Lending Sociodynamics, Economic Instability, and the U.S. Farm Credit Crisis

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Abstract:

Since the breakthrough of Keynesian economic thought, with further contributions of Minsky's (1977) Financial Instability Hypothesis, many fundamental models in the classical economic theory have incorporated quantitative psychology to model agents who behave more complex than classical models' assume. We simulate the dynamics of economic instability in the crash of the farm credit sector using Weidlich's sociodynamics of opinion formation. The model illustrates the differences in the evolutions of opinions under two assumptions: (1) independent and (2) co-dependent lending decisions. Through the use of lending sentiments within our preference parameters, we endogenously simulate the rapid rate of change in lending opinions that result from the changes in our sentiments, and produce a consistent socialdynamic as the rise and crash of the farm credit crisis of the late 1980s. Furthermore, we use the simulation to test Carey's (1990) assumption concerning the temporal evolution of opinion dynamics during the farm credit crisis; our model suggests a rapid crash following a boom in markets. The parameters of our sociodynamics incorporate elements of cognitive and social psychology, which help explain the robustness of financial instability phenomenon to the recent advances in risk measurement in our economy and suggest how policy for reducing instability can formulate in an experimentally sound manner through behavioral regulations.

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1 Introduction

Through the integration of *General Theory*, Minsky (1977) constructs the *Financial Instability Hypothesis* (FIH) as a remarkable explanation for the phenomena of financial crises and structural instability within markets. Based on FIH, the focal driving factor of instability in markets are the fluctuations and polarization of lending opinions. Opinion dynamics were initially introduced by "statistical physics and the social sciences," and later developed into "statistical field theory known as sociodynamics" (Hawkins, 2011). Using sociodynamics within the bounds of FIH, we should then be able to illustrate and illuminate economic instability and financial crises through a set of new lenses, namely that of human psychology, which is the goal of this paper.

In the *General Theory of Employment*, Keynes (1936) reconstructs the elements of the trade cycle into four general stages: it begins with the boom, which takes place when new investments maintain "not unsatisfactory" returns. Then, as the value of the assets increase, the uncertainty on the reliability of these returns increases, which then promotes doubt quickly and result in a subsequent crash of the capital value where "marginal efficiency is negligible or even negative"(Keynes, 1936). Although Keynes recognizes that trade cycles are complex and influenced by multiple factors, he emphasizes on fluctuations in "marginal efficiency of capital" as the central factor in business cycles (Hawkins, 2011). While addressing multiple reviews of his General Theory, Keynes makes his departure from classical economic theory even sharper. The critical shortcoming of classical and neoclassical models by Ricardo, Marshall, Edgeworth, and Pigou, per Keynes, is that we "deal with present by abstracting from the fact that we know very little about the future" (Keynes, 1937). Not only our knowledge of the future is negligible, but the "uncertainty [of the future] is also intrinsic" (Hawkins, 2011). Keynes addresses these shortcomings in the following passage:

> "[a]bout these matters there is no scientific basis on which to form any calculable probability whatever. We simply do not know. Nevertheless, the necessity for action and for decision compels us as practical [hu]men to do our best to overlook this awkward fact and to behave exactly as we should if we had behind us a good Benthamite calculation of a series of prospective advantages and disadvantages, each multiplied by its appropriate probability, waiting to be summed" (Keynes, 1937).

And intrinsic risk within our economy, in Keynes's view, is the social psychology of economic agents:

> "We assume that the present is a much more serviceable guide to the future than a candid examination of past experience would show it to have been hitherto. In other words, we largely ignore the prospect of future changes about the actual

> character of which we know nothing. We assume that the existing state of opinion as expressed in prices and the character of existing output is based on a correct summing up of future prospects, so that we accept it as such unless and until something new and relevant comes into the picture. Knowing that our own individual judgment is worthless, we endeavor to fall back on the judgment of the rest of the world which is perhaps better informed. That is, we endeavor to conform with the behavior of the majority or the average" (Keynes, 1937).

Keynes sees the aforementioned intrinsic ignorance as the primary catalyst behind the fluctuations of the marginal efficiency of capital, which then reflects in the business cycle:

> "Now a practical theory of the future based on these three principles has certain marked characteristics. In particular, being based on so flimsy a foundation, it is subject to sudden and violent changes. The practice of calmness and immobility, of certainty and security, suddenly breaks down. New fears and hopes will, without warning, take charge of human conduct. The forces of disillusion may suddenly impose a new conventional basis of valuation. All these pretty, polite techniques, made for a well-paneled Board Room and a nicely regulated financial market, are liable to collapse. At all times the vague panic fears and equally vague and unreasoned hopes are not really lulled, and lie but a little way below the surface" (Keynes, 1937).

As compelling as Keynes argued for a behavioral view of macroeconomics, it was largely neglected in what we know today as the "Keynesian economics" (Hawkins, 2011); The omission of the social psychology from Keynesian economics was resolved by Minsky's (1977) *Financial Instability Hypothesis* (FIH). Minsky builds on Keynes's (1936) explanation of business cycles and models financial crises by focusing on the role of lenders, as primary agents who use marginal efficiency of capital while making decisions on extending credit.

Minsky's (1977) FIH begins in the period following a financial crisis. He portrays financial crises as an intrinsic within our economy that is robust to our current risk management models without incorporation of social psychology. Much like Keynes, Minsky's model starts with the period post crisis, when lenders are humbled by "bad loans," and thus behave "extremely cautious" in their practices (Hawkins, 2011). As the passing of time heals the problems created in the period of crisis, balance sheets start to improve again. Loans in the period of improved balance sheets have low losses, suggesting more credit can be issued and that current guidelines are perhaps too cautious. Based on the support of adjusted empirical evidence of low loss rates criteria, loan volume increases, and general lending practices are considered as economically sound; sound lending practices have loss rates lower than or equal to expectations. Under such circumstances, "lending volume increases [even more,] and profitability improves" (Hawkins, 2011). Furthermore, providing credit to previously disqualified communities or minorities make lenders feel as if they are providing a social service. Altogether, with improvements of the gross domestic product, they create a strong psychological validation for current lending practices. However, just as loss rates fall, they can rise, which generally occurs at a faster rate. Eventually, as lenders face higher loss rates, attention shifts to holding capital for "provision for bad loans" (Hawkins, 2011). However, how can they evaluate the risk imposed by bad loans if the practices in the previous period are considered to be sound? Thus, provision is done in an ex-post basis as bad loans reveal themselves. Consequently, as the number of bad loans increases, allocation of resources to take care of these bad loans reduces profitability, and when the increase in the provision cost is significant enough, lending institutions begin to fail. Through such a psychological modeling of trade cycles, Minsky shows that what is commonly viewed as "measurable risk" in lending practices is in fact an "intrinsic uncertainty" within our economy(Hawkins, 2011). Having been humbled by the crash, lenders then readjust their guidelines again and extend credit cautiously, and the cycle continues.

An example of financial crisis as a consequence of exclusion of social psychology in macroeconomic views and risk management is seen during the farm credit crisis of late 1980s. We will provide some qualitative background on the farm credit crisis of the 1980s in section 2. We explain the dramatic boom followed by a crash in farmland values, and how it impacted the farmers and lenders at the time. We will also connect the story to Minsky's explanations of the trade cycle, and illustrate the importance of the role of lenders in economic downturns within the bounds of the farm credit crisis of the 1980s. Moreover, we formalize the background story through empirical evidence and illustrations in section 3.

We then introduce the opinion formation model by Weidlich to account for behavioral factors to illustrate the core elements in arguments made by Keynes and Minsky. Our model is introduced by Weidlich (1972), developed by Weidlich and Haag (1983), and further implemented to sociodynamics of lending by Hawkins (2011) who uses simulations from Lux (2009a,b). More recently, our model was also applied to the specific problem of lending opinion formation by Ghonghadze and Lux (2012) and Ghonghadze and Lux (2016).

We then complete the model in Section 5 by introducing two proxies created from empirical data on land and debt values. Our data was collected from Carey (1990), FRED (2020), and Agricultural Land Values and Markets Situation Outlook Reports by USDA (1988, 1990).

The purpose of the proxy within our model's preference parameter is to reflect the key determinants for lender's perspective on a loan, which based on Keynes and Minsky, are loan profitability (balance sheets) and marginal efficiency of capital (low observed risk) in a stochastic environment.

We produce various versions of 3-D probability densities in section 6. The 3-D graphs illustrate the time-variant evolution of probability distribution of relative opinions in a given society of lenders, influenced by factors of previous and current state of (i) opinions, (ii) profitability on the underlying asset.

They also illuminate the difference of these distributions under different behavioral assumptions for an agent's decision-making process. The two types of behavioral assumptions that we illustrate are: (i) agents decide independently from one another, and (ii) an agent's decision is impacted by the opinion of the group. We then finalize with our conclusions and interpretations through 3-D social configurations given by our simulations.

Moreover, we use our simulations to test Carey's (1990) assumption, which suggest opinion formation and transition occurs in three stages. According to Carey (1990), the opinion distribution transforms from the stage in which most lenders are willing to lend, to the second stage distribution with high variance and high dispersion, and finishes with the final distribution of opinions where most lenders are not willing to lend. We found that our model suggests a different transformation of opinion distributions than Carey's (1990) assumption.

