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Transmission of Banking Crises Using a Proximity Based Learning Model

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Transmission of Banking Crises Using a Proximity Based Learning Model

By

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A Thesis Submitted to the Department of Economics
of Trinity College in Partial Fulfillment of the
Requirements for the Bachelor of Science Degree
Abstract

In financial markets, banks play a key role in transforming illiquid assets into more liquid assets. However, their ability to spread the risk of liquidity shocks over a body of agents generates a positive probability for non-efficient bank runs. Building off of the classic Diamond-Dybvig framework, this paper uses an agent based model to observe the two equilibria, efficient risk sharing and the bank run. While previous literature has looked at under what conditions could a bank run equilibrium occur, this proximity based learning model (PBLM) focuses on the development of a panic driven bank run in light of limited information, proximity based learning, and localized interactions among heterogeneous agents. This simulation approach is novel in that it allows for the inclusion of more realistic conditions (e.g. heterogeneity and learning) that would make such a model difficult to solve, if not mathematically intractable. This paper finds proximity based learning to be an effective method of communication and a panic transmission mechanism when consumers only have limited information.
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Friends
You make Trinity a place I’m sorry to leave.

Family
Thank you for the never-ending support through everything.

Words of Wisdom
It’s amazing what you can do in one night.

Economic intuition is like peeing. It starts with a trickle, but when it flows it flows.

To view the final presentation of this thesis, please visit:
https://drive.google.com/open?id=0B0MoyidSAj1zdE1XdXZ1dnhrUzg

To view the source code for this project, please visit:
https://github.com/syee/Lending-Market-ABM/tree/master
Introduction

Banks are able to transform underlying illiquid assets into liquid assets that are preferable to risk averse consumers. However, this liquidity service comes at the cost of creating a positive probability of a bank run. Diamond and Dybvig (1983) explored this concept using a framework that would become the standard in bank run literature. The Proximity Based Learning Model (hereafter referred to as the PBLM) expands on Diamond and Dybvig’s model (hereafter referred to as the DD model) by using proximity based learning as an explicit panic transmission mechanism. This is a clear diverging from the DD model which assumes all consumers have access to the same information so they can simultaneously panic and essentially coordinate a bank run. Through the use of proximity based learning, the PBLM is able to uniquely observe how panic can start at the individual level and organically develop into a system wide phenomenon.

Since the DD model is discussed throughout this paper both directly and in comparison to the PBLM, I will now give only brief overview of the DD model. In the DD model, consumers are each endowed with an illiquid asset that offers a low return after one period or a high return after two periods. Type 1 consumers will wish to consume their asset after one period and type 2 consumers prefer to consume after two periods. Starting in period 0, consumers do not know their type. Thus they each face “a privately observed, uninsurable risk of being of type 1 or of type 2.” A bank is able to pool these assets and offer a liquid asset that offers a higher return after one period and a lower return after two periods. Assuming

\[^{1}\text{DD (1983) p.405.}\]
consumers are sufficiently risk averse, banks can create an optimal risk sharing that provides greater utility to both type 1 and type 2 consumers. However, if a larger than expected proportion of consumers are identified as being of type 1, the system is at risk for a bank failure where all consumers attempt to liquidate their asset after one period regardless of their type.

Each consumer has one opportunity to withdraw assets from the bank after one period and they do so under the sequential service constraint. They essentially line up and are served in a random order one at a time until the bank has no more assets. Any remaining assets are distributed equally among any consumers that elected not to withdraw in the next period. In the DD model, each consumer is aware of the intended withdrawals of all other consumers. If enough consumers intend to withdraw their assets after one period that the bank will not be adequately endowed for the next period, all consumers are aware of the impending liquidity shortage. In this case, all consumers will attempt to withdraw assets from the bank regardless of their type (i.e. type 2 consumers would also attempt to withdraw). This is considered the bank run equilibrium that “provides allocations that are worse for all agents than they would have obtained without the bank.”

The idea that consumers all share the same complete knowledge is criticized in several other papers as not being realistic. Goldstein and Pauzner (2005) build off of the DD model but instead have investors “observe noisy signals” regarding the fundamentals of the economy. All noisy signals are based off of fundamentals, but there is no communication between investors regarding the different signals.

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Goldstein and Pauzner find that the noisy signals can give investors incorrect expectations regarding the state of the system and actually lead to bank runs

“even when the economic environment is sufficiently strong that depositors would not have run had they thought other depositors would not run.”

This idea of a panic or run occurring even though fundamentals were strong will be referred to in the PBLM as unnecessary. Goldstein and Pauzner determine the “probability of panic-based runs and relate it to the [banking] contract.” They find that the more risk sharing created by the banking contract, the greater the probability of a bank run.

Chari and Jagannathan (1988) use an idea where if a group of consumers withdrawing was unusually large, “uninformed individuals will be misled and will precipitate a run on the bank.” This is consistent with the popularized idea of the Great Depression where observing long lines outside of banks made consumers nervous about the possibility of bank failures and thus inspired them to join the line and also withdraw their money. Not only would this increase liquidity strains on banks, the line would get longer encouraging even more individuals to panic. Chari and Jagannathan found the above idea could lead to bank runs “even if no one has any adverse information about future returns.” In their study, these unnecessary panics impose social costs as well as liquidation costs.

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5 Ibid
A key differentiator between the PBLM and the other studies that have been mentioned is the focus the PBLM places on the panic transmission process. The PBLM uses learning where consumers have the opportunity to gather information from their peers. A consumer then uses that information to form beliefs about the state of the system. Consumers use these “ad-hoc expectations” that are not entirely rational to then make decisions regarding panics. For example, Consumer A might look at his neighbors and see they are all withdrawing large sums from the bank. Consumer A would use that information to infer that overall liquidity demands on the bank are so high that Consumer A panics and withdraws his money too because he thinks the bank might fail. Consumer A’s decision to panic will affect any other consumer that observes him. Thus readers can see how the learning process allows information to spread in a social network like manner.

Kelly and O Grada (2000) conducted an empirical study based on this

“idea of market panics spreading through social contagion—where individuals hear some bad news and communicate it to their acquaintances, who pass it on in turn, leading to a market panic.”

They looked at two bank runs that occurred in a New York bank in the 1850s. Using old marriage records and large amounts of background information on depositors, Kelly and O Grada were able to reconstruct the social networks of account holders of the bank. They found “the most important factor in whether they [depositors] panicked...was county of origin.” This was indicative of the social network structure of many of the Irish immigrant depositors. Using a social network as a

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8 See Proximity Based Learning Section for details.
source of information and communication like the PBLM does through learning is supported by the empirical results found by Kelly and O Grada.

The reason this project is significant is that bank runs are bad. Bernanke (1983) and Friedman and Schwartz (1963) found that bank runs imposed huge costs on the U.S. economy in the 1930s. Diamond and Dybvig also argue “runs are costly and reduce social welfare by interrupting production (when loans are called) and by destroying optimal risk sharing among depositors.”

While bank runs can be inevitable if initial withdrawals are large enough, bank runs can also develop if consumers unnecessarily panic due to what Goldstein and Pauzner call bad expectations. All of the studies mentioned thus far indicate panic create panic. Thus enough unnecessary panics can actually increase liquidity demands on a system to the point where it will fail when it should not have had consumers not been fearing a panic. The PBLM uses learning so that the panic transmission process can actually be modeled in a way where factors that affect the probability of unnecessary panics can be identified.

Learning allows the PBLM to identify how the spread of panic at the individual level can translate into patterns on a larger scale. While consumers technically panic individually in the DD model, they all share the same information and draw the same conclusion at the same time. Either no one panics in the DD model (the good risk sharing equilibrium) or everyone panics and the bank fails (the bad bank run equilibrium). The DD does not provide for any middle ground where

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12 Panics are bad in very similar ways to bank runs. Using terminology of the DD model, a type 2 consumer could unnecessarily panic and withdraw her assets after one period. This would be an inefficient outcome given that she could have held the asset longer and received a higher payout.
some consumers may panic but others may not. The PBLM is able to provide this middle ground when consumers have only limited information to act upon. Further, this information is transmitted to and from a social network like process like what was empirically supported by Kelly and O Grada regarding two bank runs in the 1850s. The PBLM applies this idea of networking via proximity based learning to the standard DD framework. The results of this study support that proximity based learning is an effective method of panic transmission in light of limited information. The results are also consistent with the idea that increasing risk sharing increases the probability of bank failures. Most importantly, this paper finds that information from limited sample sizes can cause consumers to inaccurately diagnose system fundamentals so increasing the visibility in the system can prevent costly, unnecessary panics.
Model Overview

The PBLM is essentially the DD model repeated continuously. This will be made clearer in following sections. In each time period the following actions are executed in the order below.

