THREE ESSAYS ON SYSTEMIC RISK

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ABSTRACT

I examine three topics related to systemic risk which not usually considered in mainstream research. I find evidence that coffee price risk might be hedged by Ugandan producers, possibly mitigating the risk of economy-wide devastation. I provide evidence that there is a long history of a relationship between real estate lending and bank failures, which have threatened economic collapse several times in American history. And I show the potential benefits of an options market for temporary shelter for persons fleeing natural disasters, history's most unforgiving threat to individuals and nations. All three papers contribute to the understanding of systemic risk, providing important insights for policymakers and avenues for further research.

DEDICATION

This dissertation is dedicated to my father, Rod Woodruff.

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1. INTRODUCTION

The three essays that follow address events or situations related to systemic risk. In the first essay I examine the potential for Ugandan coffee producers to hedge price fluctuations. In the second essay, I test for a long-run relationship between real estate lending and bank failures in the United States. In the final essay, I demonstrate the potential benefit of individual purchases of options for shelter in the event of hurricane evacuation.

Systemic risk has reemerged as a rich research topic since the financial crisis of 2007-9, and much of the research has focused on threats to, or emanating from, the financial system. Broadly defined, systemic risk is the threat that some shock or series of shocks will lead to a series of very bad economic consequences that could ultimately threaten the health of an entire economy. Improved understanding of systemic risk, and events related to either the causes or effects of systemic events, could potentially aid policymakers and market participants in their efforts to mitigate the possibility or potential harm from systemic events.

The essays that follow directly address issues important to policymakers and others regarding systemic risks. The Ugandan economy has been devastated, and could be again, by coffee price shocks. Properly hedged, the economy-wide risk of price declines could be greatly reduced. Bank failures have threatened the national and regional economies of the U.S. several times throughout history. If better forecasted, threats to bank viability might be mitigated, hence reducing systemic risk. Hurricanes and similar natural disasters can be systemic events for regional economies in the U.S., and can threaten entire nations' economies elsewhere—consider the Haiti earthquake of 2010 or the tsunami of 2004, each of which killed hundreds of thousands and wrecked entire nations. I contribute novel evidence regarding all three topics below.

2. UGANDAN COFFEE MARKET PRICE RISK MANAGEMENT

2.1 Introduction

Coffee exports are the lifeblood of the Ugandan economy. The Ugandan coffee industry employs ten percent of the country's population, who work 500,000 farms and generate more than a quarter of the country's export earnings. Prodded by development assistance programs sponsored by the World Bank, Ugandan leaders recently doubled the amount of arable land dedicated to new coffee tree growth, further increasing the nation's reliance on coffee export success (Barivo, 2014). Given Uganda's reliance on coffee exports and concerns about price stability, World Bank officials have proposed that coffee industry participants hedge against price instability by taking positions in global derivatives markets. I examine the feasibility of one of the proposed hedging strategies, the purchase of coffee futures contracts on international markets. I find evidence of a close relationship between the movements of Ugandan coffee producer prices and futures market prices, supporting the feasibility of hedging price risk in international markets. Due to the limitations of the focus and methodology of my study, however, should give potential Ugandan hedgers pause until further research in conducted.

Two-thirds of developing countries depend on commodities for at least fifty percent of their export earnings, and more than half of African countries derive at least eighty percent of export earnings from commodities (UNCTAD, 2012). Over the short- to medium-term, commodity prices can be highly volatile, and over the last decade commodity price volatility rose substantially (Fry, Lai, & Rhodes, 2011). Given that most commodity-exporting developing nations are price-takers and under diversified, commodity price fluctuations, "create macro-economic instabilities and complicate macroeconomic management. Erratic price movements generate erratic movements in export revenue, cause instability in foreign exchange reserves and

are strongly associated with growth volatility;…and, (price volatility) can significantly reduce national revenue, cost millions of jobs and render farmers' crops nearly worthless in one fell swoop" (Seth, 2011, p. 58). Deaton estimates that for African nations dependent on commodity exports, "a 12 percentage point swing in commodity price growth will eventually lead to a change of 1.8 percentage points in the [*GDP*] growth rate" (Deaton, Summer, 1999, p. 38).

Uganda relies heavily on coffee for export earnings, and price instability affects the entire economy from the ground up. A combination of market liberalization reforms pushed by the World Bank and IMF in the 1980s and the collapse of the International Coffee Agreement (a price stabilization scheme that relied on export quotas) in 1989 ushered in increased price volatility in East African coffee markets (Lukanima & Swaray, 2014). Price risk in the Ugandan coffee market affects small farmer production decisions (Hill, 2006) and directly affects farmer and coffee intermediary welfare (Lukanima & Swaray, 2014). Also, price risk can erode within-country intermediaries' profits, forcing "some operators (to) leave the trade altogether if they generate price risk losses, or they may no longer be willing to accept the levels of risk that they are exposed to, thereby lessening competition and eroding farm gate prices" (Parizat, 2011, p. 11)

To address price risk in Uganda and elsewhere, the World Bank, the United Nations, and other nongovernmental organizations have advocated developing countries reliant on commodity exports seek to hedge against price instability using market-based instruments such as futures, forwards, and options contracts (Larson, Anderson, & Varangis, 2004). Various pilot projects have tested training courses aimed at educating commodity producers in developing countries, and Uganda, about hedging instruments (CFC, Study of Marketng and Trading Policies and Systems in Selected Coffee Producing Countries, 2000) (CFC, 2005) and fostered contact with

financial services firms willing to provide access to price risk management products such as futures contracts (Jaffee, 2008). Subsequently, Hill (2006a) found substantial demand and willingness to pay for price insurance amongst Ugandan coffee market players.

Considerable research has investigated the viability of hedging strategies available to developing nations reliant on commodity exports. Johnson (1960) provided the seminal work on hedging price risk using futures, and McKinnon (1967) examined the particular issues facing farmers and other primary producers when hedging. Some studies of developed countries' futures and spot markets found evidence these markets are cointegrated and/or efficient (e.g. Thraen, 1999; McKenzie & Holt, 2002; Zapata & Fortenbery, 1996), while some found evidence rejecting efficiency, or yielded mixed results (e.g., Lai & Lai, 1991; Bessler & Covey, 1991; Beck, 1994; Fortenbery & Zapata, 1997). And yet another study found hedging commodity price risk is viable, though problematic over long time frames (Schwartz, 1997).

Various institutional barriers and other wedges between developed countries' futures markets and developing countries' spot markets might prevent cointegration and/or market efficiency between the two markets, making the findings of research on developed countries inapplicable. Focusing on developing countries, some researchers found developing nations' spot markets are cointegrated with developed nations' futures markets and concluded hedging to be a viable policy alternative for addressing price instability (e.g., Morgan, Rayner, & Ennew, 1994). Others focused specifically on coffee markets, with some finding evidence for cointegration of futures and spot coffee markets (e.g., Sabuhoro & Larue, 1997; Lence, 2003; Krivonos, 2004; Mohan & Love, 2004; Fry, Lai, & Rhodes, 2011; Gemech, Mohan, Reeves, & Struthers, 2011; Reyes, 2012), and others rejecting cointegration between developing country coffee markets and global futures markets (e.g., Kebede, 1992; Mohan & Love, 2004). To date, few have examined

the Ugandand coffee market, which presents a special case due to the advanced state of market liberalization there and because it serves as a model for policies in similar African countries (Lukanima & Swaray, 2014). Those who have examined the Ugandan coffee market did so for periods that preceded the collapse of price controls concurrent with the demise in 1989 of the International Coffee Agreement, or relied on nonstandard methodologies unsubstantiated by the literature. I correct both of these shortcomings.

With contradictory findings regarding cointegration and/or efficiency in the coffee markets, and especially considering the mixed results regarding market efficiency in developed nations' futures markets, where foreign exchange risk is not a concern, there is reason to further test for conditions required for futures-based hedging for Ugandans. I test Ugandan coffee spot market prices and London and New York futures prices for cointegration using the Engle-Granger two-step method, the Johansen maximum likelihood method and an error correction model. There is evidence of cointegration, though I cannot reject market inefficiency. I also find evidence of time-varying conditional variance in spot price changes, prompting suggestions for further research. Given the importance of commodity price risk to so many countries and recent efforts to push developing nations to adopt market-based risk management strategies to reduce price risk, my findings are important to policymakers, market participants and researchers.

2.1 Coffee Producer Market-based Price Risk Management

Ever since the collapse of the International Coffee Agreement, which had successfully set export quotas and stabilized world coffee prices, in 1989, researchers have examined the possibility of market-based price risk management for coffee exporting nations. Ouattara, Schroeder, & Sorenson (1990) test the hedging against price fluctuations in coffee prices for Côte d'Ivoire producers. They form optimal hedges and test their performance over the years

1973 to 1987 (years when prices where controlled via the International Coffee Agreement), and found that had Côte d'Ivoire assumed futures positions equal to 125 of expected annual production, they could have reduced the standard deviation of revenues by 29%.

Kebede (1992) examined pre-ICA collapse data (1977-1987) to test for Granger causality between New York spots and various length futures prices. Kebede found that 1) causality runs from futures to spot prices for contracts with more than eight weeks to maturity; 2) that spot and futures markets were efficient for contracts less with less that 55 weeks to maturity, but not for contracts with more than 55 weeks to maturity. Morgan, Rayner, & Ennew (1994) tested coffee spot and futures price series over the 1984 to 1993 period using the Augmented Dickey-Fuller test and concluded the series were cointegrated.

Sabuhoro & Larue (1997) test New York futures and spot price series covering 1979 to 1990. Cointegration of the series is verified using the Engle-Granger two-step method and Johansen Liklihood method. Using the Johansen method they test 1) a restriction implying elasticity between future spot price and spot price; and 2) a restriction implying futures price is an unbiased estimator of the spot price. They could not reject the restrictions, which implies efficiency in the New York coffee price markets. However, since the data for the four above studies came from a period of price controls, and/or are limited to developed markets, the results are of limited applicability today.

Krivonos (2004) examined twenty years of futures and producer price data from fourteeen coffee exporting countries, including Uganda. The series dates straddle market liberalization efforts (including the collapse of the ICA) to permit tests for increased cointegration due to liberalization. Only nine countries producer prices series are cointegrated with futures markets prior to liberalization, but all fourteen countries' producer prices are

cointegrated after liberalization. Using an error correction model, Krivonos estimated the speed of adjustment of producer prices to world price changes and found responses to have increased after liberalization.

Bush (2009) formed a series of simluated hedges using various combinations of futures strategies to test the outcomes for hypothetical coffee producers in Mexico, Brazil and Uganda. Revenues from the strategies are compared to a benchmark of not hedging. The period tested for Uganda is the coffee price crisis dated from 1998 to 2002. Bush found the results to be ambigous, that some strategies stabilized farmer income while some failed to protect income.

Fry, Lai, & Rhodes (2011) tested price indices of Colombian and Brazilian coffee spot prices for interdependence with New York and London futures prices. Vector autoregression analysis suggested a bi-directional causal relationship between spot and futures markets. Granger causality tests and generalized forecast error variance decomposition showed that the relationship changed over time, with spot market volatility increasingly driving futures market volatility.

Reyes (2012) analyzed monthly coffee producer prices from Honduras, Guatemala, Colombia and Brazil and average monthly New York nearby futures prices from 1990 to 2013. The Johansen approach based on an error correction model found Brazil and Honduras producer prices, (with optimal lags of 8 and 4, respecitively), to be cointegrated with futures prices. For Colombia and Guatemala, the Johansen cointegration test fails to reject the null of no cointegration at the 10% level. Also, Reyes was unable to reject no cointegration between producer prices and export prices for all but Brazilian coffee.

2.2 Data

I examine two producer price series and two futures price series. The producer price series, which I will refer to as spot (S) prices below, are the monthly farm gate prices for Uganda Arabica and Uganda Robusta from October, 2003 to September, 2012. (n=109.) Farm gate prices (the prices small farmers receive from national distributors), provided by the Uganda Coffee Development Board. For futures prices, I use the Arabica Coffee "C" continuous contract and the Robusta continuous contract, both of which trade on ICE (Intercontinental Exchange). Farm gate prices are translated from Ugandan shillings to U.S. dollars using the Bank of Uganda's reported "Official Mid-Rate," which equals the weighted average inter-bank rate at mid-trading day. I present descriptive statistics in Table 1.

2.3 Tests for Efficiency

Assuming[1] zero transactions costs, no risk premium and competitive, liquid markets, the following relationship between futures and spot prices must hold:

$$F_{t-1} = S_t \quad \text{or} \quad F_{t-1} = E_{t-1}(S_t/\Omega_{t-1}) \tag{1}$$

where $\Omega_{t-1}$is the set of all available information at time t-1. In other words,

$$E_{t-1}(S_t) = F_{t-1}. \tag{2}$$

Assuming rational expectations, it follows that:

$$S_t = F_{t-1} + \varepsilon_t, \tag{3}$$

which can be rewritten as:

[1] For the most part, I follow the methodology of (Holt & He, 2004).

$$S_t = \alpha + \beta F_{t-1} + \varepsilon_t. \tag{4}$$

The futures price is an unbiased estimator of the spot price if: $\alpha = 0, \beta = 1$. So, if the null hypothesis of ($\alpha = 0, \beta = 1$) cannot be rejected, the forward rate unbiasedness hypothesis (FRUH) holds. If $\beta = 1$ cannot be rejected, the market efficiency hypothesis is accepted. The joint FRUH is a joint hypothesis that markets are efficient and there is no risk-premium.

Rejection of the null hypothesis ($\alpha = 0, \beta = 1$) implies three possible conclusions. First, the market may be inefficient. Second, intermediaries between Ugandan coffee growers and end-users may charge a risk premium for carrying the produce to market. Given the long time to market and relatively low value-to-weight, it seems likely that intermediaries would extract a premium for this risk. The existence of a risk premium would bias forecasts of future spot prices, but would not necessarily entail market inefficiency. Third, the risk-premium may vary over time, thus preventing futures prices from providing unbiased predictors of future spot prices at any given time (McKenzie & Holt, 2002).

Consider the case where two I(1) series that are, by definition, nonstationary. Now consider a linear combination of the two series:

$$\varepsilon_t = S_t - \alpha - \beta F_{t-1} \tag{5}$$

If there exist an a and b such that ε_t is stationary, then:

$$S_t = \alpha + \beta F_{t-1} + \varepsilon_t, \tag{6}$$

and futures prices predict spot prices; and the series are said to be cointegrated. If ε_t is not stationary, then the futures and spot prices deviate from each other. For the Ugandan coffee producers to be able to hedge in the futures market, there must not be evidence that the futures

and spot prices are not cointegrated. (Cointegration is a necessary, but not sufficient, condition for the possibility of hedging success.)

Before testing for cointegration, two key characteristics of the data series must first be examined. First, each data series must be nonstationary, in this case both series must be order of integration 1. Second, the data series must be examined for structural breaks. Structural breaks, if not properly accounted for, can result in false inferences regarding the can result in false inferences about the nature of the cointegration relationship, as noted in Frank & Garcia's (2009) critique of McKenzie & Holt (2002). McKenzie & Holt (2002) tested four commodity series (live cattle, hogs, corn, and soybean meal), and found evidence for time-varying risk premiums in the cattle and hogs futures markets. When Frank & Garcia (2009) examined the same series accounting for structural breaks in the data series, evidence for time-varying risk premiums disappeared.

Besides structural breaks, other factors can lead to false inferences when conducting tests of cointegration. As noted by McKenzie & Holt (2002), data series that are nonstationary in levels and can only be made stationary by differencing leads to unreliable regression results, invalidating inferences based on traditional test statistics. To address these concerns, and possible determine the market factors that may be driving indicators of inefficiency, I incorporate the solution offered by McKenzie & Holt (2002), who estimated an error correction model (ECM) and an ECM within a generalized quadratic ARCH (GQARCH) in-mean framework. (For a detailed explanation of what follows, see McKenzie & Holt, 2002.)

Incorporating an ECM into Equation 6 yields the following:

$$\Delta S_t = -\rho\varepsilon_{t-1} + \beta\Delta F_{t-1} + \sum_{i=2}^{m}\beta_i\Delta F_{t-1} + \sum_{j=2}^{m}\gamma_i\Delta S_{t-j} + v_t \qquad (7)$$

where Δ is the fist difference operator, ε_{t-1} is the error correction term from Equation 6, and v_t is stationary white noise. Cointegration implies $\rho > 0$, because deviations from long-run equilibrium should result in spot price changes. Short-run market efficiency implies the following restriction on Equation 7:

$$\rho = 1,\ \rho\delta = \beta \neq 0,\ \ and\ \beta_i = \gamma_i = 0 \tag{8}$$

$\beta \neq 0$ is consitent with short-term efficiency because β partly measures the effect of new information on futures prices and subsequent spot prices.

The remaining restrictions are best illustrated by rewriting Equation 7:

$$S_t = (1-\rho)S_{t-1} + \beta F_{t-1} + (\rho\delta - \beta)F_{t-2} + \rho\alpha + \sum_{i=2}^{m} \beta_i \Delta F_{t-i} + \sum_{j=2}^{m} \gamma_i \Delta S_{t-j} + v_t \tag{9}$$

where $(S_{t-1} - \alpha - \delta F_{t-2})$ has been subsituted for the ε_{t-1}, which is the error correction term defined by Equation 7. If tests reject the restrictions $\rho = 1,\ \rho\delta = 0$, then past futures and spot prices contain information not yet impounded into current prices, implying inefficiency in the market. If $\rho = 1, \beta = 1$ and $\beta_i = \gamma_i = 0$ hold, short-run unbiasedness is implied; however, these restrcitions do not preclude the presense of a constant risk premium (Beck, 1994).

There are limitations to the error correction model described above. The ECM does not account for time-varying risk premiums, nonlinear dynamics in the conditonal varaince of spot price changes or the effects characterized by volatility clustering (GARCH effects). McKenzie & Holt (2002) justify testing for short-run unbiasedness and efficiency with a generalized quadratic ARCH-in-mean error correction model (GQARCH-M-ECM), which was first proposed by (Sentana, 1995). Incorporating GQARCH-M terms into Equation 7 yields:

$$\Delta S_t = -\rho\varepsilon_{t-1} + \beta\Delta F_{t-1} + \sum_{i=2}^{m} \beta_i \Delta F_{t-1} + \sum_{j=2}^{m} \gamma_i \Delta S_{t-j}$$

$$+\theta_t\sqrt{h_t} + v_t \tag{9a}$$

$$v_t = e_t\sqrt{h_t},\ \sim IN(0,1) \tag{9b}$$

$$h_t = w_t + \sum_{i=1}^{r} \varphi_i h_{t-i} + \sum_{i=1}^{s} a_{jj} v^2{}_{t-j} + \sum_{j=1}^{s} a_j v^2{}_{t-j}$$

$$+\sum_{j=1}^{s} a_j v_{t-j} + \sum_{j\neq k}^{s} a_{jk} v_{t-j}\, v_{t-k} \tag{9c}$$

where h_t denotes the conditional variance of spot price changes, and is a function past variances, errors, and squared errors. In this form, short-run market efficiency implies:

$$\rho = 1,\ \rho\delta = \beta \neq 0,\ \ and\ \beta_i = \gamma_i = 0 \tag{10}$$

Short-run unbiasedness implies:

$$\rho = 1,\ \beta = 1,\ \ and\ \beta_i = \gamma_i = 0 \tag{11}$$

There are several advantages of incorporating an ECM into Sentana's (1995) GQARCH-M model. McKenzie & Holt (2002) outline three advantages: First, since GQARCH-M accounts for the possibility of GARCH effects, it improves on the OLS model which can generate spurious results by failing to incorporate possible GARCH effect (Gao & Wang, 1999). Second, the GQARCH-M-ECM specification accounts for a possible time-varying risk premium, evidence for which has been observed in commodity markets (Beck, 1994; Frank & Garcia, 2009). Third, GQARCH-M-ECM can capture nonlinear relationships between the conditional

mean and conditional variance of spot price changes driven by feedback effects, which a standard GARCH model may not capture.

