, changes in agricultural long-term interest rates, and changes in stock price indexes explain the probability of credit risk migration. Additionally, Brehanu and Fufa (2008) look into determinants of loan repayment rates for Ethiopian farmers. They find group lending, land size, livestock holding amount, contact with lender, income from off-farm activities, use of agricultural extension services, and rainfall for the area to be important determinants of loan repayment rates.

III. Model Specification

Recall that the expected profit for a lender is given by:

$$E(d) = (1 - PD)Q - \check{r}(L)Q - (PD)Q - r(L - LGD)C \quad (1)$$

where d is profit, r is interest rate, L is loan amount, PD is probability of default and LGD is loss given default.¹²

The lender's objective is to maximize their return on a loan. From equation (1), this implies minimizing the expected losses due to borrower defaults. These expected losses depend on the probability of default and loss given default. The magnitude of the probability of default provides a signal about the creditworthiness of farmers (and by implication, the repayment capacity of farmers). One way to obtain an estimate of probability of default is to use farm financial data, which reflects the farmer's creditworthiness. Therefore, variables used in this study for farmer repayment capacity are constructed to reflect measures of the farmer's creditworthiness.

All variables analyzed in this study are recommended by the Farm Financial Standards Council (FFSC). Splett et al. (1994) argue that greater uniformity of the explanatory variables used can be achieved if all researchers employ only the FFSC recommended variable measures. FFSC recommends specific financial measures to

¹⁰ Collateral is the property promised as a guarantee for loan repayment.

¹¹ Note here that farm-specific factors do not mean farm-specific effects. Also, the asset turnover ratio measures the farm's efficiency of asset utilization.

¹² Exposure at Default is the value of the farm debt at the time of default. Loss Given Default is the percentage of the Exposure at Default that is lost in the event of default. Essentially, Loss Given Default measures the severity of the default, and is set by the lender. For instance, the lender can ask for collateral or loan insurance so that the lender won't be affected adversely in the case of default. Probability of Default, on the other hand, is set by the borrower and shows the frequency of loss. Characteristics of the borrower determine this probability.

evaluate liquidity, solvency, profitability, repayment capacity, and financial efficiency of farmers.¹³ Previous studies have also used these FFSC standards to explain farm performance and to determine creditworthiness and credit scoring for farmers (Phillips and Katchova, 2004; Barry et al., 2002; Mishra et al., 1999).

Following Miller and LaDue (1989), the equation defining farmer repayment capacity is given as

$$Y_{it} = \beta_0 + \beta_1 X_{1i(t-1)} + \beta_2 X_{2i(t-1)} + \beta_3 X_{3i(t-1)} + \beta_4 X_{4i(t-1)} + \beta_5 X_{5i(t-1)} + D_t + e_{it} \quad (2)$$

where Y_{it} is creditworthiness, which is a continuous random variable proxied by repayment capacity and measured by the coverage ratio for individual i at time t ; $X_{1i(t-1)}$ is financial efficiency of the borrower measured by the asset turnover ratio for individual i at time $t-1$; $X_{2i(t-1)}$ is liquidity of the borrower measured by the working capital ratio for individual i at time $t-1$; $X_{3i(t-1)}$ is solvency of the borrower measured by the debt-to-asset ratio for individual i at time $t-1$; $X_{4i(t-1)}$ is profitability of the borrower measured by the rate of return on equity (ROE) for individual i at time $t-1$; and $X_{5i(t-1)}$ is other potential measurements that help to explain the repayment capacity of the borrower, such as family expenditure and tenure ratios, operator age, soil productivity, and acreage for individual i at time $t-1$.¹⁴ These measurements capture the effects of the farmer's experience, soil quality, economies of scale, etc. (Ellinger and Barry, 1987; Purdy et al., 1997; Gloy et al., 2002; Barry et al., 2001; Mishra et al., 1999). Additionally, D_t is the time dummy where t ranges from 2001 to 2004. Note that 2005 and 2006 are the base years for the study and that observations in the year 2000 are lost because one year lagged values are used as explanatory variables.¹⁵

Note that in equation (2), creditworthiness is based on the previous period's farm financial data, which explains why the model specification includes the one period lagged value for each explanatory variable. Using the lagged explanatory variables implies that the variables are pre-determined. Consequently, there is no endogeneity bias caused by correlation between the matrix of explanatory variables and the error matrix. Table 1 contains the definitions of the variables, as well as expected signs. A discussion of the dependent variable and the explanatory variables for the model follows.

This study uses the coverage ratio (dependent variable) as a measure of repayment capacity, and thus to measure creditworthiness. Previous studies have examined default classification as an indicator of creditworthiness (Turvey and Brown, 1990; Escalante et al. 2004; and Phillips and Katchova, 2004). A problem with default classification is that it

¹³ Profitability reflects wealth and the ability of the farmer to generate profit; liquidity shows how quickly one can generate cash; financial efficiency shows how efficiently one can convert financial inputs into financial output; and solvency and repayment capacity show whether one has enough capacity to pay debt. Solvency is a long-term, whereas repayment capacity is a short-term dimension of debt payment.

¹⁴ Since age, soil productivity, and acreage do not change significantly from year to year, this study uses the lagged values instead of the present values, just to keep consistency among the explanatory variables.

¹⁵ Possible unobservable time fixed effects, such as changes in farm bills or policies, in a panel data setting is handled through including time dummies.

is based on subjective judgment on the part of the lender (Lufburrow et al., 1984). Recent studies have also used debt repayment capacity measured by the coverage ratio obtained from farm-level data as an alternative indicator of creditworthiness (Zech and Pederson, 2003; and Novak and LaDue, 1994). The advantage of this measure is that it uses a continuous, quantitative measure instead of a discrete, qualitative measure. However, debt repayment capacity cannot distinguish between variations in profitability and debt levels (Novak and LaDue, 1997). For instance, a large (small or negative) coverage ratio implies a highly (less) profitable or less (highly) leveraged farmer.

Based on Miller and LaDue (1989) and Zech and Pederson (2003), the evaluation in this study focuses on financial efficiency, liquidity, solvency, profitability, and other farmer descriptive variables as explanatory measures to explain creditworthiness. Following FFSC recommendations, the asset turnover ratio is used to measure the financial efficiency of the farmer. The asset turnover ratio measures the efficiency of asset utilization. As the ratio increases, the more effectively assets are used to generate profits. Greater financial efficiency results in a higher repayment capacity. Therefore, a positive relationship is expected with the coverage ratio.

The FFSC recommends using the working capital-to-gross farm return ratio as a liquidity indicator. A higher ratio indicates the farmer has a greater ability to generate cash to meet short-term financial obligations. Thus, a positive relationship between the working capital ratio and the coverage ratio is expected. The debt-to-asset ratio is recommended by FFSC as a measure of farm solvency. It measures both the solvency of the farmer and the degree to which the farmer can meet long-term debt commitments. Higher debt levels indicate greater financial obligations. Thus, the coverage ratio is expected to be lower (Zech and Pederson, 2003).

FFSC suggests that rate of return on farm assets (ROA) and ROE are useful measures of a farmer's profitability. ROE determines the return on equity after paying interest expense, whereas ROA does not account for the leverage position of a farm. Boessen et al. (1990) show that higher leveraged farms exhibit greater variability in the ROE compared to ROA. For these reasons, ROE is chosen over ROA as a measure of farm profitability. As ROE increases, cash inflow is expected to increase, thereby improving the coverage ratio.

Other variables, such as family expenditure and tenure ratios, age, soil productivity, and acreage, may also help to explain farmer repayment capacity. This paper investigates the effects of these variables in explaining farmers' repayment ability. Examples of family expenditure include consumption, utilities, medical expenses, clothing, and household durable items. Lower family expense levels provide the farmer with more cash to cover financial obligations. Therefore, a negative relation is expected with the coverage ratio.

The tenure ratio indicates the percentage of owned acres compared to total acres operated. Farmers with a higher ratio tend to be less financially leveraged, exhibit less liquidity and earn a lower rate of return on assets (Ellinger and Barry, 1987; and Barry and Robison, 1986). Since most of the assets in a Midwest farm operation are tied to farm

real estate, a larger portion of total returns occurs as unrealized capital gains on farmland. Since the farmer may not generate sufficient cash flow from the land itself to meet annual debt payments, the tenure ratio is expected to exhibit a negative relationship with the coverage ratio.

Age of the farm operator may provide some information about the likelihood of the lender being fully repaid. Older farmers face declining profitability and lower debt use since they are less productive. The reduction in productivity adversely affects the repayment capacity (Barry et al., 2001). Thus, a negative relationship between age and the coverage ratio is hypothesized.

Higher soil productivity is also a factor that may increase/maintain production, thereby enhancing the repayment capacity. Soil productivity is likely to be positively correlated with the coverage ratio. Also, as acreage increases, farmers take greater advantage of economies of scale or scope. Intuitively, this likely results in a greater repayment capacity and higher coverage ratio.

IV. Data and Descriptive Statistics

The empirical analysis uses farm financial records collected from the Illinois FBFM Association to identify factors that explain borrower repayment capacity. The FBFM data comply with “FMV Balance Sheet Certification” and “Family Living/Sources and Uses Certification”.¹⁶ Although it may be more beneficial to use real lender data instead of farm-level data, obtaining lender data is both difficult and costly. Previous studies have successfully employed farm-level data as a proxy for lender data (Katchova, and Barry, 2005; Escalante et al., 2004). Zech and Pederson (2003) and Novak and LaDue (1994) have also used farm business data to determine creditworthiness, proxied by the coverage ratio. An advantage of farm-level data is that it often includes farmers with low and high credit risks, in contrast to lender data that contain only low credit risk farmers (Escalante et al., 2004).

This study uses a balanced panel of 184 unique farmer identities from 2000 to 2006. This time period is chosen because it provides the greatest number of unique farmer identities given the available dataset. Table 2 displays mean values for variables under both “overall” and “year categories”. In Table 2, column one contains the overall mean values for all variables from 2001 to 2006.¹⁷ For instance, the coverage ratio has a mean value of 0.52. Since this ratio is less than one, it implies that on average cash inflow is less than cash outflow for a sample of Illinois farmers. Lagged asset turnover, working capital and debt-to-asset ratios all have mean values around 0.30. Lagged ROE, which represents profitability, has a mean value of 0.11. The second, third, fourth, fifth, sixth, and seventh columns of Table 2 report the mean values for each year from 2001 to 2006. The highest average annual coverage ratio is 0.72 in 2006, while the lowest is 0.36 in 2001. The standard deviation of the coverage ratio is moderately stable over the time period. Meanwhile, lagged ROE reaches its maximum value in 2004 with a mean value

¹⁶ FMV and Family Living/Sources certified data are the most reliable data available.

¹⁷ The year 2000 data point is deleted from the data since the explanatory variables are lagged one period.

of 0.47 and a standard deviation of 4.47, whereas lagged family expenditure ratio reaches its maximum mean value of 3.73 with a 25.55 standard deviation in 2006. The lowest lagged asset turnover ratio for an average Illinois farmer is recorded in 2004, with a value of 0.20 and a standard deviation of 0.40. The mean of lagged acreage for Illinois farms also increases each year attaining the highest value of 845.92 acres in 2006. Mean values for the lagged working capital and tenure ratios as well as age and soil productivity show only slight changes from 2001 to 2006.

V. Panel Data Estimation Procedures

To identify the best linear unbiased estimator (BLUE) to use, recall that the general static panel data model is given by

$$Y_{it} = \sum_{g=1}^k (x_{itg})' \beta_g + v_{it}, \quad (3)$$

where Y_{it} is dependent variable for individual i at time t ; x_{itg} is explanatory variable g for individual i at time t where g ranges from 1 to k ; $v_{it} = c_i + u_{it}$ where t ranges from 1 to T and i ranges from 1 to N ; c_i is unobserved effect (time-invariant individual-specific effect); and u_{it} is idiosyncratic error term (time- and individual-variant disturbance term).

Pooled OLS (PLS) is consistent if

$$E(x'_{it} v_{it}) = 0 \text{ for } t = 1 \text{ to } T, \quad (4)$$

If $\text{Var}(v_{it})$ is constant, then PLS is also efficient (Wooldridge, 2002). Equation (4) indicates that the data must satisfy strict exogeneity. To test for strict exogeneity, a test by Wooldridge (2002) is applied. The model for the test is as follows:

$$Y_{it} = x_{it} \beta + M_{i(t-1)} \gamma + u_{it}, \quad (5)$$

where x_{it} refers to the explanatory variables at time t for individual i , which in this case are the lagged values for the financial measures used in our model, such as one year lagged value of ROE, one year lagged value of working capital ratio, and so on, and $M_{i(t-1)}$ refers to the value of the explanatory variable at time $t-1$. After running this regression with FE, we performed a joint F-test to test for the significance of γ , where $H_0: \gamma = 0$. The F-statistic result shows that there is possibility of endogeneity caused by individual-specific effects and non-constant variance.