All consumers execute each action in a random order. E.g. all consumers move in some random order. Then all consumers discover their net income in a random order. The order can change from action to action and period to period.

1. Consumers move – Consumers randomly move around the bank.
2. Bank pays operating cost if period > 0
3. Consumers discover net income for period
   - If net income is positive, it is deposited it into the bank.
   - If net income is negative, the consumer withdraws assets from the bank to cover deficit.
4. Consumers perform proximity based learning
   - Consumers can decide to panic and withdraw all their assets from the bank.
5. Consumers pay back deficits
6. Consumers go bankrupt if they have an unpaid deficit
7. Bank goes bankrupt if it was unable to meet any obligations
8. Consumer and bank assets grow
**Consumer Net Income Overview**

In the beginning of each time period, each consumer earns income $Y_i,t$, consumes a fixed proportion of that income $C_{i,t}$, and faces a positive probability of a negative monetary shock $X_{i,t}$. Together, in each period, these three variables determine each consumer’s net income $I_{i,t}$ which is described by

1. $I_{i,t} = Y_{i,t} - C_{i,t} - X_{i,t}$

**Consumer Gross Income**

Each consumer’s income is randomly drawn from a truncated normal distribution with mean $Y_i^*$. In doing this, the PBLM breaks away from the common modeling assumption that incomes are standard across all agents. This is important in that the agents here are consumers that almost certainly have varying incomes in real life. Further, this increased heterogeneity plays out in meaningful ways as consumers have interactions that depend on their levels of wealth and net incomes.

To be exact, each consumer’s income in a single period is randomly drawn from that consumer’s normally distributed income curve. This is to reflect possible fluctuations in areas such as hours worked or bonuses accrued such that a consumer’s income is not necessarily constant over time. A consumer’s income curve is identical from period to period to represent the assumption that a consumer’s income is consistent over time. The consumer’s income curve is determined as soon as the consumer is instantiated. However, the mean of each

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13 The distribution is truncated so that consumers only have positive incomes.
consumer’s income curve is initially and singularly randomly drawn from a truncated normal distribution with mean $Y^*$.\textsuperscript{14} This step generates the heterogeneity in consumer income curves.

**Consumer Consumption**

When consumers are instantiated and their income curves determined, their level of consumption for the entire simulation is also determined. Each consumer’s level of consumption is individually and randomly drawn from the same truncated normal distribution with mean $\gamma^*$ and remains constant throughout the model.\textsuperscript{15,16} Similar to the way each consumer’s income curve has a mean initially drawn from a random distribution, this further adds to the level of heterogeneity into the model in a way representative of actual consumers and meaningful in consumer interactions. Where a consumer’s income in the period $t$ can be described by $Y_{i,t}$ and the consumer’s rate of consumption is $\gamma_i$, the consumer’s consumption $C_{i,t}$ is described by

2. \[ C_{i,t} = \gamma_i(Y_{i,t}) \]

An analogous argument to the one above regarding the consistent but not constant incomes of consumers could be made about their levels of consumption. However, what are most important to this model are the varying levels of wealth

\textsuperscript{14} Hence the expected mean of every consumer’s income curve is $Y^*$ before they are instantiated. 
\textsuperscript{15} The distribution is truncated so that no consumer’s level of consumption is greater than 1 or less than 0. 
\textsuperscript{16} The expected level of consumption for each consumer is $\gamma^*$ before they are instantiated.
and net income. Both of these are already significantly affected by varying one’s income from period to period. While drawing a consumer’s level of consumption each period would certainly add to the model’s heterogeneity, it does not do so in a way not already captured by the model.\textsuperscript{17} For the sake of simplicity, each consumer’s level of consumption is assumed to be constant over time.

**Consumer Negative Shocks**

Each consumer also faces a positive probability $\lambda$ of a negative monetary shock in each period. These shocks are idiosyncratic and proportional to the consumer’s income in the period.\textsuperscript{18} Where the proportion of the shock to the consumer’s income is $\Psi > 0$, the monetary value of the shock for a consumer in period $t$ $X_{it}$ can be described by

$$X_{it} = \begin{cases} 0 \text{ if the shock does not occur} \\ -\Psi(Y_{it}) \text{ if the shock does occur} \end{cases}$$

\textsuperscript{17} It could be argued that varying income alone creates much of the heterogeneity needed in the model and that consumption could be constant across all consumers and time periods. However, the benefits of making consumers more heterogeneous in this manner were deemed to outweigh the cost of making programmatic changes to the simulation.

\textsuperscript{18} Much thought was given as to whether or not there should also be systemic shocks in the model. A systemic shock would be interesting, especially given recent financial crises. However, accurately reflecting the fear of a systemic shock in each consumer’s decision to panic is not a simple task nor is adding a systemic shock to the simulation at all. There also arose the question of the place of a systemic shock in the overall significance of the model. The two main panic conditions compare liquidity demands to the bank’s capitalization and the idea of panic directly leading to more panic. A systemic shock would have an impact on both as it would push liquidity demands even higher, causing consumers to panic which, causes consumers to panic. But it does not clearly add a new element of panic to the model as it is currently designed. If this model were designed to analyze optimization behavior, a systemic shock could have greater meaning depending on how risk aversion was defined in the consumers.
This shock is large enough such that when it occurs, it is larger than the consumer’s expected savings (income – consumption).\textsuperscript{19} Thus the consumer will experience negative net income or a deficit when a shock occurs.

The probability of the shock occurring, $\lambda$, and the proportion of the shock to the consumer’s income, $\Psi$, are constant across all consumers for the entire simulation. As mentioned previously, an argument that these should have been idiosyncratic and possibly fluctuating from period to period could have been made. However, the heterogeneity in income is sufficient for this model such that $\lambda$ and $\Psi$ can be held constant for the sake of simplicity.

This shock could be thought of as a medical emergency or any type of large unforeseen expense. It mirrors the DD in which consumers do not know whether they are type I or type II consumers until they need to make a liquidity decision. In the PBLM, consumers need extra liquidity should they be struck by a shock in the period. The random nature of the shock is essential in creating private risk for consumers. Further, this shock is directly uninsurable.\textsuperscript{20} “An investor cannot buy direct insurance against his need for liquidity, because the need is private information” and thus unobservable.\textsuperscript{21} This risk creates the risk-averse consistent behaviors at the cores of both the DD model and the PBLM.\textsuperscript{22}

\textsuperscript{19} It will later be shown that $\lambda \Psi > 1 - \gamma^*$ in order to keep the system stationary.
\textsuperscript{20} See Diamond and Dybvig page 403 for a full explanation as to why this shock is uninsurable.
\textsuperscript{22} Diamond (2007) calls this the uncertain horizon of holding the asset. Consumers are able to hold an asset that yields a higher return if held for two periods as opposed to just one period. This idea will be elaborated on in more detail later.
**Consumer Net Income**

A consumer’s net income $I_{i,t}$ is determined by the consumer’s income, the consumer’s consumption, and whether or not a shock is experienced. Since all these variables have consistent expected values over time, $\mathbb{E}[I_{i,s}] = \mathbb{E}[I_{i,t}]$ for any periods $s,t$. In any period for a specific consumer, the expectation of $I_i$ can be written in terms of $Y_i$ as shown below

4. $\mathbb{E}[I_i] = \mathbb{E}[Y_i](1 - \gamma_i - \lambda \Psi)$

Note that before the model is created and consumers are instantiated, all consumers are expected to be identical so the subscript for the consumer can be dropped. The expectation of any consumer’s net income in any period is

5. $\mathbb{E}[I] = Y^*(1 - \gamma^* - \lambda \Psi)$

In a later section, $\mathbb{E}[I]$ will be shown to be crucial in keeping the expected level of wealth in the overall system constant over time.