2.4 Empirical Results

Before testing for cointegration it must be determined whether both series are non-stationary and the order of integration of each series must be verified. To test for non-stationarity and order of integration, I conduct unit root tests using both the Augmented Dickey Fuller test and the Phillips-Perron test. (Unit root tests (Kramer & Davies, 2002) and cointegration tests (Corradia & Swanson, 2006) are not robust to transformation from level to log form. I conducted all tests in both level and log form, but report only results of tests performed using level form data, with the sole exception being the descriptive statistics in Table 1. The results for both level and log are qualitatively similar.) Optimal lag length is determined by Akaike information criterion (AIC) and Schwartz information criterion (SIC), and AIC-estimated lags are presented in table 2.2. I cannot reject that both the Arabica and Robusta series are non-stationary in level form; alternatively, I can reject that both series are non-stationary in difference form. Both series appear to be I (1). I present the results of the unit root tests in Tables 2.2 and 2.3. Failing to reject that all series are nonstationary, I proceed to test for cointegration.

Before testing for cointegration according to McKenzie & Holt's (2002) specification (GQARCH-M-ECM), I conduct the more commonly applied Johansen (1998) test for cointegration according to Equation 6. First I run the Johansen (1998) without restrictions, then I test for cointegration with the restrictions most commonly applied in the literature, i.e., $(\alpha = 0, \beta = 1, (\alpha = 0, \beta = 1)$. I run both versions of Johansen's test for cointegreation (trace statistics and maximum eigenvalue tests), which consistently indicate that both the Arabica and Robusta spot and futures price series are cointegrated. Each test indicates that both pairs of series each

have one cointegrating relation. I present those results in Tables 2.4.1-2.4.4. (Also, graphical depictions of variance decompositions for both the Arabica and Robusta series are presented in Figures 3-4.)

Next, I test the restricted cointegration model, imposing $\alpha = 0, \beta = 1$, and the joint restriction $(\alpha = 0, \beta = 1)$. Results are reported in Table 2.5. For both the Arabica and Robusta series, I can reject the restriction that $\alpha = 0$, but I cannot reject the restriction $\beta = 1$. For both series I can reject the joint-restriction of $(\alpha = 0, \beta = 1)$. Rejection of the restriction $\alpha = 0$ indicates that for both series there exists a constant risk premium. Rejection of the joint restriction may be a result of what appears to be a large constant risk premium associated with both series and/or inefficiency in both Arabica and Robusta markets. Rejection of the null hypothesis, as noted above, could also result from model mispecification or characteristics of the data series such as structural breaks—though structural breaks are usually associated with inference errors associated with time-varying risk premiums.

I test for structural breaks using the Bai & Perron (2003) method. Employing 15% trimming percentage, using 5% significance level and heteroscedasticity and autocorrelation consistent (HAC) standard errors, I testeed all series in both level and log form. Tests indicate one break in the Robusta series and one in the Arabica series. The Arabica futures price series has a structural break at 07/2010 (t=82), and Robusta has a structural break at 05/2005 (t=20). Given that Prodan (2008) finds evidence that Bai & Perron's (2003) test too often rejects the full hypothesis of no structural breaks, it is possible the identified breaks only weakly affect the above test results. Nevertheless, I conduct the Johansen cointegration tests acounting for the indicated breaks to discern their effect. Results for the structural break test are presented in Table 2.6. See Figures 7 and 8 for graphical depictions of the break points.

The presence of structural breaks result in false inferences when conducting cointegration tests. Frank & Garcia (2009) argue that failing to account for structural breaks led McKenzie & Holt (2002) to falsely infer the existence of a time-varying risk premium when applying Johansen's cointegration test to commodity series. Johansen, Mosconi, & Nielsen (1990) offer a cointegration model that is robust to known break points and still permits testing of restrictions of slope parameters. Giles & Goodwin (2012) provide program code for calculating p-values and critical values for the modified trace tests offered in Johansen, Mosconi, & Nielsen (1990). Additionally, Giles (2013) provides Eviews (and R) program code for estimating the cointegration test; however, testing for restrictions proved exceedingly difficult.

Once again, both pairs of price series must be tested to ensure the proper order of integration, since the presence of structural breaks can bias ADF and PPT tests for nonstationarity. I confirm the proper order of integration for all four series using Perron (Perron, 1997), which permits estimation of the Perron unit root test with specified breaks. Results presented in Table 2.7. I fail to reject nonstationarity for both series in level form. Both series are stationary in differenced form, verifying that both pairs of price series are amenable to cointegration tests.

I conduct the cointegration tests using the Johansen, Mosconi, & Nielsen (1990) methodology, with programming code provided by Giles (2013). The test for cointegration offered by Johansen, Mosconi, & Nielsen (1990) requires first estimating a VAR and then applying what they call an $H_L(r)$ test, which is very similar to the trace test used for the typical Johansen methodology. Critical values and p values were estimated using the program code offered by Giles (2013), and both p values and critical values were verified to be identical to critical values reported elsewhere. The Johansen, Mosconi, & Nielsen (1990) test verifies that

both series cointegrated, each pair of series is characterized by a single cointegrating relation. Results for these cointegration tests are presented in Table 2.8. Though both pairs of series each had one series that has a structural break, both cointegration tests (Johansen and Johansen, Mosconi, & Nielsen), return similar results. I address below the potential bias in the GQARCH-M-ECM estimates due to structural breaks.

The first step in estimating the GQARCH-M-ECM is to identify the appropriate model specification. Residual diagnostics and log likelihood tests indicate that the best specification for Arabica is the GARCH(1,1)-M-ECM. Robusta is best specified by ARCH(1)-ECM. I estimated the mean equation for Arabica with zero to three lags for both spot prices and futures prices; but the only lag that proved significant for was a one-period lag of the spot prices. (Since the data series are monthly, it is not too surprising that estimates of lagged variances' effects were not significant.) The estimates of the error correction model are presented in Table 2.9.

The hypotheses of short-run efficiency and unbiasedness are rejected for both Arabica and Robusta series. There is no significant evidence of non-linear price dynamics in the Arabica series, as the test results presented in Table 2.10 indicate. Additionally, the lack of statistical significance of θ for both series indicates that evidence of short-run unbiasedness and inefficiency cannot be attributed to a time-varying risk-premium.

2.5 Conclusion

I find evidence that coffee futures markets are weakly efficient, in the sense that $\beta = 1$, but that futures prices are not an unbiased predictor of spot prices, which perhaps reveals a risk premium. A risk premium will be consistent with the fact that there are many wedges between farm gate prices in Uganda and futures prices in New York. It is also consistent with the fact that

the Ugandan coffee markets are notoriously shallow and illiquid—data from these markets are only available for monthly intervals. Also, exchange rate risk may be a factor, since Ugandan Shillings may not be a perfect hedge for currencies in which futures contracts are denominated (either dollars or pounds). However, when adopting a model specification for the express purpose of teasing out the possible reasons for short-term deviations of prices over time, I fail to rule our unbiasedness/inefficiency and fail to find evidence favoring the time-varying risk-premium hypothesis.

Though there is evidence that coffee futures markets are efficient for Ugandans, there are reasons to give potential hedgers pause. First, the raw coffee production cycle is long, from three to five years, and there is evidence that long-term hedges fail to mitigate risk (Schwartz, 1997). (The longest duration coffee futures contract is Lence and Hayenga (2001) specifically examine the feasibility of long-term hedges from the standpoint of coffee growers and conclude that the costs of hedging outweigh the benefits realized in simulations of long-term hedges. Also, there is reason to believe that hedge ratios are unstable even in strongly efficient markets, such as developed world markets, so hedging with futures could still result in result in substantial risk (Castelino, 1992). And hedge ratios are a key determinant of hedging success in agricultural markets (Tomek & Peterson, 2001).

In conclusion, it appears that Ugandan producer prices are cointegrated with global futures markets and there is evidence supporting the feasibility of successfully hedging price risk for Ugandan coffee industry participants, but there is also evidence that one of the key determinants of hedging success is unstable over time. There is no evidence that Ugandans have started hedging price risk using futures. And until further research resolves these issues,

Ugandans should remain cautious about hedging using futures markets until more research answers some key questions.

Table 2.1: Descriptive Statistics for Spot (S) and Futures (F)

Level	Arabica		Robusta	
	S	F	S	F
Mean	73.80	138.16	555.49	1544.91
Standard Error	33.15	53.90	187.79	537.67
Variance	1099	2905	35,267	289,089
Kurtosis (excess)	1.97	0.82	-0.99	-0.91
Skewness	1.40	1.14	-0.06	-0.03

Log	Arabica		Robusta	
	S	F	S	F
Mean	4.21	4.86	6.25	7.27
Standard Error	0.41	0.36	0.38	0.39
Variance	0.16	0.13	0.14	0.15
Kurtosis (excess)	0.01	-0.07	-0.46	-0.64
Skewness	0.27	0.26	-0.65	-0.56

N=109 for all four series. Arabica spot refers to the farm gate price for Ugandan Arabica coffee. Robusta spot refers to farm gate price for Ugandan Robusta coffee. Farms gate prices provided by Uganda Coffee Development Authority. Arabica future prices are the Coffee "C" continuous contract and Robusta futures the Robusta continuous contract; both futures contracts data are from ICE.

Table 2.2: Augmented Dickey Fuller Test on Spot (S) and Futures (F) Prices

	Arabica		Robusta		Critical Value
	S	F	S	F	
Levels	-2.35 (2)	-2.00 (2)	-3.32 (0)	-2.27 (0)	-3.15[a]
Differences	-6.20**(1)	-3.60**(3)	-11.81**(0)	-8.61**(1)	-3.49[b]

Optimal lags determined by AIC in parentheses. a: 10% critical value for level form tests based on ADF with constant and trend. b: 1% critical values for constant, no trend. n=107 for all series.

Table 2.3: Phillips-Perron Test on Spot (S) and Futures (F) Prices

	Arabica		Robusta		Critical Value
	S	F	S	F	
Levels	-2.31	-1.94	-3.31	-2.21	-3.15[a]
Differences	-11.51**	-14.32**	-11.94**	11.24**	-3.49[b]

a: 10% critical value for level form tests based on PP with constant and trend. b: 1% critical values for PP test with constant, no trend. n =106 for all series.

Table 2.4.1: Unrestricted Cointegration Rank Test (Trace) Arabica

Rank	Eigenvalue	Trace	.05 Critical Value	p-value**
None	0.206776	26.34876	15.49471	0.0008
At most 1	0.023875	2.488908	3.841466	0.1146

Table 2.4.2: Unrestricted Cointegration Rank Test (Max. Eigenvalue) Arabica

Rank	Eigenvalue	Maximum Eigenvalue	.05 Critical Value	p-value**
None	0.206776	23.85985	14.26460	0.0008
At most 1	0.023875	2.488908	3.841466	0.1146

Table 2.4.3: Unrestricted Cointegration Rank Test (Trace) Robusta

Rank	Eigenvalue	Trace	.05 Critical Value	p-value**
None	0.210155	27.73008	15.49471	0.0005
At most 1	0.025359	2.722722	3.841466	0.0989

Table 2.4.4: Unrestricted Cointegration Rank Test (Max. Eigenvalue) Robusta

Rank	Eigenvalue	Maximum Eigenvalue	.05 Critical Value	p-value**
None	0.210155	25.00736	14.26460	0.0007
At most 1	0.025359	2.722722	3.841466	0.0989

Table 2.5: Johansen Test with Imposed Restrictions

	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha} = 0, \hat{\beta} = 1$
Arabica	.96 p=.002	.84 p=.39	3.7 p=.008
	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha} = 0, \hat{\beta} = 1$
Robusta	.8 p=.0003	.34 p=.63	2.3 p=.009

The null hypotheses are shown in the tables: $\alpha = 0$; $\beta = 1$; $\alpha = 0, \beta = 1$. A likelihood ratio test statistic for the various restrictions is shown and has a χ^2distribution with the degrees of freedom equal to one and two, for single parameter test and joint test, respectively.

Table 2.6: Bai & Perron (2003) Structural Break Tests

	Arabica		Robusta		Critical Value**
	S	F	S	F	
Levels	19.52*	--		--	8.58
Logs	--	--	28.54*	--	8.58

Bai & Perron (2003) test for structural breaks test was performed on 108 observations. Trimmed 15%, the first and last 7.5% of the observations from test sample. Lag length =1 for all series. Heterogeneous error distributions allowed across breaks. **Bai-Perron (Econometric Journal, 2003) critical values for F-test for 0 versus 1 break. *Significant at the 5% level. Test statistics employ Heteroscedasticity and autocorrelation consistent covariance.

Table 2.7: Perron (1998) Unit Root Test w/ Structural Breaks

	Arabica		Robusta		Critical Value
	S	F	S	F	
Levels	-5.45	4.444152	-5.636899	-4.409070	-5.59**
Differences	-16.82361	-8.000569	-12.61856	-12.76587	-5.92***

Optimal lags fixed at same as that identified for ADF tests above. **5% significance level critical value. ***1% significance level critical value.

Table 2.8: Johansen, Mosconi, & Nielsen (2000) Coint. w/ Structural Break Tests

	Arabica		Robusta		
Number of Cointegrating Equations	HL(r)	5% Critical Value	HL(r)	5% Critical Value	p. value
Zero	38.496**	17.79	26.841**	16.65	.044**
At Most 1	19.244	35.21	18.888	53.31	0.89

Johansen, Mosconi, & Nielsen (2000) cointegration test as coded for Eviews by (Giles & Goodwin, 2012). Critical value for Arabica series test calculated as: V1=82/108=.76; and calculated for Robusta as: V1=20/108=.185. Critical values for HL(r) are 144.92 and 53.31, respectively for 5% significance level.

$$\Delta S_t = -\rho\varepsilon_{t-1} + \beta\Delta F_{t-1} + \sum_{i=2}^{m}\beta_i\Delta F_{t-1} + \sum_{j=2}^{m}\gamma_i\Delta S_{t-j}$$

Table 2.9 Error Correction Models

	Arabica	Robusta
Parameters		
ρ	-.58	-.351
	(-0.88)	(.191)
β	0..68	.90
	(10.87)	(.00)
γ_1	.003	---
	(2.12)	
R^2	.954	.845
Log Likelihood	110.86	60.76
$H_0: \beta = 1$	2.84**	3.32**
$H_0: \rho = 1$	3.00**	4.08**

$$\Delta S_t = -\rho\varepsilon_{t-1} + \beta\Delta F_{t-1} + \sum_{i=2}^{m}\beta_i\Delta F_{t-1} + \sum_{j=2}^{m}\gamma_i\Delta S_{t-j} + \theta_t\sqrt{h_t} + v_t$$

$$h_t = w_t + \sum_{i=1}^{r}\varphi_i h_{t-i} + \sum_{i=1}^{s} a_{jj}{v^2}_{t-j} + \sum_{j=1}^{s} a_j{v^2}_{t-j}$$

Table 2.10 GARCH(1,1)-ECM

	Arabica	Robusta
Parameters		
ρ	-.44	-.59
	(-0.54)	(.96)
β	0.23	.81
	(4.99)	(.03)
γ_1	.05	---
	(1.06)	
w	2.3	1.2
	(2.11)	(.99)
a_{11}	.03	.06
	(.03)	(.09)
θ	.24	.05
	(.09)	(.04)
Log Likelihood	142.63	86.77