We then provide qualitative economic reasoning and interpretation for the role of our parameters in the results. Then, we illustrate the consistency of our results with the literature in the field. Finally, we close with some discussion on policy implications based on what we conclude from our results in section 7.

2 U.S. Farm Credit Crisis of the 1980s

During the 1980s, American farmers experienced an economic crisis more severe than any incident since the Great Depression.[1] The crisis moved families out of their generationally owned lands, and the agricultural community lost their identity. The late 1980s turned into a turmoil, filled with activists and protesters pushing for policies and resolutions to protect the isolated communities of farmers who had lost virtually everything that they valued. By the end of the decade, "an estimated 300,000 farmers defaulted on their loans," and more banks became insolvent in 1985 than any year since the 1930s. The conditions imposed on farmers during the farm crisis was exceptionally tough on these communities because they were isolated as the only group in the nation that dealt with such losses.

2.1 Overview

The rise of agriculture as a profitable industry began before the 1960s, when the environmental conditions of the world lead to the US becoming the leading force in feeding the world's

[1]The information in this section comes from a 90-minute film produced by Iowa Public Television that examined "economic and personal disasters" of the farm credit crisis of the 1980s (IPTV, 2017).

hunger for agricultural goods. Politicians promoted this role and influenced farmers to turn their production even higher to "feed the world." Following these events, as the demand and role of the sector increased, the prices of their goods and resources increased.

Similar to the housing bubble of 2008, as land values increased, lenders and farmers mistakenly concluded that the new conditions would become the new norm. "Borrowing became the order of the day," and lenders were eager to accommodate the optimistic farmers. The competition increased intensely in farmland lending. According to Alan Tubs from First Central State Bank in Iowa, banks were competing with a "very aggressive farm credit system," and even within the relatively smaller farm credit system, the competition induced their practices to "become very aggressive in farmland loans." The competition between aggressive farm-specific creditors and standard institutional lenders over the boom of farmland prices made the new lending practices and risk assessments overly relaxed; this competition further influenced the prices to increase, which then increased the profitability of their practices; we can start to see the connection with Minsky's (1977) trade cycle.

All sorts of new borrowers, private and public, were entering the farmland lending. With the establishment of institutions such as FMHA, known as Lender of Last Resort, created by Farmers Home Administration in 1947, money to borrow became easily accessible. Thus, farmers began to leverage their land as collateral, and as Minsky (1977) hypothesized, lenders were eager to allow them to secure new loans; upgrading and expanding farm operation was "unquestioned acts of faith" and dirt become the new "black gold." (IPTV, 2017)

Economists and bankers, whom farmers viewed as experts, were actively urging young and ambitious farmers to buy now than later, because "land prices could not go down." However, as Minsky's (1977) trade cycle explains, just as speedy as loss rates fall on loans, they can also rise, if not faster.

Eventually, in 1981, the potential for the rise of loss rates spiked when the Federal Reserve had to implement monetary policy to battle inflation at the time. The Fed increased the Fed Fund Rate to levels "not seen since the civil war… with record-high 21.5% in 1981. Story continues to reflect Minsky's (1977) trade cycle, as both lenders and farmers now face a higher cost, and trouble starts to build; people cannot pay their interest, let alone their principal payment. Loans became larger and extended, and "bad loans" revealed themselves on an ex-post basis. Consistent with Minsky (1977), the number of bad loans increased, and the allocation of resources to take care of bad loans reduced profitability; eventually, most loans revealed themselves as bad, implying too great of a provisioning cost, and the farm credit crisis of the 1980s took place.

The economic conditions of the farm credit crisis got more severe; total interest payments on farm loans exceeded total farm income for the first time reported. In January 1984, Federal Reserve Board issued a report estimating one-third of American farmers held two-thirds of nation's total farm debt. Farmers experienced a sudden change in the way their lenders treated them; lenders changed from “[giving] out money [on] a handshake,” to foreclosing on farmers’ properties and criticizing their farm operations. After land values peaked at in 1981-82, they crash soon in 1983-84, and took two decades to fully recover. The prolonged recovery reveals the generational impact of this crisis.

3 Temporal Evolution of the Farm Credit Crisis

In the previous section, we familiarized ourselves with the overall story of the 1980s farm credit crisis. We noted that unlike others financial crises, the burden of the farm crisis was solely carried by communities of farmers.

The sentiment around farmland was significantly different in the years prior to the crash. In fact, starting in 1960s, the farming sector witnessed revolutionary advances in agricultural technology, seeds, pesticides, and fertilizers. These advances led to achieving greater efficiency and productivity, which consequently generated higher profitability and an overall positive sentiment around rural life (IPTV, 2017).

Then, in the 1970s, the U.S. grain reserves were lowered which in turn raised the price of grain. Meanwhile, poor weather conditions around the world diminished yields overseas. Multiple international factors led to the demand for the U.S. agricultural products to rise significantly. A strong factor in creating the demand was ”The Soviet Union multiyear contract for wheat and feed grains in 1972” (IPTV, 2017).

Following the significant rise of the demand for US agricultural products was the increase in prices and revenue for farmers. Earl Butz, who was President Nixon’s Secretary of Agriculture, called upon American farmers to plant ”fencerow to fencerow,” and urged farmers to “get big or get out.” Considering that the farming sector was supported by political leaders and was helping to save the world’s hunger, the sentiment around the farming sector became highly optimistic; providing farm goods could be thought of as providing a social service (IPTV, 2017).

Then, the farmers bought into these sentiments and ”the race to feed[ing] the world started” (IPTV, 2017). As farmers looked to increase their crops to feed the world, farmland was commonly viewed as a high quality underlying asset amongst loan creditors given the revenue, social responsibility, and political climate surrounding the sector. We can see this narrative play out in figure below, where the total outstanding government-backed debt and mortgage debt issued on farmlands rise through this timeline.

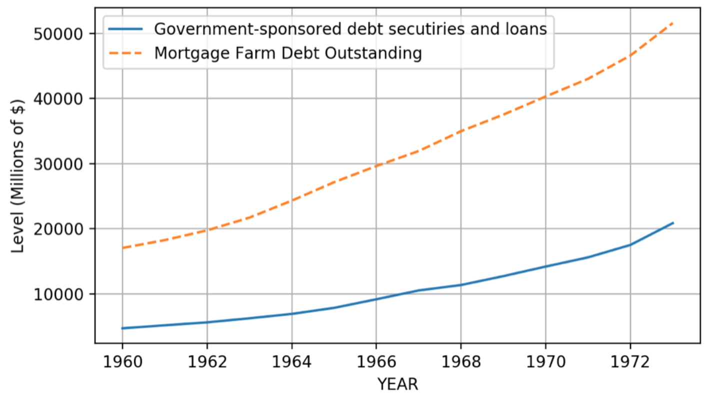

Figure 1: USDA (1990) U.S. Mortgage and Government-Backed Debt Issued on Farmland Assets

To understand the factors that played a role in the crash of farmland values, we have to analyze the criterion that is used in the process of credit extension by lenders while underwriting loans. Based on the Handbook on Agricultural Lending by Comptroller's (2018), the farm credit lenders evaluate the quality of assets based on solvency, profitability, income, liquidity, and efficiency (Comptroller, 2018). First, we present the efficiency factors in figure 2. The only trends that have significant shifts are those factors of efficiency that are intercorrelated with profitability and income; factors that are not linked to income and profitability remained fairly consistent during the period from 1960s to 1988. Thus, efficiency factors suggest that we should look at elements that directly impact net income and profitability to understand the indirect impact of efficiency of assets.

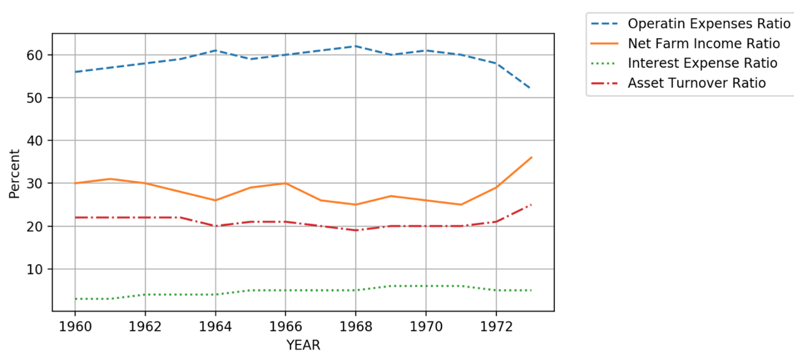

Figure 2: USDA (1990) U.S. Farm Lending Guidelines on Efficiency of Asset

As we look further into the credit extension process, we find more evidence supporting income and profitability as the driving force that initially gave rise to the practice of aggressive lending in the farm sector. Within factors of liquidity, income, and profitability, we observe a rapid upward trend during the 1972-1973 timeline. The trends in earnings (income), net income (profitability), and debt service ratio [2] (liquidity) illustrate that profitability of agriculture sector could have been the main force in initiating and carrying out the practice of aggressive lending in the sector.