Next, a test for homoscedasticity in a panel data setting is executed. The specific test applied is the White test. The null hypothesis of homoscedasticity is rejected, and thus, existence of heteroskedasticity is concluded. Hence, we have to account for heteroskedasticity when we are running our regressions.

To check for AR (1) serial correlation in the idiosyncratic error terms of the linear panel data model, Wooldridge's test of serial correlation is used. The F-statistic result

shows that there is serial correlation among idiosyncratic error terms. This means that any estimator that is selected as the BLUE estimator should necessarily account for autocorrelation.

The possibility of endogeneity caused by individual-specific effects and non-constant variance means that Pooled Least Squares (PLS) is often inconsistent or inefficient, so an alternative estimator, such as random effects (RE) or fixed effects (FE), may be preferred.

We employ a test designed by Hausman (1978) and reproduced in Wooldridge (2002) to decide between the FE and the RE estimator.¹⁸ To operationalize this test, individual means are added to the rest of the explanatory variables and estimation is done by fixed effects. The null hypothesis that all the individual means are jointly zero is tested against the alternative that the null is not true. Failure to reject the null hypothesis means that RE is the preferred estimator. By contrast, a rejection of the null implies that FE is the preferred estimator. The chi-squared test shows that the null hypothesis is rejected and FE is consistent and efficient. The selection of FE over RE implies that there are individual effects and that there is correlation between the unobserved time-invariant individual effects and the explanatory variables. This means that individual-specific effects exist and they are causing endogeneity bias. Based on the outcome of the Wooldridge test, we select the FE estimator as the preferred estimator. To account for serial correlation and heteroskedasticity, we use the *robust* option in Stata to compute the robust version of the FE estimator.

VI. Results

Table 3 displays the main results of the study. These results are obtained by using balanced panel data from 2000 to 2006, with 184 unique farmer identities. As mentioned in the econometric section of this paper, the panel data analysis is performed for the balanced panel data from 2000 to 2006 to achieve two main objectives: (1) identify which explanatory variables are significantly correlated with the dependent variable and (2) investigate whether individual, farmer-specific effects are causing endogeneity bias in the coverage ratio regression. Accounting for endogeneity bias in this model is pragmatic because there are likely farmer-specific effects that are time-invariant but vary from farmer to farmer because no two farmers are exactly identical in their savings behavior. These farmer-specific effects may cause endogeneity bias. The null hypothesis of strict exogeneity is tested and rejected. Also, the Wooldridge test results indicate that there is correlation between the unobserved time-invariant farmer effects and the explanatory variables. Hence, the FE estimator is chosen as the best candidate for the BLUE estimator.

By using the coverage ratio as the dependent variable, we find one year lagged working capital ratio, debt-to-asset ratio, and age to be the significant variables. The one

¹⁸ In order to decide between RE and FE estimation, the traditional Hausman test is performed, which is identical asymptotically to the Wooldridge test. The results from the Hausman test indicate a chi-sq of 45.09, with p-value of 0.0000. Again, the null is rejected meaning the difference of coefficients from FE and RE estimation is systematic. Therefore, the FE estimation is consistent and efficient.

year lagged working capital ratio is significant at the 10 percent level, with a negative value of 0.354. For each additional unit increase in the lagged working capital ratio, the firm's coverage ratio goes down by 0.354 units. One possible explanation for the negative relationship between the one year lagged working capital ratio and the coverage ratio is that as the firm faces a higher working capital ratio, it may be considered to be financially more liquid by the lenders; hence it might have gotten more loans that year and the coverage ratio may be going down because of the increase in the loans.

The one year lagged debt-to-asset ratio explains the coverage ratio negatively at the 5 percent significance level. This result conforms to our expectations and is consistent with the results of most previous studies, such as Zech and Pederson (2003) and Mortensen et al. (1988). As the lagged debt-to-asset ratio increases, the financial obligation of the farmer increases. This implies that there is a higher probability that the farmer will not be able to repay debt. Therefore, the coverage ratio is negatively correlated with the debt-to-asset ratio. The regression results indicate that as the lagged debt-to-asset ratio increases by one unit, the coverage ratio decreases by 2.12 units.

Another significant variable is the lagged age variable. As the farm operator gets older, the coverage ratio increases by 0.312 at 1 percent significance level. This positive relation may be due to the fact that young farmers just getting started become more productive as they gain more experience but after some point they start to become less productive. Another possible explanation for the positive relation between coverage ratio and lagged age variable is that farmers in their later stages generally get lower loans. Moreover, the year dummies for 2001 to 2004 are significant at 1 percent significance levels; hence showing that there are differences over time in terms of the repayment capacity of farmers.

When joint significance of the variables is tested under the null hypothesis that coefficients of all explanatory variables are zero, an F test statistic of 3.04 with a p-value of 0.0014, is obtained and the null hypothesis is rejected. The rejection of the null hypothesis implies the model is valid. Also, a look at the R-squared statistics for the random effects model shows that it is 4.96 percent, 0.21 percent, and 0.17 percent for within, between, and overall, respectively. Although these numbers are relatively small, they are consistent with estimates in the previous literature that include ROE measures in their analyses.

VII. Summary

This paper aims to identify those factors that are pertinent in explaining farmer repayment capacity by using the FBFM data for Illinois farms. A related objective is to help agricultural lenders more accurately evaluate credit risk, better screen borrowers, arrange their loan loss reserves, price their loans more accurately, and decrease the probability of bankruptcy due to defaulted loans. A reduction in the costs associated with defaulted loans will ultimately translate into lower costs borne by the government and taxpayers.

Although various studies in the literature have used different financial measures to explain creditworthiness, no research has considered the possibility of endogeneity bias due to farmer-specific effects in a panel data setting. After controlling for individual-specific effects, the FE estimator is chosen as the BLUE estimator. By employing panel data techniques for a sample of Illinois farmers, this study finds one year lagged values for working capital ratio, debt-to-asset ratio, and age to be the most significant factors in explaining farmers' coverage ratios. The results suggest that these explanatory factors should be included in any set of variables used in credit scoring models.

The result from this study is significant in that previous studies have come up with different indicators of creditworthiness depending on the explanatory variables used. This paper considers how the possible existence of individual farmer-specific effects impacts the factors for the determination of farmer repayment capacity.

Future study might consider using aggregate as well as individual loan quality information. The possibility of nonlinear relationships between farmer repayment capacity and explanatory variables might also be a topic worthy of future research. Additional effort can also be directed toward acquiring a larger dataset, since the central limit theorem maintains that the consistency of parameter estimates improves as the dataset expands. Another opportunity for further research can be to include the lagged dependent variable as one of the explanatory variables and repeat the analysis performed. This will invariably involve the use of dynamic panel estimators and will provide a medium to investigate the role, if any, for dynamics.

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Table 1. Variable Definitions and Expected Signs

Dependent Variable: Coverage ratio^a		
Explanatory Variables	Definitions	Expected Signs
Financial Efficiency:		
Asset turnover ratio ^b	Value of farm production / Total average farm assets	+
Liquidity:		
Working capital ratio ^c	Working capital / Value of farm production	+
Solvency:		
Debt-to-asset ratio ^d	Total debt / Total assets	-
Profitability:		
ROE ^e	Net farm operating income - Unpaid labor charge for operator and family / Average farm equity	+
Other:		
Family expenditure ratio	Family living expenses / Total acres operated	-
Age	Age of the operator	-
Tenure ratio	Owned acres / Total acres operated	-
Soil productivity	Soil productivity rating	+
Acres	Acres operated	+

^aCoverage ratio=Cash inflow/ Cash outflow

^bTotal average farm assets is expressed in fair market value

^cValue of farm production = Crop returns + Livestock return above feed + Custom work + Other farm receipts
Working Capital = Current assets – Current liabilities

^dDebt-to-asset ratio is also based on fair market value.

^eNet farm operating income = Gross farm revenue – Purchases of market livestock – Cost of purchased feed/grain– Total farm operating expenses – Total interest expense

Avg. farm equity = Market value of total assets – Total liabilities, and equity is expressed in fair market value

Cash inflow= Net farm income from operations + Non-farm income + Depreciation + Interest on term–Debt + Interest on capital – Income taxes – Family living withdrawals. Also, depreciation is included within the calculation since it is already subtracted when calculating the net farm income from operations.

Cash outflow= Annual scheduled principal + Interest payments on term debt and capital leases

Table 2. Mean Values for Variables

Variables	All	Year 2001	Year 2002	Year 2003	Year 2004	Year 2005	Year 2006
Coverage ratio	0.52 (1.06)	0.36 (0.78)	0.44 (0.74)	0.58 (1.39)	0.63 (1.08)	0.38 (0.65)	0.72 (1.42)
Lagged asset turnover ratio	0.33 (0.25)	0.38 (0.21)	0.35 (0.20)	0.34 (0.20)	0.20 (0.40)	0.39 (0.21)	0.34 (0.18)
Lagged work. capital ratio	0.30 (0.50)	0.34 (0.53)	0.28 (0.55)	0.25 (0.50)	0.29 (0.46)	0.32 (0.43)	0.30 (0.50)
Lagged debt-to-asset ratio	0.36 (0.18)	0.36 (0.19)	0.37 (0.18)	0.37 (0.17)	0.36 (0.17)	0.34 (0.17)	0.34 (0.18)z
Lagged ROE	0.11 (2.03)	-0.08 (1.98)	0.02 (0.38)	0.04 (0.71)	0.47 (4.47)	0.16 (0.39)	0.04 (0.19)
Lagged family expen. ratio	0.76 (18.27)	0.76 (5.87)	-0.08 (21.16)	-0.14 (17.67)	1.17 (2.56)	-0.90 (23.36)	3.73 (25.55)
Lagged age	50.59 (9.22)	48.09 (9.08)	49.09 (9.08)	50.09 (9.08)	51.09 (9.08)	52.09 (9.08)	53.09 (9.08)
Lagged tenure ratio	0.23 (0.24)	0.21 (0.22)	0.22 (0.22)	0.23 (0.22)	0.24 (0.26)	0.24 (0.26)	0.25 (0.24)
Lagged soil productivity	82.51 (9.98)	82.62 (10.04)	82.63 (9.91)	82.43 (10.06)	82.45 (9.96)	82.47 (10.03)	82.49 (9.99)
Lagged acres	786.13 (478.63)	716.75 (416.07)	752.34 (434.32)	771.03 (453.30)	798.30 (488.66)	832.44 (525.41)	845.92 (535.32)
Number of observations	1,104	184	184	184	184	184	184

The numbers in parentheses are standard deviations.

Table 3. Panel Data Estimation Procedures Results

Tests applied	Null Hypothesis	Test statistics	P-Values	Conclusions
Strict exogeneity by Wooldridge	Exogenous	F-statistic of 1.76	0.0807	Endogeneous
White test for Homoscedasticity	Homoscedastic	Chi-sq of 256.1316	5.90E-17	Heteroskedastic
Wooldridge's test of serial correlation	No serial correlation	F-statistic of 11.617	0.0008	Serial Correlation
Hausman test by Wooldridge	Random Effects	Chi-sq of 43.07	0.0000	Fixed Effects

Table 4. Fixed-effects Model Results

Lagged working capital ratio	-0.354* (0.192)
Lagged debt-to-asset ratio	-2.122** (1.027)
Lagged age	0.312*** (0.099)
Year 2001	1.291*** (0.422)
Year 2002	1.050*** (0.328)
Year 2003	0.868*** (0.244)
Year 2004	0.563*** (0.147)
Constant term	-14.897*** (5.343)
F(13,907)	2.75
Prob>F	0.0008
R-sq within	4.96%
R-sq between	0.21%
R-sq overall	0.17%
Number of observations	1,104
Number of groups	184

*The numbers in parentheses are standard errors, and ***, **, * represent significances at 1, 5, and 10 percent respectively.

IMPROVING RECESSION FORECASTS WITH BUSINESS LOAN DATA FROM COMMERCIAL BANKS

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Abstract

This paper focuses on forecasting recessions utilizing bank loan commitment data. During the sample period, the yield curve alone has no predictive power. However, bank C&I (commercial and industrial (C&I) loans and C&I loan commitments data provide information easily included in a parsimonious forecasting model. Bank lending through loan commitments is an interest-rate sensitive activity; an off-balance sheet commitment from a bank allows a borrower to get a loan, if desired, over a designated future time period. Loan commitment data allows us to take advantage of diffuse information, such as forecasting by firms and loan " q h h k e g t u " v j c v " o k i j v " p q v " u j q y " w r " k p " q prediction of economic cycles like the yield curve spread. The goal of our research is to improve the ability to forecast economic downturns by employing variables related to C&I lending in probit regressions predicting recessions. We find that the yield curve, with the S&P 500 and ratio of growth in C&I loans to C&I loan commitments, can accurately predict the start of recessions at a four quarter time horizon. This result is significant because it allows for greater accuracy in predicting US recessions, assisting economic planning professionals, consumers, and educators.