Figure 1: Arabica Futures and Spot Prices

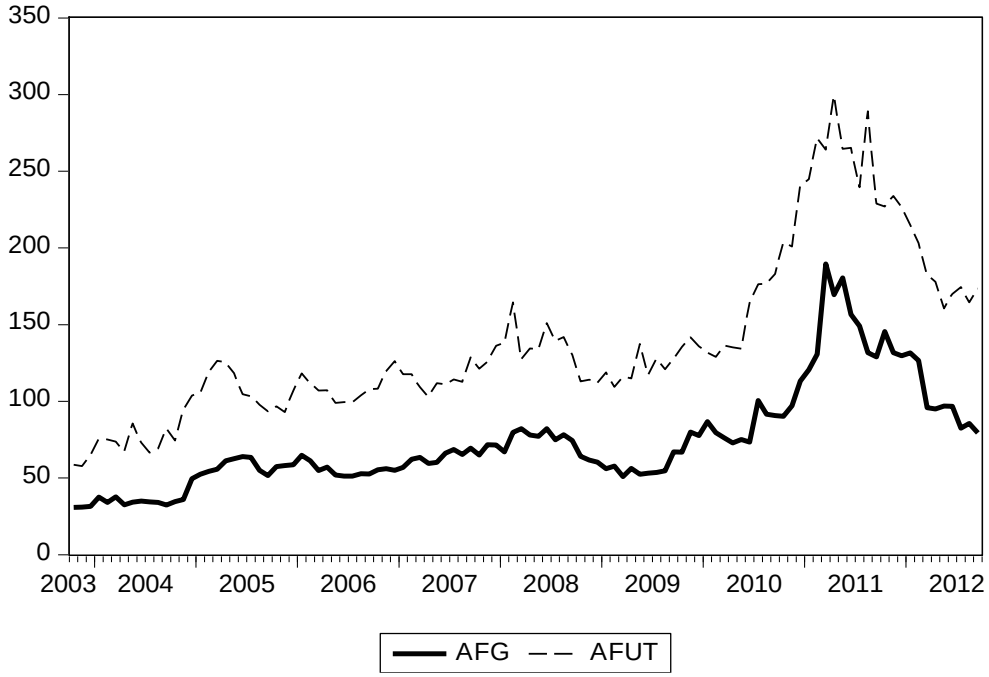


Figure 2: Robusta Futures and Spot Prices

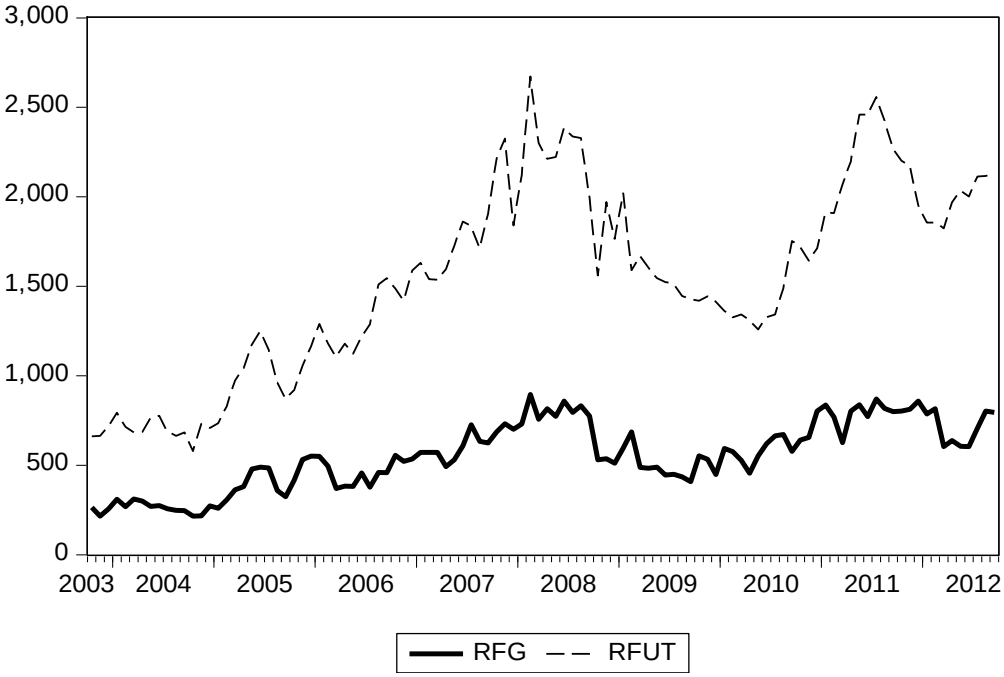


Figure 3: Variance Decomposition for Arabica Futures and Spot Prices

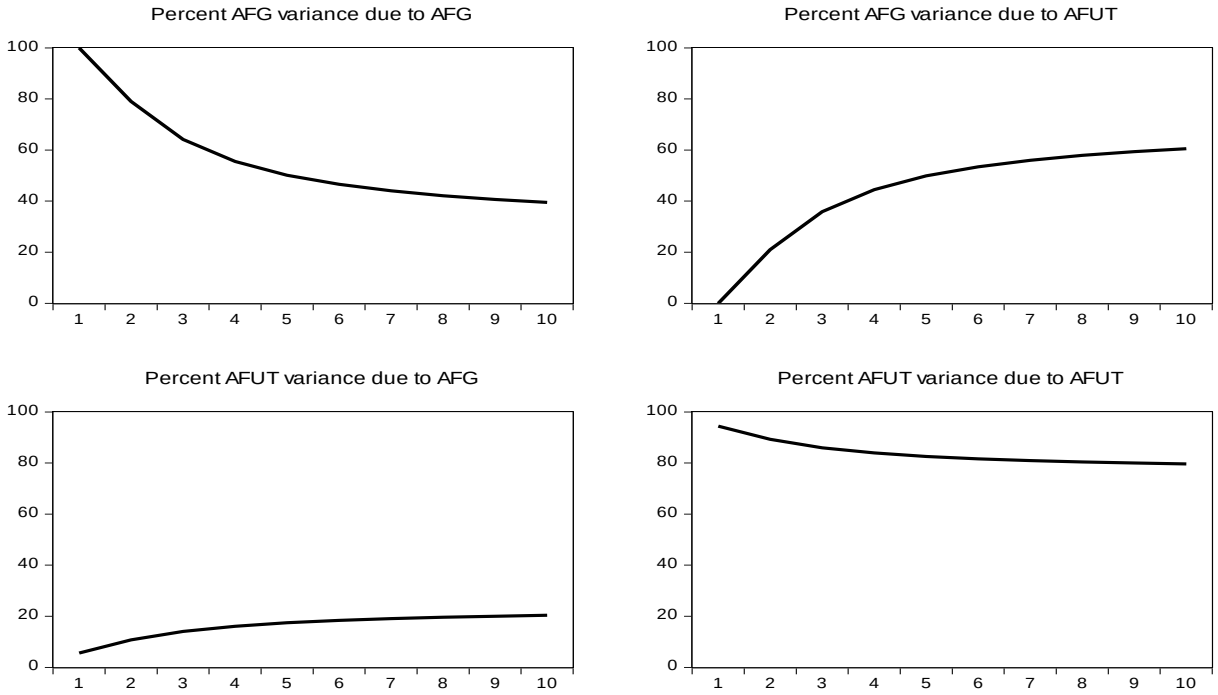


Figure 4: Variance Decomposition for Robusta Futures and Spot Prices

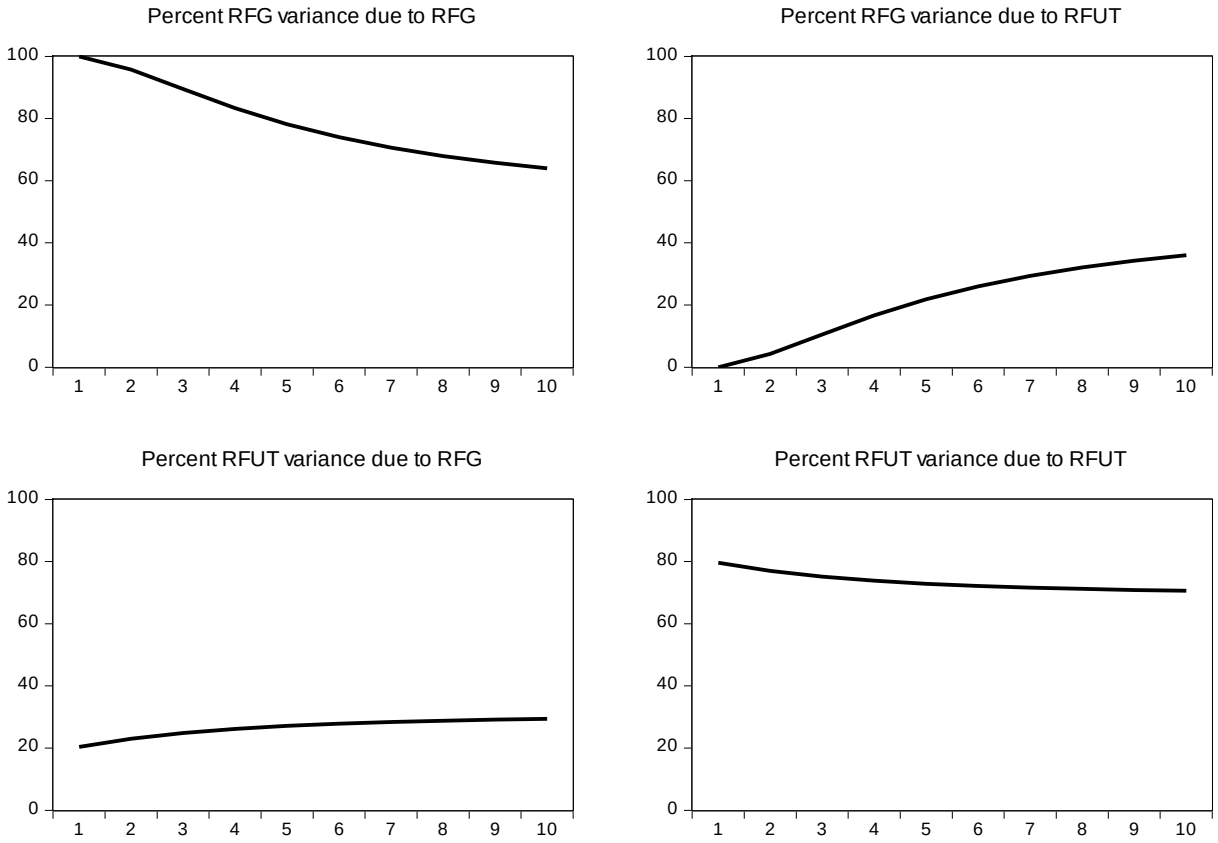
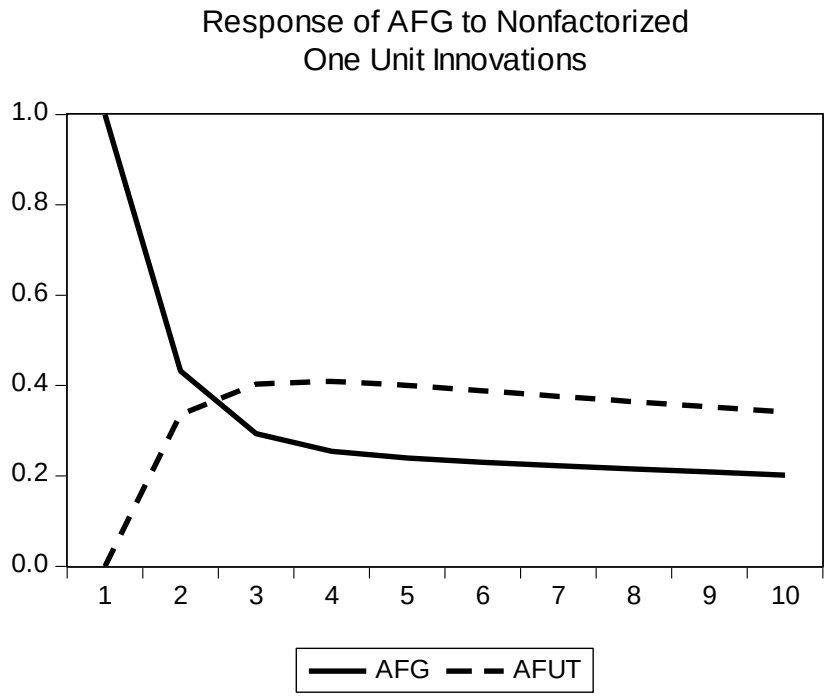


Figure 5: Impulse Response Functions for Arabica Price Series



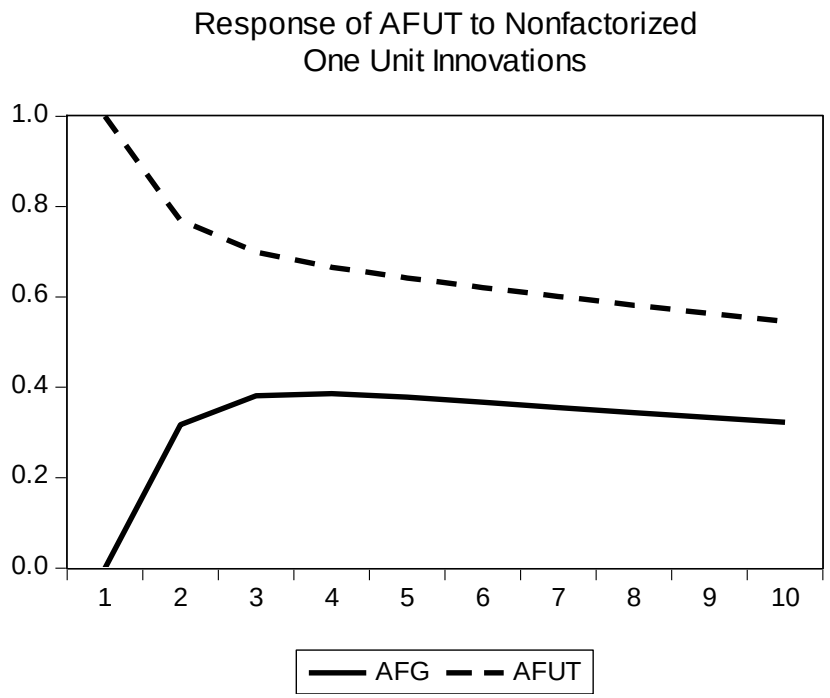
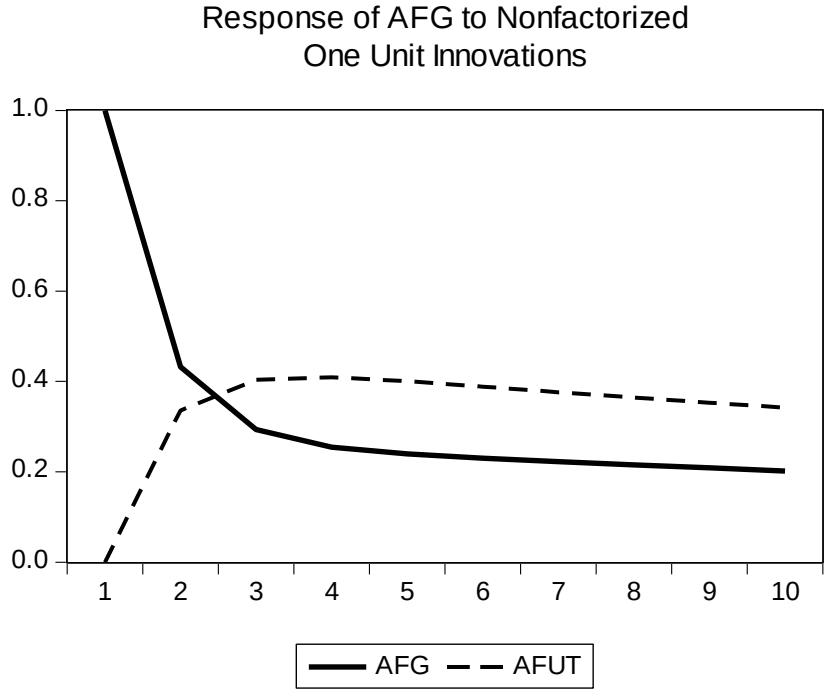


Figure 6: Impulse Response Functions for Arabica Price Series



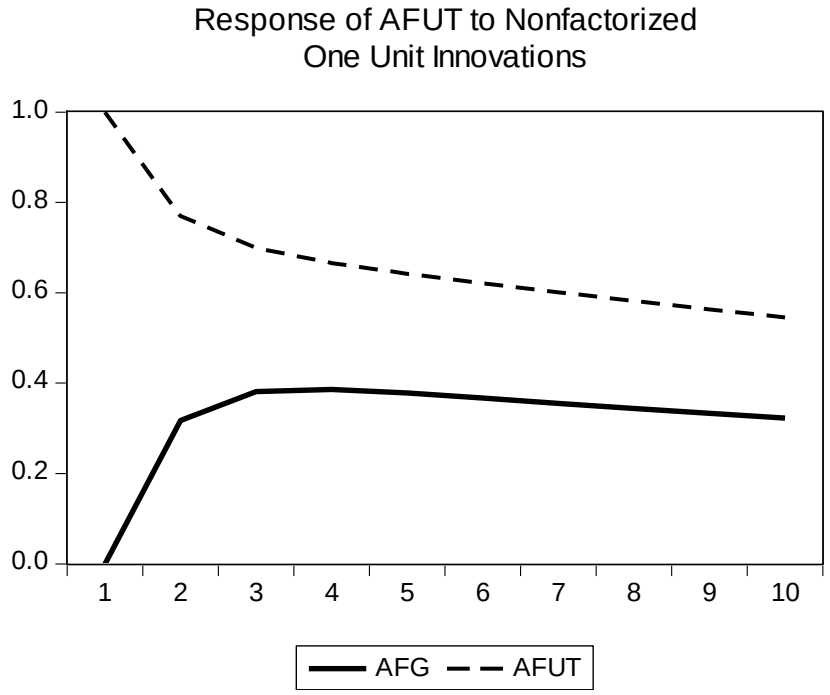


Figure 7: Arabica Break Point

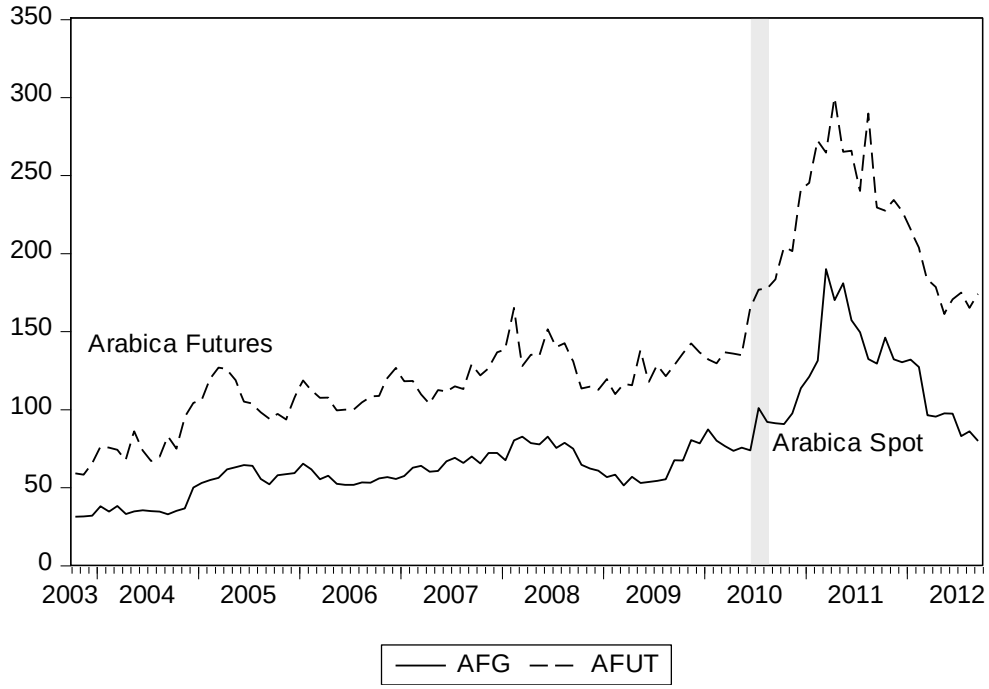
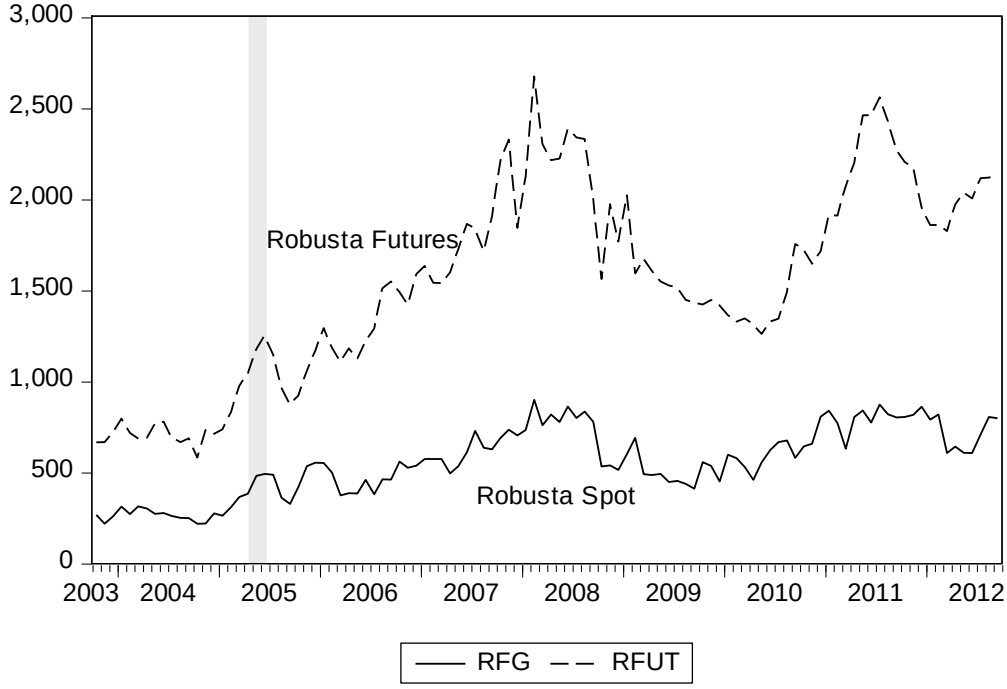


Figure 8: Robusta Break Point



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3. HISTORY OF REAL ESTATE LENDING AND BANK FAILURES

3.1 Introduction

Financial system stability is vital to economic growth, and banking system stability is foundational for financial system stability. Bank failures threaten financial system stability and pose an obvious systemic risk to the American economy. Over the January 2008 to February 2015 period, 524 banks have failed in the United States (FDIC, 2015). These failures and the gravity of the threat to economic growth posed by them in the wake of the financial crisis of 2007-2008 warrant revisitation of the causes and/or predictors of bank failures. I construct a novel long-term data set of banks' real estate loans, banks' total assets and bank failures to test for a relationship between banks' real estate lending and subsequent bank failures. I find evidence of a relationship between banks' real estate loans as a percentage of total assets and failures in subsequent years.