If a consumer has net income such that $I_{i,t} > 0$, they can invest $I_{i,t}$ in an asset with a two-tiered return (a low return if held for one period or a high return if held for two periods) and carry these savings into the future. A consumer will earn positive net income if they do not experience a negative shock since $X_{i,t} = 0$. In this case,

$$I_{i,t} = Y_{i,t} - C_{i,t}$$

$$I_{i,t} = Y_{i,t} - \gamma_i Y_{i,t}$$

$$I_{i,t} = Y_{i,t} (1 - \gamma_i) \quad \text{where } 0 < \gamma_i < 1$$

6. $I_{i,t} > 0$
If a consumer has net income such that $I_{1t} < 0$, the deficit must be paid back in the current period through accumulated savings; otherwise the consumer goes bankrupt and must leave the simulation. As mentioned above, this deficit occurs when a consumer experiences a negative shock.

The heterogeneity in the net incomes of consumers allows for the observation of heterogeneous consumer interactions and how those interactions can lead to bank panics.
**Underlying Asset**

At the heart of this model is an illiquid riskless asset. The illiquid asset here is defined as one that yields a high return if it is held for a long period or a low return if it is only held for a short period. If the asset were held for zero periods, it would simply return its face value (or purchase price). This asset is illiquid because its early liquidation value is less than its full maturation value.

Diamond and Dybvig attribute the illiquidity of the asset to a number of possible reasons. It could be that the asset “provides low levels of output per unit of input if operated for a single period but high levels of output if operated for two periods”\(^\text{23}\) or there are selling costs when consumers are “unexpectedly forced to ‘liquidate’ early.”\(^\text{24}\) The exact nature of the illiquidity is immaterial to both the DD model and the PBLM so long as the asset is illiquid. The real cost of early liquidation makes bank panics that “are costly and reduce social welfare by interrupting production (when loans are called) and by destroying optimal risk sharing among depositors.”\(^\text{25}\) Friedman and Schwartz (1963) found that bank runs in the 1930s imposed large costs on the United States economy.

The PBLM illiquid asset is in the same vein as that of the DD model. The asset has a price of 1 and can be purchased fractionally and in unlimited quantities.\(^\text{26}\) The

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\(^{24}\) Ibid

\(^{25}\) Ibid

\(^{26}\) The supply of assets is infinite and exogenous to the system. For the sake of this model, banks are also able to invest in this underlying asset. This allows banks a greater level of autonomy needed to operate in an environment with an unbounded number of periods. It is unclear whether or not this type of operation would be permissible in the original DD model. In the DD model, consumers provide the
illiquid asset here yields a full maturity return $\beta_b$ if it is held for two periods, or a lower return $\alpha_b$ if the asset is liquidated before maturity after only one period. The holding duration does not need to be determined a priori and the return is determined solely by the holding duration. The PBLM returns follow the inequality $\beta_b > 1$ and $\beta_b > \alpha_b > 0$. The lower the ratio $\frac{\alpha_b}{\beta_b}$ (ceteris paribus), the more illiquid the asset. Further,

7. $\beta_b > \alpha_b^2$

The above indicates that the holder of the asset receives a greater payoff for holding the asset for two periods consecutively as opposed to holding it for one period, liquidating it, and then reinvesting it for a second period. Thus there exists a real penalty for liquidating the asset before full maturity. The cost of liquidating an asset after one period instead of two is the difference in returns, so it has a value of

8. $\beta_b - \alpha_b > 0$

From hereafter, this underlying asset will also be referred to as the bank asset. The reasoning for this new name will be fully described in the next section. In essence, this is the asset that banks hold and use to offer a more liquid asset that a sufficiently risk-averse consumer would prefer.
Consumer Asset

Diamond found “sufficiently risk-averse investors, but not risk-neutral investors, are willing to give up some expected return to get a more liquid asset.” 27 “Sufficiently” depends on the differences between the full maturity and the early liquidation returns as well as the probability of the negative shock occurring. 28 The negative shock has already been identified as not directly insurable due to its unobservable nature. However, banks are able to pool the underlying assets and create a more liquid asset that provides more utility to sufficiently risk-averse consumers. 29 “In this role, banks can be viewed as providing [indirect] insurance that allows agents to consume when they need to most.” 30

This more liquid asset will be referred to as the consumer asset since it will effectively be the only asset consumers hold via the bank. 31 Let the consumer asset yield a full maturity return of $\beta_c$ if held for two periods, or a lower return of $\alpha_c$ if the asset is liquidated before maturity after only one period. All rules applied to the underlying asset still apply to the consumer asset. Thus $\beta_c > \alpha_c > 0$ and $\beta_c > \alpha_c^2$ and

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28 This statement should be analyzed by observing the decisions investors make to optimize their returns. The problem of optimization is beyond the scope of this paper as it would require much more complex decision making rules than what the PBLM currently uses. More specifically, the optimizing consumer would most likely not choose to invest all of his or her resources into the liquid asset as this would expose the consumer to a positive probability of a bank run. Calculating this probability is likely intractable in a model as dynamic as the PBLM but it would be necessary for a consumer to optimize. Instead the consumer would invest a portion of their assets in the riskless underlying asset directly and hold the other portion in the bank's liquid asset.
29 Diamond (2007) pp.191-192. Diamond provides a concrete example where this is true.
31 The underlying asset is called the bank asset by this same reasoning.
the real penalty for liquidating the consumer asset before full maturity has a value of

9. \[ \beta_c - \alpha_c > 0. \]

Since this consumer asset is more liquid than the bank asset,

10. \[ \frac{\alpha_c}{\beta_c} > \frac{\alpha_b}{\beta_b} \]

Essentially, the bank takes the relatively illiquid underlying asset and creates a new asset with a higher return after one period, but a lower return after two periods compared to the underlying asset. Mathematically, this statement means

11. \[ \beta_b > \beta_c \]

12. \[ \alpha_b < \alpha_c. \]

This allows consumers to access the higher two period return after just one period should they suffer a negative shock and need extra liquidity. This set of the bank asset returns and consumer asset returns can be thought of as the banking contract or demand deposit contract between banks and consumers.

Notice that when consumers liquidate their assets after a single period, the bank experiences a real loss with a value of \( \alpha_c - \alpha_b > 0. \) When consumers wait until their assets fully mature, the bank earns a real profit with value \( \beta_b - \beta_c > 0. \)

In the DD model, the bank is a mutual bank meaning that consumers “not withdrawing in period 1 get a pro rata share of the bank’s assets in period 2.”

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32 It will be discussed later, but this mismatch of returns exposes all agents to bank failures.

33 DD (1983) p.408. The banks return all profits to the consumers. This would mean a type 2 consumer receives either no return in the event of a bank failure or a return equal to the bank’s remaining assets divided by the number of type 2 consumers.
certainly reasonable for a 3 period (single cycle) model, it does not make sense for a model with an unbounded number of periods. In the PBLM, banks carry over any profits from period to period and reinvest them to better meet any future obligations.\textsuperscript{34}

In the PBLM, banks are not able to provide this liquidity service without cost. Each bank must pay an amount $D > 0$ each period. This can be considered as the operating cost of the bank. This is not unreasonable, as one would expect such a system to at least need a highly capable teller handling consumer deposits and withdrawals.\textsuperscript{35}

This operating cost does not exist in the DD model, but it is not a significant change to the model. As described in the previous paragraph and footnote 33, this would be a decrease in the bank’s worth after period 1. This would simply lead to slightly lower returns to type 2 consumers in a way that does not thematically change the model. This will be made clearer in the following section on DD equilibria.