I. Introduction

Forecasting recessions is an important part of the planning process for a number of businesses and financial institutions in the United States. As we have seen in the most recent recession, cash flow issues and the lack of available credit have slowed business activity. Financial institutions have cut back on their lending because of the poor economic climate and because the number of loan delinquencies has increased. Businesses have experienced problems as cash inflow from customers has slowed in the slow economic environment. Therefore, if businesses have advanced knowledge of a potential recessionary environment, they may be better able to obtain funding to take them through the recession. For the Federal Reserve and other policy makers, the ability to forecast an upcoming recession allows them to take corrective action in advance of the recession to mitigate the impact on the overall economy. Households and non-financial businesses may choose to go ahead and make big ticket purchases in advance of a recession if the equipment will be necessary to their business or well-being in the near future and they have concerns about the availability of credit in a recessionary environment. Other businesses may choose to delay large acquisitions prior to a recession to preserve cash reserves. For financial institutions, the ability to forecast recessions accurately will allow them to better manage their risk exposure during the recession. These reasons and others provide the impetus for numerous complex macroeconomic forecasting models that have been designed to predict recessions in the United States.

The search for parsimonious, easy-to-use forecasting models has exerted a lasting attraction on researchers (see, e.g., Estrella and Mishkin, 1998, and Stock and Watson, 2003). We join this search by including a new source of potentially relevant, dispersed information: the relationship between commercial banks' commercial and investment (C&I) C&I loans and their C&I loan commitments. We find that including this forward-looking, commercial bank information improves the four-quarters-in-advance predictive power of parsimonious, dichotomous recession forecasting models.

In the past, researchers have investigated the relationship between interest rates and inflation. Higher interest rates correlate with periods of higher inflation (Koenig and Emery, 1992; Mishkin, 1992) when long-term treasury yields are examined. Higher short-term rates, and, thus, a flatter yield curve, may suffocate the economic expansion and push the economy to contract or to slow down the rate of expansion. Haubrich and Dombrowsky (1996) also analyze the forecasting ability of the yield curve and find that the yield curve spread has forecasting power. However that forecasting power breaks down in the last decade of the study, which ends in 1995. The authors suggest that the predictive failure may be due to the changing economic environment, growth of technology and information availability, or (potentially) a change in the Federal Reserve's policies. Rudebush and Williams (2009) also examine the predictive power of the yield curve. They show that professional forecasters are worse at predicting recessions than a real-time forecasting model that is based on the yield spread.

Estrella and Mishkin (1998) propose that the various macroeconomic models in use are too complex when a more simplified model can be used to determine whether a recession is likely over a one quarter and up to an eight quarter time horizon. Estrella and Mishkin demonstrate that, over the time period they examine, a parsimonious forecasting model employing the yield spread between three-month Treasury bills and ten-year Treasury notes is most useful in predicting recessions at time periods of three to six quarters in the future. This model works well for both with-in-sample estimation and out-of-sample tests. However, the authors also indicate that the yield spread does not appear to accurately forecast recessions in the final years of their sample from 1991 to 1995.

Dueker (1997), Estrella and Trubin (2006), Stock and Watson (2003), and Hu (1993) support the findings of Estrella and Mishkin (1998). These authors concur that the yield spread has the greatest forecasting power; however, they concede that at some points it inconsistently predicts economic performance and output. Their findings indicate that the yield curve is generally upward sloping, however, prior to recessions, an inverted yield curve or a flat yield curve may occur. The lack of forecasting power in more recent years may be due to the Federal Reserve raising short-term interest rates as the dual mandate of growth and inflation may keep the Federal Reserve's focus on inflationary pressures during the periods of prolonged expansion. The reason for this has not been determined, but one possibility may be the increased use of the short-end of the Treasury market as a policy tool in trying to stimulate the economy through open market operations. The short-end of the Treasury market is also influenced by the Fed's announced target for short-term rates. Since the Fed is, in effect, manipulating the short-end of the yield curve, this may explain why the yield curve is no longer an adequate predictor by itself. In the past, an inverted or flat yield curve provided a signal of economic weakness. Now, if the Fed perceives economic weakness, they take actions to lower short-term rates which may keep the yield curve from flattening as dramatically in advance of a recession.

McConnell and Perez-Quiros (2000) and Kim and Nelson (1999) offer another potential reason for lower predictive power of forecasting models in more recent years. These studies find that the gap between the highs and lows of the GDP during times of economic recessions and expansion is shrinking. Therefore, as economic volatility declined, with it declined forecasters' ability to predict economic activity. Chauvet and Potter (2005) mention that the inability of probit models to predict recessions with accuracy may be due to the fact that the models, such as used in Estrella and Mishkin (1998), do not allow for multiple breakpoints and autocorrelation of errors, and also fail to account for the duration of the expansion cycle preceding the decline. The researchers find that forecasting is more accurate in predicting the 2001 recession when more sophisticated models are used. It is possible, however, that their results are influenced by the depth of the 2001 recession, which was exacerbated by the September 11th attacks, making it easier to predict than the 1991 recession.

Koenig and Emery (1991) use the U.S. Department of Commerce composite index of leading indicators (CLI) for predicting economic downturns and upturns. They conclude that the indicator has some limitations. First, the Commerce Department released it with a one month lag, and it is generally based on the preliminary data that is typically later revised.

Second, the index works better when researchers used it to predict the size of the decline from the peak (or from the moving average of economic activity) than the number of months of decline. Stock and Watson (2003) study the 2001 recession and measure how well economic indicators predict the downturn. Specifically, they focus on the Survey of Professional Forecasters (SPF) by the Federal Reserve Bank of Philadelphia, which was forecasting an expansion while the economy was contracting. They conclude that the term spread and stock returns did not provide a clear warning of the economic downturn, neither did the housing starts, nor orders for capital goods. They conclude that economic downturns all have individual characteristics, making them difficult to predict. To combat this issue, the authors show evidence that by using as many as twelve different indicators such as various yield spreads and stock returns together, the 2001 recession may have been predicted with greater degree of accuracy. Watson and Stock (2002) corroborate these findings by developing a forecasting methodology using components of different indicators, which they conclude may increase the accuracy of forecasts.

Hakkio and Keeton (2009) provide another way of examining financial stress within the economic system and how that can be used to forecast future economic conditions. They develop a measure which they call the Kansas City Fed Financial Stress Index (KCFSI). This measure is made up of ten indicators including six different interest rate spreads, the correlation between Treasury returns and stock returns, the volatility of overall stock prices, the idiosyncratic volatility of bank stock prices, and the cross-section dispersion of bank stock prices. This KCFSI was shown to perform well in identifying periods of financial stress from 1990 to 2008.

Our study focuses on determining whether there is interest-rate sensitive activity in the economy in addition to the yield curve spreads which can be used to improve recession forecasting models. We primarily focus on bank lending activity as an additional predictor of future economic activity. We contribute to the existing literature by considering not only current commercial and industrial lending activity but also the impact of commitments for commercial and industrial loans. Loan commitments represent an off-balance sheet commitment from a bank to make a loan, if desired by the business, over a designated future time period. Deshmukh, Greenbaum, and Kanatas (1982), and Ricart Costa and Greenbaum (1983) develop theoretical models of banks' forward lending policies in different risk environments. They conclude that in an environment with increased uncertainty, the level of bank loan commitments will decline.

II. Hypothesis

From the previous discussion of some of the literature on the topic of economic forecasting, it is evident that accurate forecasting of economic activity is of paramount importance. The goal of our research is to try to improve the ability to forecast economic downturns by employing variables related to commercial and industrial lending in probit regressions predicting recessions, similar to those of Estrella and Mishkin (1998). We propose that bank C&I loans and C&I loan commitment data can be used to predict economic downturns. By agreeing on the terms of a loan commitment, the commercial bank will standby ready to make the loan to the business which is able to hedge the risk of

obtaining a future loan as well as hasten the process of accessing funds when and if there is a need to borrow. We believe that loan commitments may be a more sensitive predictor of economic activity than pure C&I loan data. C&I lending activity and C&I commitments data allow us to take advantage of diffuse information and forecasting by firms and loan officers that might not show up in other “summary” measures of forecast economic activity, like the yield curve spread.

In considering the C&I loans and commitments, the overall level of loans in the economy will be potentially significant as an indicator of overall economic activity, and the growth in C&I activity should be significant too. The pecking order hypothesis of the capital structure argues that firms that need capital will raise funds first through internal sources, then through debt, and as a last resort by issuing common stock. Therefore, increases in the level of C&I loans would be expected if economic activity were increasing in the economy. However, the change in lending activity by the bank may be even more important. A bank will make loans when it expects the economy to grow and the firm to prosper in the future. The in-depth credit analysis for a commercial loan requires a full review of the company’s financial position. In general, an economic forecast predicting growth should coincide with businesses having more growth opportunities with corresponding increases in the amount of business loans outstanding. Therefore, the growth in C&I loans or in commitments may be a significant indicator of overall economic conditions. In addition, a potential recession will increase the uncertainty for banks and may cause a decline in the willingness of banks to make loan commitments ahead of an anticipated recession.

At the same time, a bank may have an incentive to make good loans before a recession in anticipation of monetary policy actions designed to stimulate the economy which may lead to lower interest rates and result in lower profitability for banks in the future. A bank will prefer to lock-in a good loan ahead of a recession. Therefore, the growth rate of C&I loans relative to the growth rate of C&I loan commitments may also be indicative of perceived future changes. If commitments are declining because of perceived uncertainty, actual loans may still be growing as banks lock-in the good borrowers. Overall, bank lending activity may be a useful predictor of recessions.

The study consists of utilizing C&I loan amounts and loan commitments along with their respective growth rates in concert with the popular forecasting tools, the yield spread and stock market performance, to test whether we can create a model that better and more accurately forecasts U.S. recessions since 1992, which is when previous forecasting models appear to become less accurate. This portion of the study is limited because loan commitment data are only available since 1992.

III. Data

The commercial bank data on C&I lending and loan commitment data were obtained from bank call report data filed with the Federal Deposit Insurance Corporation (FDIC) for the period of 1992-2008. Our sample period is constrained because the FDIC began requiring banks to report their C&I off-balance sheet commitments only in 1992. Additional financial data to compute yield spreads and market data were obtained from The Federal

Reserve Bank of St. Louis and the U.S. Department of Treasury. Like Estrella and Mishkin (1998), we derive our recession measure from National Bureau of Economic research (NBER) business cycle timing data. A recession indicator is obtained from NBER recessions dates, such that R_t equals one if the economy is in recession, and zero otherwise. The spread variable is calculated by taking the yield on the ten-year Treasury note and subtracting the yield on the three-month Treasury bill. As in Estrella and Mishkin (1998) and others, the market rate of return is measured as the quarterly return on the S&P 500 index. C&I loans measures the total amount of commercial loans on the balance sheets of US banks. C&I commitments are the levels of C&I commitments. We also calculated the growth rates in C&I loans and commitments. A final variable that we examine is a growth ratio which is calculated by dividing growth in C&I loans by the growth in C&I commitments. This variable allows us to examine a bank's willingness to take on extra risk in the commitments market relative to the spot loan market. We organized the data quarterly from 1992Q1 to 2008Q4. This time period was determined by the availability of loan commitment data. Over this sample period, we observed that loan commitment data were very strongly positively correlated with commercial and industrial loan volume. Table 1 provides a description of the variables and Table 2 provides some descriptive statistics of each of the variables. Table 3 provides the correlations between the variables.

IV. Model

Because the dependent variable in our models – the recession indicator – is a binary variable, we choose to rely upon a probit estimation process to predict the likelihood of a recession, similar to Estrella and Mishkin (1998). Probit analysis fits maximum likelihood estimates in the form of:

$$R_t = \Phi(x_t\beta) \quad (1)$$

where Φ is the standard cumulative density function, and $x_t\beta$ is the probit index. The results of the regression coefficients are described as the impact that independent variable x has on the probability of the dependent response variable y being different from zero. Like Estrella and Mishkin, our dependent variable is a recession indicator obtained from NBER recessions dates, such that R_t equals one if the economy is in recession, and zero otherwise. We estimate all models with the recession indicator leading by two quarters and four quarters out. We have not included estimates for eight quarters ahead because of the relatively short time series available for C&I commitments.