The Federal Deposit Insurance Corporation has tracked the failure of 524 banks since 2008. Total deposits at these institutions have totaled $507 billion and total assets at these institutions have totaled almost $700 billion, and these failures resulted in $85,339,645,000 in losses for the FDIC ((FDIC, 2015). Of course, FDIC losses understate the total losses bank failures imposed in terms of lost economic growth and regulatory costs. A Government Accountability Office report, reviewing research on the financial crisis' effects on unemployment, output losses and regulatory costs estimated that "losses associated with the recent crisis could range from a few trillion dollars to over $10 trillion" (Financial Crisis Losses and Potential Impacts of the Dodd-Frank Act, 2013, p. i). In terms of regulatory costs, the financial crisis and subsequent bank failures led to increased regulation such as *The Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010*, which the Congressional Budget

Office "estimated to increase direct spending by $37.8 billion" (Congressional Budget Office, 2011, p. 1). These reports, which may very well underestimate total costs, are significant and undoubtedly posed a systemic risk to the American financial system and perhaps even to the economy as a whole.

The recent financial crisis was preceded by a real bubble that ultimately burst. The S&P/Case-Shiller 20-City Composite Home Price Index shows that home prices more than doubled between 2001 and 2006. The same index measures show home prices declined by more than 10% from the 2006 peak to the beginning of the 2008 recession and decreased approximately 32% from the 2006 peak to May 2009 (S&P Dow Jones Indices LLC, 2015). A survey of large banks found that bank profitability was strongly tied to real estate lending during the recent crisis (Peni, Smith, & Vahamaa, 2013). Real estate lending is related bank profitability and therefore to risk of bank failure.

There is a large body of research which examines the causes and predictors of bank failures throughout history, much of it focusing on banks' real estate loans. (While bank failures have been tied to leverage, capital adequacy, liquidity, moral hazard, wars, asymmetric information, bank structure, lack of diversification, population growth, monetary and other real economic shocks and other predictors, this paper focuses on real estate lending only.) Various international banking crises that occurred over recent decades have been tied to bank real estate lending (e.g., Berg, 1993; Bartholomew & Gup, 1997; Seidman, 1997; Gup, 1999). Focusing on American history, Gup (2014) showed that "real estate loans were the primary cause of large scale failures of banks and other financial institutions that occurred during the 1921-1933, the 1980s, and 2008-2012 periods" (p. 1). However, to my knowledge, no paper to date has examined long-term time series data to establish a link between bank real estate lending and

bank failures, and I seek to remedy this paucity by extending Gup's (2014) line of research for such a link.

3.2 Bank Failures throughout American History

Bank failures that occurred between 1837 and 1863, during the so-called "Free banking era", were likely caused by falling asset prices. Arguing against the then-conventional view that bank failures during that time were caused by wildcat banking, Rolnick and Webber (1984) construct and examine a dataset on free banks in Minnesota, Indiana, Wisconsin and New York and banks' bond holdings in those states. Of the 104 free bank failures in those states during that time, Rolnick and Webber concluded that a significant number were attributable to falling assets prices.

Bank failures that occurred during the National Banking era, the period from 1863-1913, has been researched relatively more extensively, and a variety of causes have been attributed to bank failures during that period. Calomiris & Gorton (1990) examine five banking panics between 1873 and 1907 and the bank failures emanating from those panics. 104 total bank failures were examined. Calomiris and Gorton concluded that 11 were attributable to real estate-related causes, and the rest were attributed to asset depreciation, fraud and monetary policy changes. Gorton (1988) linked bank failures during the National Banking era to consumer behavior during nonpanic times through depositors' changing evaluations of bank risk. Park (1991) linked bank runs and banking panics to asymetric information, specifically to depositors' lack of bank specific information about deposit risk that quickly turned to panics, runs and insolvency. Bank failures during the National Banking era have been weakly linked to real estate lending.

Almost 4,500 banks failed during between 1920 and 1928, after the end of the National Banking era but before the Great Crash that precipitated the Great Depression. Alston, Grove, & Wheelock (1994) attributed the bulk of failures (80%) during the 1920's to agricultural distress and government policies. Davison & Ramirez (2014) found that bank panics and failures during that period was caused by "overbanking" in many states, lack of deposit insurance and lack of diversification due to a high degree of unit banking. Real estate lending was not directly related to bank failures by either research team.

Great Depression-era bank failures constitute the largest number of failures in American history. Walter (2005) attributed the failures of the early 1930's to a great shakeout, when falling agricultural prices and government policy shifts weeded out the overgrown banking sector. (The number of banks had doubled between 1900 and 1930 as measured by the number of banks divided by real GDP, which Walter concluded was far more than the economy and regulation could sustain, even when accounting for population growth.) Richardon (2007) examined bank failures that occurred between 1929 and 1933 and concluded that declining asset values induced liquidity crises that turned to panics, then failures. Again, neither study directly attributed bank failures during the Great Depression to banks' real estate lending.

Several studies have examined bank failures in the post-depression era, finding varieties of causes of failures. Agricultural and energy price collapses, underdiversification and overbanking were linked to bank failures during the 1980's and 1990's (Freund, Curry, Hirsch, & Kelly, 1997). Demsetz & Strahan (1997) also examined the 1980's and 1990's, but contested the finding that under diversification led to failure. Instead, they concluded that increased bank consolidation into bank holding companies led to increased risk-taking, which led to increased failures.

Several studies examined long time-series data similar to what I examine here. Gambs (1977) constructed a data set spanning 1900 to 1975 and concluded that number of banks' branches, deposits per population and agricultural price changes were predictors of bank failures over the entire time series. Saunders & Wilson (1999) and Kane & Wilson (2002) constructed and examined a century-long data set (from 1893 to 1992) of bank failures in the United States, Canada and the United Kingdom and attibuted failures agricultural price volatility and inadequate capitalization.

3.3 Real Estate Lending and Bank Failures

Several papers link bank failures directly to real estate lending. The bulk of these papers focus on specific periods during American history. Alston, Grove, & Wheelock (1994) link bank failures during the 1920's to bank real estate lending. Likewise, Wiggers & Ashcraft (2012) link a significant number of Great Depression-era bank failures to defaults and losses on commericial real estate bonds. Freund, Curry, Hirsch, & Kelly (1997) link bank failures during the 1980's and 1990's to real estate lending. And finally, Peni, Smith, & Vahamaa (2013) and Ivashina & Scharfstein (2010) established links between real estate lending to the most recent financial crisis. Also, studies which examined international banking crises and failures established a link to real estate lending (e.g., Berg, 1993; Bartholomew & Gup, 1997; Seidman, 1997; Herring & Wachtel, 1999; Gup, 1999).

To my knowledge, only a single study examined the relationship between bank real estate lending and bank failures a comparable time period to mine. Gup (2014) showed that "real estate loans were the primary cause of large scale failures of banks and other financial institutions that occurred during the 1921-1933, the 1980s, and 2008-2012 periods" (p. 1). While Gup also considered other related causal factors, such as population growth, increased labor force

participation of women and capital standards, he concluded that real estate loans were the primary causes of failures. Building on Gups' findings, I construct a data set of real estate lending as a percentage of total assets for all banks and bank failures over the 1896 to 2013 period and test for a long-run relationship using graphical and time-series analysis.

3.4 Four Data Sources

To my knowledge, there is no comprehensive data set containing all of the data required for this paper over the time series I examine. I construct a novel data set using four different sources. I hand-collected data on bank failures, the total asset values of failed banks and total asset values of all banks for the time period 1863-1931 from the Annual Report of the Comptroller of the Currency (1932). These data were cross-checked and supplemented by the *Board of Governors of the Federal Reserve System All-Bank Statistics, United States, 1896-1955*, a report released in 1956 (Board of Governors of the Federal Reserve System (U.S.), 1956). I rely on this report for data on real estate loans and total assets of all banks. Both of the above data sets are available from the Federal Reserve Archive, FRASER.

The other two data sources are provided by the Federal Deposit Insurance Corporation, (FDIC) and the Board of Governors of the Federal Reserve System (FRS). I collect data on bank failures and failed banks' reported assets from 1934 to 2013 from the FDIC's "Failures and Assistance Transactions" database. This database contains data on all bank failures from 1934 to date. These data include only limited information, such as bank name, data of bank failure and total assets of each failed bank at time of failure (FDIC, 2015). I collect data on real estate loans from 1947-2013 from the Board of Governors of the Federal Reserve System Data Download Program website, specifically the "H.8 Assets and Liabilities of Commercial Banks in the United States" file (Federal Reserve , 2015).

Reliable real estate loan data are available for the years 1896-2013. I checked the overlapping data from the various reports to ensure consistency. Real estate data overlap between the *Board of Governors of the Federal Reserve System All-Bank Statistics, United States, 1896-1955* report and the "H.8 Assets and Liabilities of Commercial Banks in the United States" file, and there are some minor discrepancies. I constructed two data sets, one using the data solely from All Bank Statistics and one using only the H.8 file, and the results were qualitatively identical. For those few instances when discrepancies existed, I used the H.8 file, since it is more up-to-date and more readily accessible.

To conduct time-series analysis, it was necessary to use level-form data. I transformed all data series to year 2000 dollars using inflation data from two sources. For the years up to 1913, I used the *Historical Statistics of the United States: 1789-1945* (U.S. Census Bureau, 1949). For the years 1913-2013, I used the "Consumer Price Index for All Urban Consumers: All Items", available on the FRED website (US. Bureau of Labor Statistics, 2015).

3.5 The Methodology of Pesaran and Shin (1999) and Pesaran et al. (2001)

I follow the following steps to conduct a so-called Autoregressive Distributed Lag (ADL) "bounds test" to see if there is a long-run relationship between real estate loans and bank failures. (For a more detailed explanation, see (Pesaran & Shin, 1999; and Peni, Smith, & Vahamaa, 2013.)

1: I use the Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests to make sure that neither of the series are I(2), since both series must be either I(0) or I(1);

2: I formulate the following model:

$$\Delta y_t = \beta_0 + \sum \beta_i \Delta y_{t-i} + \sum y_j \Delta x_{1t-j} + \sum \delta_k \Delta x_{2t-k} + \theta_0 y_{t-1} + \theta_1 x_{1t-1} + \theta_2 x_{2t-1} + e_t \quad (1)$$

Pesaran, Shin, & Smith (2001) call this a "conditional error correction model";

3: I used the Schwarz Bayes Information Criterion to select appropriate values for the maximum lags;

4: I test for serial independence of the errors in the above model using an Lagrange Multiplier test of the null hypothesis that the errors are serially independent, against the alternative hypothesis that the errors are AR(m) or MA(m), m=1, 2, 3, ….;

5: I test that the model is dynamically stable by checking the inverse roots of the characteristic equation lie strictly within the unit circle;

6: I perform an F-test (of the model formed in step 2), of the hypothesis $H_0: \theta_0 = \theta_1 + \theta_2 = 0$. A rejection of the null implies a long-run relationship. Exact critical values for the F-test are unavailable. However, Pesaran, Shin, & Smith (2001) provide lower and upper bounds on the critical values. If the computed F-statistic falls below the lower bound, then no cointegration is possible. If the F-statistic falls between the bounds, then the test is inconclusive. If the computed F-statistic exceeds the upper bound, then there is evidence of a cointegration relationship. Then;

7: Given the step 6 indicates there is cointegration between the two series, then I will attempt to estimate a relationship between the variables of the following forms:

$$y_t = \alpha_0 + \alpha_1 x_{1t} + \alpha_2 x_{2t} + v_t \qquad (2)$$

and the error correction model:

$$\Delta y_t = \beta_0 + +\sum \beta_i \Delta y_{t-i} + \sum y_j \Delta x_{1t-j} + \sum \delta_k \Delta x_{2t-k} + \varphi z_{t-1} + e_t \qquad (3)$$

where:

$$z_{t-1} = (y_{t-1} - a_0 - \alpha_1 x_{1t-1} - \alpha_2 x_{2t-1}). \quad (4)$$

8: Noting that x_1 and x_2 are:

$$-\left({\theta_1}/{\theta_0}\right) \text{ and } -\left({\theta_2}/{\theta_0}\right), \quad (5)$$

respectively, I can then attempt to extract estimates of the long-run effects from the unrestricted error correction model.

3.6 Graphical Analysis of the Link between Real Estate Lending and Bank Failures

Bank failures spike several times in American history. There are nine periods in American history since 1863 when bank failures spiked. Bank failures spiked in the 1870s, 1904-5, 1908-9, 1913-6, the 1920s, the 1930s and 40s, 1982-89 and most recently in from 2008-13. (See Figures 1, 2, 3.) From 1863-1931, the percentage of banks that failed in a given year was relatively high and volatile. For state banks, the average number of banks that failed was 2.43% and reached at least six percent on seven occasions. National banks were far less likely to fail. The average rate of bank failure for national banks from 1863-1931 was .48%. (See Figure 4.)

When the bank failures of 1863-1931 are measured in terms of the assets of the failed banks as a percentage of all banks, the story changes. State banks were relatively small, and the average value of assets of failed state banks as a percentage of total assets of all state banks in any given year was .71%. For national banks, failed banks' assets accounted for an average .2% of total national bank assets over the period 1863-1931. (See Figure 5.)[2] Aggregating the data on national and state banks shows that over the 1863-1931 period, that the average percentage of

[2] Years 1931-4 were excluded due the to extraordinary banking climate at that time.

banks that failed was 1.14%. In terms of asset sizes, national and state banks combined failures accounted for an average of .34%. (See Figures 4-7.)

The post-FDIC data, from 1934 to 2013, tell a different story. The average number of banks that failed as a percentage of total banks was .38%, peaking at 4.81% in 1989. Measured as a percentage of assets, failed bank assets averaged .31% over the same time period. Again, this figure peaked in 1989, when failed banks' assets accounted for 4.99% of all total bank assets. (See Figures 8 and 9.)

Banks' real estate loans as a percentage of total assets over the period 1896 to 2013 was also volatile. The average percentage of bank real estate loans as a percentage of total assets for the entire time series is 15.26%. The peak year was 2009, when real estate loans accounted for 32.5% of total bank assets. The trough was 5.05% in 1947. (See Figure 10.)

Examining the percentage of real estate loans of total assets in relation to bank failures in graphical form makes a prima facie case for a link between real estate lending and bank failures. (See Figures 11-16.) Examining either state/national/or combined state and national bank data on real estate lending and bank failures, whether measured as a percentage of bank failures of all banks or percentage of failed bank assets of all banks' assets, there appears to be a slight uptick in real estate lending either preceding or commensurate with bank failures for the period 1896-1930. The period from 1947 to 2013 yields the same conclusion. The graphs of real estate loans as a percentage of total assets seem to uptick either immediately preceding or commensurate with bank failures, again when measured both by percentage of failed banks and percentage of failed bank assets of all banks' assets. However, researchers are prone to seeing what they want to see. So, I run a simple time-series test to verify or reject my graph-based analysis.

3.7 Time-series Tests of Relationship Between Real Estate Loans and Bank Failures

Both the Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests confirm that neither series is I(2) (again note that the series can either be I(0) or I1), but not I(2)), so I form the Pesaran, Shin, & Smith (2001) conditional error correction model[3]:

$$\Delta bank\ failure = \beta_0 + \sum \beta_i \Delta bank\ failures_{t-i} + \sum y_j \Delta real\ estate\ loans_{1t-j} + \theta_0 bank\ failures_{t-1} + \theta_1 real\ estate\ loans_{1t-1} + e_t \quad (6)$$

A maximum number of lag of 2 is suggested for real estate loans and 1 for bank failures, and with these lags I confirm serially independent errors of the above equation and that the inverse roots of the characteristic equation are within the unit circle. Next, I conduct a "bounds test" for a long-run relationship between real estate lending and bank failures. The critical values for the F-statistic are from (Pesaran, Shin, & Smith, 2001, p. 300): at the 1% significance level, the upper and lower bounds are 4.81 and 6.02, respectively. I compute the F-statistic in this model to be 15.33, which means that my results are significant at the 1% level. Therefore is very strong evidence of a long-term relationship between real estate loans as a percentage of total assets and bank failures. Estimating the long-run multiplier between real estate loans and bank failures yields an estimate that a one percentage increase in real estate loans as a percentage of total assets increases the number of total bank failures to increase by:

$$-\left({}^{\theta_1}/_{\theta_0}\right) = \left({}^{2492.04}/_{876.31}\right) = 2.84$$

banks, which is not necessarily economically significant.

[3] All of these tests were conducted using the data in level form except for the ADF and KPSS tests.

This result must be interpreted with caution, however, since this does not necessarily imply a causal link between real estate lending and bank failures. (First, the model that I employ assumes strict exogeneity of the error terms, which seems unlikely. Second, the estimates are probably detecting correlations between variables related to real estate lending, such as those noted in the papers described above, and bank failures. However, my findings do provide evidence that real estate lending has value as a predictor of bank failures, which warrants further research.