There are also other DD assumptions made about each consumer initially having the same endowment and they only liquidate their assets in their entirety.\textsuperscript{34} See footnote 15 for an explanation on why PBLM banks are able to directly invest in the underlying asset.\textsuperscript{35} DD (1983) elected to make the underlying asset illiquid through the imposition of some unknown cost in a perfectly logical manner. That same logic is now also being applied to the banks in that operating banks should not be cost free.
Diamond and Dybvig Equilibria

Diamond and Dybvig Tipping Point

In the DD model, if a large enough proportion of the consumer population elects to withdraw their consumer assets after just one period, the bank cannot possibly meet all of its obligations, as the value of its assets will be less than the value of its liabilities. Consider the case where 100 consumers each have $1 so they collectively deposit $100 into the bank. After one period, the bank’s assets have a present value of $\alpha_b$($100$) but liabilities with a present value of $\alpha_c$($100$) and $\alpha_b < \alpha_c$. If the proportion of type 1 consumers, who fully withdraw their money from the bank after one period, $T_1$, is large enough such that

$$\beta_c = \frac{\beta_b \left( \alpha_b - \alpha_c(T_1) \right)}{\alpha_b (1-T_1)} < \alpha_c$$

the bank will fail. If $\beta_c < \alpha_c$, all consumers, not just type 1 consumers, have an incentive to withdraw their assets after one period instead of waiting another period to receive a lower return. Thus all consumers would attempt to withdraw their money after one period.

Essentially, bank runs occur any time that withdrawals in period one are too large. At this point, the bank’s leftover assets are so small that when they are evenly distributed among the remaining consumers in period two, those consumers receive a return less than what they could have received from the bank after just one period, $\alpha_c$. Thus the benefit of waiting an additional period to receive returns is now

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$36$ This follows the idea that type 2 consumers receive a pro rata share of the bank’s remaining assets as described previously. The operating cost mentioned in the previous section would decrease the total remaining assets for the bank (the numerator) such that consumers would receive a lower $\beta_c$. 

negative so all consumers would attempt to withdraw their money after one period regardless of their type.

**Sequential Service Constraint**

Both the DD and PBLM operate under the sequential service constraint. In Diamond and Dybvig’s words, this means

“Withdrawal tenders are served sequentially in random order until the bank runs out of assets. This approach allows us to capture the flavor of continuous time (in which depositors deposit and withdraw at different random times) in a discrete model.”

Consider Consumer A and Consumer B waiting in line to withdraw their money from the bank. If Consumer A withdraws the last $10 of the bank’s assets, Consumer B and every consumer after him will receive nothing from the bank and lose their entire savings. Thus if consumers realize that their collective withdrawals are large enough relative to the value of the bank’s assets, they have an incentive to withdraw all of their money from the bank regardless of their personal liquidity needs. This is how Diamond and Dybvig and the PBLM define a consumer panicking.

In the DD model, at the tipping proportion of type 1 consumers $T_1$ (described above) or any proportion larger than $T_1$, all consumers panic and make a run on the bank.

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38 “Large enough” as defined by the tipping point mentioned earlier.
39 Consumers do not want to be the last ones holding that hot potato that is a worthless IOU.
40 This idea of panicking will be addressed more thoroughly later in this paper.
bank, causing a bank failure.\footnote{This idea of all consumers panicking together will be explored more in depth. This idea makes the terms bank panics and bank failures synonymous in the DD as consumers only panic if the bank is going to fail and if the bank is going to fail, consumers panic.} This tipping point is unavoidable due to the nature of an effective banking contract. “A demand deposit contract which is not subject to runs provides no liquidity services.”\footnote{DD (1983) p.409.} As long as the liquidities of the underlying asset and asset offered to consumers do not perfectly match, there exists a positive probability of a bank run since in theory all consumers could elect to redeem all assets at the higher bank return which is greater than the actual return of the assets.

Extending this idea to the PBLM, the tipping point is deemed to be when the bank’s assets are not sufficient to cover expected obligations in the next period (and the current period too). At this point, consumers expect the bank to be unable to service all withdrawal requests in the immediate future. In this situation, consumers will panic and withdraw their money early to avoid being among those consumers that will lose all assets when the bank fails.

Diamond and Dybvig call this the bank run equilibrium. It “provides allocations that are worse for all agents than they would have obtained without the bank (trading in the competitive market)” because “all production is interrupted at $T = 1$ when it is optimal for some to continue until $T = 2$.\footnote{Ibid} Further, any consumers that are not served by the time the bank runs out of assets receive no return at all and lose the entire value of their initial investment.

If the tipping point of withdrawals is not reached, consumers will not panic and there will be no bank run. Diamond and Dybvig refer to this as the efficient risk
sharing or good equilibrium. In this outcome, the consumers that needed the extra liquidity were able to obtain it and the consumers that were not shocked are able to tap into the higher full maturity return of their investment while still having protected themselves from the potential shock.

It is interesting to note that the sequential service constraint is actually only present in period 1 of the DD model. The idea of the pro-rata share eliminates the sequential service constraint in period 2. This change is unaddressed by Diamond and Dybvig. However, it is reflective of their uses of mutual banks, a “flexible” banking contract, an abstraction of true risk-aversion and optimization, the fact that there are exactly 3 periods, and homogeneity assumptions about consumers. Under the assumption that the banks are mutual banks, it is logical that each consumer should receive a pro-rata share of assets assuming they put in the same amount initially as Diamond and Dybvig assume. The flexibility of the banking contract is shown in equation 13.\textsuperscript{44} The full maturity return consumers expect, $\beta_c$, does not actually have a definite value. $\beta_c$ is essentially a function of the proportion of consumers that are type 1.

If the consumers were promised at least an actual value for $\beta_c$ (let it be $\beta_c^*$), the tipping point would change to

\begin{equation}
14. \quad \frac{\beta_b \left( a_b - a_c(T_1) \right)}{a_b(1-T_1)} < \beta_c^*
\end{equation}

This would reflect the fact that even if the pro rata share of bank assets in period 2 is larger than $\alpha_o$, each consumer would be entitled to $\beta_c^* > \alpha_c$. Thus the pro rata share

\textsuperscript{44} There is no strict value of $\beta_c$. It is simply the pro-rata share of all leftover assets in period 2. It is considered flexible because it depends on withdrawals in period 1.
must be at least $\beta_c^*$ as is reflected in equation 14. If the pro rata share were between $\alpha_c$ and $\beta_c^*$ exclusive, under the sequential service constraint at least one consumer would not receive the full $\beta_c^*$.\footnote{All consumers would attempt to receive a share of $\beta_c^*$. Under the sequential service constraint, all consumers would receive the full $\beta_c^*$ so long as the bank had the assets. By the pigeonhole principle, this necessitates that at least one consumer would receive a share less than $\beta_c^*$.} Hence, consumers correctly fearing that they might not receive a return after two periods would panic in period 1 and withdraw all their money then.\footnote{This statement is somewhat untrue given that true risk aversion does not exist in the model. The impetus for seeking to avoid losing one’s money implies that there is some utility possibly derived from having money. Although that utility function is not defined in the PBLM (or DD in specific terms), consumers behave consistently with risk aversion (i.e. they derive some utility from holding money so they seek to avoid losing it in a bank failure).}

The pro-rata return is certainly reasonable given that the DD model only has three periods. After period 2, the model ends so the bank, consumers, and assets all disappear. However, in the PBLM where there is an unbounded number of possible periods, consumers must have a definite full maturity return. The idea of a pro rata return does not fit a model where assets can carry over from period to period. This carryover prevents the PBLM from having any rest points similar to period 2 in the DD model. Without a defined stopping point, there can be no final distribution of assets.

Since the PBLM model extends the number of periods in the DD model, it is only natural that the idea of a pro rata return be replaced by a definite full maturity return. This extension is reflected in comparisons of the new tipping point in equation 14 and the old tipping point in equation 13. Both reflect the idea that consumers have behaviors that are consistent with risk aversion and utility
maximization in their given situations.\textsuperscript{47} Incorporating the bank’s operating cost $D$ into equation 14 yields the first form of the PBLM tipping point proportion $T_1^*$

\[
15. \quad \frac{\beta_b \left( \alpha_b - \alpha_c(T_1-D) \right)}{\alpha_b(1-T_1)} \leq \beta_c^*
\]

\textbf{Risk Averse Behavior}

In the DD model, consumers are risk averse. The important result of their risk aversion is that if consumers are of type 1 (analogous to being shocked in the PBLM), they prematurely withdraw their money from the bank because their utility function is only dependent on consumption in period 1. “If investors were not risk averse and had constant marginal utility of consumption, they would not prefer” to hold the more liquid asset.\textsuperscript{49} Diamond and Dybvig derive mathematically how under certain assumptions about the utility functions of consumers, a sufficiently liquid asset is desirable. However, the exact level of or definition of risk aversion is not important to fundamental structure of the model as long as it is known to exist.\textsuperscript{50}

In the PBLM, the desire to avoid bankruptcy makes consumers risk averse. An unpaid deficit would mean bankruptcy which means the consumer is forced to leave the simulation. Thus consumers are willing to liquidate any assets to pay off

\textsuperscript{47} i.e. consumers want to avoid getting a lower return than what is sensible in the case of DD or than what is guaranteed in the case of the PBLM.