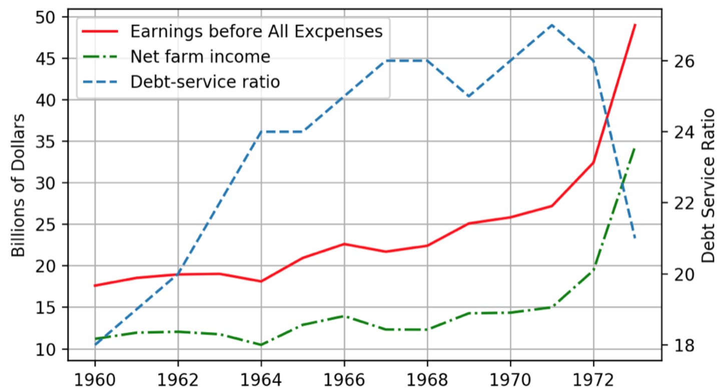

Figure 3: USDA (1988) The Growth Period Leading to the Farm Credit Market Bubble

We further examine profitability indicators of farm assets, as defined by the guidelines of Comptroller's (2018). We see almost a uniform trend across total rate of return, current income, and real capital gains on farmland assets, which further proves that profitability could have been the underlying factor. [3]

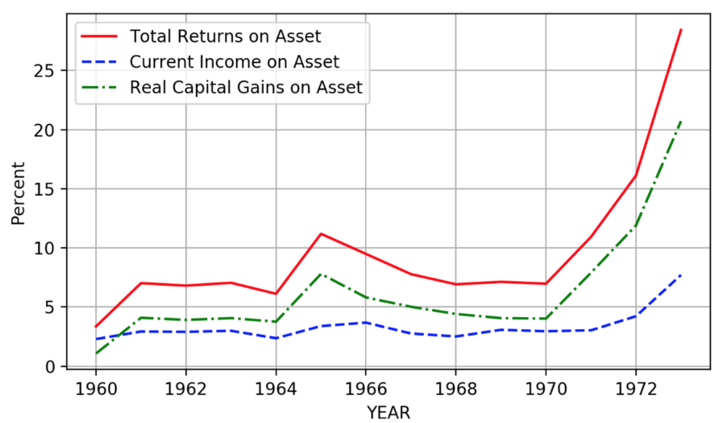

Figure 4: USDA (1990) U.S. Farm Lending Guidelines on Profitability of Asset

Moreover, we see a drop in debt service ratio after its earlier increase, which implies that

[2]Debt service ratio is the farmers' ability of being able to serve their debt obligations, which relies on income and profitability with respect to debt payments.

[3]The same indicators for equity follow nearly the exact same pattern.

the farmers income is high enough to easily finance their debt. Indicators of profitability show almost an exponential growth in their returns, which not only make for a great signal to lend, but also forms an extremist view per properties of exponential growth; such extreme case of growth creates overoptimism with most lenders being willing to lend on the asset, and consequently makes lending practices even more aggressive through the rise of competition within lenders.

The factors of solvency within the farm credit guidelines remained fairly consistent throughout 1960 to the end of 1980s, as show below; so it is safe to assume that lenders' decision of lending was not driven by any drastic changes in solvency. Furthermore, since land prices have an impact on all three of these ratios, it suggests that it is plausible that nominal fluctuations in land prices were not the origin of shift of opinions on farmland assets within lenders. Furthermore, these measurements are misleading for reliability and risk of solvency; because revenue and income were the actual driving factor in their lending decision, it implies that in order for the asset to not become insolvent, the farm revenue must remain consistent until the time of maturity, which is an extremely alarming and risky commitment.

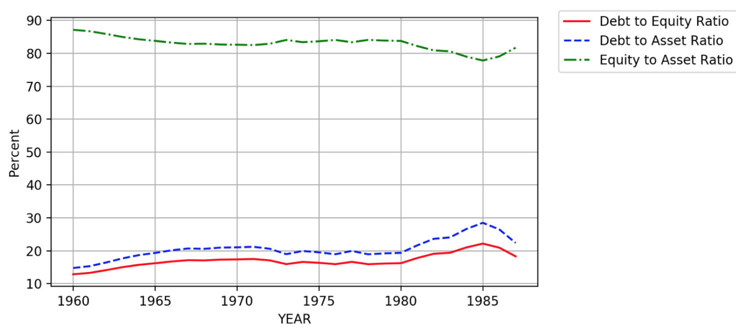

Figure 5: USDA (1988) U.S. Farmland Solvency Measures

As land values increased, lenders and farmers alike mistakenly accepted the current conditions as the new norm. Borrowing became the order of the day and there were plenty of lenders eager to accommodate optimistic farmers. However, in the end of 1970s, the political climate of the Middle East resulted in an oil price shock for the united states, which then took a toll on the farmland asset quality (IPTV, 2017).

The drop in asset quality had multiple underlying factor, but our data suggest that it started from the massive oil shock to the economy. The oil shock raised the farmers cost of using machinery and technology immediately as a function of their cost of operation. In addition to these expenses, in 1979 the Soviet Union invaded Afghanistan and President Jimmy Carter enacts a grain embargo that stopped shipments of grain to the Soviet Union. The embargo wasn't lifted until 1980 when President Ronald Reagan took office.

As a consequence of the oil shock, the U.S. faced a massive rise in inflation. In order to fulfill its mandate to stabilize inflation, the Federal Reserve had to enact policies to hold the line on inflation. In 1979, we recorded the highest jump in the Federal Funds Rate of 20 percent. The Fed's actions made the cost of borrowing money prohibitive for all Americans. However, the impact on the farming community was especially severe since they had larger amounts of debt accompanied with a drop in their net income; the rise of interest rates adds to the cost of servicing their loans, and resulted in an even lower net income. We see the historic peak of year-to-year Fed Fund Rate during the years 1979 to 1982 in the figure below.

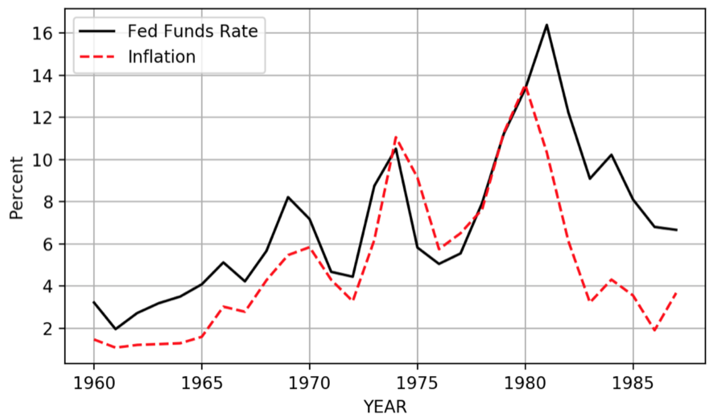

Figure 6: FRED (2020) U.S. Economic Oil Shock of Late 1970s

These factors imposed severe expenses on farmers and caused a drop in their revenue and demand. Moreover, such decline in their income increased their debt-servicing ratio, which made their assets very risky altogether.

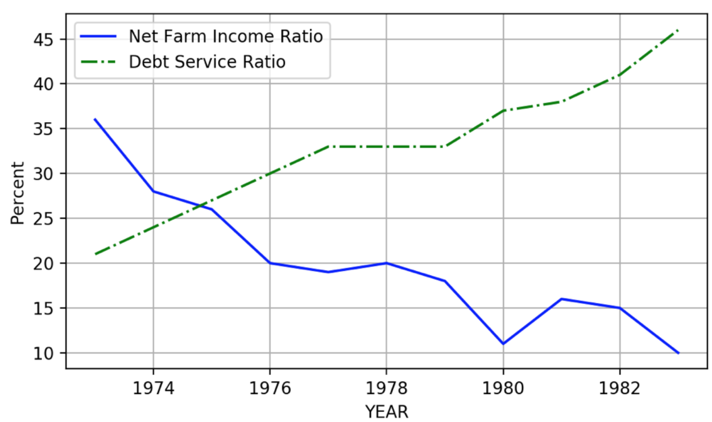

Figure 7: USDA (1988) U.S. Farmland Quality Responds to Late 1970s Economic Shocks

We can observe below that the both ratios of interest and operating expenses increased as the economic shock took place. Simultaneously, we see that the total rate of return on farmland drops from around 30 percent in 1973 to below 20 around 1979, and rapidly lowers to levels below zero by 1981. Through such shift in economic conditions, loan quality changed rapidly, and consequently, the farmers went from being able to borrow over a handshake, to being foreclosed and losing their jobs and going through a financial crisis.