3.8 Conclusion

Bank failures have cost billions, even trillions of dollars in the past, and those failures have been linked to real estate booms and busts, and to real estate lending by banks. Real estate lending is already recovering from the last bubble. Since the last trough in February 2012, the S&P/Case-Shiller 20-City Composite Home Price Index has increased from 137 to 174, an increase of 27% in less than three years (S&P Dow Jones Indices LLC, 2015). Real estate lending is rising. I find graphical evidence supporting other researchers' findings (e.g., Gup, 2014) that real estate lending is related to bank failures. Time-series analysis verifies these findings, but the results must be interpreted with caution. Given the importance of banking system stability to economic growth, and the systemic risk posed by bank, more research should be conducted testing banks' real estate lending relationship to bank failures.

Figure 1:
Total Bank Failures from 1863 to 2013

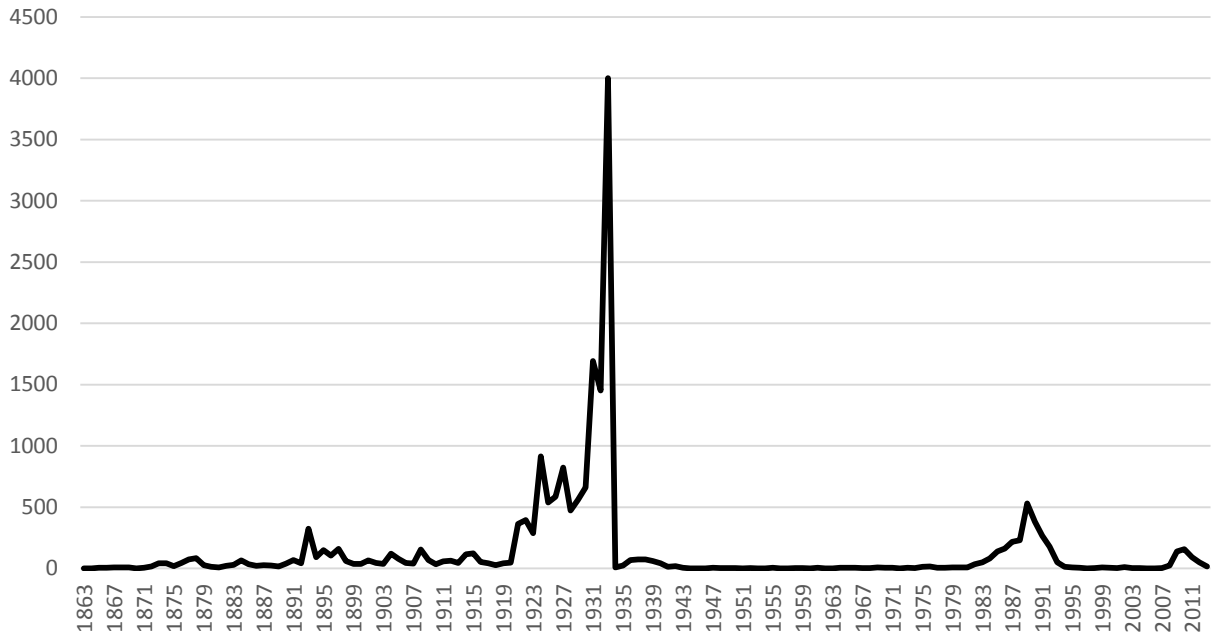

Figure 1: Data for 1863 to 1920 is from Annual Report of the Comptroller of the Currency (1931), and includes all reported National and State Bank failures. Data from 1921 to 1933 is from FDIC (2015), and includes all bank failures and suspensions. Data from 1934 to 2013 is also from FDIC (2015), and includes all bank failures.

Figure 2:
Total Bank Failures From 1863 to 1931

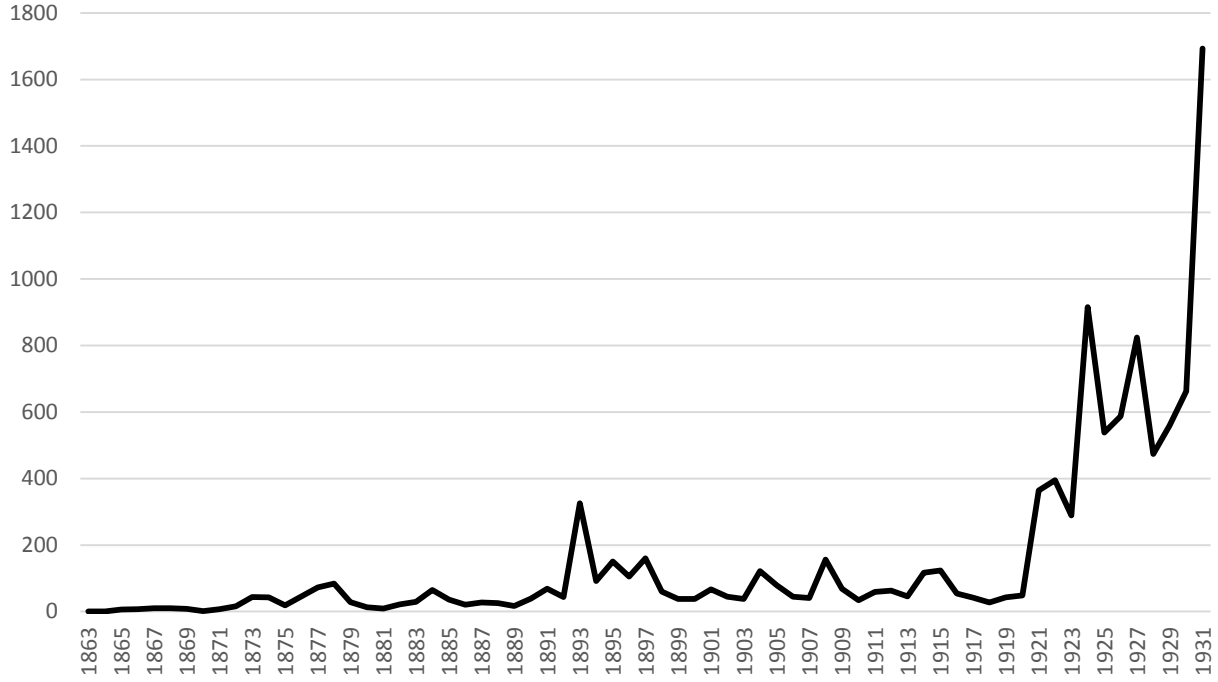

Figure 2: Data on bank failures from 1863 to 1931 is from Annual Report of the Comptroller of the Currency (1931). Included in data are all state and national bank failures.

Figure 3:
Total Bank Failures from 1934 to 2013

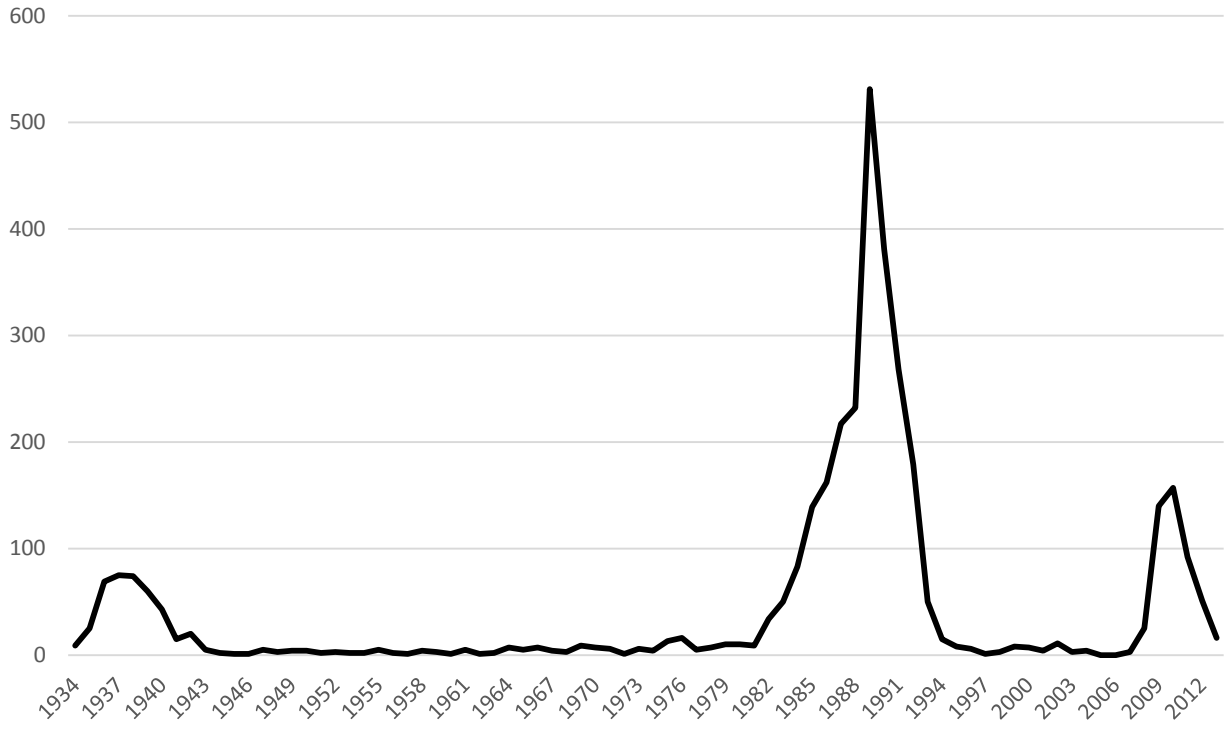

Figure 3: All data are from FDIC (2015) and include all bank failures.

Figure 4:
Failures as Percentage of Banks 1863-1931

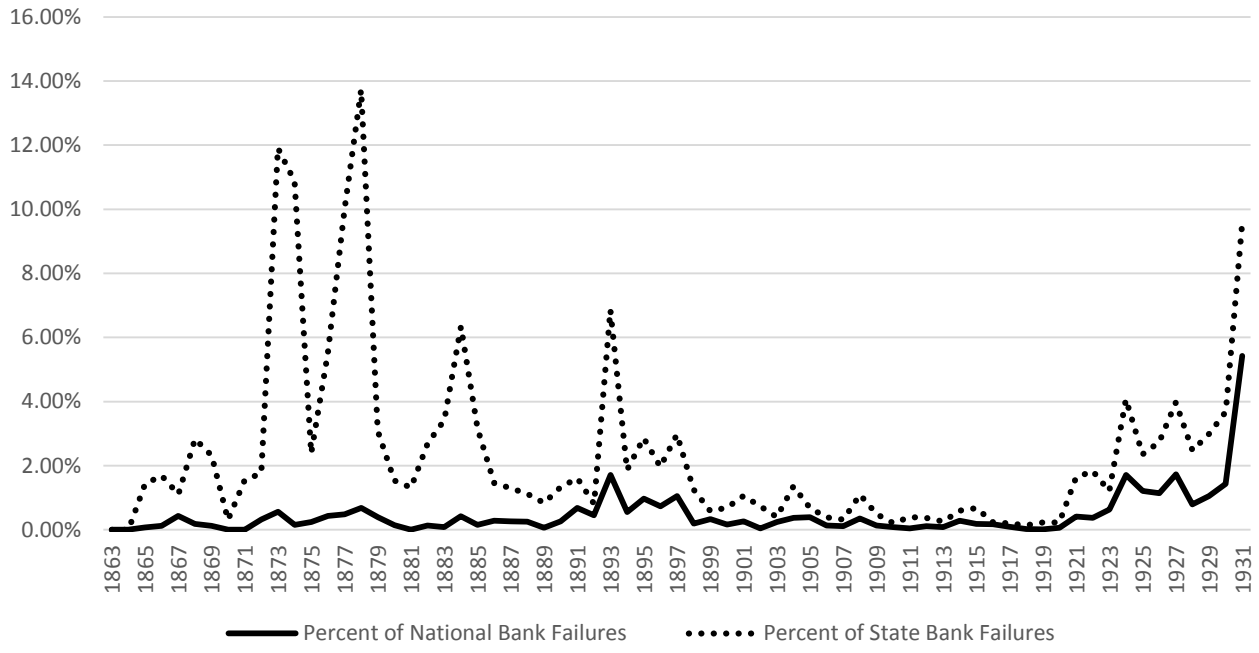

Figure 4: Data from Annual Report of the Comptroller of the Currency (1931). Percent of national/state bank failures calculated as number of failures/estimated number of bank (by type).

Figure 5:
Failures as Percentage of National/State Assets 1863-1931

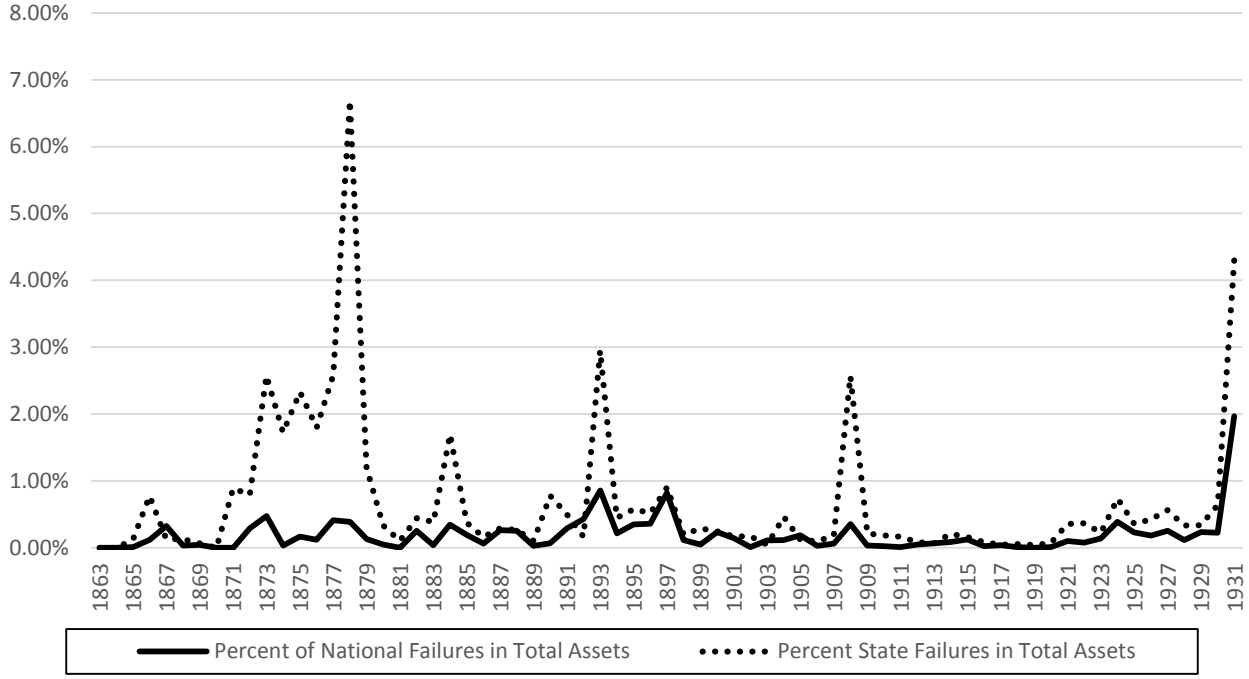

Figure 5: Data from Annual Report of the Comptroller of the Currency (1931). Percent of national/state bank failures calculated as assets of failures/estimated assets for all banks (by type).

Figure 6:
Total Bank Failures by Percentage of Total Banks 1863 to 1931

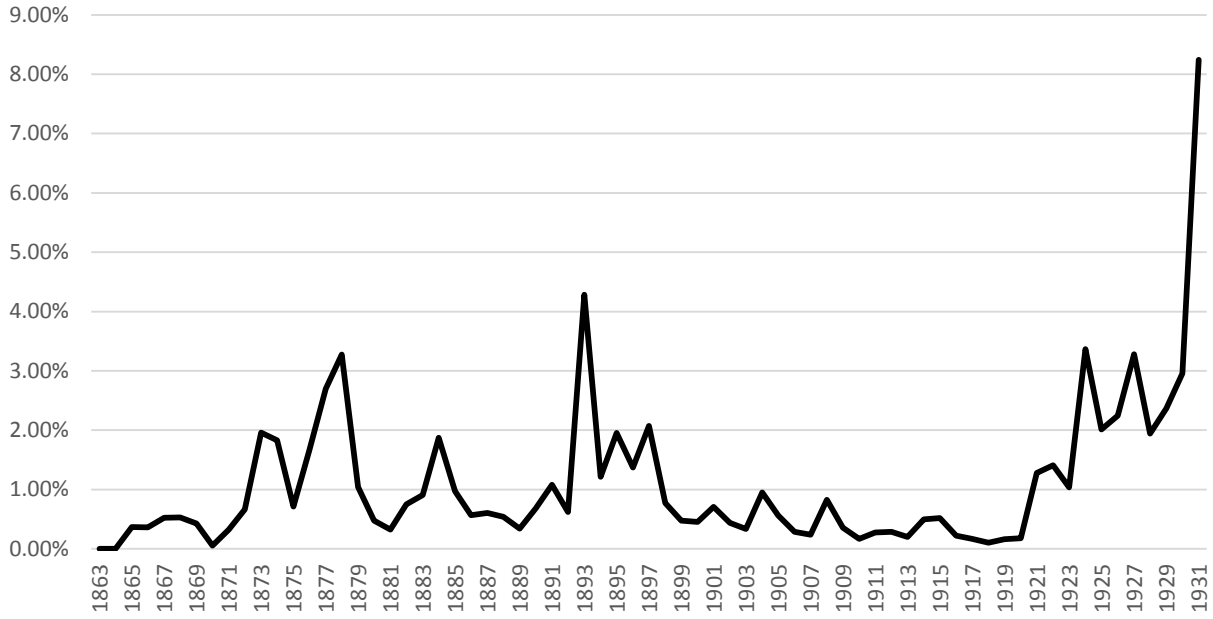

Figure 6: Data from Annual Report of the Comptroller of the Currency (1931). Percent of all bank failures calculated as number of failures/estimated number of banks.