The Estrella and Mishkin (1998) models indicate that the 3-month to 10-year yield curve spread is an accurate predictor of whether the U.S. economy is in a recession from four to eight quarters of lead time. That is, the yield curve spread is a parsimonious, effective leading indicator of the recessionary condition of the U.S. economy. We seek to determine whether the information implicit in commercial loan commitments and in C&I loans allows us to improve predictive power over models using the spread and/or S&P 500 data by themselves.

After estimating the initial models, we develop a series of recursive regressions which allow us to test out-of-sample predictive power. For example, consider that the time series begins with 1992Q1. Using data available at the time to form expectations about recession four quarters ahead, we first estimate our model's coefficients in 2000Q3 by using data from 1992Q1 to 2000Q3. In 2000Q4, we re-estimate the coefficients using data going back to 1992Q1 up to 2000Q4. In 2001Q1, we re-estimate the coefficients using data going back to 1992Q1 up to 2001Q1, and so on.

Using these coefficients, we extract the estimated probit index value for the quarter's forecast, which we convert into a probability using the normal distribution. We then create a new variable, "predicted recession," which indicates the probability of a recession occurring four quarters in the future. This process allows us to estimate iterative, adaptive predictions that correspond to market participants forming adaptive expectations. This process also allows for an out-of-sample test of the robustness of the various models by comparing our predicted recession variable to the NBER-derived recession variable, R_t . Similar to Estrella and Mishkin (1998), we calculate the average percentage error rate (APER) for each model which allows us to determine whether one model does a "better" job of predicting than another model. APER divides the number of incorrect predictions by the total number of predictions using the model. A more accurate model will have a lower APER.

V. Results

Table 4 provides the estimation results for models where the recession variable is forecasted two quarters ahead. In this set of models, the dependent variable is the recession and all explanatory variables are lagged two quarters to allow for the forecast. These results are fairly typical of what has been reported in the past by Estrella and Mishkin (1998) and other researchers. At the short forecasting period of six months, the stock market return and the yield spread are useful in predicting economic downturns. The consistent negative and significant coefficients for the yield curve and the S&P 500 return indicate that a flattening yield curve and negative stock market growth are consistent with an increased probability of a recession in the next six months. C&I loan levels also have some explanatory power in predicting recessions at this time horizon. As C&I loan levels increase, the probability of a recession is reduced. This result is consistent with our expectations that increased economic growth as represented by businesses requesting loans and banks agreeing to make these loans will decrease the probability of a recession. However, when C&I commitments are included in the models, the C&I level is no longer significant. Another interesting result is seen in Model 5: When the ratio of growth in C&I loans to growth in C&I loan commitments is included, the spread variable is no longer significant. This seems to indicate that the information content of the yield spread may also be captured in the growth ratio in some way; however, the two variables do not seem to be highly correlated as seen in Table 3.

Table 5 presents model results in which the probability for recession is estimated using variables that are lagged four quarters. This model estimates coefficients that are useful for forecasting recessions one year in advance. In these models, the spread coefficient is consistently negative and significant again; however, the stock market is not statistically significant in any model in which it is included. These results again appear consistent with

Estrella and Mishkin (1998). However, when the models are examined more closely using the recursive regression techniques, the robustness of the model is questionable. For example, in Model 8, which includes the yield spread only as the explanatory variable, in 32 time periods from the third quarter of 2001 to the second quarter of 2009, only 7 times does the yield curve model accurately predict the future state of the economy (recession or non-recession). This corresponds to the APER of 78.13 percent. For Model 1, which incorporates the S&P 500 return, the APER decreases to 15.63 percent. This model is a significantly better predictor of future recessions even though the S&P 500 is not a significant variable in the regression analysis. This result may be due to the high standard deviation of the S&P 500 variable during this time period. The sample period is relatively short because of the constraint imposed by the availability of loan commitment data. This short time period and the high volatility of the stock market in this time period may be masking the impact of the stock market on predicting returns. This effect will have to be examined further in the future with an expanded data series.

For the bank lending variables, an interesting result appears in the four-quarter forecasting horizon. While C&I loan levels are again statistically significant when they are included by themselves, the most significant lending variable is the growth ratio. Our results indicate that when the growth ratio is negative, there is an increased probability of a recession. This result may seem counter-intuitive at first, but it becomes clearer when the variable is examined more closely. The growth ratio takes on a negative value when one variable is growing while the other is declining. For example, the growth ratio is negative if the level of C&I commitments is falling while the level of C&I loans is growing. This result is consistent with banks reducing their risk exposure prior to a possible recession by reducing the number of commitments when there is increased uncertainty in the economy, while also “locking-in” good potential loans before monetary policy—which may lead to decreases in interest rates—becomes necessary. These empirical results support the theoretical work of Deshmukh, Greenbaum, Kanatas (1982) and Ricart I Costa and Greenbaum (1983).

Model 4 which includes the spread, the S&P 500 return and the growth ratio performs as well as or better than any other model in the out-of-sample forecasts, with an APER of 15.63 percent. However, this model provides a much clearer signal in forecasting recessions. Figures 1 and 2 provide the forecasted probabilities forecasted from the recursive regression using data from the four quarters prior to the observation and plot them with the actual outcome observed four months later. For example, in 2000Q3, our Model 1 predicted a recession would occur in 2001Q3 with a 75 percent probability. This probability appears in the graph as the probability for 2001Q3. The difference between forecasting with the spread and S&P 500 return (Model 1, Figure 1) versus forecasting using the spread, S&P 500 returns and the growth ratio together (Model 4, Figure 2) is that the model including the growth ratio gives a much stronger signal of future recessions. Figures 3 and 4 present information for the growth only model and the yield spread only model, respectively. Here, it becomes clear that the yield spread is no longer an accurate predictor of recessions by itself as seen in Figure 4 and the growth ratio falls short in predicting recessions when used in isolation as well (Figure 3). Overall, the model with the strongest predictive power is Model 4 which incorporates the spread, the S&P 500, and the C&I growth ratio. Although related, it appears that these three variables derive from pools of knowledge dispersed through the

economy that do not perfectly overlap.

VI. Conclusions

Our study provides two significant contributions to the previous literature. First we confirm that the Estrella and Mishkin (1998) results are time period sensitive. In our sample period (1992-2008), the yield curve by itself has no accurate predictive power for recessions in out-of-sample tests. However, the yield curve, in conjunction with the S&P 500, and growth of C&I loans divided by growth of C&I loan commitments can be used to accurately predict the start of recessions at a four quarter time horizon. The forward-thinking, planning activities that occur within commercial banks and within firms add additional, relevant information that is not fully captured by the yield curve or the S&P 500. This information may be accessed through commercial banks' loan data. This result provides forecasters with the opportunity to improve their predictions of future recessions by incorporating a widely available piece of information in their forecasts. An accurate forecast of economic activity is as important as ever because it allows financial institutions to adjust their balance sheets according to future expectations of economic activity and interest rates in order to hedge the risks associated with economic cycles. Industrial companies benefit from enhanced ability to forecast the economic environment because it allows for more accurate planning in regard to capital expenditures, hiring new employees, and product cycles. Consumers benefit from increased economic visibility by being better prepared both financially and psychologically to deal with the stresses of ever changing economic conditions. Finally, due to the data and computational ease of setting up and then updating the model, it could easily be introduced into finance or economics classes to facilitate discussion of a broad range of topics, from expectations, to efficient markets, to informational asymmetries, to general forecasting.

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Table 1: Variable Definitions

Variable	Definition
Spread	Spread in yields between a 10-year and a 3-month Treasury securities
S&P	Quarterly return on the S&P 500 index
C&I	Total volume of annual commercial and industrial loans reported by all banks filing Call Reports with the Federal Reserve
C&I Commit	Total volume of loan commitments reported by all banks filing Call Reports with the Federal Reserve
Gr C&I	Growth of commercial and industrial loans computed annually for all banks filing Call reports with the Federal Reserve
Gr C&I Commit	Growth of loan commitments computed annually for all banks filing Call reports with the Federal Reserve
GRatio	This variable is calculated by taking the growth in C&I and dividing by the growth in commitments in each quarter

Table 2. Variable Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Spread	1.63	1.19	-0.77	3.63
S&P	0.0149	0.0808	-0.2697	0.2087
C&I Loans	7322.8	3403.9	1077.8	12517.2
C&I Commit	1768.9	665.7	854.8	3751.4
Gr C&I	0.0055	0.1405	-0.4006	0.5879
Gr C&I Commit	-0.0117	0.1289	-0.5096	0.3607
GRatio	0.7606	1.0319	-3.7917	2.0540

Table 3. Correlations between Variables

	Spread	S&P	C&I Loans	C&I Commits	Gr C&I	Gr C&I Commit	GRatio
Spread	1.0000						
S&P	-0.0799	1.0000					
C&I loans	0.0898	0.0694	1.0000				
C&I Commits	-0.2450	-0.1088	0.3592	1.0000			
Gr C&I	0.0086	-0.1424	-0.0814	0.1533	1.0000		
Gr C&I Commit	0.1134	-0.1232	0.1066	0.0388	0.8303	1.0000	
GRatio	0.1032	0.1560	0.2771	0.0098	0.0204	0.1135	1.0000

Table 4. Probit Models Forecasting 2 Quarters Ahead

	Model 1	Model 2	Model 3	Model 4	Model 5
Spread	-0.344*	-0.323*	-0.377*	-0.348*	-0.308
	-1.78	-1.66	-1.87	-1.66	-1.52
S&P	-8.437***	-9.553***	-8.734***	-9.712***	-8.621***
	-2.84	-2.95	-2.88	-2.95	-2.77
C&I Loans		-0.0001*		-0.0001	
		-1.65		-1.58	
C&I Commits			-0.0002	-0.0001	
			-0.60	-0.31	
GRatio					-0.197
					-1.23
Constant	-0.647**	-0.037	-0.186	0.214	-0.656*
	-2.06	-0.08	-0.23	0.23	-1.93
LR chi2	12.32	15.13	12.71	15.23	13.15
Prob>Chi2	0.002	0.002	0.005	0.004	0.004
Log likelihood	-23.144	-21.741	-22.952	-21.691	-20.553
Pseudo R2	0.21	0.258	0.217	0.26	0.242

*-Significant at 90%, **-Significant at 95%, ***-Significant at 99%

Table 5. Probit Models Forecasting 4 Quarters Ahead

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Spread	-1.201*** -2.65	-1.176** -2.44	-1.251** -2.31	-1.514*** -2.63	-1.558** -2.17		-1.212*** -2.64
S&P	-5.076 -1.33	-7.452 -1.58	-7.643 -1.60	-7.456 -1.37	12.322 -1.53		
C&I Loans		- 0.0001*	- 0.0001*		- 0.0002		
C&I Commits		-1.74	-1.68		-1.45		
GRatio				-0.939** -2.04	-0.811* -1.66	-0.51** -2.38	
Constant	-0.172 -0.51	0.603 1.10	1.151 0.67	0.366 0.73	1.003 0.41	0.953* -3.74	-0.241 -0.74
LR chi2	18.92	22.22	22.36	24.51	27.45	6.53	17.08
Prob>Chi2	0.0001	0.0001	0.0002	0	0	0.011	0
Log likelihood	-15.65	-14	-13.93	-10.5	-9.031	19.49	-16.57
Pseudo R2	0.377	0.442	0.445	0.539	0.603	0.144	0.34

*-Significant at 90%, **-Significant at 95%, ***-Significant at 99%

Figure 1. Probit Model 1 (Spread and S&P 500) Forecasting 4 Quarters Ahead Using Recursive Regression Forecast