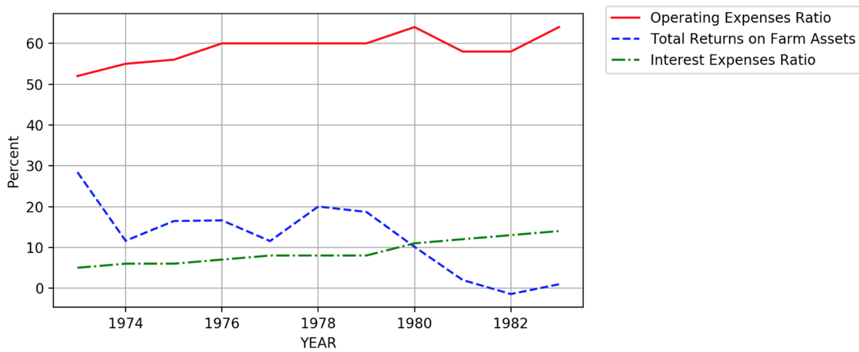

Figure 8: Impact of Late 1970s Oil Shock on U.S. Farm Sector

We see the transformation of quality of farmland assets as a function of their profitability in figure 9. Evidently, all determinants of profitability of farmland assets drop to negative levels by 1981, and remain negative all the way through 1986. [4]

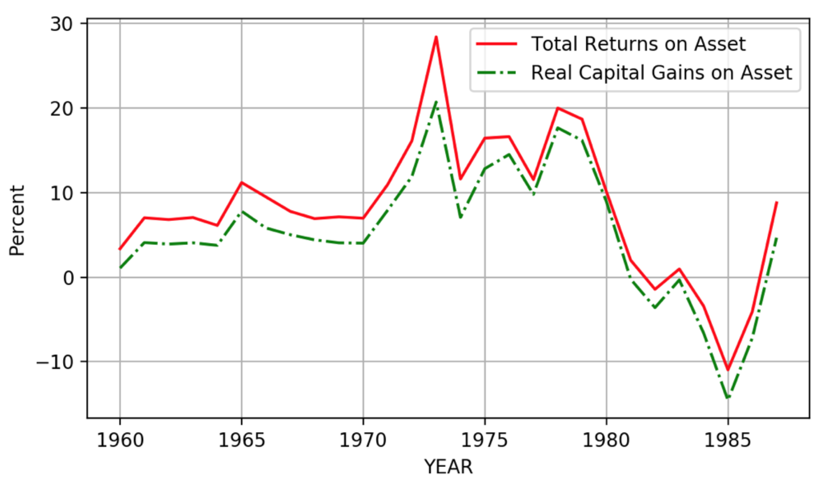

Figure 9: USDA (1988) U.S. Farm Asset Returns

As the operation cost and interest payments increased, farmers were unable to meet their

[4]These trends are consistent when we looked at data on farm land equity.

debt obligations by 1979, and subsequently, bad loans began to reveal themselves through new defaults. Subsequently, the bubble of overoptimistic farmland asset values crashed. Thus, we can formally conclude based on our data that profitability of farmland assets were the first signal to the crash: 1) economic shock occurs, 2) farm net income drops, then 3) quality of the assets drops, and as a consequence, both 4) demand and supply of loans should drop and 5) decrease the value of farmland assets.

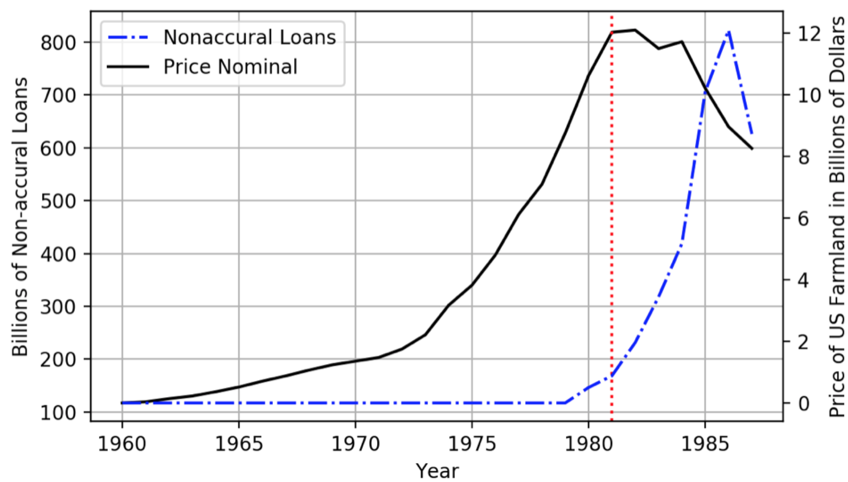

Figure 10: Carey (1990) Non - Accrual Loans in the Farm Credit System

The figure above indicates that unpaid debt obligations and bad loans start to rise 1979; however, the land value is increasing during this timeline and until 1981-82, which is when it peaks. Since price drop occurred after bad loans started, then it must be that the loan quality dropped the price bubble and not the opposite. Moreover, the timeline of bad loans perfectly corresponds to profitability trends timelines, which start around 1978-79 and drops below zero by 1981-82 and remain in the negatives until 1986; prices changed after lenders changed their opinions on lending after the change in on loan profitability and farmers' income while assessing quality of credit. This also makes a compelling case for our use of real values of farmland as the proxy for lenders' opinions, which we will introduce in the forthcoming sections of this paper.

Based on the evidence provided above, we can conclude that the farm credit system (farmers) viewed the temporary international conditions and social support to be everlasting and loaned (borrowed) aggressively; as revenues and income peaked, overoptimistic borrowing on farmland asset market was not prepared to face the economic conditions that 1979 oil shock sparked, and resulted in a crash of the sector.

Finally, we look at the total government-sponsored debts and mortgage farm debt outstanding throughout the period leading to the boom and until the end of the crash. We see the timelines of total debt also corresponds with profitability of farmland being the main drive behind the aggressive lending practice, where issuance increases in 1970, slows down by 1980, and starts to drop by 1981-192 as the bubble crash takes place.

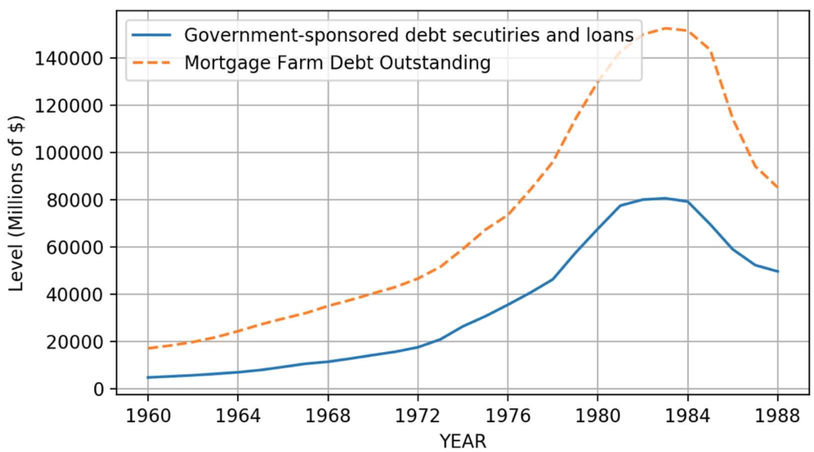

Figure 11: USDA (1988) Government Sponsored U.S. Farm Debt and Mortgages

Consistent with Minsky's trade cycle, profitability and income (marginal efficiency of capital) drove up the land prices, and consequently, lenders and farmers behaved too optimistically and did not prepare their guidelines for unsatisfactory economic conditions; as a result of an exogenous economic shock of late 1970s, loans start to default and lead to the farm credit crisis in the mid 1980s; post crisis, the lending guidelines became conservative again.

4 Lending Sociodynamics

Using the model first introduced by Weidlich (1972), later developed by Weidlich and Haag (1983), and further utilized on sociodynamics of lending by Hawkins (2011) through implementation of simulations from Lux (2009a,b), we established a model to illustrate the lending social dynamics for the Farm Crisis of the 1980s.

To establish the basis for the model, we begin by the definition of socio-dynamics (social dynamics) to understand what our analysis examines. Social dynamics are the characteristics of the behaviors within groups, as a result of interaction within individual members of the group. In our research design, the society of interest is the relatively small sector of farmland loan underwriters from 1960 to 1987, and the core behavioral question we seek to analyze is the basic of lending questions: to lend or not to lend in a given market Hawkins (2011).

Contrary to standard economic theory, this powerful model addresses both oversimplified preference assumptions incorporated in microeconomic models, where lenders' decisions are modeled independently, but also we illustrate the interaction and codependent of agents' opinions and peer pressure through our model.

The most basic opinions that lenders form on any given asset — to loan to lend or not to lend — is equivalent of the fundamental question of the "asset allocation" in "portfolio construction" (Hawkins, 2011). We establish homogeneity within the sociodynamics of lenders through the commonality of behavioral probabilities embedded in the process of "opinion formation" while extending a loan offer (Hawkins, 2011). In contrast, lenders are treated as a "heterogeneous population" when we examine opinions on lending in a specific market, at a specific time (Hawkins, 2011).

The research design explained above allows for the use of Weidlich and Haag (1983) master equation, which is constructed through the following steps: First, we establish a single variable to represents the state of opinions in the society. Then, using heterogeneity of the population, we define the probability of transitioning between the two states of opinions (lend or not lend) for one individual lender on a given asset (farmland) at time t_0. Finally, because of homogeneity of behavioral probabilities, we can produce a single function that illustrates the social configurations within our model, namely the master equation, which measures the probability of the group's opinion distribution as a function of time.