Figure 7:
Total Bank Failures by Percentage of Assets from 1863 to 1931

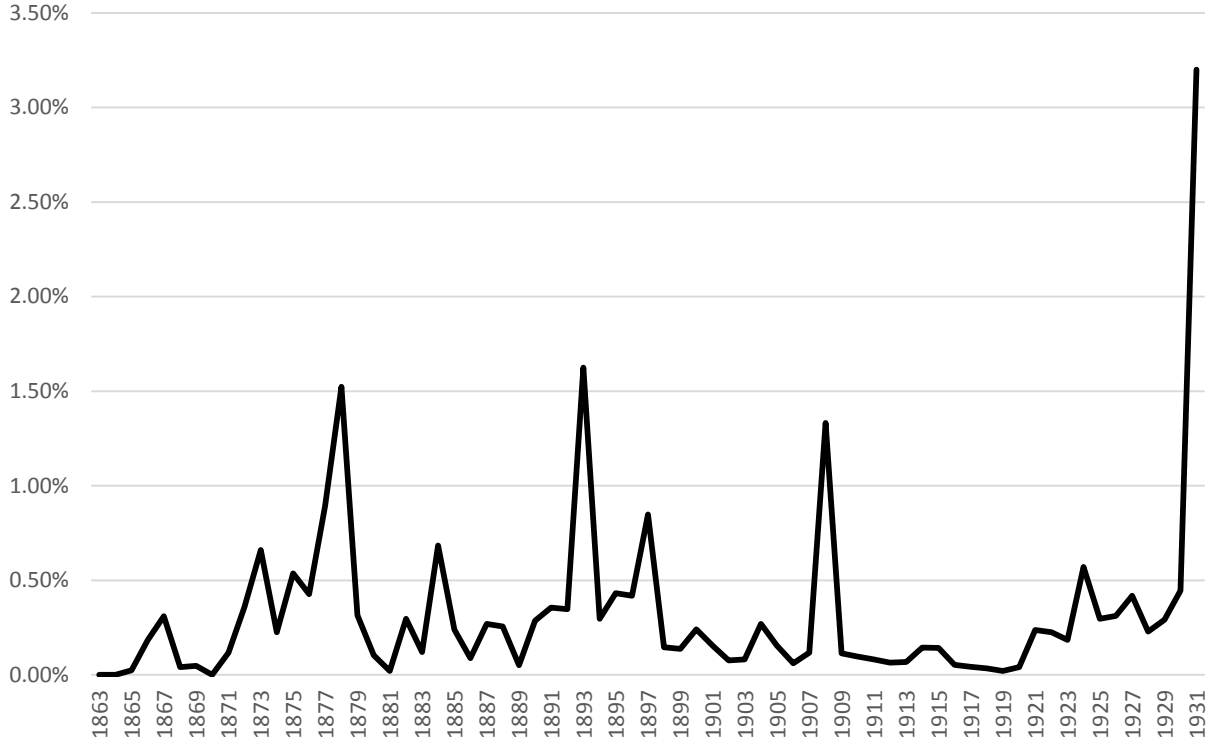

Figure 7: Data from Annual Report of the Comptroller of the Currency (1931). Percent of all bank failures calculated as assets of failed banks/estimated assets of all banks.

Figure 8:
Total Bank Failures by Percentage of Total Banks 1934-2013

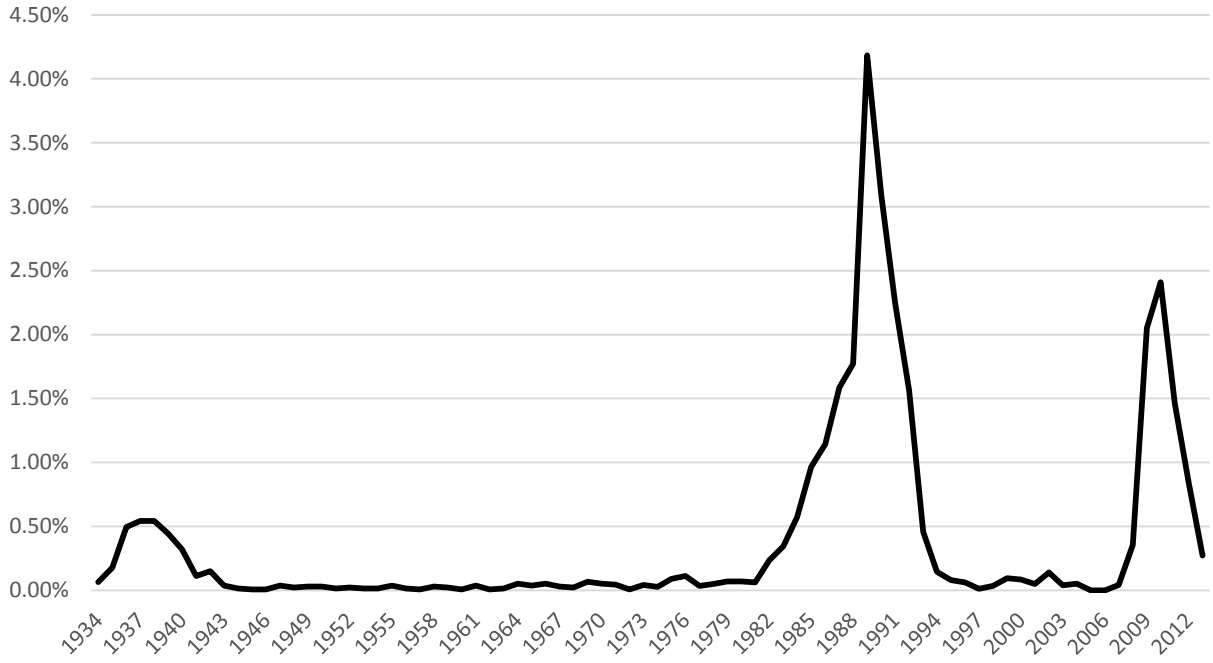

Figure 8: Data from FDIC (2015). Percent of all bank failures calculated as number of failures/ number of all banks.

Figure 9:
Total Bank Failures by Percentage of Assets 1934-2013

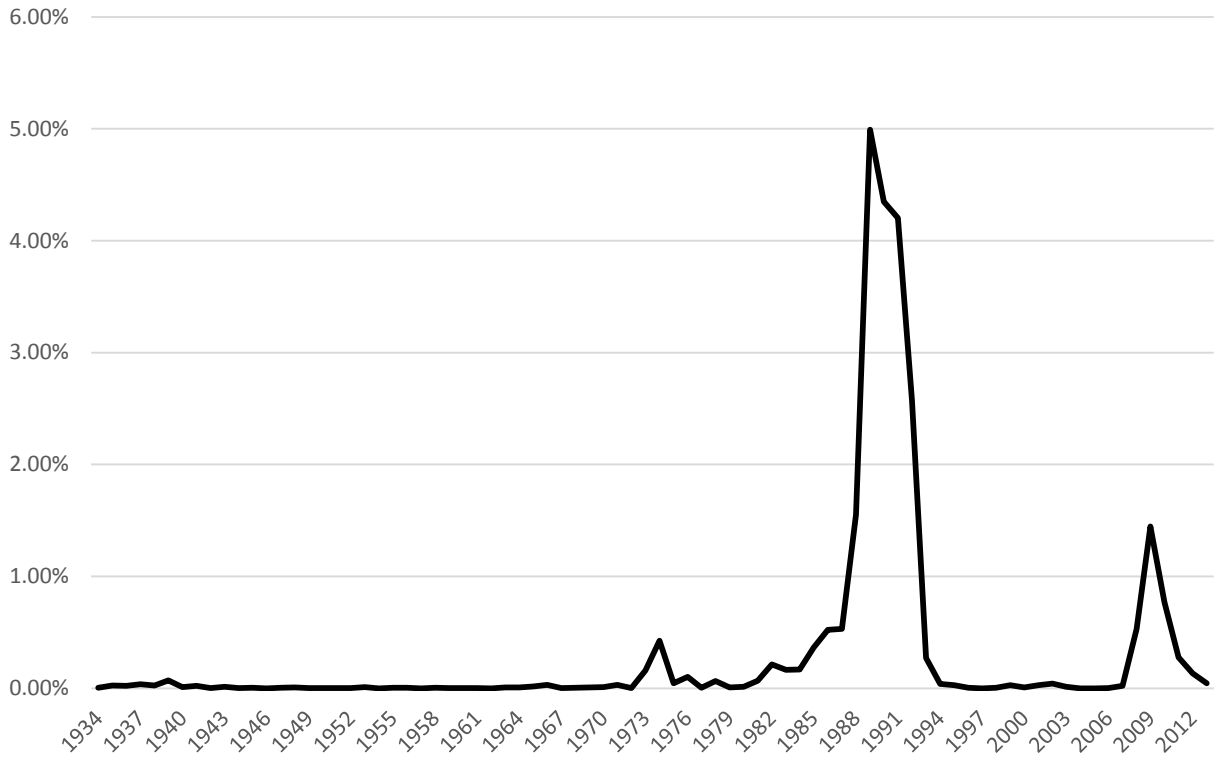

Figure 9: Data from FDIC (2015). Percent of all bank failures calculated as assets of failed banks/assets of all banks.

Figure 10:
Real Estate Loans as Percent of Total Assets 1896-2013

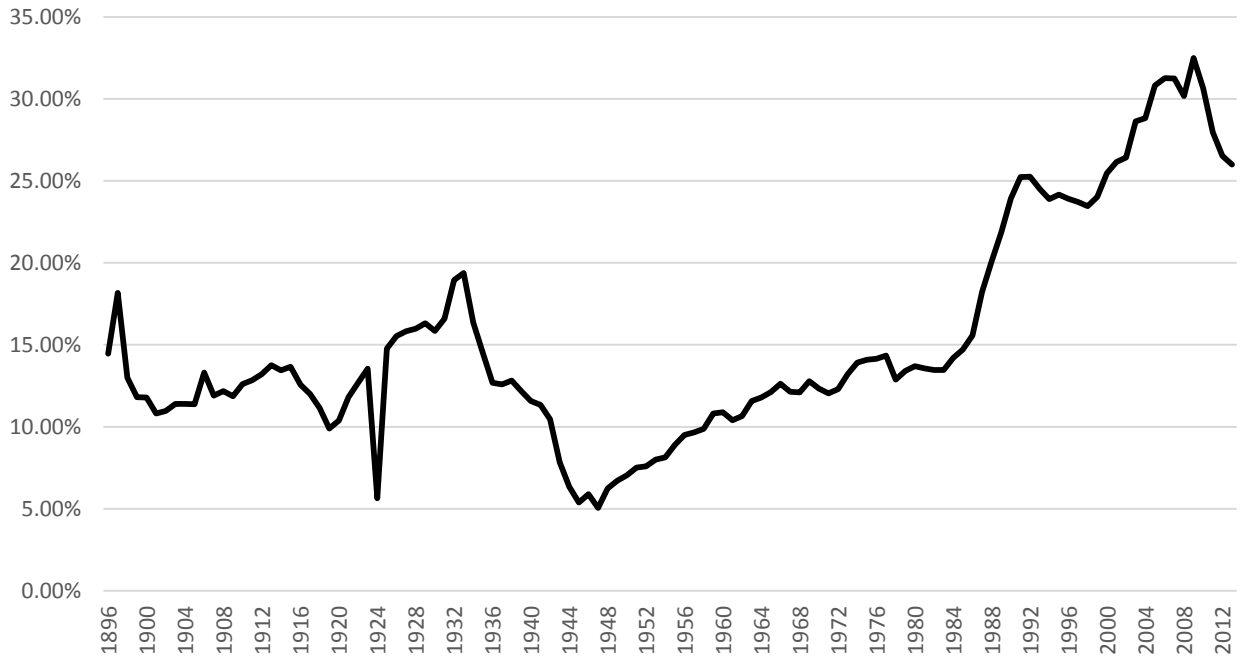

Figure 10: Data from 1896 to 1947 from Annual Report of Comptroller of the Currency 1896-1980 (1981). Data from 1947-2013 from FDIC (2015). Real estate loans calculated as percentage of total assets for all banks.

Figure 11:
Real Estate Loans and Total Failures, National Banks 1896-1931

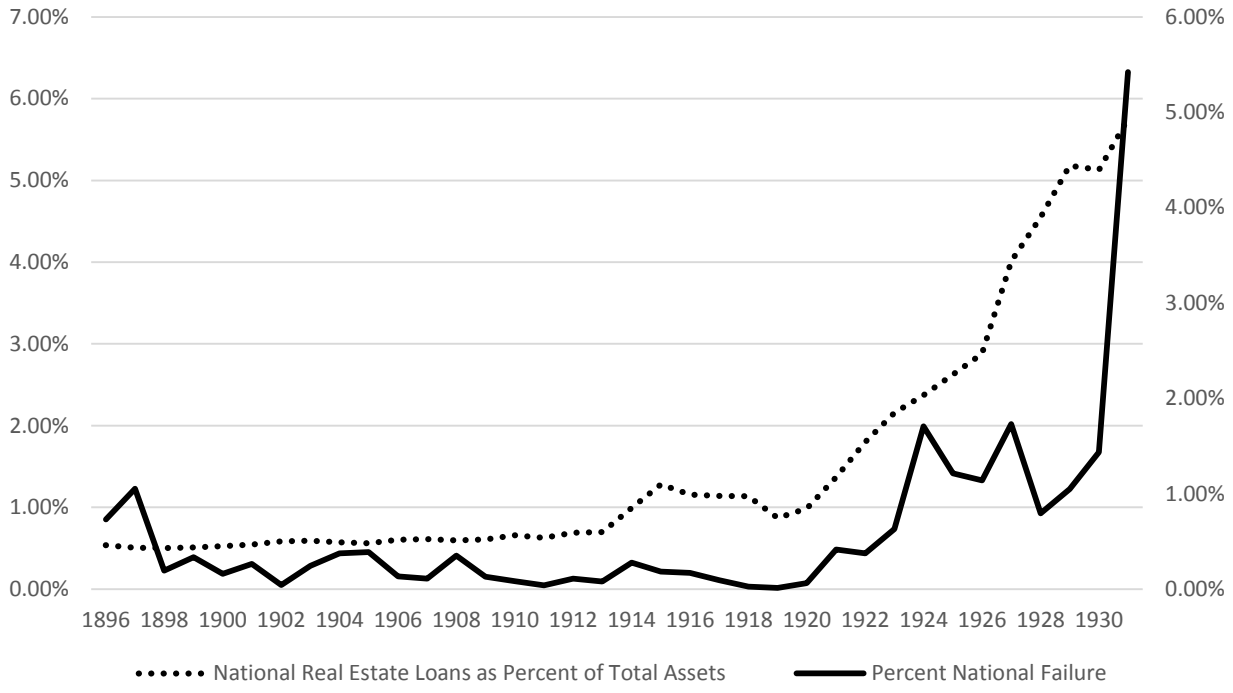

Figure 11: All data from Annual Report of Comptroller of the Currency 1896-1980 (1981). National real estate loans as a percentage of assets of total assets equals total real estate loans/total assets. Percent national failures equals number of national failures/number of national banks.

Figure 12:
Real Estate Loans and Percentage of Failures, National Banks 1896-1931

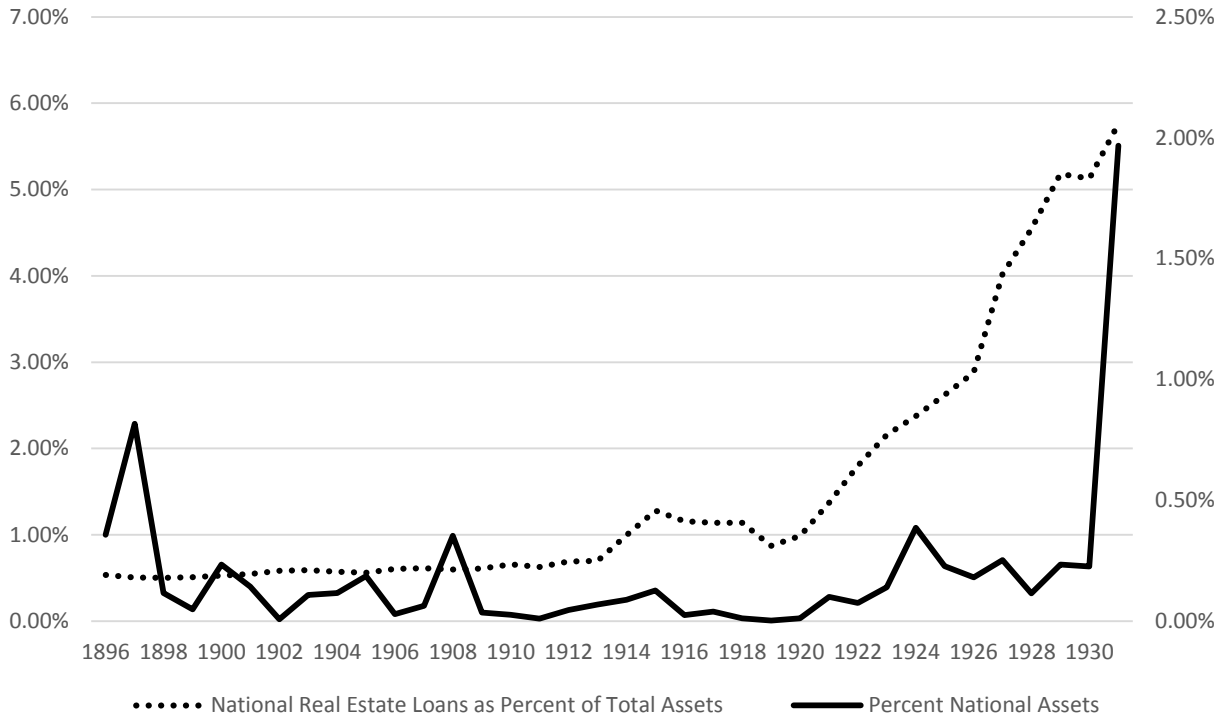

Figure 12: All data from Annual Report of Comptroller of the Currency 1896-1980 (1981). National real estate loans as a percentage of total assets equals total real estate loans/total assets. Percent national assets equals assets of national failures/assets of all national banks.

Figure 13:
Real Estate Loans and Total Failures, State Banks 1896-1931

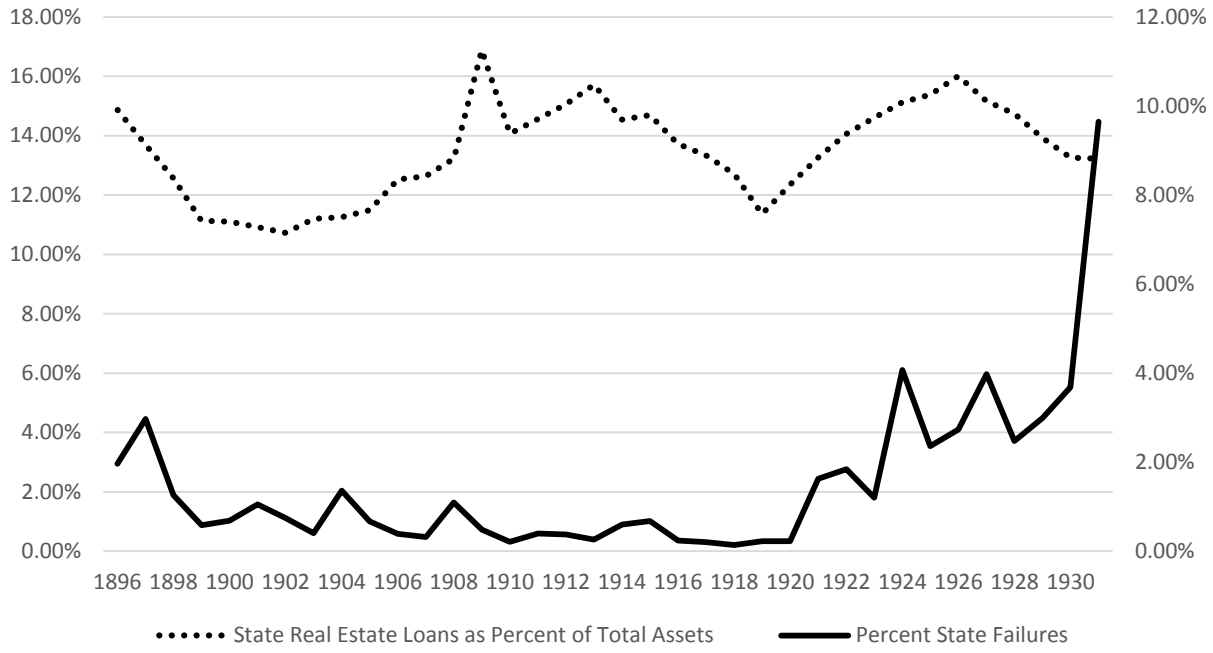

Figure 13: All data from Annual Report of Comptroller of the Currency 1896-1980 (1981). State real estate loans as a percentage of assets equals total real estate loans/total assets. Percent of state failures equals number of state failures/number of state banks.