\textsuperscript{48} It will later be shown that the PBLM tipping point is different from equation 15 due to the relaxation of several DD assumptions and differences in the models.

\textsuperscript{49} Diamond (2007) p.192. Although Diamond says this about a concrete example, it is widely applicable to these banking contracts.

\textsuperscript{50} See footnote 28.
deficits regardless of the maturities of those assets.\textsuperscript{51} Therefore consumers prefer the more liquid asset.\textsuperscript{52} This risk averse behavior even drives them to accept a lower expected return over finite periods of time through the consumer asset as opposed to holding the higher yield underlying asset directly.\textsuperscript{53}

In the DD model, the idea of risk aversion and optimization is somewhat abstracted away. They note that

“[Sufficiently risk averse] agents will choose to deposit at least some of their wealth in the bank even if they anticipate a positive probability of a run, provided that the probability is small enough, because the good equilibrium dominates holding assets directly.”\textsuperscript{54}

They do not attempt to identify what portion of wealth consumers would deposit in the bank or what portion consumers would hold directly in underlying assets. That question is beyond the scope of their model. True risk aversion and optimization will also be considered beyond the scope of the PBLM.\textsuperscript{55} While the PBLM does not

\textsuperscript{51} A risk averse consumer’s utility function in the PBLM could be one in which utility is dependent on how many periods the consumer survives in the simulation. Hence in each period, the consumer maximizes his utility by liquidating any assets necessary to prevent bankruptcy and extend his stimulation time. He also maximizes utility by carrying as much assets into the next period so as to pay off future deficits. Thus it is in the PBLM consumer’s best interest to pay off deficits and avoid bank failure so he can have as much money as possible.

\textsuperscript{52} Again, this statement could be proved mathematically with defined risk aversion. The PBLM assumes risk averse consistent behavior such that this is true.

\textsuperscript{53} Over infinite periods of time, the expected returns are both infinite.


\textsuperscript{55} The PBLM consumer’s panic conditions are not based on truly rational expectations. Consumers have ad-hoc expectations based largely on their personal information as well as whatever they glean from their proximity based learning. This idea is consistent with the fact that consumers are often not perfectly rational but act logically according to what they can feasibly comprehend.
have explicit risk aversion, consumers’ behaviors and ad hoc expectations are consistent with risk aversion.\textsuperscript{56}

**Short Term Assets and Long Term Assets\textsuperscript{57}**

From this point on, both consumer and bank assets that have been held for zero periods will be referred to as short term assets. Both consumer and bank assets that have been held for one period will be referred to as long term assets. When long term assets are held for an additional period (two periods total), they are converted into short term assets at $\beta$ times face value where they are then considered to have been held for zero periods.

In the previously defined consumer asset, when a consumer has invested her $100 into the underlying asset in period $t$, she is now said to hold $100 in short term assets which can be liquidated in period $t$ for $100. In period $t+1$, these short term assets are rolled over into long term assets with the original face value of $100$. These long term assets can be liquidated in period $t+1$ for $\alpha(100)$ where $\alpha$ is the return on consumer assets held for one period. If the consumer holds those long term assets for an additional period, they are converted back into short term assets at $\beta$ times the face value of $100$ so she now has short term assets with face value $\beta(100)$ in period $t + 2$ where $\beta$ is the return on consumer assets held for two periods. These “new” short term assets are treated like any other short term assets so she could liquidate them at their face value of $\beta(100)$.

\textsuperscript{56} Ad hoc expectations are discussed in the Proximity Based Learning section.
\textsuperscript{57} In this section, the subscripts on the asset returns are dropped. The principles described are applicable to both consumer assets and bank assets.
This change from the original asset terminology to the new short term assets and long term assets may seem unnecessary upon first glance. However, from a programmatic sense, short term and long term assets are much easier to manage than a single asset with a two-tiered set of returns.\textsuperscript{58} Also, this new terminology better fits a system with an unbounded number of periods as opposed to the DD model which had exactly three periods.

If one were to extend the DD model as the PBLM does, in the third period, the underlying asset after being held for two periods would just be liquidated at $\beta$ times the original face value and then reinvested as new underlying assets with face value $\beta$ times the original face value. Upon reaching maturity in the third period, the underlying asset is really just treated like the consumer’s initial endowment in the first period which was only worth its face value. This has the same effect as holding long term assets for an additional period and then converting those long term assets into short term assets at $\beta$ times face value. Thus the short term/long term system is a natural extension of the original DD model to the PBLM which has additional periods.

The table on the next page indicates the analogs between the original terminology and the new terminology. Notice that the liquidation or present values for holdings in the same row are equivalent. The liquidation values capture the present worth of the assets, thus the holdings in the same rows are equivalent.

\textsuperscript{58} It is really a three-tiered system if one includes liquidating after 0 periods.
Table 0: Asset Conversions

<table>
<thead>
<tr>
<th></th>
<th>Face Value</th>
<th>Liquidation Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holding $100 in underlying assets for 0 periods</td>
<td>$100</td>
<td>$100</td>
</tr>
<tr>
<td>Holding $100 in underlying assets for 1 period</td>
<td>$100</td>
<td>α($100)</td>
</tr>
<tr>
<td>Holding $100 in underlying assets for 2 periods</td>
<td>$100</td>
<td>β($100)</td>
</tr>
</tbody>
</table>

Table 0 describes the analogs between original asset terminology and short term and long term asset.
Asset Liquidation

As mentioned in the previous section on consumer net income, consumers face the possibility of a negative monetary shock in any period. Hence they may need resources now to pay off any deficit in the current period. An event of this nature could cause the consumer to liquidate a portion of their assets after just one period even though they would have to pay the aforementioned early liquidation penalty. However, the utility-maximizing consumer would always attempt to liquidate any short term assets before liquidating any long term assets.

Consider the following example where Consumer A has short term assets with a face value of $100, long term assets with a face value of $100, and a deficit of $40 in the current period. Let long term assets be liquidated at 1.1 times their face value and converted into short term assets at 1.4 times their face value if held for an additional period. If Consumer A first liquidates her short term assets, she must cash in short term assets with a face value of $40 (present value of $40), leaving her with short term assets with a face value of $60 and long term assets with a face value of $100. In the next period excluding any net income, Consumer A has short term assets with a face value of $140 and long term assets with a face value of $60 for a total present value of $224.

Now suppose Consumer A had first liquidated her long term assets. To do so she must have cashed in long term assets with a face value of $36.36 (present value

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59 In this section, the subscripts on the asset returns are dropped. The principles described are applicable to both consumer assets and bank assets.

60 See Equation 9.

61 This is consistent with the rough description of risk aversion in the PBLM in footnote 51.
of $40), leaving her with short term assets with a face value of $100 and long term assets with a face value of $63.64. In the next period excluding any net income, Consumer A has short term assets with a face value of $89.10 and long term assets with a face value of $100 for a total present value of $199.10.