To construct the basis of the society as our first step, let's assume that the population ($2N$) is made out of two subgroups, one with opinion 1 (lend) and the other with opinion 2 (not lend), we get $n_1 + n_2 = 2N$ and $n_1 - n_2 = 2n$ (Weidlich and Haag, 1983); we assume $2n$ as the level of difference between agents who lend and those who are not willing to lend. By doing some algebra on these two proposed equations, we can then represent each subgroup in our society of lenders by $n_1 = N + n$ and $n_2 = N - n$ (Weidlich and Haag, 1983). Assuming N is constant, which we input as 50 in our model to representing the small sector of lenders in farmland loan underwriting in the 1980s, we find that the fundamentals within our society are as follows:

$$\begin{aligned} n_1 &= 0 \to n = -N \\ n_2 &= 0 \to n = +N \end{aligned} \tag{1}$$

Since $2N = 100$, then $-50 \leq n \leq +50$. Since n_1 is representing an agent willing to lend, the more we move towards $+50$, it represents a society with most lenders willing to lend, whereas at $+50$, all lenders are willing to lend. Since n_2 is representing an agent unwilling to lend, the more we move towards -50, it represents a society with most lenders unwilling to lend, whereas at -50, no lender is willing to lend. Thus, defining n in this manner allows us to imply and learn both number of lenders willing (n_1) and unwilling (n_2). Using n as the description of opinion configuration of the group, we can then model a time dependent transitional probability for lenders in farmland sector as the likelihood of out-flux from the current state of opinions n plus the likelihood of influx deeper into current state of n opinions.

The transition probability is interpreted as probability of moving from one state to another, and it is originated from statistical physics. As previously mentioned, our two states are represented as the two basic opinions in lending. Then, the probability of moving from being willing to lend to unwilling to lend is represented as $p_{+-}(n)$; similarly, if the probability of transition is in the opposite direction, from being unwilling to lend to being willing to lend, we denote it as $p_{-+}(n)$(Hawkins, 2011).

The probability that a society is configured of n_1 lenders and n_2 unwilling lenders at time t_0 is represented through $p[n_1, n_2; t] = p(n; t)$, and normalization implies $\sum_{-N}^{N} = p(n; t) = 1$. Thus, the time evolution of the distribution of opinions becomes the sum of probabilities of increase of initial n plus the probability of decrease in initial n, at time t for all combinations of the configuration. The following equation represents the master equation for each lender is (Hawkins, 2011):

$$\frac{dp(n;t)}{dt} = [w_{\downarrow}(n+1)p(n+1;t) - w_{\downarrow}(n)p(n;t)] + [w_{\uparrow}(n-1)p(n-1;t) - w_{\uparrow}(n)p(n;t)] \quad (2)$$

Equation (2) measures the probability of movement away from current social configuration of opinions (n_1, n_2) willing lenders and unwilling lenders as time changes. Equation (2) is for all two-opinion based social configurations; to make our master equation applicable to lending dynamics, we specify certain parameters within our model that reflect lending behaviors in the next sections.

The behavioral aspect of the model enters the model through $w_{\uparrow} = (N-n) \times p_{+-}(n)$and $w_{\downarrow} = (N+n) \times p_{-+}(n)$. Qualitatively, $w_{\uparrow}$ is an increase in probability of the configuration distribution to move towards $n = +50$ with additional net lenders. Alternatively, $w_{\downarrow}$ is described as the decrease in configuration probability, for a movement towards $n = -50$ as net unwilling lenders increase (Hawkins, 2011).

In the following sections, we introduce the behavioral parameters. We incorporate lending sentiment proxies within our psychological parameters in the master equation and simulate results that effectively capture the behavioral tendencies of lenders in the farmland sector from 1960 to 1987.

5 Psychological Dynamics

The uniformity within the behavioral probabilities originates from the "traditional credit culture" and the training that lenders go through; they tends to "systemizes credit analysis" as the ideal practice that is encouraged by the regulators (Hawkins, 2011). Such commonality in behavior raises two influential consequences on lending decisions: first, the "independent credit analysis by a given lender," and second, the influence of the given lender's decision on other competing lenders (Hawkins, 2011). Through incorporation of our parameters, we can take both of these uniformities under consideration, which we will introduce after we specify our functional form.

To finalize our model on lending socio-dynamics, we specify the functional form of the transition probabilities $p_{+-}(x)$ and $p_{-+}(x)$. Based on my prior literature review on Keynes and Minsky, the "leading influences in lending dynamics" are:

(i) banks decisions are made by relying on their own independent observations and analysis.

(ii) bankers are "willing to adapt to the peers' opinions once it becomes the majority," and that

(iii) bankers' "preference and their willingness to adapt may vary over time" (Hawkins and Kuang, 2017).

Incorporating these views as assumptions into opinion formation model equation, it implied our transitional probabilities are follows:

$$\begin{aligned} p_{+-}(n) &= we^{-(\delta+\frac{\kappa n}{N})} \\ p_{-+}(n) &= we^{+(\delta+\frac{\kappa n}{N})} \end{aligned} \tag{3}$$

Within these transition probabilities, we can now implement behavioral forces. δ becomes our preference parameter, where positive (negative) values reflects a disposition toward (against) lending in a particular market; The role of δ is to merge economic decisions with psychological attitude towards liquidity (Hawkins, 2011). To capture this role, we incorporate the profitability of farm sector as a proxy within δ. Based on our statistical review in section 3, we concluded that profitability of the farm sector was the driving factor in fluctuations of price and consequently, the fluctuations in lenders' opinions. Thus, the use of total rate of return on farm assets captures the core driving factors, which then would reflect in the evolution of social dynamics of our simulations and accurately influence the sentiment of the period towards farmland assets.

As the total rate of return (TRR) on farm assets increases, the quality of assets improve. To obtain our $\delta(t)$ as a function of TRR, we first normalized the values of TRR. When we normalize TRR, the range of $\delta(t)$ becomes 0,1, which then would not reflect the actual sentiment because the total rate of return on farm assets is negative in some ranges, and should certainly be accounted for within our sentiment. Thus, we subtracted the normalized value of the initial stage of $\delta(1960)$; subtracting the first stage allows our delta to start from zero and evolve into positive and negative ranges, which precisely reflects the sentiment around farmland assets from 1960 to 1987; we see a large increase in our $\delta(t)$ by 1973, then slowing down by 1978-1979 as the sudden changes in economic conditions unfold, and dropping down to negative values thereafter to show that the lenders were not inclined to lending.

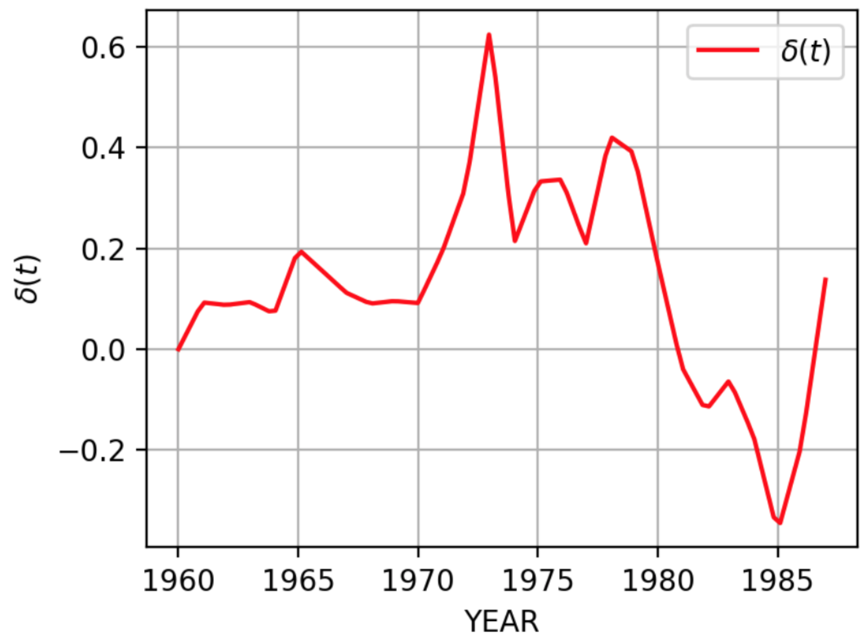

Figure 12: TRR: $\delta(t) = \pi_{\text{norm}}(t) - \pi_{\text{norm}}(1960)$

The effectiveness of profitability (TRR) as shown in the figure above as our main proxy is due to its ability to capture multiple factors of cost and income altogether. Moreover, our statistical analysis shows that the original and core factor in initiating the escalation in the boom and bust of farmland prices was profitability of farm sector. Furthermore, this proxy is superior to using price because it moves both in negative and positive direction, as does any boom and crash, whereas than price only rises for the most part and does not influence lenders' decisions until after the crash has occurred; therefore, we can conclude that using price as a proxy would not reflect the true sentiment of the period.

Next, we introduce κ as the adaptation parameter to capture the configuration under different decision-making processes; when $\kappa > 0$, the individual's opinion of asset is highly influenced by the opinion of the majority, and when κ is zero, they form their opinions in isolation and independently, as standard economic theory suggests. A non-zero κ also implies an addition of the factor of $\frac{n}{N}$, which further accounts for the strength of the general sentiment of the majority's opinion.