Figure 14:
Real Estate Loans and Percentage of Failures, State Banks 1896-1931

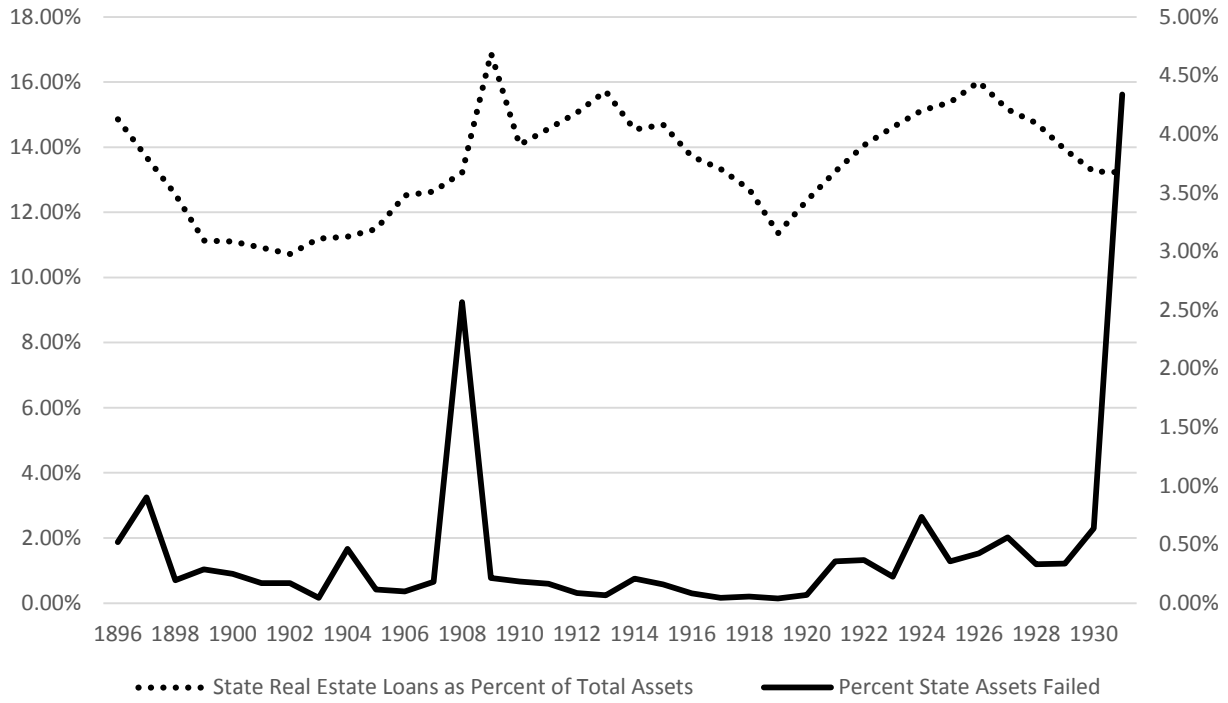

Figure 14: All data from Annual Report of Comptroller of the Currency 1896-1980 (1981). State real estate loans as a percentage of assets equals total real estate loans for state banks/total assets of state banks. Percent of state assets failed equals assets of state failures/assets of all state banks.

Figure 15:
Real Estate Loans and Total Failures, All Banks 1896-1931

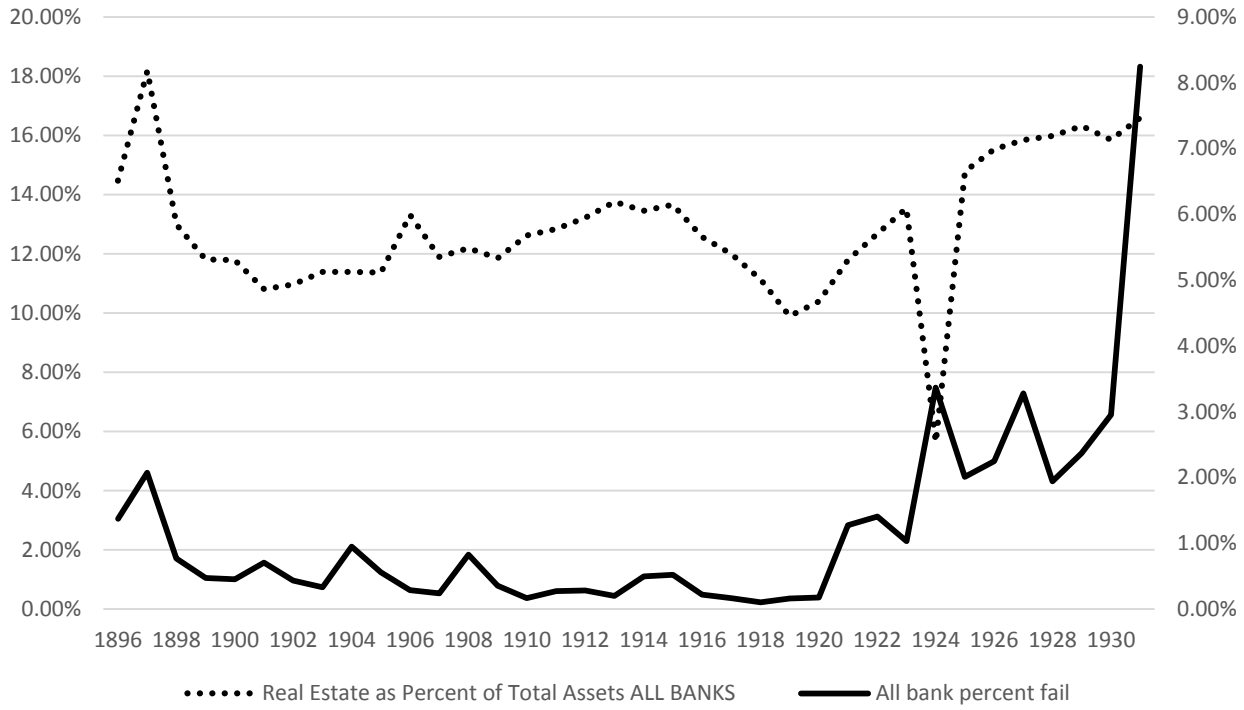

Figure 15: All data from Annual Report of Comptroller of the Currency 1896-1980 (1981). Real estate loans as a percentage of total assets ALL BANKS equals total real estate loans/total assets. Percent of all bank percent failures equals number of bank failures/number of banks.

Figure 16:
Real Estate Loans and Percentage of Failures, All Banks 1896-1931

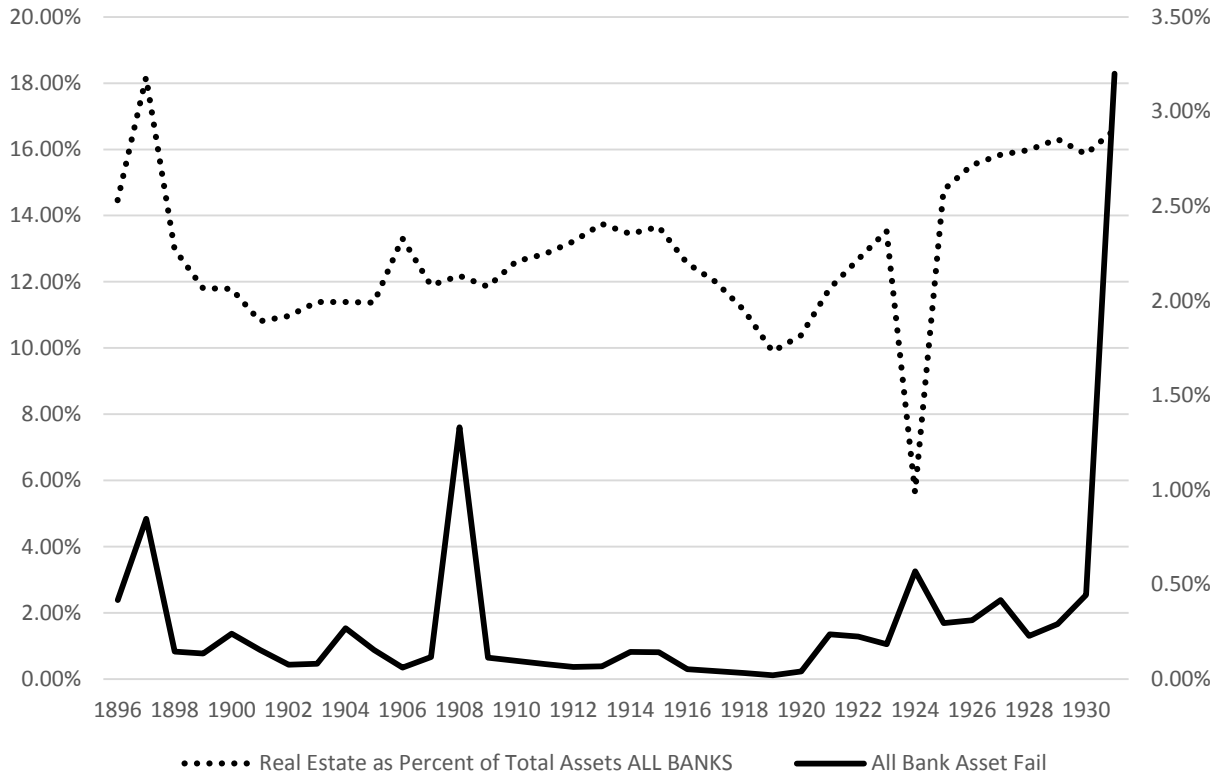

Figure 16: All data from Annual Report of Comptroller of the Currency 1896-1980 (1981). Real estate loans as a percentage of assets ALL BANKS equals total real estate loans/total assets. Percent of All Bank Asset Fail equals assets of all banks' failures/assets of all banks.

Figure 17:
Real Estate Loans and Total Failures, 1947-2013

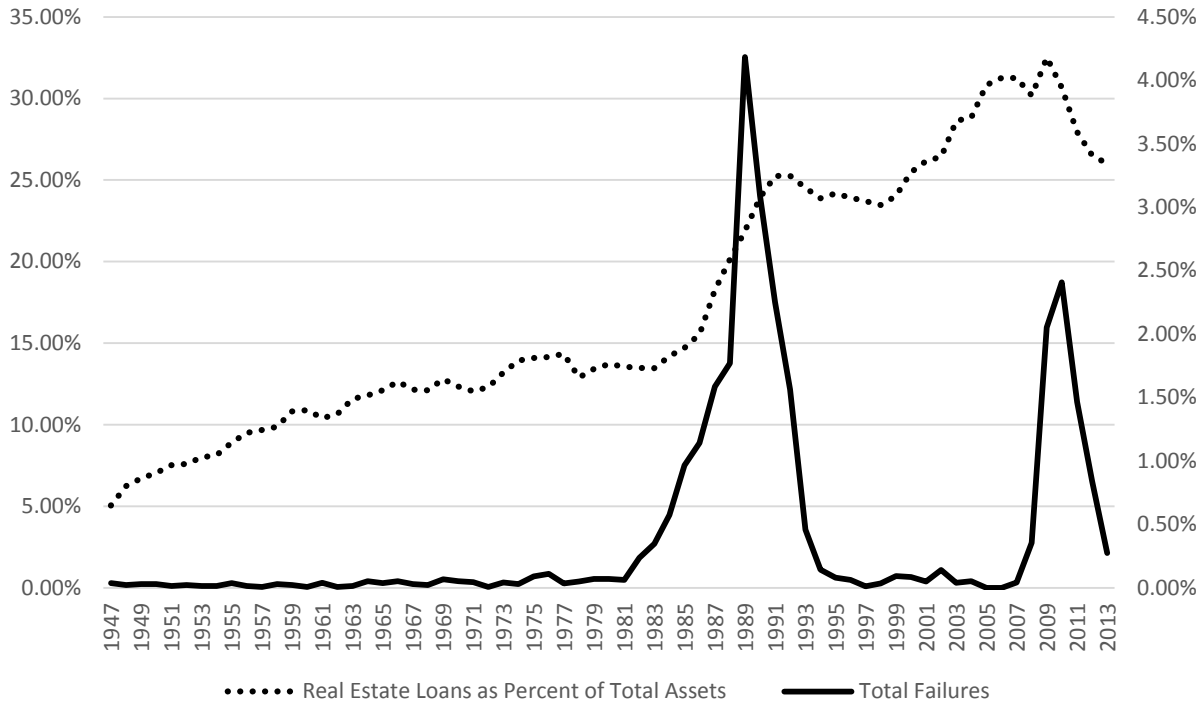

Figure 17: All data from FDIC (2015). Real estate loans as percent of total assets equals real estate loans/total assets. Total failures equals number of bank failures/number of all banks.

Figure 18:
Real Estate Loans and Percentage of Failures by Assets, 1947-2013

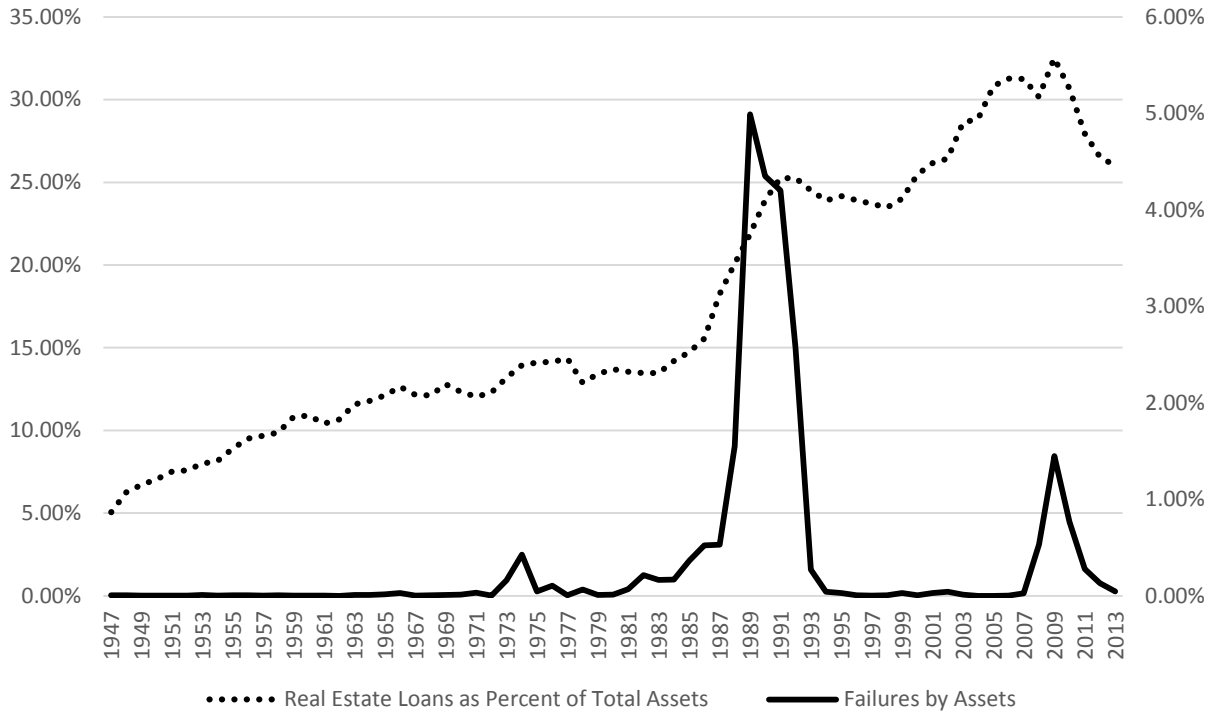

Figure 18: All data from FDIC (2015). Real estate loans as percent of total assets equals real estate loans/total assets. Failures by assets equals assets of failed banks/assets of all banks.

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4. HOTEL HURRICANE OPTIONS

4.1 Introduction

Revenue management scholarship and practices have extensively examined sellers' options for maximizing revenue under various conditions. Systems have been designed to allocate production capacity and inventory holdings which rely on customer segmentation schemes in order to maximize total revenue. I extend this literature by applying it to hotel revenue management concerns arising during natural disaster evacuations. I use a binary option pricing model to predict hotel room prices when customers are segmented into two groups, customers who reserve rooms (by purchasing an option for a room in advance of a natural disaster) and customers who do not hold an option. I find that hotels enjoy higher revenues under conditions which might confound expectations. For example, given the higher probability of evacuation, hotels that offer refund rates paid to those option-holding customers in the event of service failure will not only suffer from lower room prices, but lower total revenue as well. These findings are an important first step in examining revenue management issues related to natural disasters.

For the six months of hurricane season, coastal residents must be prepared for the possibility of a hurricane impacting their area. To mitigate hurricane-related damage, state and local governments take actions to protect beaches and estuaries with the intentions of minimizing the impact of onshore wind storms and providing for quicker recovery after the a storm for tourism and fishing, as well as other related industries. Those governments are also responsible for long-term planning efforts, such as ensuring strict building codes and implementing zoning to manage building in flood prone areas. Actions are also taken to educate the population about

available emergency shelters and the evacuation routes to take in the event of an evacuation order.

Part of the normal preparations for individuals includes more structural resilience to mitigate damage such as better roof construction with tie down straps, removing debris which can become airborne, and removing trees with the possibility of striking structures. These measures come with the benefit of lower insurance premiums. Also, individuals and families often take the precautionary measure of shelter planning, which might be needed in either mandatory or voluntary evacuations.

Individuals which are sheltering in place will make preparations such as buying and storing water, acquiring food which requires little preparation in the event of a long-term loss of electricity and other utilities, having communication such as weather radios which will work even if mobile service is interrupted, and keeping sufficient fuel for generators. Individuals will also often store tarps and hardware to replace or repair damaged areas so that further damage does not occur. Individuals may choose to stay in place because of the difficulty in travelling. Families which include individuals which are very young, elderly, infirm, or suffering with mobility issues may find the possibility of a last minute drive for several hundred miles to be too burdensome. Others may choose to stay in place because of the possibility for additional after-storm losses, such as rain causing water damage after a roof becomes damaged or looting of empty structures. The various reasons for choosing to stay or evacuate depends on the perceived reliability of the storm track, the difficulty in driving out of the affected area, and the existence of sufficient resources in the home (Gladwin, Gladwin, and Peacock 2001). Evacuating individuals will still have many of the above preparations for their residence. These individuals, however, will also need to secure lodging for the duration of the evacuation order. While

normally there are government and NGO sponsored evacuation sites, those are usually used as a last resort by individuals who are unable to leave the immediate area. Some individuals who evacuate have the option of staying with family. This presumes that they have family within reasonable driving distance but far away enough that they are not in the affected area. It further presumes that the family has sufficient space to house additional family members. Some may find that an evacuation causes enough stress without such a burden and choose to seek hotel accommodations. Many affected individuals will have neither the option of emergency shelter or nearby family, and will also desire to stay in a hotel.