The example above highlights the real benefit of liquidating one's most liquid assets (their short term assets) before one's less liquid assets (their long term assets). This benefit holds because the marginal benefit of holding short term assets with a face value of $1 an additional period is $\alpha - 1$ whereas holding long term assets with a face value of $1 an additional period has a marginal benefit of $\beta - \alpha. \beta - \alpha$ is always greater than $\alpha - 1$ as long as $\beta > 1, \beta > \alpha > 0, and \beta > \alpha^2$, the two previously stated conditions on the asset returns.\(^{62}\)

This concept will now be explained algebraically in the context of the PBLM. Suppose Consumer A has short term assets with face value $S_t$ and long term assets with face value $L_t$. Consumer A is shocked and has negative net income $I_t$ in period $t$. She first attempts to offset her net income $I_t$ with her short term assets $S_t$. If $|I_t| \leq S_t$, then the consumer’s remaining short term assets are $S_t + I_t$. If $|I_t| < S_t$, the consumer initially uses all of her short term assets such that she has 0 short term assets remaining and a leftover deficit of $S_t + I_t$. She then attempts to pay the leftover deficit by liquidating any long term assets at a rate of $\alpha_c$ times their face value. Hence the consumer must liquidate $|S_t + I_t| / \alpha_c$ in face value of long term assets to pay the deficit. If she has fewer than $|S_t + I_t| / \alpha_c$ in face value of long term assets, she

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\(^{62}\) See the section on underlying asset returns. The proof is simple if the substitutions $\beta_0 = 1 + \beta$ and $\alpha_0 = 1 + \alpha$ are plugged into equation 7.
liquidates all of her long term assets to pay off as much of the deficit as she can before she will later go bankrupt in the period.

Similarly, banks also choose to liquidate their short term assets before any long term assets to pay off any obligations.

**Asset Conversions**

Consumers are able to invest any net positive income into their bank. In any period $t$, a consumer’s net income, $I_{i,t}$, is described by

$$ I_{i,t} = Y_{i,t} - C_{i,t} - X_{i,t} $$

$I_{i,t}$ can be considered as the first part of the potential change in a consumer's short term assets in period $t$. Should the consumer hold any long term assets in period $t-1$, in period $t$, those assets are converted into short term assets at the long term return $\beta$. However, any long term assets held in period $t-1$ would necessitate that the same face value amount of short term assets had been held in period $t-2$. Hence in period $t$, the total amount of short term assets, $J_{i,t}$, is described recursively by

$$ J_{i,t} = I_{i,t} + \beta(J_{i,t-2}) \text{ for } t \geq 2 $$

For periods 0 and 1, let $L^*$ be the consumer's initial face value endowment of long term assets. Let $S^*$ be the consumer's initial face value endowment of short term assets, so we have

$$ J_{i,0} = I_{i,0} + S^* $$

---

63 In this section, the subscripts on the asset returns are dropped. The principles described are applicable to both consumer assets and bank assets.

64 This only holds if $J_t \geq 0$ for all $t$. $E[J_t] > 0$ for all $t$. 

19. \( J_{i,1} = I_{i,1} + \beta (L^*) \)

Any short term assets held in the previous period are rolled over into long term assets in the current period. Thus the total amount of long term assets in period \( t \), \( L_{i,t} \), can be described by

20. \( L_{i,t} = J_{i,t-1} \) for \( t \geq 1 \)

Since short term assets are liquidated at face value and long term assets can be liquidated in the current period at the short term return \( \alpha \), the present value of a consumer's total assets in period \( t \), \( K_{i,t} \), is described by

\[
K_{i,t} = \alpha (L_t) + \beta (J_{i,t-2}) + I_{i,t} \text{ for } t \geq 2, \text{ substituting equation } 20 \text{ yields}
\]

21. \( K_{i,t} = \alpha (J_{i,t-1}) + J_{i,t} \) for \( t \geq 2 \)

For periods 0 and 1,

22. \( K_{i,0} = I_{i,0} + S^* + \alpha (L^*) \)

23. \( K_{i,1} = I_{i,1} + \alpha (J_0) + \beta (L^*) \) with the substitution in equation 18

Although subscripts indicating that these are values specific to each consumer are included, the expectation of each consumer's attributes are identical before the consumers are instantiated. Thus the subscripts indicating the consumer can be dropped when expectations are taken. The time subscript on net income could also be dropped as described in the Net Income section.

Bank assets convert similarly to the consumer assets using the bank rates instead of the consumer rates.

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65 There is no subscript on either initial endowment as it will be the same for every consumer.
66 Assuming \( J_{i,t-1} \geq 0 \). If \( J_{i,t-1} < 0 \), \( L_{i,t} = 0 \);
67 Assuming \( J_{i,t-1} \geq 0 \).
Stationarity

This section discusses the expectations of numerous variables under the condition of stationarity. To simplify the notation, let the expectations of any variables be denoted by italics. The expectations of each variable are taken before the consumers or banks are instantiated. Since each consumer has attributes drawn from the same random distributions, all consumers are expected to have the same values for these attributes. Thus subscripts indicating individual expectations will be removed (e.g. \( Y_i = Y_j = Y \) for all \( i \) and \( j \)).

Stationarity in this model is defined as keeping the system wide expected levels of short term assets and long term assets (and therefore total assets) for the consumers and banks constant over time. If stationarity is imposed at the system wide expected levels of assets, it follows that the same must be true for individual consumers and the bank.

Stationarity is important because it eliminates any effects of growth and allows the examination of critical points in meaningful ways. Without stationarity, the inclusion of a growth trend would be necessary. This would significantly complicate any expectations in the model. Without stationarity imposed, the system would constantly be in flux. While this is in of itself is not problematic, the purpose of the PBLM is to examine critical points and critical behaviors. If a system is constantly in flux, the question of what is meaningful becomes less clear as a baseline for stability no longer exists. It is possible that critical points may be identified during a period of flux, but it is unclear if those points would still be meaningful during other periods of flux or stability. Thus stationarity is important
for not unnecessarily complicating the model and allowing decisive results to be found.

True stationarity does not exist in the PBLM. Although consumers and banks operate under the belief that there is stationarity, the system actually experiences a decrease in wealth each period due to the negative expected value of a bank failure. Solving this issue would require calculating the probability of a consumer losing all of his or her money in a bank failure in a stationary system. This would be extremely difficult once proximity based learning is accounted for since learning can lead to consumers panicking and panic induces more panic. Further, calibrating the system for stationarity incorporates the expected loss due to a bank failure which must be calculated in a stationary system. This is a circular issue that prevents true stationarity from being imposed. There is also the added complication of debt forgiveness. If a consumer only has $100,000 but needs to pay off a debt of $120,000, the remaining $20,000 is essentially written off. But this is not accounted for in the standard expectations taken in the PBLM. Thus the expected value of consumer actions should actually be greater since full losses are not able to be absorbed by the system.

There are two opposing forces on stationarity that are not accounted for in the PBLM. The expected loss due a bank failure makes the system tend negative

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68 These ideas are elaborated on in the Proximity Based Learning Section. Readers may want to read that section before coming back to the problems with stationarity in this model.
69 “Revising is like pooping. You need to get it all out there first and then pick through it for kernels of truth.” – Micah Lau (2012).
70 There is no true receiver of the deficits paid by consumers. The amounts consumers pay out are simply assumed to leave the system.
while debt forgiveness makes the system tend positive. It is absolutely not the
tention of this study to assume the two forces cancel each other out.\textsuperscript{71} Neither
issue could be resolved at this time. Hence all results from this project should be
taken with the caveat that the assumption that assets are stationary may or may not
be true.\textsuperscript{72} The stationarity excluding the possibility of a bank failure and debt
forgiveness is as close to true stationarity as this study could come.\textsuperscript{73,74}

\textbf{Individual Consumer}\textsuperscript{75}

Applied to the individual consumer, stationarity means the consumer’s
expected total assets do not change over time. \textsuperscript{76} Since before instantiation all
consumers are expected to have the same attributes, the subscript indicating the

\textsuperscript{71} Although this would be extremely convenient.
\textsuperscript{72} The problems created by the lack of stationarity will be discussed in the section
on proximity based learning.
\textsuperscript{73} The author expects this issue to be a tree with depth equal to the number of
consumers in the model. At each node, a consumer learns. Each branch stemming
from the node indicates the various “combinations” of consumers the consumer
might see. But these combinations are dependent on the states of each of those
consumers. For example, Consumer A might have been shocked, might have not had
the opportunity to learn, might have panicked, might not have panicked, etc. The
order in which the consumers learn also matters so that would further multiply the
already immense number of branches from each node. Taking expectations would
also be made even more difficult by the fact that the panic process is so affected by
heterogeneity that to use consistent expectations would rob the model of the
learning process that makes it so unique.
\textsuperscript{74} The issue of stationarity in the DD model is not relevant. In the DD, there is just
one cycle after which all agents and assets disappear. The lack of continuity means
agents are unconcerned with the future. However, if there was growth over time,
any future tipping points should account for that growth.
\textsuperscript{75} Let $\beta = \beta_c$ and $\alpha = \alpha_c$.
\textsuperscript{76} The expected levels are constant at the same points in the period across periods.
I.e. a consumer’s expected level of short term assets after receiving her net income is $S_t + I_t$ for all t. However, the consumer’s expected level of short term assets before receiving her net income is $S_t$ for all t. Timing is very important here.
specific consumer will be dropped. Let the consumer’s expected current total level of assets before she receives her net income in period t be represented by $K_t$.