To construct a realistic $\kappa(t)$, we use the inverse of our $\delta(t)$, which implies as driving factors of the sentiment escalate, both the competitive effect and co-dependence of agents increase; however, our $\kappa(t)$ remains flat after it reaches its peak maximum value, which is reasonable because as the sentiment around the asset worsens in quality, the codependence and interaction of agents' does not drop, but instead either increases or flattens; thus, we allowed our $\kappa(t)$ to remain constant after it reaches its peak.

The following graph illustrates the evolution of our $\kappa(t)$ and $\delta(t)$ parameters:

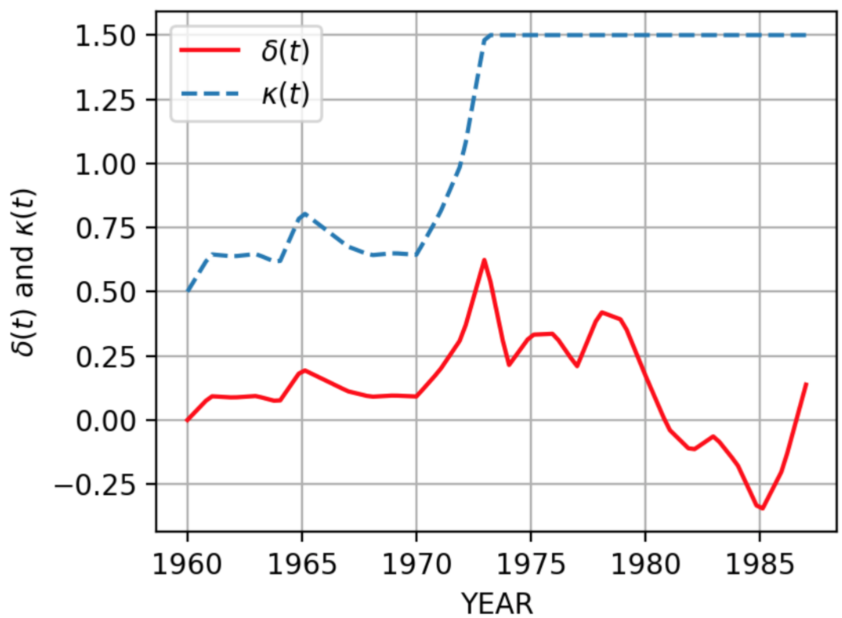

Figure 13: Sentiment and psychological parameters for our simulation.

Finally, ω as our flexibility parameter, measures how rapidly markets can collapse. Alternatively, ω is also interpreted as the frequency at which opinion changes occur in the society of lenders, which would be higher in a society with advanced technology, or one where agents are close friends and communicate often. In contrast, if lenders are forbidden to talk to each other or frictions exist in changing opinions on loans, then ω would be very low. We simulate our ω endogenously based on its relative relationship with the two other parameters, as a function of time.

As a robustness check, we used different proxies to illustrate the differences between independent and grouped decision-making; the results remained robust to different different proxies. Also, the 3-D configuration reflects the natural movements of the farmland sector as a function of time, which confirms our use of correct proxies and modeling of the 1980s farm credit crisis.

When we then change to $\kappa > 0$ to incorporate the underlying psychological preferences, we expected the distribution to show significant changes and polarize the distribution of opinions; the results unfolded as we expected. The implications of these findings are: holding everything else equal, even if we can build a nearly perfect and robust behavioral preferences for lender sentiment, we cannot eliminate impact of κ; when we account for interactions, majority opinion dominates, configuration polarizes, and becomes a basis for economic instability.

6 Simulations

6.1 Opinion Evolution in the Farm Credit Crisis

Now that the parameters of our model are fully established, we implement the simulation techniques used by Hawkins (2011) and Lux (2009a,b), and generate the 3-D illustration of the time dependent transition of opinion dynamics of lenders in the farmland sector in late 1980s. [5] The first illustration below shows the evolution of the lenders' state of opinions from 1960 to 1987, as a function of time and relative profitability of loans while $\kappa = 0$, which implies lenders decisions were being made independently from one another.

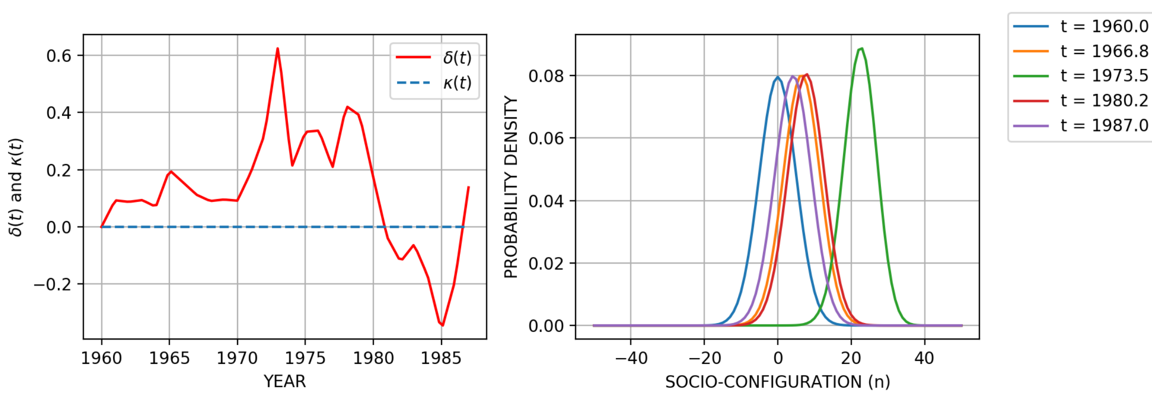

Figure 14: Evolution of Opinion Dynamics under Assumptions: $\delta = x_1, \kappa = 0$

[5] We illustrate the results from one of our proxies because the results remains robust to different proxies.

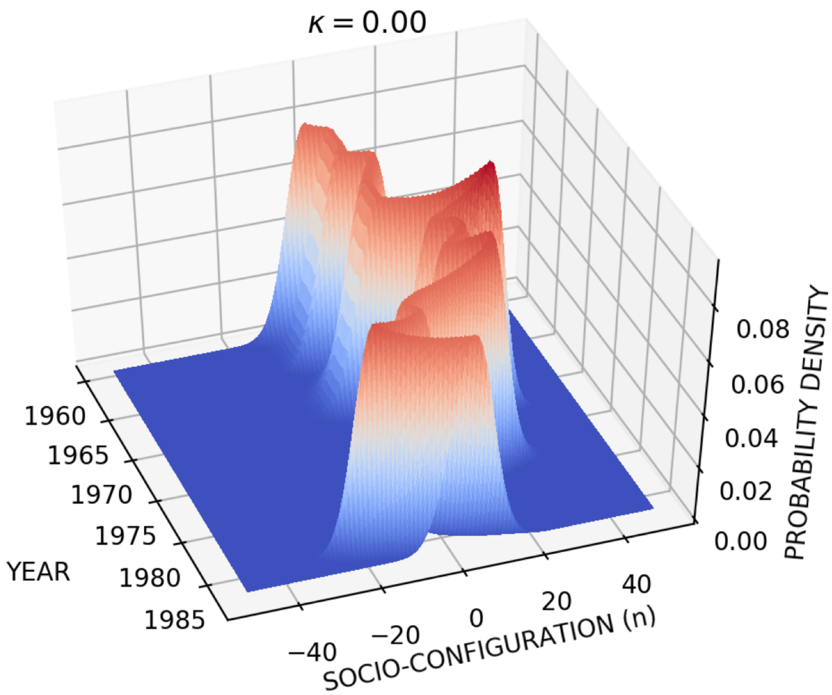

Figure 15: Evolution of Opinion Dynamics under Assumptions: $\delta = x_1, \kappa = 0$

Given $\kappa = 0$, we assume that all decisions to extend credit were made independently; however, based on Minsky's FIH, and proven by real industry experience and testimonials, it is not a realistic assumption to think agents' decisions are made without outside influence of colleagues and competitors; we need to account for the peer effects within the society of lenders to find a realistic transformation. We also see that the evolution of opinions from our simulation with $\kappa = 0$ contains no dramatic crash or polarization, which further implies the necessity for positive levels of interaction ($\kappa > 0$) between lenders for the crash to had evolve in reality.

Our model allows us to account for co-dependence and interactions amongst agents as we set $\kappa > 0$. As κ increases more, the impact of the majority opinion becomes greater on each individual lender's opinion formation. Eventually, group opinion is valued greater than individual, which makes the distribution more polarized, suggesting that the conditions can go from a boom to a bust in negligible time. In figure below, we illustrate the differences between the social dynamics of opinion formation under the assumptions of independent and co-dependent decision-making process for the lenders in the sector.