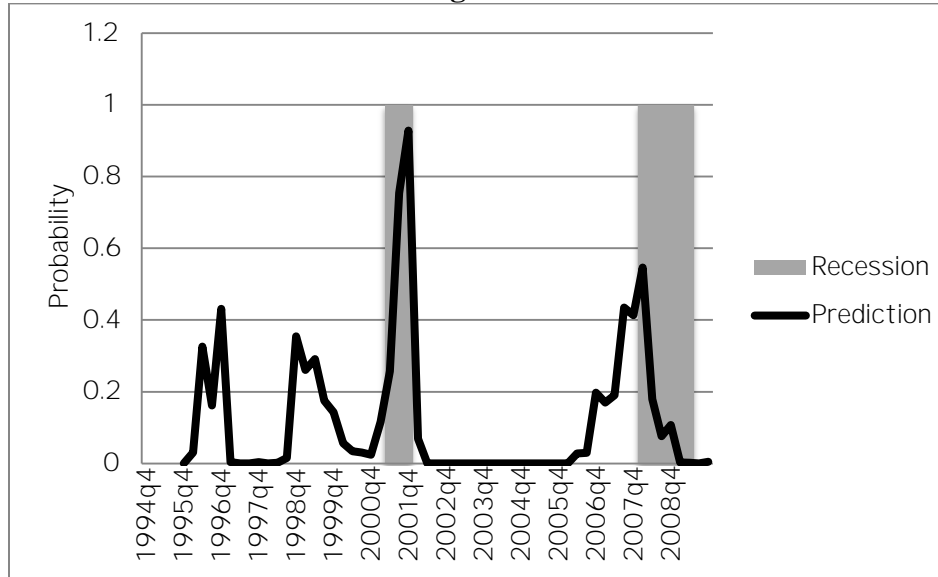


Figure 2. Probit Model 4 (Spread, S&P 500, and Growth Ratio) Forecasting 4 Quarters Ahead Using Recursive Regression Forecast

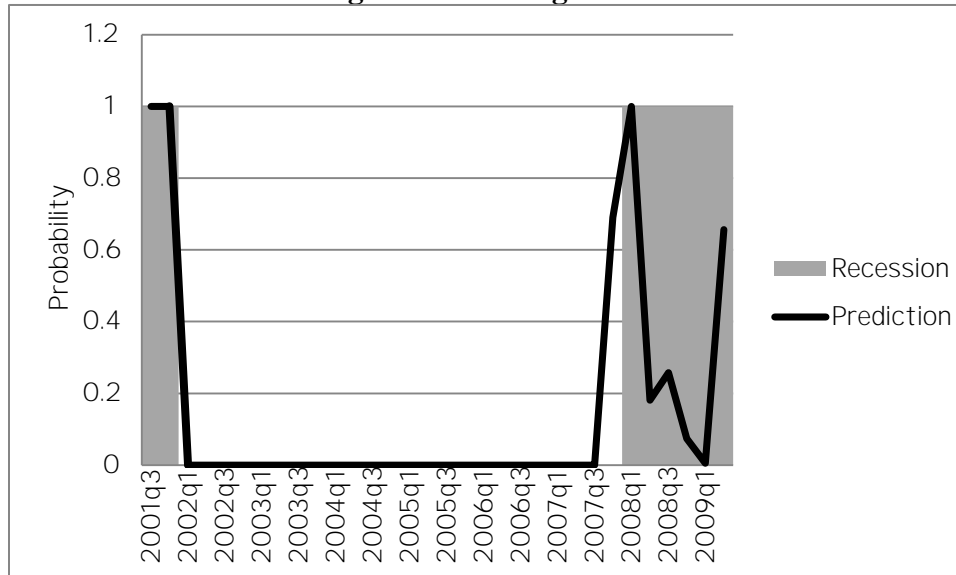


Figure 3. Probit Model 6 (Growth Ratio Only) Forecasting 4 Quarters Ahead Using Recursive Regression Forecast

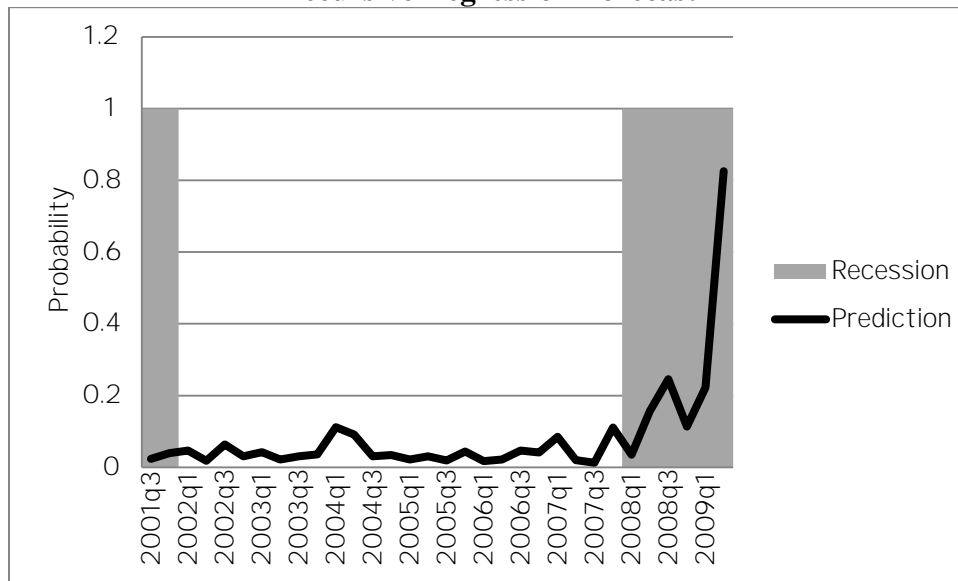
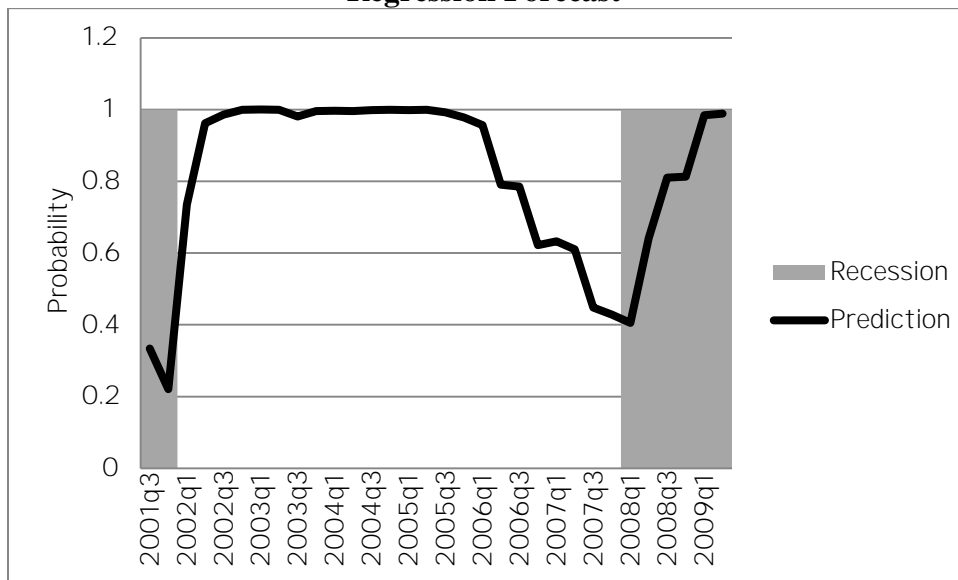


Figure 4. Probit Model 7 (Spread Only) Forecasting 4 Quarters Ahead Using Recursive Regression Forecast



THE EQUIVALENT RISK STANDARD AND ALLOWED ROES IN THE GAS AND
ELECTRIC UTILITY INDUSTRIES

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Abstract

This paper investigates the empirical connection between allowed returns on common equity set by state regulators in U.S. electric and natural gas utility proceedings and various financial, market and regulatory risk variables. The modeling results suggest that allowed returns are positively related to market conditions. However, they show that allowed returns are not necessarily consistent with either a common regulatory standard of setting returns equal to return on investments of equivalent risks or recognized financial theories. The empirical findings also suggest that, in some instances, the structure of the regulatory agency may influence allowed returns.

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I. Introduction

When setting the allowed returns on common equity of jurisdictional utilities, state regulatory authorities apply the virtually universal principle that the allowed returns on common equity (ROE) should equal returns on common equity investments in companies of equivalent risk.¹ Such returns are generally accepted as a “fair rate of return” if they are no higher than necessary and still sufficient to attract investment, or the minimal return to maintain a financially healthy utility. From this legal principle it follows, as an economic standard, that the greater the risk, the greater the required return. Furthermore, a return that meets this risk-return-equivalency standard will be sufficient for the utility to operate successfully and attract capital and compensate investors.²

The analysis requires two steps to meet analytically the risk-return-equivalency legal standard. The first is to determine the current competitive common equity returns in the marketplace necessary to attract and maintain capital of the regulated utility. The second is to account for distinguishing risk differentials between the regulated utility and the competing investments. In the first instance, one can expect regulators to set allowed returns on common equity that vary over time with changing capital market conditions. Second, one can expect regulators to set allowed returns on common equity that distinguish among the relevant risks of jurisdictional utilities. This analysis attempts to measure whether these two steps produced distinguishable components in recent allowed ROEs for gas and electric utilities.

To test these two propositions, the study examines the allowed ROEs of 85 natural gas distribution and 91 electric utility³ decisions by state regulatory bodies during the period 2001-2007. As to the first proposition regarding setting returns relative to competitive investments, the data reveal that regulatory authorities granted higher and lower allowed ROEs in these decisions as bond rates varied; however, the allowed returns did not vary by the same amount as the bond rate changed. That is, allowed ROEs varied upward and downward consistently with changing long-term bond rates, but by a lesser amount. As to the proposition regarding setting returns according to investments of equivalent risks, generally the empirical evidence does not link allowed returns according to relevant risks, with the apparent exception of regulators recognizing the risks of regulatory lag and stock price volatility of electric utilities. In the gas utility decisions,

¹ The frequently cited sources of this equivalent risk standard are two decisions by the United States Supreme Court: *Bluefield Water Works and Improvement Company vs. Public Service Commission*, 262 U.S. 679 (1923) (“*Bluefield*”), and the *Federal Power Commission vs. Hope Natural Gas Company*, 320 U.S. 591 (1944) * $\delta J q r g \ddot{o} + 0$ ”

² In addition to the allowed ROE that utilities design into their rates, regulatory treatment of many other factors, such as depreciation methods, determination of the test year, recovery of fuel and operating costs, allowance of capital investment into rate base, including new and forthcoming security issues into the capital structure and market competition will undoubtedly affect actual ROEs. The net result of these many regulatory influences, plus market conditions and management’s responses to them, will determine the ultimately achieved ROE.

³ The sample size is slightly larger. However, it lacks information regarding some decision variables, and we excluded those regulatory decisions from our regressions.

the links between the allowed ROEs and the measures of the utilities' financial and business risks are not statistically significant.⁴

This study addresses a gap in recent utility regulation literature that is surely important in the attraction of capital in key utility industries. To date there is scant recent literature in the topic area. Due to the need for capital investment in utilities, the attraction of sufficient investment capital becomes a policy issue.⁵ Examining the more recent data, this study reveals recent empirical inconsistencies between the determination of allowed ROE's and the stated regulatory policy objectives plus it sheds light on this important, yet under-investigated issue. This is interesting in itself since the regulatory environment has changed when compared to the conditions present in previous studies.

II. Precedent Research

Precedent research concerning utility-allowed ROEs addressed regulatory authority and the influences on the allowed returns set by regulators and now appears dated.⁶ For example, Joskow (1974) argued that, despite legal guidelines, regulatory authorities have considerable freedom in rate decisions because their mandates are broad and often vague. One group of early studies specifically investigated whether ROEs allowed by regulatory authorities were consistent with financial theories. For example, Joskow (1972) examined 20 electric and gas utility cases during the 1960s and 1970s and found that the allowed returns were consistent with financial theories.

Somewhat later empirical studies measured risk and allowed ROEs, and these were mixed regarding whether the results were consistent with financial theory. A study of electric utility decisions, Hagerman and Ratchford (1978), did find allowed ROEs to be consistent with financial risk theories, i.e., allowed ROEs were negatively related to the utilities' common equity ratios.⁷ However, other later studies showed no, or weak, evidence of a positive relationship between financial risk of the regulated firms and allowed ROEs. Fitzpatrick, Settle and Petry (1988) found no significant connection between allowed returns and economic and political variables. Fan and Cowing (1994), in a study of 401 electric utility rate cases in the 1980s, found that the ratio of debt to total capital variable, as a measure of financial risk, was not statistically significant. In a

⁴ Other variables, namely regulatory structure and requested ROEs, are significant predictors of allowed ROEs. Conceivably, these variables could represent or mask some unspecified utility operating or regulatory risk factors that we could not separately identify and include as variables in our regressions specifications.

⁵ At the time of this study national policy issues address environmental emissions, alternative fuels in automobiles and industries, expansion of the U.S. power transmission system, and changes in the mix of generating facilities. Each of these could have significant impact on the gas and electric utility industry capital expenditure requirements.

⁶ The literature in the area is small and analysis regarding recent regulatory policies regarding returns to utility capital investment is especially so.