Stationarity implies

24. $K_t = K_s = K^*$ for all periods $s$ and $t$ where $K^*$ is the total value of the consumer’s initial endowments of resources

Stationarity is also defined here to mean that the consumer’s expected levels of short term and long term assets are constant. Let the consumer’s expected face value amounts of short term and long term assets in period t before she receives her net income be $S_t$ and $L_t$, respectively. Stationarity implies

25. $S_t = S_s = S^*$ for all periods $s$ and $t$

26. $L_t = L_s = L^*$ for all periods $s$ and $t$

where $S^*$ and $L^*$ are the initial endowments of short term and long term assets for all consumers.

Consider the actions the consumer undertakes in each period. She initially receives her net income which has an expected value $I^*$. Since consumer assets grow over time at positive rates $\beta_c$ and $\alpha_c$, $I^*$ must be negative to keep the expected total value of assets constant over time. Using equation 5, this means

$$I^* = E[I] = Y^*(1 - \gamma^* - \lambda \Psi) < 0$$

which implies

27. $1 - \gamma^* - \lambda \Psi < 0$

In the section on net income, $\gamma^*$, $\lambda$, and $\Psi$ are all at least 0 since they are the consumer’s expected average consumption rate, probability of getting shocked, and

---

77 Initial resource endowments are identical for all consumers.
the income multiplier of the shock. Equation 27 yields a relationship indicating the necessary magnitudes of these variables.

Following the principles outlined in the Asset Liquidation section, consumers liquidate all short term assets before any long term assets due to the real cost associated with early liquidation. Thus the consumer expects to pay a deficit of $|I'|$ each period.

Suppose $|I'| \geq S^*$. Then she is expected to exhaust her entire supply of short term assets each period. This is unsustainable as this means she is expected to have 0 long term assets in the next period following the asset conversion guidelines. This is impossible under the definition of stationarity unless her initial long term asset endowment is 0. We will ignore this case as it would be trivial. Therefore we assume

28. $|I'| < S^*$

After the consumer pays off her deficit, she has $S^* + I'$ in short term assets and $L^*$. Following the asset conversion process, this means in period $t+1$ before she receives her net income she will have $S^* + I'$ in long term assets and $\beta(L^*)$ in short term assets. Since we have been using expected values this entire time, according to stationarity of short term assets, equation 25 means

$$S^* = \beta(L^*)$$

29. $$L^* = \frac{S^*}{\beta}$$

Equation 29 indicates the balance between the initial face value of the short term asset endowment and initial face value of the long term asset endowment for all consumers under the assumption of stationarity. This is a key calibrating relationship in the PBLM.
According to the stationarity of long term assets, equation 26 means

\[ S^* + I^* = L^* \quad \text{substituting equation 29 into this yields} \]

\[ S^* + I^* = \frac{S^*}{\beta} \quad \text{which simplifies to} \]

30. \[ \beta = \frac{S^*}{S^* + I^*} \]

Equation 30 indicates that the long term return rate for consumers is a function of the consumer’s initial short term endowment and expected net income. This is another key calibrating relationship in the PBLM.

Together, equations 27, 28, 29, and 30 provide several key relationships required to keep consumer assets stationary in the PBLM.

**Bank**

Nearly all of the steps for finding the relationship that keeps the bank assets stationary parallel that for the consumer assets. Banks are endowed with no assets of their own. Hence their starting endowments of short term and long term assets are equal to those of the consumer. Banks are also subject to the same change in assets due to the net incomes of consumers that consumers are. Thus if all of the bank’s “equations” are divided by the initial number of consumers, the steps for finding stationarity are nearly identical. However, banks also face the aforementioned operating cost \( D \).\(^{78}\) Let the operating cost per consumer by \( d \).\(^{79}\) Note that changes in bank assets due to returns on investments are in terms of the underlying asset returns, not the consumer asset returns.\(^{80}\)

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\(^{78}\) This cost is only incurred after the initial period and its timing is crucial.

\(^{79}\) Assume \( d < 0 \).

\(^{80}\) i.e. banks’ long term assets are converted into short term assets at \( \beta_b \) not \( \beta_c \), etc.
Consider the bank’s expected asset levels per consumer in period 0. Initially, before consumers make any withdrawals, the bank holds \( S^* \) in short term assets and \( \frac{S^*}{\beta_c} \) in long term assets. Notice that the ratio of short to long term assets is in terms of \( \beta_c \) not \( \beta_b \). Once consumers make their expected withdrawals each of \( I^* \), the bank has \( S^* + I^* \) in short term assets and \( \frac{S^*}{\beta_c} \) in long term assets. Following the asset conversion process, in period 1 the bank is expected to have per capita short term holdings of \( \frac{S^*}{\beta_c} (\beta_b) \) and long term holdings of \( S^* + I^* \). Immediately after the asset conversion process, the operating cost is imposed on the bank. We will assume \(|d| < \frac{S^*}{\beta_c} (\beta_b)\) such that the bank now holds \( \frac{S^*}{\beta_c} (\beta_b) + d > 0 \) in short term assets.

Since we are still using expectations, under the definition of the stationarity of bank assets, we have

\[
S^* = \frac{S^*}{\beta_c} (\beta_b) + d \quad \text{which can be rewritten as}
\]

\[
31. \quad \frac{\beta_b}{\beta_c} = (1 - \frac{d}{S^*}) \beta_c
\]

Equation 31 indicates that the long run return on the bank asset must be sufficiently large to offset the operating cost imposed on banks. Note that equation 30 equates the expectations of the bank’s long term assets in the same way that it does so for consumers. Thus equation 31 in conjunction with the previously mentioned calibrating relationships for consumers create stationarity among bank assets.\(^{82}\)

\(^{81}\) Since \( d < 0, \beta_b > \beta_c \) which is consistent with equation 11 in the section on the consumer asset.

\(^{82}\) The reader may find these calibrating relationships interesting since neither \( \alpha_c \) nor \( \alpha_b \) are anywhere to be found. How is it possible that \( \alpha \) is irrelevant in
Proximity Based Learning

Proximity based learning is at the core of how the PBLM expands upon the DD model. Proximity based learning means a consumer is able to look at the wealth distributions of several near consumers and use that information to make a decision. This allows the actions of one consumer to affect the decisions of any other consumers that observe his or her actions. This mechanism will be used to transmit panic between consumers so that the panic process can actually be modeled. A panic here is a decision by a consumer to withdraw all their assets from the bank immediately even though he or she may not have an immediate liquidity need. This means liquidating short term assets at face value and long term assets at $\alpha_c$ times face value and holding cash instead.

Proximity based learning is the process by which a consumer can observe others consumers, see the consumers’ net incomes or any additional withdrawal the consumers chose to make, and whether or not the consumers panicked in the current period. For example, Consumer A might observe Consumer B. Consumer A determining stationarity in the system? The PBLM is only stationary excluding the expected loss due to a bank failure. It is only when consumers panic and banks fail that any agent would choose to liquidate their assets early and actually receive a return of $\alpha$. Since consumers and banks do not actively expect losses due to a bank failure, $\alpha$ is not considered in any calibrating equations that are necessary for “stationarity.” However, true stationarity would almost surely include both $\alpha_c$ and $\alpha_b$ as those are expected to affect how likely the bank is to fail. Once a consumer has the opportunity to do proximity based learning, the consumer may choose to withdraw his or her entire remaining assets from the bank and instead hold that amount as cash. Hence a consumer that may have had positive net income of $400 but later panicked and withdrew $3000 from the bank would be
could see that Consumer B is holding $300 in cash and has not yet panicked in the period. If Consumer B executes his proximity based learning later and then decides to panic and withdraw his remaining $2000 from the bank, Consumer A is unable to change her actions. Each consumer only learns once in each period and they act upon the information they receive as soon as they receive it. Hence consumers have no ability to receive updated information or change their decisions once they have been made.