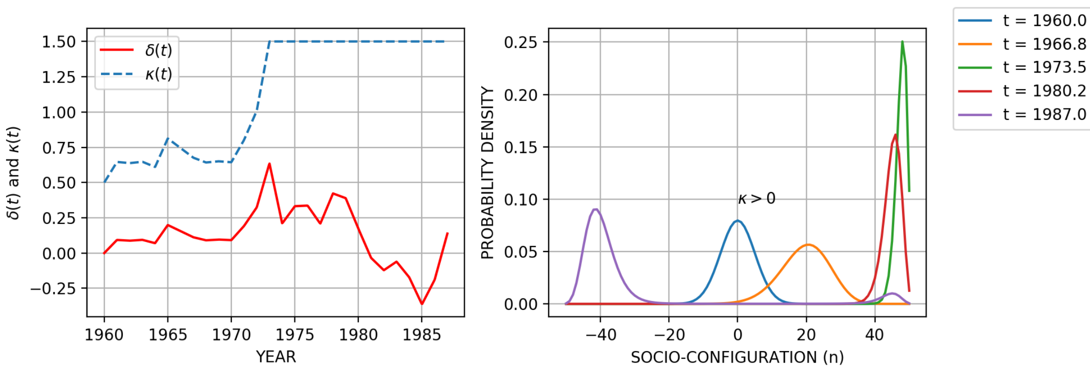

Figure 16: Evolution of Opinion Dynamics under Assumptions: $\delta = x_1, \kappa > 0$

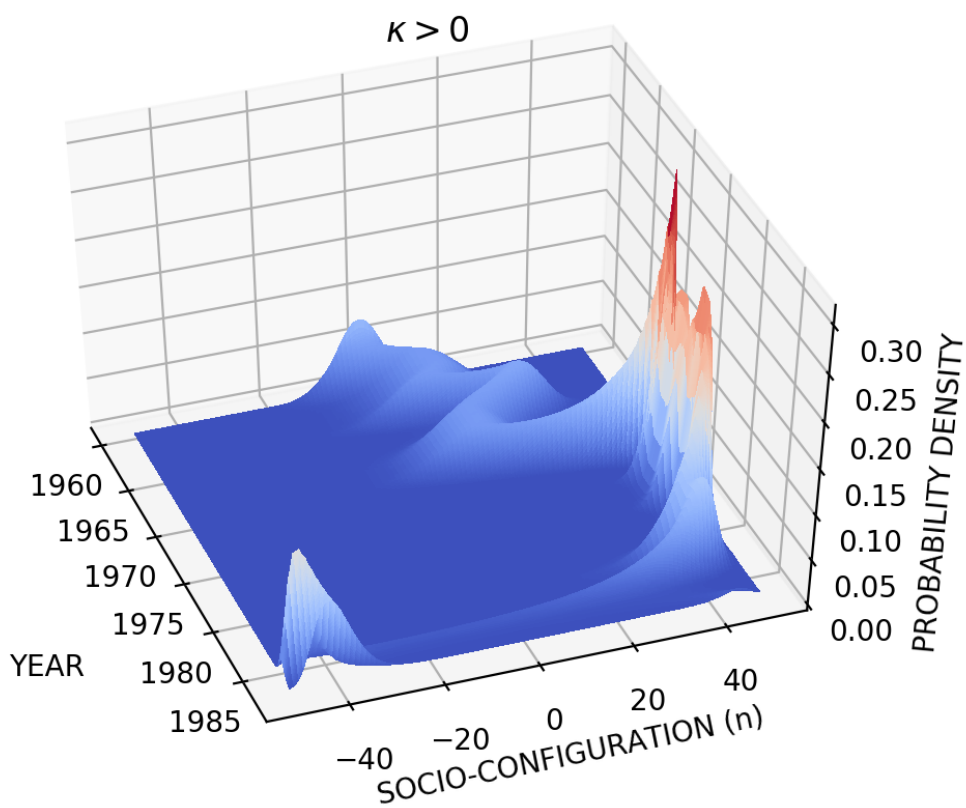

Figure 17: Evolution of Opinion Dynamics under Assumptions: $\delta = x_1, \kappa > 0$

The difference between the two assumptions are evident between our two figures. We can clearly observe the large shift and polarization when we set $\kappa > 0$, which reflects the shifts in opinions during the farm credit crisis. As the sentiment and competition increases, each agents decision to extend credit will be influenced more and more by their peer. We can conclude that higher κ imposes higher risk and much more polarization in opinions, at a much faster rate. Furthermore, the bubble and crash only occur in our simulation when we set $\kappa > 0$, which implies that accounting for interaction amongst lenders is essential while measuring risk and quality of assets. Most importantly, we observe the differences in the rate at which critical economic conditions could unfold when we account for the impact of majority opinion; based on our results, we can say that existence of co-dependence in agents' decision-making increases the rate of opinion formation to significantly higher levels than the assumptions made by classical economic models; even if we define preference parameters to nearly perfectly follow the true sentiment, the interaction impact is inevitable. Such results imply that incorporating κ into our risk allocation is crucial; failure to do, as we have seen it many times in history, can lead to financial crises.

"Bad loans" are made by those who are considered "good lenders" during economic booms. As the saying goes, a "financial genius is someone in good times with short term memory," and most times, average individuals cannot afford such short-term optimization due to the long-term implied risk. Thus, from the contrast in lender and borrower behavior in post-crises timelines, we can find potential moral hazard problems in this interaction. Therefore, in the last parts of this paper, we provide policy implication based on our model that could suggest potential solutions to these behavioral tendencies within the lending sector.

6.2 Lending Opinion Dispersion in a Boom

The results we produced suggest that if we account for psychological and behavioral parameters, then the transition of opinions becomes polarized quickly as time evolves. Moreover, our transition shifts from a low dispersion distribution around being willing to lend, to being highly concentrated with low dispersion around the opinion of unwilling to lend; such a quick shift occurs in one step, with two low spread distributions before and after the crash, which move directly from a boom to a bust. However, Carey's (1990) dissertation assumes an opinion formation that is contrary with the findings from our model. He assumed that opinion formation has three stages of evolution, which implies a much lower rate of transformation and crash in financial crises.

Carey's (1990) assumption on opinion formation follows with three stages of (1) most being willing to lend on farmland during a boom, (2) then a stage of high dispersion and variance amongst opinions of lenders in the market, and finally (3) to most being unwilling to lend. His assumption is illustrated in the following figure:

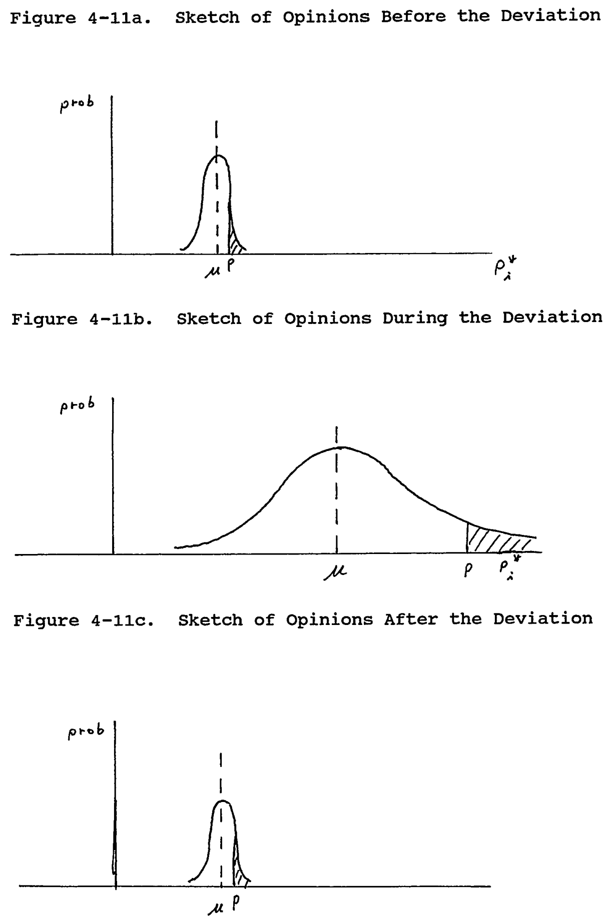

Figure 18: Figure 4-11 of (Carey, 1990, p. 137).

An interesting assumption on Carey's part is the high dispersion phase shown in panel B of Fig. 18. Given that our simulation and the actual story suggests a quicker shifts of opinions, we attempted to replicate and interpret such transition by using different parameters for $\delta(t)$ and $\kappa(t)$ to see if Carey's assumption are possible or even realistic.

Based on our replications and simulations that we showed in the last section, we did not see any high dispersion phases after the boom regardless of the values of $\delta(t)$ and $\kappa(t)$. Moreover, with the use of different proxies in our simulations, our results remained robust, strongly supporting that under any $\delta(t)$ and $\kappa(t)$, Carey's (1990) assumption does not hold.