⁷ In a study of U.S. telephone industry Labor (1988) found that the relationship between allowed returns and equity ratios was not statistically significant and inconsistent with financial theory. This finding may or may not be a contradiction of the findings in the electric and gas industries because of the competitive and rate of technical change differences among the three industries.

more recent article, Murry, Zhu and Knapp (2008), also failed to find any positive relationships between allowed returns and financial risks, as measured by either equity ratios or bond ratings, in both the natural gas and electric utility industries.

III. Current Study

This paper identifies broader measures that may influence allowed ROEs and expands the types of risk that could affect determination of recent allowed ROEs in the electric and gas industries. More specifically, it attempts to measure empirically whether the stated policy objectives of setting allowed returns at levels that are (1) competitive market returns of alternative investments, and (2) consistent with corresponding measures of risk in the gas and electric utility industries. This research also identifies some distinguishing structural characteristics of regulatory bodies that could affect allowed ROEs. After taking these characteristics into account, the analysis isolates the relationships between allowed ROEs and current market conditions and then between allowed ROEs and measures of risk. In this way it empirically links the regulatory allowed ROEs to the legal standard of “returns of equivalent risk.”

This analysis designates competitive long-term bond interest rates as representative of returns of alternative investments and enumerates separate measures of financial, business and regulatory risks. It examines the links of each measure to allowed ROEs. In this way, it applies the common legal standard of setting allowed returns equal to alternative investments of equivalent risks and broadened the empirical approaches by identifying and characterizing the potential influences on allowed ROEs in this context. This study specifically focuses on allowed returns on common equity set by state regulatory bodies for electric and gas utilities during the period 2001-07.

A. Regulatory Structure

The legal structure of regulatory organizations, normally prescribed into state law, may provide an environment affecting the tendencies of the authorities when setting allowed ROEs. For example, during the period of analysis, 15 state regulatory bodies were elected⁸ and 36 were appointed. Enabling legislation positions regulatory authorities among the competing wants of customers desiring low-cost service, company investors wanting higher returns and the broad public needs of reliable utility service and economic development.

A plausible proposition is that elected officials will be relatively more sensitive to increasing rates to voter-ratepayers than appointed, seemingly more independent, officials. For his reason we tested the following hypothesis:

Hypothesis 1: Elected regulatory authorities, on average, will set lower allowed ROEs than appointed authorities.

⁸Two of these elected commissions are selected by legislative bodies.

A second structural proposition is a variant of the first. Regulatory officials, whether elected or appointed, with longer terms in office may be somewhat more independent from customer pressures than officials with shorter terms. This implies the second hypothesis:

Hypothesis 2: The longer the terms of office of regulatory authorities, on average, the higher allowed ROEs.

B. Comparable Returns

The legal and economic standard for setting allowed ROEs to attract investment capital implies that allowed ROEs will adjust to returns of competitive investments such as long-term debt instruments. Because of relatively inflexible risk premiums in the short-term, as levels of long-term interest rates change, one can expect allowed ROEs to adjust similarly. Therefore, this suggests the third hypothesis:

Hypothesis 3: Allowed ROEs are positively related to the level of long-term interest rates.

C. Requested ROE Differential

In addition to changes in the market returns to competitive investment instruments, an ROE will embody other industry, jurisdictional, and utility factors, some of which will be unique to the particular utility. Government policy mandates, changing competitive structures, planned investment for projected capital expenditures, replacement of storm losses, expected changes in inflation and interest rates, load shifts, accounting, and rate treatment are examples of factors appropriate for consideration in a ROE request. Consequently, to assess the importance of these non-interest-rate factors underlying the requested ROE, we introduced a variable which was the difference between the actual requested return and the current level of interest rates. The proposition indicates the fourth hypothesis:

Hypothesis 4: The allowed ROEs are positively related to the difference between the requested ROE and the current level of interest rates.

D. Allowed ROEs and Measures of Risk

Applying the principle of returns of equivalent risks proposes investigation of three distinct categories of risks relevant to common stock investors, namely, financial risk, business risk, and regulatory risk.⁹

⁹ The Requested ROE Differential variable surely incorporates some of the unique risks of the specific regulated utility as this variable is the difference between the specific utility's requested ROE and the prevailing market interest rate.

Financial Risk. Consistent with the literature precedent, financial risk exposure to a common stock investor is the uncertainty whether sufficient funds will be available to achieve expected dividends and capital gains after payment of interest on debt and preferred stock dividends, each of which has precedence over common stock returns. Generally, a lower equity ratio implies that a company has greater fixed cost obligations to holders of securities that have precedence to revenues, and the lower the common equity ratio the greater the financial risk exposure to the common stock holders. Consequently, the common equity to total capitalization ratio is a direct measure of financial risk¹⁰. Thus, the fifth hypothesis concerning the allowed ROE and financial risk:

Hypothesis 5: Allowed ROEs are negatively related to equity ratios.

Business Risk. Business risk is the exposure of investors' anticipated returns to the uncertainties of a company's day-to-day business activities. Significant business risks to electric and gas utility equity investors derive from untimely and uncertain recovery of operating costs. For example, rates designed to recover fixed costs through volumetric charges expose utilities to non-recovery when customers reduce consumption levels, bypass or leave the system. Other business risks include such items as untimely recovery of fuel and gas costs and unanticipated capital requirements from such factors as storm damage and maintenance expenses.¹¹ We tested two metrics that may indicate the relative business risks of electric and gas utilities.

Beta. A common stock's beta shows the relative volatility of the price of a common stock to the market fluctuations and is a direct measure of risk (or beta is a measure of volatility of a stock of a firm or portfolio in relation to the remainder of the instruments in the financial markets).¹² The market beta is the regression coefficient of a firm's returns on market returns. In the cross-sectional study, as a measure of business risk, after controlling for the level of interest rates, the regulatory structure and other risk factors, a utility's allowed ROE should be positively related to its beta value. Therefore, we tested the sixth hypothesis:

Hypothesis 6: Allowed ROEs are positively related to beta.

¹⁰ Although bond rating agencies describe other factors that influence their ratings in addition to the common equity ratio, Murry, Zhu and Knapp (2008) found bond ratings and equity ratios to be substitute predictors of allowed returns by state regulators for gas and electric utilities.

¹¹ The regulatory process sets a utility's rates in anticipation of a level of sales to customers to produce a level of revenue, the "revenue requirement," that will recover both fixed and variable costs. If sales volumes do not meet or exceed the anticipated levels, unrecovered fixed costs will adversely impact common equity returns.

¹² Regulatory authorities commonly accept the beta as a measure of risk when they adopt the Capital Asset Price Model as a method to measure the cost of common equity. In this case, the firm i's ROE is positively related to the beta of the firm as in the following equation: $ROE_i = R_f + b_i(R_m - R_f)$, where b_i is the beta of firm i , R_f is the risk-free rate and R_m is the market return. Normally, analysts accept beta as a positive constant, and for most utilities beta is less than 1.

Cross-sectionally, the CAPM model also implies that the higher the firm's market beta, the higher the returns, everything else, including market returns and risk free rate, being equal.

Size. A second measure of gas and electric utilities' business risk is company size. Larger gas and electric utilities have greater presence in the financial markets, and analysts and institutional investors are more likely to follow and take positions in them. Additionally, large utilities have more diversified service territories than small utilities as well as more diversified fuel and gas supplies and transportation sources. At minimum, this diversification should reduce larger companies' business risk exposure, and one could expect smaller utilities to receive larger allowed ROEs on the average. This postulate is consistent with Ibbotson (2008).¹³ Therefore, the analysis examines the seventh hypothesis:

Hypothesis 7: Allowed ROEs are negatively related to company size.

Regulatory Risk. A special risk of regulated utilities is regulatory lag, or the risk of delay of recovery of incurred costs. Normally, this delay results from the elapsed time of a regulatory proceeding¹⁴. For example, when a utility has the information necessary to support a rate increase and files a rate case, the elapsed time before approval and the authorization to collect additional revenues is regulatory lag. If a utility issues securities when interest rates are rising, or if operating expenses increase beyond levels designed in rates, a delay in implementing compensating rates means the achieved ROE will be below the allowed level. The analysis calculates the length of time between the filing date and the approval date as representative of regulatory lag, and this delay is a form of regulatory risk.¹⁵ If regulators recognize and compensate for the risk associated with the delay between requested and approved rates of return, the longer the regulatory delay, the higher the allowed ROEs, thus, the eighth hypothesis:

Hypothesis 8: Allowed ROEs are positively related to regulatory lag.

IV. Data

The sample of allowed ROEs includes decisions involving 91 electric and 85 local gas distribution utilities' cases¹⁶ reported by Regulatory Research Associates (RRA), a division of SNL Financial Inc. These electric and gas utilities' decisions cover the period from January 2001 through October 2007. The study developed the cross-section of allowed ROEs and other data, including the dates of filing and a decision from data provided by RRA.

¹³ Ibbotson (2008) has noted, "One of the most remarkable discoveries of modern finance is that of a relationship between firm size and return. The relationship cuts across the entire size spectrum but is most evident among smaller companies, which have higher returns on average than large ones."

¹⁴ In contrast to utility business risk, which is the risk of recovery of unexpected loss of revenues or increased costs, the risk of regulatory lag is the delay of recovery of known and reasonably incurred costs.

¹⁵ Regulatory treatment of other factors is a significant influence on achieved utility returns (i.e., flow through recovery of fuel and gas costs, depreciation treatment of invested capital, and rate design) but the disparate treatment among utilities and jurisdictions does not lend itself readily to empirical measurement.

¹⁶ To arrive at the number of the utilities in the dataset, we removed the cases with no available data values for variables such as risks, equity ratios, and bond ratings.

RRA was also the source of the regulatory agencies' structural variables. RRA reported that elected regulatory authorities made 17.6% of the gas decisions and 15.1% of the electric decisions in our sample. This analysis used a dummy variable with an elected regulatory agency taking the value of 1 and an appointed agency a 0. SNL reported that the terms of the regulators involved in these decisions varied from four to eight years.

Moody's Baa rated corporate bond yield is representative of the market interest rate as reported by the *Federal Reserve Statistical Release*, H15. We selected the interest rates as reported at the time that the authorities issued a decision.¹⁷ The non-market requested ROE variable is the differential between the requested return reported by RRA and the interest rate variable.¹⁸

To develop the financial risk data for this analysis, we identified and associated the allowed returns with the common equity ratios of the utility as reported by RRA at the time of the decision. The measures of business risk and size are the market beta and the total capitalization for the utility as reported by *Value Line* at the time of the rate filing. At least one measure of regulatory risk is the length of time from the date of filing to the date that the regulatory authorities issue a ROE decision.

V. The Estimation Method

The empirical model took the following form:

.....

where *ROE* is the allowed rate of return on equity, *ReqROEDiff* (Requested ROE Differential) is the difference between a utility's requested ROE and the current market interest rate level¹⁹, *ER* is the utility's equity ratio, *R* is current market interest rate, *Cap* is the utility's market capitalization, *Elect* is a dummy variable with the value of 1 representing elected regulatory authorities and 0 representing appointed authorities, *Term* is length of the regulators' term in office, *DL* is regulatory lag, as measured by the time from filing to the time of decision, and *Beta* is the market beta of the utility.

For both the electric and gas utilities, the allowed returns are similar in means, standard deviations, and minimum and maximum values. For the decisions studied, the allowed returns are generally in the range of 8.75% to 11.75%, with a mean around 10.35%. On average, the utilities' requested ROEs are approximately 1% higher than the

¹⁷ The market interest rate at the time of filing is likely to affect the requested ROE; however, the interest rate at the time the regulators set the allowed ROE may have a stronger influence on the allowed ROE.

¹⁸ The investigation also modeled the non-market requested ROE as the difference between the requested ROE and the projected requested ROE based on market interest rate. The empirical results are essentially the same.

¹⁹ Forming a difference variable can eliminate or mitigate the possible endogeneity problem in the requested ROE variable due to changes in market conditions.

allowed ROEs. Table 1 lists the variables and their descriptive statistics used in this study.

The mean common equity ratios for both electric and gas utilities are similar. For the electric utilities the mean common equity ratio is approximately 49%, and ranged between 25% and 62%. For the gas utilities the mean common equity ratio is 48% and ranged between 32% and 62%. The beta values, as a single dimensional measure of business risk, show that electric utility stock prices tended to be more volatile than the gas utility stock prices during this period. The total capitalization of electric utilities also tends to be larger than gas utilities' capitalization.

The investigation conducted separate regressions for the two industries.²⁰ The model corrected for heteroscedasticity problems by using the ROBUSTERROR option in the RATS statistical package.