Evacuations are typically ordered 24-36 hours before landfall (Urbina & Wolshon 2003). This short lead time is necessary because of the limitations in planning a storm track further out. While hurricane modeling has become more precise in the last several decades, the chaotic nature of weather has placed limits on the effectiveness of projected storm tracks. Government officials therefore must balance mandatory evacuation orders over larger possible affected areas with having sufficient lead time for individuals to actually leave the area (Fairchild, Colgrove, and Jones 2006). Even "mandatory evacuation" is not strictly mandatory as noted by the authors and therefore there is some debate about that evacuation being misnamed and giving a false presentation on how individuals will behave under such an order. Having sufficient egress routes and ready information flow can reduce that time but with some residual physical constraints (Lindell and Prater 2007).

Given the limited time and the sudden change in pricing which can occur due to an order being given, individuals may benefit from the price stability of a hotel option. Hotels can use those options similarly to get early cash flow and to maximize revenue under the uncertain environment. This will result in the greatest possible benefit for all parties.

4.2 Literature Review

Revenue management systems serve to allocate capacity among products with different prices in order to segment customers to maximize expected revenue. Revenue management began as yield management in the 1960s as a way to maximize revenue for the airline industry. The airlines wished to maximize revenue in an environment with cancelations, no show customers with reservations, and the arrival of last minute customers without reservations. These issued were first addressed by Simon (1968, 1970), Falkson (1969), and Rothstein (1971, 1985). And an extensive literature has developed since then. Rothstein in particular looked specifically at overbooking policies for airlines. These papers made use of dynamic programing to find optimal policies as well as other operation management techniques. This was extended by Belobaba (1989), Kimes (1989) and Subramanian et. al. (1999) to determine the optimal policies for allocating seats with multiple classes of customers and with the time of the reservation. Gallego and Sahin (2010) examined the possibility of managing inventory under partially refundable fares and found that even with risk neutral customers the provider will have higher revenue by announcing the future price early. This holds even if a new type of customer emerges in later periods with different preferences.

Taking this same approach of segmenting customers to maximize revenue with no inventory and applying it to the hotel industry, Rothstein (1974) Ladany (1976, 1977), Williams (1977) and Liberman and Yechiali (1978) found solutions using dynamic programing and Markovian Sequential Decision Processes. Gallego and Van Ryzin (1994) examine perishable stock and stochastic demand. Bitran and Gilbert (1996) added the complexity of walk-in and no show customers with a stochastic dynamic programing model to determine how to optimally allocate rooms. Gu and Caneen (1998) develop two revenue maximization models. The first

optimizes the revenue per room while the other considers cost and optimizes the profit per room. Baker and Collier (1999) tested multiple heuristics and found that simple heuristics worked as well as complex ones under a simulated environment. Toh and DeKay (2002) proposed a model for the optimal level in overbooking. Baker and Collier (2003) also examined the advantage of bid pricing compared to traditional pricing methods.

More recently, several researchers examined issues more directly related to revenue management issues concerning customer segmentation when early-purchase customers are offered refunds. Akçay, Boyacı, & Zhang (2013) used a single period model to examine the effect of offering customers money-back guarantees. Nasiry & Popescu (2012) examine the effect of customer regret and its impact on total revenues. Gallego & Sahin (2010) used an inter-temporal choice model under uncertainty which permits customer valuations to evolve over time, and they show that customer choice can be priced as a call option, the price of which is contingent on capacity constraints. Extending this literature, I use a binary option model to examine realistic and predictable factors that can drive prices of hotel room rates (which are subject to short-term capacity constraints), and examine the impact of room rates predicted by the model on total revenues.

For extensive reviews of this literature, see Vinod (2004), Ivanov and Zhechev (2011), and Talluri & Van Ryzin, (2004).

4.3 Guest Choice Model

Consider a two period problem where customers have independent and identically distributed valuations on the room. The distribution of the valuation of the room can be modeled as

$$F(p) = P(V \leq p) \tag{1}$$

where $F(p)$ is the cumulative distribution function and is equal to the probability that the willingness to pay (V) is less than or equal to the price set by the hotel (p). While this distribution is known to the hotel and guests, the realization does not occur until period two. I assume that $F(p)$is continuous and differentiable. V is not restricted to have strictly positive values. Therefore the value of $F(0) \leq 1$. The implication is that it is possible some people would not take a room even if it was free because the value of the free room is negative. This holds logically as some people view the hassle of travelling to a hotel and sleeping in unfamiliar room to be itself some cost.

In period one, the hotel will announce the price p_1 and p_2 so that $p_1 < p_2$ and the subscripts denote which time period the price is officially offered. I assume that guests are maximizing their expected consumer surplus. Consumer surplus ($x(p_i)$) is the difference in the willingness to pay (subjective valuation or V) and the actual cost of the room ($p_1$or p_2) and acts as a measure of consumer satisfaction with the purchase.

Using a model where the guest is attempting to maximize their expected surplus, the choice to purchase in period 1, paying a price of p_1 , results in an expected surplus of $x(p_1) \equiv E[V] - p_1$. Given that the price paid in period one is a sunk cost, rational agents will ignore that price in deciding to use the room which was already purchased. Instead they will use the room if the realized value is strictly non-negative. Similarly it can be shown that

$$x(0) = E[V]$$

Since consumers will use the room already purchased in period one if the realized value is zero or greater and later consumers will only purchase a room in period two if the realized value minus the higher price is greater than zero.

$$E[V] - p_1 = E[V - p_2] \tag{2}$$

$$x(0) - p_1 = x(p_2) \tag{3}$$

With this model, the hotel simply must announce the prices under the following constraints to induce purchase at time 1.

$$p_1 \leq x(0) - x(p_2) = 1 - \int_0^{p_2} F(y)dy \leq p_2 \tag{4}$$

Similarly if one wishes to view this as a real option, the guest can pay a price X in period one which will allow them to purchase the room in period two at the strike price of P. Logically it holds that both must be strictly non-negative. Since purchasing the option at price X is a sunk cost, again a rational agent will ignore that consideration when deciding to exercise the option in period two. To maintain the rationality assumption, the strike price is restricted so that $P \leq p_2$ and the strike price must be less than or equal to the value of the exercised option or $X \leq x(P) - x(p_2)$.

Using the surplus value definition, the value to the guest is the surplus value of purchasing the room at price P minus the cost of the option itself, or similarly

$$S = x(P) - X \tag{5}$$

So using that we have a non-trivial value for the guest in purchasing the option.

4.4 Hotel Choice Model

The hotel has to set the price of the room ($p_1$and p_2) but has other issues to concern themselves with as well. We can assume that this hotel has some finite capacity, C, and this is further reduced by a need to set some booking limit to the number of options being sold, b. They do not know in period 1 the number of customers which will choose to buy the option and there is some unknown demand in period 2 for rooms in general.

There is an overbooking penalty, d, if a customer has paid for an option and no room is available with $d > p_2$. This has some minimum value because the customer is choosing to exercise the option with the assumption that the value is greater than the cost of the room therefore to simply make the person whole would require a minimum value ($\underline{d}$) with the form

$$\underline{d} = X + E[V - X|V > P] \tag{6}$$

$$\underline{d} = E[V|V > P] \tag{7}$$

with that value being what is necessary to make the guest whole. I use that as a lower bound however as the actual payment $d \geq \underline{d}$ will be to prevent legal action later for breach of contract or other forms of customer ill will. This can be prevented by restricted the booking limit to be less than the capacity of the hotel (b < C) but this is not found in practice as overbooking is often used to account for some rooms being held and the customers choosing to not come with the hotel not know which customers will not show until period two.

If exercising this option were a simple valuation question, it would be possible to treat this as a partially refundable room with the forfeited portion equal to the option price. This holds when one ignores the time value of money but even with an assumption of some discount rate it is still possible to formulate it in such a way. In this hurricane option case, the option would be sold and it can only be exercised if an order for evacuation were issued. This order is formulated in the following manner

$$\varepsilon = \begin{cases} 0 \; if \; no \; order \; for \; evacuation \; is \; given \\ 1 \; if \; an \; order \; for \; evacuation \; is \; given \end{cases} \tag{8}$$

Even if an order is given however, since the value of the room is not restricted to positive values it is possible to have individuals with options choose to not exercise them and if no other walk in customer arrives then that no show results in an empty room and lost revenue. While it is not known until period 2 if an order is given, there is a known probability of an evacuation order

in period 1, $0 \leq p(\varepsilon) = E[\varepsilon] \leq 1$, that can be used by the hotel in setting price or booking limits.

I assume that some number of customers, Λ, will choose to purchase the option so that the number of options sold will be

$$\Lambda_b = \min(\Lambda, b) \tag{9}$$

where b was the booking limit that the hotel self-imposed. The number of customers that will actually exercise the option in the event of an evacuation order will be

$$\Lambda_b^* = \Lambda_b(1 - F(P))(\varepsilon) \tag{10}$$

There are also walk in customers in the second period, Γ. These customers will pay the higher price of $p_2 > P$ and so would be preferred from a revenue consideration. The Poisson arrivals in period two will have different subjective valuation and in the event of an evacuation that valuation will be assumed to have a higher mean. This cannot be captured by the hotel by raising the price in period two under the assumptions at the beginning. While this may seem to present a problem, anti-gouging legislation as well as other goodwill considerations may prevent this in an actual evacuation order and so it will hold logically.

This also holds mathematically under the assumption that the revenue function, $Rev(p) \equiv p\big(1 - F(p)\big)$, is a concave function of price. If follows by Jensen's inequality that $Rev(E[p]) \geq E[Rev(p)]$ meaning having a known price is preferred by a revenue maximizer to a random price determined in period 2.

The number of customers that will show in the second period and be able to acquire a room will therefore be

$$\Gamma_b = \min(\Gamma, C - \Lambda_b^*) \tag{11}$$

since the number of exercised options are known in the second period.

4.5 Revenue Management

Ignoring any time value of money considerations between the two periods, the revenue for the hotel will then take the following form.

$$
\begin{aligned}
&Expected\ Profit \\
&\qquad = Expected\ number\ of\ sold\ options \\
&\qquad * (option\ price + options\ exercised\ under\ the\ room\ price \\
&\qquad * option\ room\ price) \\
&\qquad - expected\ option\ customers\ showing\ in\ excess\ of\ available\ rooms \\
&\qquad * penalty\ for\ no\ available\ rooms + walk\ in\ customers * higher\ price
\end{aligned}
\tag{12}
$$

$$\hat{\pi}(C, \Lambda, b, \Gamma, P, p_2) = E[\Lambda_b]\big(X + P\big(1 - F(P)\big)(E[\varepsilon])\big) - \max(0, E[\Lambda_b] - C)(d + P)(E[\varepsilon]) + E[\Gamma_b]\, p_2 \tag{13}$$

If $E[\Lambda] \equiv \lambda$ and $[\Gamma] \equiv \gamma$, and the hotel has decided on the booking limit, the second period price, the option price, and the strike price may be found by the following

$$\pi(C, \Lambda, \Gamma) = \max_{X,P,p_2}(\lambda\left(X + P\big(1 - F(P)\big)(E[\varepsilon])\right) - \max(0, \lambda - C)\,(d + P)(E[\varepsilon]) + \gamma p_2) \tag{14}$$

$$such\ that \quad \lambda\big(1 - F(P)\big) + \gamma(1 - F(p_2) \leq C. \tag{15}$$

To determine the economic significance of such a decision, I ran a series of simulations under some reasonable assumptions of the demand. Customer valuation for the period one customers (Λ) was a shifted exponential distribution and had a mean of 100 and a delta of 50 and the customer valuation for the period two customers (Γ) was also a shifted exponential distribution but had a mean of 200 and a delta of 100. The expected number of customers in each group was 100 and had Poisson arrivals only if the subjective valuation was greater than or equal to the price. The results are demonstrated in Tables 4.2 and 4.3.

4.6 Simulation Results

In looking for optimal solutions for pricing the option and the room, a comparison was generated with various values for fixed portions. The solutions were calculated using a generalized reduced gradient algorithm. This algorithm was selected because the equation is nonlinear but it is assumed smooth. All factor combinations estimated began at the same pricing kernel of $100 and $150 for the two room prices with the initial value of the option a risk adjusted price of a binary option with no inflation discount factor. All scenarios converged with fewer than 3000 simulations in each case with the longest (2,926) being under all high conditions. Convergence was declared when the improvement for total revenue changed by less than 0.01% of the previous total revenue.

Given the nature of the demand distributions, exponential with the price divided by 100, and a negative factor of lambda or gamma, the number of customers was scaled to match the increased capacity; otherwise, prices would need to fall to levels that would never occur in real hotel pricing. The changes to the arrival and demand functions drove pricing more than capacity and so it was difficult to interpret the results. Those results are therefore suppressed in the following tables.

Table 4.2 looks at the generated prices with a low probability of evacuation. With a lower probability of an evacuation, a binary option has a lower intrinsic value. The factor changes which had the greatest impact on the pricing kernel was the shift in customer valuation. When changing the valuation of the second period customers, the price of rooms in the second period fell; but not as quickly as the price for first period rooms. The option price itself changed to the market-clearing price, with an option price that was a function of the difference in the price of the early room and of the late room. Changing the valuation function for the early purchase

individuals causes a significant drop in the price of the early room. This causes a sympathetic drop in the price of the later room. The lowest total revenues result when both groups express the higher values for the valuation equations.

Evaluating the same changes to the factors for the valuation formula and penalty but under the assumption of a high probability of evacuation, results in the values found in Table 4.3. While the prices are higher under the low assumptions for valuation factor, the prices are less variable under all high assumptions for factors. Given the results of the greatest sensitivity being for the valuation function, clearly the most important first step is knowing the price sensitivity of the customers. This is information that hotels will undoubtedly have available. The more sensitive the individuals are, the less important the probability becomes; which could be valuable when selling year after year.

4.7 Conclusions and Future Research

It has been demonstrated that the benefit exists for consumers with the introduction of such an option. Even with an assumption that individuals will gain no benefit, i.e. the surplus is equal to zero, there are significant revenue gains for the hotel if such an option was available. This benefit is greatest when the uncertainty around evacuation is the greatest which is the best time to offer such an option from a customer welfare standpoint. This was also under the assumption of risk neutral consumers. An exploration was begun on assumptions of risk averse consumers and while there was additional benefit for those consumers, the seller still benefits.

While the results are promising, having a multi-period model would require more advanced dynamic programing than what has been presented here. This multi-period model could account for multiday stays which would be more consistent with reality.

I envision such a product not being offered directly to the consumer. Instead, this could be contracted between homeowner's insurance companies and hotel chains. This assumption is due to the fact that standard insurance contracts (such as the HO3) explicitly include the cost of lodging in the event one is forced to evacuate their home even if no damage is sustained to their home. This would be a possible way for insurance companies to control costs in the event of a catastrophic event which will present significant simultaneous claims.

Table 4.1: Assumed Factor Values

Factor	Low	High
C (Hotel Room Capacity)	20	80
E[ε] (Probability of evacuation)	0.20	0.80
λ (Demand Factor Early Buy)	0.50	2
γ (Demand Factor Late Buy)	0.50	2
d (Penalty for overbooking)	$150	$600

Table 4.2.1: Low Probability of Evacuation

P(Evacuation)	L	L	L	L
λ	L	L	L	L
γ	L	L	H	H
d (Penalty)	L	H	L	H
Option Price(x)	\$2.77	\$17.07	\$3.76	\$4.89
P	\$125.20	\$125.20	\$42.50	\$38.80
P_2	\$139.05	\$210.57	\$61.28	\$63.25
$X + P$ or $X + P_2$	\$127.97	\$142.27	\$46.26	\$43.69
Total Revenue	\$2,433	\$2,729	\$931	\$909

Table 4.2.2: Low Probability of Evacuation (cont.)

P(Evacuation)	L	L	L	L
λ	H	H	H	H
γ	L	L	H	H
d (Penalty)	L	H	L	H
Option Price(x)	\$9.38	\$5.72	\$2.60	\$4.13
P	\$46.92	\$35.00	\$26.25	\$22.50
P_2	\$93.83	\$63.61	\$39.23	\$43.16
$X + P$ or $X + P_2$	\$56.30	\$40.72	\$28.85	\$26.63
Total Revenue	\$1,589	\$2,472	\$629	\$641

Table 4.3.1: High Probability of Evacuation

P(Evacuation)	H	H	H	H
λ	L	L	L	L
γ	L	L	H	H
d (Penalty)	L	H	L	H
Option Price(x)	\$55.68	\$34.13	\$24.97	\$26.39
P	\$69.60	\$69.60	\$31.22	\$32.99
P_2	\$139.21	\$112.27	\$62.43	\$65.98
$X + P$ or $X + P_2$	\$125.29	\$103.74	\$56.19	\$59.38
Total Revenue	\$3,044	\$3,730	\$1,133	\$1,168

Table 4.3.2: High Probability of Evacuation (cont.)

P(Evacuation)	H	H	H	H
λ	H	H	H	H
γ	L	L	H	H
d (Penalty)	L	H	L	H
Option Price(x)	\$37.11	\$23.23	\$17.38	\$9.33
P	\$46.39	\$34.86	\$21.72	\$16.89
P_2	\$92.78	\$63.90	\$43.45	\$28.55
$X + P$ or $X + P_2$	\$83.50	\$58.09	\$39.10	\$26.22
Total Revenue	\$1,998	\$2,737	\$836	\$1,843

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5. CONCLUSION

Prior to the financial crisis of 2007-8, the consensus view of economists was that the American economy had settled into the Great Moderation. Orthodoxy was upended after the world watched America's financial system teeter on the brink of a total meltdown, threatening not only devastating shocks to the American economy, but to the global economy as well. Ironically, economic researchers have developed tunnel-vision once more, but this time with regards to the focus on systemic risks related to financial institution collapse. Our understanding of systemic risks, and events related to it, should not remain so confined.

I examined three topics related to systemic risk not usually considered in mainstream research. I find evidence that coffee price risk might be hedged by Ugandan producers, possibly mitigating the risk of economy-wide devastation. I provide evidence that there is a long history of a relationship between real estate lending and bank failures, which have threatened economic collapse several times in American history. And I show the potential benefits of an options market for temporary shelter for persons fleeing natural disasters, history's most unforgiving threat to individuals and nations. All three papers contribute to the understanding of systemic risk, providing important insights for policymakers and avenues for further research.