To generalize and form our conclusion on Carey's (1990) assumption, we first have to connect his illustrations to our simulation and show how they related to our results. To start from the case under behavioral assumption of $\kappa(t) > 0$:

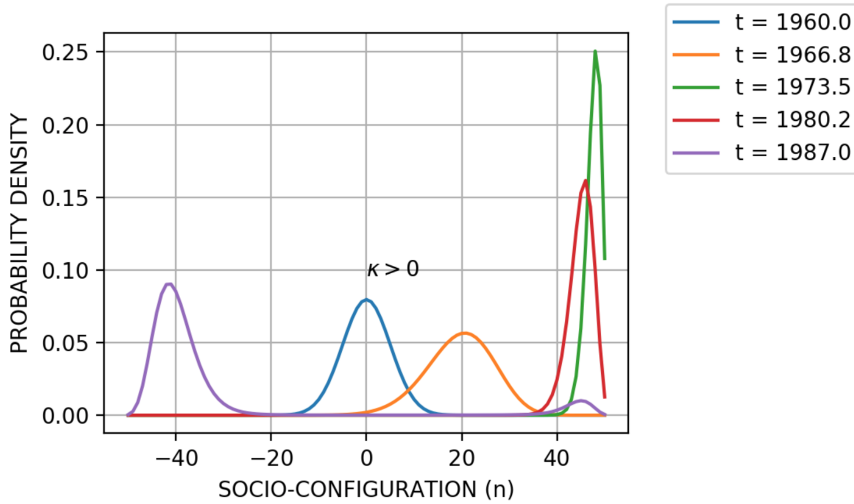

Figure 19: Result of Testing Carey's Assumption: $\delta = x_2, \kappa = 0$

We see that leading the boom, we have a period of high dispersion; however, since this period (1966) is prior to boom and crash, this distribution is unrelated to Carey's (1990) assumption. Carey focuses how opinions transform from boom to bust, and our market boom occurs post 1970.

The boom takes place in 1973, as we can see in the period $t = 1973.5$ of our simulation and in the panel of A of Fig. 18 of Carey (1990). We then see an intermediate time period of $t = 1980.2$ in our simulation, which leads before the crash to find any signs of increase in variance and spread of opinions as farm credit sector crashes in $t = 1987$; however, Fig. 19 shows that our transition of opinion from boom to crash is immediate. The opinions change from willing to lend towards unwilling to lend without any increase in variance and spread in distribution for the period of $t = 1980.2$. Thus, when the final stage of crash takes place, as seen in the period of $t = 1987$ of our simulation and panel C of Fig. 18, there exist no signs of intermediate stage of panel B in Fig. 18.

We then questioned whether $\kappa(t) > 0$ plays a role in our conclusions on Carey's assumption. Thus, we set our $\kappa(t) = 0$ to see if his assumption would hold.

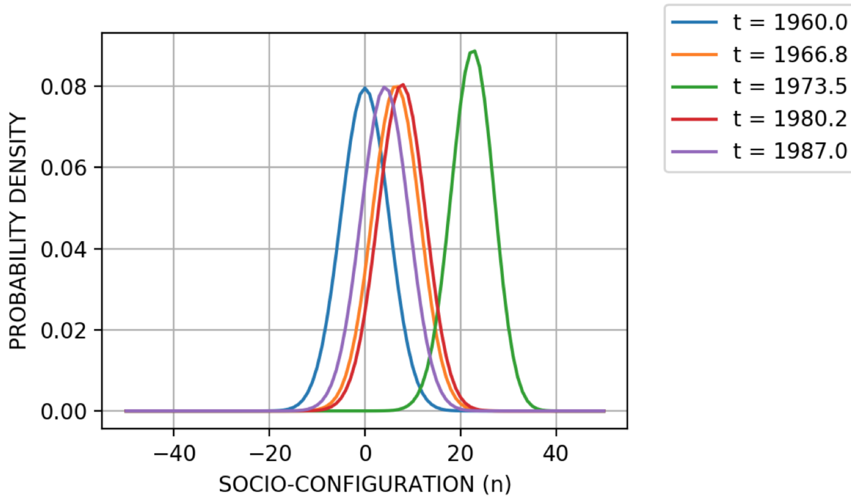

Figure 20: Result of Testing Carey's Assumption: $\delta = x_2, \kappa = 0$

Important to note is the necessity of having a positive κ for a crash to have happened, as we see no dramatic boom or bust in opinions, having assumed agents' decisions are independent of one another. We see in our socio-configuration that when $\kappa = 0$, we see that our distribution moves towards $n = 50$ by the period $t = 1973.5$ and relaxes back towards $n = 0$ by $t = 1980.2$; however, we see no change in dispersion and variance of our distributions in any of the stages of our transition between 1960 to 1987. Thus, with consistent results that are robust to κ and δ, we can conclude that the existence of the intermediate stage of panel B in Fig. 18 is not possible nor realistic assumption by Carey (1990).

7 Discussion and Summary

Financial crises affect people beyond the monetary value of default since people mostly choose jobs and careers based on their particular interest, passion, or status in life; the opportunity cost of time should also be considered since careers are a product of several years of hard work and dedication. Thus, the false prophecies of lenders who promoted loans during the booms and neglected or foreclosed when economic conditions change should not be forgotten. Instead, we ought to learn from these mistakes and never assume that economic conditions are everlasting. Our historical experiences strongly suggest that rapid booms are when lending practices should optimize most carefully; profit maximization should be under constraints of the potential risk of equally rapid, if not more, economic downturn.

As we have seen throughout history, it seems that short-term potential gains influence rationality of agents' preferences to break down and repeat the same behavioral mistakes:

making optimistic assumption of everlasting robust booms and/or having perfectly risk-adjusted lending practices. Generally, institutions and lenders have more resources to afford these costly mistakes and assumptions, given the history of bailouts and time-dependent recovery of balance sheets. In contrast, average people cannot afford these costly mistakes. Also, their risk and their potential gains are usually not measured by themselves, but rather given to them by the other party; thus, under such imperfect information, the interaction between lenders and borrowers becomes a problem of moral hazard with massive potential burdens on borrows and relatively protected lenders.

Although finding the specific policy is beyond the scope of this paper, we can examine each of our three-core behavioral parameter to find out potential directions we can take to reduce economic instability based on our model, in terms of its policy implications.

If we view ω as how rapid economic collapse can occur, we may think that somewhat less flexibility would be a good thing. However, the flexibility parameter also represents the how fast a lender can stop a mistake once they learn that it is a mistake. Under this alternate view, for both shareholders and policymakers, ω should imply that lenders can stop their mistakes as quickly as possible, as it is currently the case. Thus, this may not be the parameter of interest based on our model (Hawkins, 2011).

For δ, as our preference parameter, we might see potential useful applications for policy that reduces economic instability. Since both Keynes and Minsky argue for intrinsic uncertainty, implementing cognitive psychology into our policymaking process can in fact become key in understanding lenders behavior. Thus, δ could potentially be useful. However, finding such psychological theories are beyond the scope of this paper. Furthermore, even if we establish absolute precision of δ, we would still fail to remove economic instability (Hawkins, 2011). As shown in our graphs, holding δ equal, the influence of other lenders on the lending sentiment of a given lender is significant. Based on incorporation of Keynes's and Minsky's views in our assumptions, we see that economic instability increases for positive values of κ, and as κ increases, opinions are more polarized, and the instability worsens; even under perfect information on δ.

Supporting facts for lenders to have $\kappa > 0$, and value the opinion of the majority over their own, is almost certain. For example, during the 2008 housing crisis, Morgan Stanley's then CEO commented, "I missed a piece of business… I can live with that, but as soon as I hung up the phone someone else put up 10 times leverage. We cannot control ourselves. You have to step in and control the Street" (Hawkins, 2011). His comment clearly shows the general views of lenders on their peers' opinions.

Given that the adaptation parameter is positive, based on our results, we can conclude that lowering κ, in terms of our parameters, is the best potential approach for policies that lower economic instability. Lowering κ directly is challenging, since it would damage the freedom and the lifestyle of lenders; asking individuals not to interact or think of other's opinions seems unrealistic. Government interventions have also shown historic evidence of inefficiency and partisanship. Alternatively, we can indirectly remove the negative effects associated with κ through pooling lenders by their sector. Since lenders rely on the opinion of the majority too much, if we influence the opinion of the majority, then we have effectively solved the issue of interaction within lenders as implied by κ. Through enforcing a large shared punishment for the entire sector as a consequence of mistakes made by lender, we can align the group's goal with that of the individual. Subsequently, it would influence them to behave optimally and avoid reckless lending during booms. Through such policy, we effectively lower κ, and indirectly lower economic instability.

In summary, we have developed a sociodynamic simulation to represent the macroeconomic Keynesianism as articulated by Keynes and Minsky. Through Weidlich's model of opinion dynamics, we illustrate the case for decision-making of lenders in isolation, as well as codependent decision-making where lenders' influence the opinions of one another. The risk associated with lending is incorporated through lenders' sentiment around loan profitability, which views short term booms as the new norm. In our simulations, we endogenously generate the rapid changes in the lending opinions that reflect the changes in the profitability of the farm sector, and find our results are consistent with the dynamics of the rise and crash of the farm credit crisis of the 1980s. Furthermore, we use the simulation to test Carey's (1990) assumption concerning the temporal evolution of opinion dynamics during the farm credit crisis; our model suggests a different evolution of opinions than Carey's (1990) assumption. The parameters of our sociodynamic model incorporate elements of social psychology of lenders to reflect their management of both calculable risk and intrinsic uncertainty. Inclusion of lenders' social psychology within our model explains the robustness of financial instability phenomenon to the recent advances in risk measurement in our economy and suggests how policy for reducing instability can be driven in an experimentally sound manner through the behavioral scope.

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