VI. Regression Results

Significantly, as hypothesized and consistent with the equivalent return standard, a strong linkage exists between the allowed ROEs and interest rates as measures of alternative investments during this period for both gas and electric utilities. However, contrary to the standard of setting allowed returns equal to returns of equivalent risks, neither the hypothesized financial nor business risks are effective predictors of gas or electric utility allowed ROEs (except for beta in the case of electric utilities).²¹ The regulatory risk variable, the lag between the filing date and the award date, is a significant variable influencing the allowed ROEs of electric utilities, but not for the gas utilities.

Although the hypothesized risk measures apparently had little influence on the allowed returns during this period, the regulatory structure variables are predictors of the natural gas allowed returns, and the Requested ROE Differential variable is a significant predictor of allowed returns in both the gas and electric utility cases. Table 2 shows the regression results of allowed ROEs on the specified variables.

The regression results for the electric utilities showed that the allowed ROE changed in the same direction as market interest rates but by a lesser amount. For each 1% change in the current level of market interest rates, as measured by the Baa corporate bond yields, the allowed return for electric utilities changed 0.47% on the average. This variable is statistically significant at the 1% level.

²⁰ We also pooled the data for the two industries. Following this pooled data analysis, identifying the differences in the distinguishable industry risk coefficients between the two industries outweighed the statistical benefits of pooling the data.

²¹ One question is whether the Requested ROE differentials have captured the impact of firm risk variables so these firm specific risk variables do not provide any additional information. However, correlation analysis among the risk variables and requested ROE does not support this explanation. These results were consistent with the more recent studies of allowed ROEs that found no negative significant relationship between allowed ROEs and financial risk as opposed to the earlier studies that found such a relationship.

The Equivalent Risk Standard and Allowed ROEs in the Gas and Electric Utility Industries

As to the hypothesized variables, contrary to the standard of setting allowed ROEs equal to investments of equivalent risks, the financial risk variable, as measured by the common equity ratio, does not have the hypothesized sign in the electric utility regressions.²² Additionally, the business risk variable, as measured by size, does not have the hypothesized sign but it is statistically significant at the 10% level.²³ This means that, on the average, larger electric utilities receive higher allowed ROEs than smaller electric utilities. The business risk beta variable has the correct, positive sign in the electric regression and it is statistically significant. Likewise, the measured regulatory risk variable of the elapsed time between filing and rate decision is a significant predictor of the level of allowed ROE in the electric regression. The Requested ROE Differential variable, which undoubtedly incorporates some utility-specific factors, is positive and statistically significant at the 1% level for electric utilities. For each 1% of additional requested ROE above prevailing interest rate, the allowed ROE increases by 0.39%.

As to the regulatory environment, in the electric utility regression the investigation detected no difference between the allowed returns set by elected and appointed regulatory authorities. Furthermore, the term of office of the regulators is not statistically significant at the 10% level.

The gas utility regression results are similar to the electric utility results in key hypothesized areas, but they also produce some seemingly important distinctions. As in the case of the electric utilities, in the gas industry the change in allowed ROEs also moves with market interest rates, but also by a lesser amount. As the market interest rate changed 1%, on the average the allowed ROE changes 0.41%.

As in the case of the electric industry, the gas regression coefficient also shows a significant and positive relationship between the requested ROE Differential above the prevailing interest rate and the allowed ROE. For example, for each additional 1% of non-interest-rate ROE requested the allowed ROE increased by 0.45% on the average. Again, contrary to the hypothesized sign, the coefficient of the common equity ratio is positive. Also, neither of the business risk variables of size and beta are significant determinants of gas allowed ROEs.²⁴ One distinction between the gas and electric

²² The common equity ratio is a direct measure of financial risk, and rather than being negative, the coefficient of the variable is positive and statistically significant at the 1% level. This finding, although consistent with some of the recent studies, is inconsistent with financial theory and the hypothesized relationship.

²³ The size variable, as measured by company capitalization, has a positive relationship with allowed ROEs of electric utilities, and it is statistically significant at the 10% level. Although this is inconsistent with financial theory regarding size and risk and the hypothesized relationship, one could speculate that this empirically determined allowed ROE-size relationship may have encouraged consolidation of smaller utilities with larger ones. As a measure of that electric utility industry consolidation, the number of investor-owned electric utilities covered by *Value Line Investors Service* declined by approximately 30% from 1998 to 2007.

²⁴ As in the case of the electric utilities regression, the failure to link company size risk and allowed ROEs does not reveal whether this has longer-term industry consequences. However, as in the case of the electric utility industry, the period studied is a period of industry consolidation. As a measure of investor owned gas distribution industry concentration, the number of natural gas distribution utilities reported by *Value Line Investors Service* decreased by approximately 40 percent during the 1998-2007 period.

regressions is the regulatory lag variable. Contrary to the result in the electric utility regression, the regulatory lag variable is not statistically significant in the gas regression.

An obvious distinction between the gas and electric allowed ROE regressions, is the apparent influence of the regulatory environment on the allowed ROEs of gas utilities. Both the elected regulatory authority and the length of term variables are statistically significant at the 10% level with the hypothesized sign. On average, during this period, elected regulatory authorities set allowed returns 0.20% lower for gas utilities than did appointed authorities.²⁵ Furthermore, the shorter the authorities' term in office the lower the allowed ROE.

VII. Conclusions

The common regulatory objective for determining a utility's allowed ROE is to set an allowed ROE that is equal to return from an investment of equivalent risk. This is both a regulatory standard for attracting and maintaining capital as well as being consistent with financial theory. However, this study of recent electric and gas utility decisions found only weak empirical evidence linking the above standard to the allowed ROEs. As to the equivalent return component of the standard, ROEs followed the overall market bond rates although the ROEs did not adjust by equal amounts over the period studied. As to the second component of the allowed ROE standard, i.e. equivalent risk, some distinction arises between the gas and the electric decisions. For the gas distribution industry, none of the financial, business, or regulatory risk variables is statistically significant with the hypothesized sign. In the case of the electric utility decisions, only the volatility measure of beta and regulatory lag coefficients are statistically significant with the correct sign.

²⁵ This result is consistent with Quast (2007) who investigated the impact of elected versus appointed commissioners on prices in the telecommunication industry.

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Table 1. Descriptive Statistics of the Variables

Electric Company					
Variable	Obs.	Mean	Std. Dev.	Minimum	Maximum
Allowed ROE (%)	117	10.37	0.50	8.75	11.75
Requested ROE (%)	116	11.25	0.51	9.75	12.75
Equity Ratio	117	47.87	5.75	25	61.75
Decision Lag (months)	117	10.36	5.11	3	42
Interest Rate (%)	117	6.71	0.64	5.79	9.1
Capitalization (\$billion)	112	5.97	7.18	0.08	48.00
Commissioner Term (Year)	117	5.41	0.89	4	8
Elected Commission	117	0.15	0.36	0	1
Beta	102	0.89	0.23	0.5	1.95
Gas Company					
Variable	Obs.	Mean	Std. Dev.	Minimum	Maximum
Allowed ROE (%)	96	10.34	0.47	9.1	11.5
Requested ROE (%)	96	11.33	0.44	10.5	12.7
Equity Ratio	96	48.69	6.35	31.8	61.81
Decision Lag (months)	96	9.19	3.20	4	20
Interest Rate (%)	96	6.78	0.83	5.79	9.29
Capitalization (\$billion)	90	4.13	4.66	0.05	26.00
Commissioner Term (Year)	96	5.50	0.87	4	8
Elected Commission	96	0.15	0.35	0	1
Beta	86	0.86	0.15	0.55	1.55

Table 2. Risks and Allowed ROEs: A Regression Analysis

Variables	Electric	Gas
Constant	2.70** (2.51)	3.428*** (3.492)
Requested ROE Differential	0.387*** (5.36)	0.449*** (4.836)
Interest Rate	0.467*** (4.16)	0.411*** (3.911)
Elected	-0.123 (-1.14)	-0.204* (-1.847)
Com. Term	0.068 (1.27)	0.087* (1.826)
<i>Financial Risk</i>		
Equity Ratio	0.0378*** (6.2)	0.0268*** (4.267)
<i>Regulatory Risk</i>		
Decision Lag	0.0132** (2.086)	0.0158 (0.966)
<i>Business Risk</i>		
a. Beta	0.473*** (2.75)	0.133 (0.473)
b. Capitalization	0.011* (1.926)	0.0212 (1.29)
# of Obs.	91	85
Adj. R Square	0.278	0.328

Note: t-values are in parentheses. ***, **, * denote significance at 1%, 5% and 10% levels, respectively.

Kentucky Economic Association
Frankfort, Kentucky
September 24, 2010

Jeffrey M. Lacker
President, Federal Reserve Bank of Richmond

I am deeply honored to accept this award. Although my family left the Bluegrass State and migrated to the Northeast early in my life, I have deep family roots here. My grandfather Sholto Spears grew up around Auburn, for example. So I retain a fond spot in my heart for My Old Kentucky Home, and I know this award would have made my Grandpa Sholto proud.

In my remarks today, I would like to share some reflections on the role of economics in policy making during this financial crisis.¹ Over the last few years, I have had the privilege of witnessing, and at times participating in, some of the most challenging economic policy deliberations imaginable. Be under no illusions about my role, however; mine was a bit part at best. But my position gave me a unique vantage point on the making of policy during this financial crisis, and the fact that my teaching and research had been focused on banking and financial intermediation gave me a special interest in the events. I should note that these reflections are my own, however, and not necessarily shared by any of my colleagues on the Federal Open Market Committee.

When you think about economics and the financial crisis, one of the first things that comes to mind is the claim that economists' inability to predict this crisis represents a failure for the profession. While this notion has led some to lambast mainstream economics for its supposed shortcomings, the claim that economists did not foresee a crisis of this sort is fallacious. As Thomas Sargent has recently pointed out,² economists sounded warnings several decades ago about the potential for troubles such as those we've experienced. In 1983, Douglas Diamond and Philip Dybvig published a celebrated paper on bank runs.³ Their model elegantly captured the economic value of *maturity transformation* – that is, borrowing via short term, demandable liabilities to fund longer term or less liquid assets. They also showed how a financial institution performing this maturity transformation function could be vulnerable to self-fulfilling “runs” in which investors who do not need the immediate return of their investment nonetheless come and seek it because they conjecture that other such

¹ I am grateful to John Weinberg for help in preparing this speech.

² Remarks at the American Economic Association panel discussion titled “Why Did Economists Not Predict the Crisis?” January 5, 2010. See also www.minneapolisfed.org/publications_papers/pub_display.cfm?id=4526.

³ Douglas Diamond and Philip Dybvig, “Bank Runs, Deposit Insurance and Liquidity,” *Journal of Political Economy*, June 1983, vol. 91 no. 3, pp. 401-19.

investors will make the same choice.⁴ Many historical episodes of financial market turmoil have been interpreted as instances of this type of self-fulfilling run.

Deposit insurance and other forms of government-provided financial safety net protection are often motivated by the possibility of bank runs. Indeed, in the Diamond-Dybvig model, government deposit insurance completely eliminates the run equilibrium. But in a 1978 article, John Kareken and Neil Wallace pointed out that deposit insurance gives insured banks and thrifts an incentive to take on socially excessive amounts of risk and dampens their creditors' incentive to monitor and constrain such risk-taking.⁵ Several years later, Kareken wrote about the critical role of regulation and supervision in constraining the excessive risk-taking incentives that result from deposit insurance.⁶ He warned of the dangers of deregulating such institutions before commensurately strengthening the supervisory regime to be able to contain the expanded bank and thrift risk-taking capabilities. More recently, former Minneapolis Fed President Gary Stern and his then-colleague Ron Feldman, in a 2004 book, warned about the distorted risk-taking incentives at large financial institutions that were viewed as *Too Big to Fail*, the title of their volume. In 2002, Richmond Fed economists John Walter and John Weinberg estimated that at the end of 1999 about 45 percent of U.S. financial sector liabilities benefited from either explicit or implicit government guarantees.⁷ At around the same time William Poole warned specifically about the moral hazard dangers posed by Fannie Mae and Freddie Mac, who were privately owned but widely viewed as implicitly guaranteed by the U.S. government.⁸ As Chairman Bernanke has observed, "There is little doubt that excessive risk-taking by too-big-to-fail firms significantly contributed to the crisis, with Fannie Mae and Freddie Mac being prominent examples."⁹

Because the implicit component of the federal financial safety net is discretionary, in contrast to explicitly legislated guarantees such as deposit insurance, policymakers face an acute time consistency problem, which my former colleague Marvin Goodfriend and I wrote about in 1999.¹⁰ Committing ex ante to well-defined limits on government support would enhance market discipline and strengthen private incentives to limit risk-taking. But in the event of financial distress, pressures can emerge to alleviate ex post inefficiency, even if that

⁴ For a summary of the literature since Diamond and Dybvig, see Huberto M. Ennis and Todd Keister, "On the Fundamental Reasons for Bank Fragility," Federal Reserve Bank of Richmond *Economic Quarterly*, First Quarter 2010, vol. 96, no. 1, pp. 33-58.

⁵ John H. Kareken and Neil Wallace, "Deposit Insurance and Bank Regulation: A Partial Equilibrium Exposition," *Journal of Business*, July 1978, vol. 51, pp. 413-38.

⁶ John H. Kareken, "Deposit Insurance Reform or Deregulation is the Cart, Not the Horse," Federal Reserve Bank of Minneapolis *Quarterly Review*, Spring 1983, vol. 7, no. 2.

⁷ John R. Walter and John A. Weinberg, "How Large is the Federal Financial Safety Net?" *Cato Journal*, Winter 2002, vol. 21, no. 3, pp. 369-99. That figure is now 59 percent: see John R. Walter and Nadezhda Malysheva, "How Large Has the Federal Financial Safety Net Become?" Federal Reserve Bank of Richmond *Working Paper* No. 2010-03, March 2010.

⁸ William Poole, "Financial Stability," Federal Reserve Bank of St. Louis *Review*, September/October 2002. See <http://research.stlouisfed.org/publications/review/02/09/Poole.pdf>.

⁹ Ben S. Bernanke, Chairman, Board of Governors of the Federal Reserve System, statement before the Financial Crisis Inquiry Commission, Washington, D.C., September 2, 2010.

¹⁰ Marvin Goodfriend and Jeffrey M. Lacker, "Limited Commitment and Central Bank Lending," Federal Reserve Bank of Richmond *Economic Quarterly*, Fall 1999, vol. 85, no. 4, pp. 1-27.

would be inconsistent with an ex ante optimal plan. Responding to those pressures sets precedents that erode market discipline and contribute to the next crisis.¹¹ In my experience, this tension between ex post and ex ante perspectives on policy choice – this time consistency problem – is what makes policymaking particularly excruciating in a financial crisis.

These three economic forces – the potential fragility associated with maturity transformation, the moral hazard associated with explicit government guarantees, and the time consistency dilemma associated with ambiguous implicit guarantees – are central to understanding the narrative of the financial crisis. Financial institutions that benefitted from implicit government guarantees – notably Fannie Mae, Freddie Mac, and several European banking institutions – fueled the demand for securities backed by risky subprime mortgages. The implicit support of these government-sponsored entities (GSEs) led them and their creditors to underweight tail risk which in turn distorted incentives for a broad range of participants in the distribution chain, from credit rating agencies to originators to loan brokers. The resulting oversupply of subprime mortgage lending contributed to over-appreciation in home prices and over-investment in new housing. Maturity transformation outside of traditional deposit banking made many financial firms vulnerable to runs when their exposure to unanticipated mortgage-related losses was suspected. Ambiguity about the extent and likelihood of safety net support meant that declining to rescue would cause investors to pull away from other similar financial firms. Policymakers faced agonizing choices between bad precedents that would weaken market discipline and the financial market fallout of rapidly realigning investor expectations regarding future government support.

The literature on these three ideas provided fair warning, I believe, that the pre-crisis regime of constructive ambiguity was capable of generating consequential risk-taking excesses and significant financial market problems. Nevertheless, economists were unable to predict the time and manner in which the crisis would play out, although a few vocal individuals foretold some sort of imminent crisis more or less continuously. The painful process of watching the financial crisis unfold revealed several implications that had not been appreciated beforehand. The U.S. housing GSEs and their low-income credit mandates exerted a larger influence on the subprime mortgage market than was known ex ante. The dollar-denominated intermediation activities of European financial institutions, particularly maturity transformation, were more consequential than expected. The so-called shadow banking system was not a parallel universe unto itself, but instead depended critically on backstop liquidity support, both contractual and reputational, from large banking organizations, whose access to the safety net made them more willing to accept tail risk. That in turn meant that large subprime losses unexpectedly boomeranged back onto the balance sheets of bank holding companies. Perhaps most importantly, the magnitude of the over-investment in housing collectively generated by these sources of moral hazard was underestimated and emerged only gradually as the fall in residential investment unfolded. As a result, until the fourth quarter of 2008, a range of mainstream macroeconomic forecasts underestimated the depth of the recession.

¹¹ See also Kartik B. Athreya, “Systemic Risk and the Pursuit of Efficiency,” Federal Reserve Bank of Richmond *Annual Report*, 2009, pp. 4-18.

I have been discussing the economics of the buildup to the crisis, but what about the unfolding of the crisis itself? The financial market turmoil that began in August of 2007 posed tough challenges for central bank policy economists. The logic of the Diamond-Dybvig fragility result was an ever present and at times urgent concern, and motivated vigilant attention to firms that were vulnerable to run-like behavior because they were engaged in maturity transformation. Because government insurance for the liabilities of a Diamond-Dybvig intermediary can eliminate run equilibria, their model appeared to recommend official intervention to prevent the spread of runs. But as investor confidence in large financial institutions fluctuated, it became clear to supervisors that the extent to which a financial entity was vulnerable to runs was a matter of business strategy choice – that is, it was endogenous. Liquid, short-term borrowings were less costly than longer-term funding that more closely matched the maturity of the borrower’s underlying assets. Thus intervention decisions required facing non-trivial trade-offs involving ex ante moral hazard, a feature Diamond and Dybvig deliberately left out of their model.¹² Moreover, the contractual mechanisms that in a Diamond-Dybvig model allows a bank to prevent run equilibria – partial suspension, or ex post trading, for example – seem quite feasible in modern financial markets. In addition, a sizable empirical and theoretical literature views runs as driven by fluctuating expectations regarding the fundamental value of the intermediary’s assets, rather than by arbitrary herd behavior (that is, sunspots), in which case a run may represent an ex ante efficient method of initiating liquidation in the appropriate states of the world. So, while the Diamond-Dybvig model provided an illuminating framework for interpreting tumultuous events in financial markets, it did not provide unequivocal guidance for policymakers contemplating intervention, because not all runs represent inefficient instability.

Other models of inherent financial fragility also played a role in policy deliberations. For example, in August 2007 investors began pulling away from asset-backed commercial paper instruments out of concern that the underlying portfolios might be exposed to subprime mortgage losses.¹³ Issuance volumes dropped and prices fell, and the notion of “fire sales” or “cash-in-the-market pricing” was invoked as an explanation for financial assets trading at prices well below fundamentals, or not trading at all.¹⁴ Crucial to such models, however, are barriers to market participation that prevent the obvious arbitrage operations. It was hard to find such barriers in the asset-backed securities market, however, given the wide array of institutional investors that had access to those securities and many other markets as well. Moreover, on-balance sheet funding costs for the sponsoring institutions were often lower

¹² Diamond and Dybvig recognized this and warned readers that potentially important moral hazard considerations had been omitted from their framework. Recent work by Huberto Ennis and Todd Keister has extended the Diamond and Dybvig model to capture the intermediary’s choice of exposure to runs. Huberto Ennis and Todd Keister, “Bank Runs and Institutions: the Perils of Intervention.” *American Economic Review*, September 2009, vol. 99, no. 4, 1588-1607.

¹³ Daniel M. Covitz, Nellie Liang, and Gustavo A. Suarez, “The Evolution of a Financial Crisis: Panic in the Asset-Backed Commercial Paper Market,” *Finance and Economics Discussion Series*, Federal Reserve Board, no. 2009-36, August 19, 2009.

¹⁴ Franklin Allen and Douglas Gale, “*Understanding Financial Crises*.” Oxford University Press, Oxford, 2007, Chapter 8.

than that implied by crisis-level market risk premia, which could explain the precipitous drop in issuance. It was difficult to reject the hypothesis that in response to legitimately elevated uncertainty about subprime mortgage loss exposures, a broad range of investors had marked down asset valuations and shifted into cash. Under this hypothesis, depressed asset prices represented reduced fundamentals, and official intervention would impede rather than aid market functioning.

This example illustrates a broader lesson regarding the use of economic models in financial policy. The formal economics of financial fragility is still in its infancy. What the economics literature provides is a collection of intriguing “possibility theorems” showing that a particular financial market phenomenon could potentially occur under a given set of assumptions. Some models of financial fragility rationalize activist intervention policies, while some models with identical price and quantity implications suggest that observed arrangements may be fairly efficient. Policymakers are thus faced with alternative models with very different policy implications. Constructive policy deliberations require that you “lay all your cards on the table” by checking the entire range of model characteristics against real world observations, both qualitative and quantitative.

Financial policy making thus places a premium on careful and objective reporting. I believe that was made more difficult by the type of language often used to describe financial market conditions. At various times we learned that a financial market was “strained,” “stressed,” “under liquidity pressures,” “dysfunctional,” “frozen,” “clogged,” or “had seized up.” While this market terminology is certainly vivid and undoubtedly helped convey the discomfort of some market participants, particularly on the sell side, I never found any of these terms all that helpful, because all they really conveyed was that prices and traded quantities were low or even at zero. They could be inefficiently low due to some market imperfection, or they could be efficiently low because buyers’ expectations regarding the asset’s fundamentals are depressed. Without a candidate model in hand of how that asset market functions, such colorful slang says nothing about policy questions.

* * *

I’d like to close by focusing on the time consistency problem, which I believe was *the* central tension in the financial crisis. I also believe that shifting investor beliefs about the government’s intention to provide or limit support was a leading source of contagion and market volatility in a number of key episodes – especially during the weeks in September, 2008, that saw distinctly different treatments of Lehman Brothers, American International Group Inc. (AIG), Washington Mutual Inc., and the former Wachovia Corp.

The difficult dilemmas that policy makers faced in the fall of 2008 were in part the legacy of a financial safety net policy that ultimately proved unworkable. Often referred to as “constructive ambiguity,” this approach encouraged financial firms and their creditors to behave as if they were not protected – by not publicly acknowledging implicit support – while policymakers actually were standing ready to act in a crisis.¹⁵ Constructive ambiguity

¹⁵Gerald E. Corrigan, “Statement before the United States Senate Committee on Banking, Housing and Urban Affairs,” Washington D.C., May 3, 1990.

essentially sought to obtain the ex ante benefits of commitment without giving up the discretion to act freely ex post. While constructive ambiguity was never formally adopted by name as official policy, I believe it is a fair description of the approach to policy followed in the decades since the Continental Illinois bail out.¹⁶

Ultimately, of course, constructive ambiguity is bound to be defeated by rational expectations. Even if you don't accept rational expectations in its strongest forms, it seems clear that a policy that relies on people being systematically and persistently wrong about how the government will behave in a crisis has little chance of imposing effective market discipline on risk-taking.

The experience of the last three years should finally put an end to the notion of constructive ambiguity as a plausible approach to financial stability. The Dodd-Frank Wall Street Reform and Consumer Protection Act in many ways reflects recognition of this fact. In the debates leading up to the Act's passage, all sides stressed the need to credibly end bailouts of large financial institutions.

Ultimately, there are two ways to achieve the long-term benefits of commitment. One is to impose legal constraints limiting policymakers' actions. The other is for the policymaker to seek, through actions and communications, to establish and maintain a reputation for a particular decision rule. This approach worked well in bringing down inflation in the 1980s, but whether it can work for financial safety net policy – or more precisely, the extent to which it can work – is an open question. My sense is that, combined with improvements to regulation, it *can* and ultimately *must* be part of an effective approach to financial stability.

The Dodd-Frank Act presents a golden opportunity for a regime change that leaves behind the dangers of constructive ambiguity. But the Act embodies two contradictory approaches to resolving the time consistency dilemma. On one hand, it sharply constrains and strengthens accountability around government funded rescues of financial firms, which would tend to limit instances of intervention.¹⁷ On the other hand, it also provides more discretionary tools to intervene to prevent the ex post distress associated with bankruptcy, which would tend to exacerbate the time consistency problem. Reducing financial instability will require clarity and commitment.

As for economics, my hope is that policymakers can make better use of it next time around. For this it would help if work on models of financial fragility moves beyond possibility theorems and begins to confront models with facts in a systematic way. And for their part, policymakers must confront head-on the tensions of the time consistency problem.

¹⁶ For corroborating evidence of the persistence of constructive ambiguity, see speeches by Chairman Alan Greenspan and Vice Chairman Roger Ferguson at the Chicago Bank Structure Conference in 1999 and 2000, in which they stated that creditors of large institutions should expect to experience losses in some states of the world, while carefully avoiding mention of whether they would.

¹⁷ For example, it eliminates Federal Reserve's authority under Section 13(3) of the Federal Reserve Act to make emergency loans to individuals, partnerships and corporations (that is, nonbank entities), apart from lending programs with "broad-based eligibility."

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