In the DD model in period 1, if consumer liquidity demands (negative net incomes) will be at such a level that the bank will fail, “everyone rushes in to withdraw their deposits before the bank gives out all of its assets.” In the sentence above, “if consumer withdrawals will be” is indicative of the fact that every consumer is able to see the liquidity demands of every other consumer before consumers actually act upon any desires to liquidate assets from the bank. The intuition behind proximity based learning is that such extensive consumer information is not actually readily available to everyone. It seems unrealistic that each consumer should be aware of every other account holder at the bank. It is more reasonable to expect that Consumer A may be aware of the liquidity needs of several of her friends. Based off of this limited information, Consumer A develops beliefs regarding the greater consumer population to make a decision.

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84 The order in which consumers perform proximity based learning is random.  
85 This is consistent with the idea of the single service constraint. Diamond and Dybvig expand on this and say “a bank’s payoff to any agent can depend only on the agent’s place in line and not on future information about agents behind him in line.”  
The bank panic process in the DD model is simultaneous and realized by all consumers. This is logical in the presence of complete knowledge of consumer actions and the bank’s assets. However, using the proximity based learning process, this study allows decisions of consumers to affect the decisions of other consumers. The PBLM lets the authors include an actual panic transmission process where if Consumer A observes Consumer B panic, Consumer A is more likely to panic because she saw Consumer B panic. This panic transmission process can lead to a “coordinated panic” like in the DD model, but this is the organic result of consumers passing on information as opposed to a byproduct of completely visible consumer and bank information.

The information a consumer receives from this process is dependent on whom the consumer observes and when the consumer observes them. Whom the consumer observes is based on actual geographical proximity and chance. In this model, each consumer looks at their neighborhood (think of a square at which the consumer is in the middle) and randomly picks $G$ consumers in that neighborhood to look at.\footnote{G is the maximum number of consumers one can observe. If there are fewer than $G$ consumers in one’s neighborhood, the consumer looks at all consumers in the neighborhood.} Although geographical proximity is used here, it could be thought of as social familiarity. Geographical proximity is convenient in that it allows information to spread with a literal domino effect. When refers to the timing of the observation. This important idea merits its own subsection below.
Timing

Timing here will generally refer to the consumer’s place in line to do proximity based learning. Timing is very important in the learning process because consumers must make their decision immediately after they learn and are then unable to take any other actions. This was highlighted in the example above where once Consumer A chose not to panic, she could not later withdraw any money from the bank in the period. Consumer A may observe Consumer B before or after Consumer B has the opportunity to learn. If Consumer B has not already learned, then Consumer B has not had the opportunity to withdraw all his money from the bank. Also, Consumer A does not have the opportunity to benefit from “informed” actions of Consumer B.

The above paragraph is also indicative of the fact that the liquidity demands on the system are dynamic. If Consumer A chooses to panic, she will withdraw all of her assets from the bank. Her panic and withdrawal increase the liquidity demand in the system. Thus Consumer A is able to impose a state change on the system when she learns. Liquidity demands can never drop below their initial level as the initial level reflects the net incomes of consumers in the system. Consumers can always panic and withdraw more money from the bank beyond their net income, but they can never choose to deposit more money into the bank beyond their net income. Since consumers panicking can increase liquidity demands on the

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88 I.e. the first consumer to learn goes “before” or “earlier” than the last consumer in line to learn.
89 This comes from the fact that consumers have no other external sources of money they could deposit.
system, as more consumers have the opportunity to learn, it becomes more likely that at least one of them will panic and increase the overall liquidity demand. Thus one would expect for the final (after everyone has learned) liquidity demands on the system to be larger than the initial demands.

Given that consumers are unable to revise any past decisions or make decisions based on future information from consumers, they can only attempt to assess the current state of the system when it is their turn to learn. The first consumer in line will see the system in its true initial state whereas the 50th person could see the system after up to 49 state changes. However, when the two consumers learn, they are actually seeing different environments due to the timing. Thus they are making decisions based off of the environment that exists around them when they make their decision. Although the system the 50th consumer sees is more likely to be closer to the system’s final state, his actions are not necessarily more correct than the one’s the first consumer undertakes. Each consumer must be judged against the environment they are in when they have the opportunity to make a decision. This idea will become clearer in the results section when the accuracy of consumer estimates is evaluated. It would be unfair to evaluate the correctness of the first consumer’s actions against the final system state when that was not the case.

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90 Technically if a consumer panicked and withdrew all their money from the bank in the previous period, they would have more money than just their net income. However, the extra money beyond the true net income would be treated as net income in the accounting of the system.

91 This study will look at the consumer’s estimate of their current environment compared to the actual state of the environment at that time to determine “correctness.”
state the first consumer acted in. Timing allows us look at whether the consumer is making a good decision at that point in time.

**Proximity Based Learning Tipping Point**

Consumers use the liquidity information they obtain from the proximity based learning process to gauge overall liquidity demands on the bank. If they feel liquidity demands are larger than the bank can meet, they panic. The balance between liquidity demands and the bank's assets will now be discussed.\(^{92}\)

Banks in the PBLM are always net negative. Consumers initially deposit short term assets which the bank offers back to them at face value. The long term assets consumers initially deposit are redeemable to the consumer at \(\alpha_c\) times face value but the bank can only liquidate long term assets at \(\alpha_b\) times face value and \(\alpha_b < \alpha_c\). Hence the bank's liabilities are greater than its assets. Under the stationarity assumptions, expected consumer assets (or the bank's liabilities) are constant and expected bank assets are constant so the bank is always expected to have a negative net worth. This is actually not problematic. In period 1 of the DD model, the bank is also net negative. In fact, any liquidity services provided by the bank at all necessitates that the bank be net negative at least sometimes and exposed to bank runs.\(^{93}\)

Similar to the DD model, the bank can be net negative and consumers are not necessarily worried. Consumers need only be worried when other consumers

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\(^{92}\) Banks use their short term and long term assets to meet obligations.  
withdraw so much money from the bank that the bank will run out of assets to meet its expected obligations in the next period. Thus the bank can exist in a net negative state as long as consumers believe the bank can meet its expected obligations. What follows will build off of ideas of the DD and PBLM equilibria discussed in the Diamond and Dybvig Equilibria section.

We will now consider the bank’s per capita level of assets. In the first period, the bank has $S^*$ in short term assets and $L$ in long term assets. The consumer has expected net income $I < 0$ and the bank’s operating cost per consumer is $d < 0$. Suppose the consumer’s actual net income in the period is

$$32. \quad I_1 = -(S^* + a_b \left( \frac{\beta_b (L) + d + I}{\beta_b} \right)) < 0$$

Then the consumer withdraws $-I_1$ from the bank. The bank must now generate $-I_1$ in value by liquidating its short and long term assets. Following the liquidation rules, the bank initially attempts to liquidate $-I_1$ using its short term assets. However, since

$$33. \quad I_1 > S^*$$

The bank liquidates all of its short term assets but must still service the remaining $a_b \left( \frac{\beta_b (L) + d + I}{\beta_b} \right)$. Since the bank liquidates its long term assets at a rate of $a_b$ times face value, it must liquidate $\left( \frac{\beta_b (L) + d + I}{\beta_b} \right)$ in face value of long term assets to fully meet the obligation. The bank is able to do so since $d, I < 0$ and $= < L$. Thus the bank will have

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94 If the bank is unable to meet its expected obligations in the current period, it surely cannot meet obligations in the next period.
95 Assume $\beta_b (L) + d + I > 0$
96 Assume that the consumer has the assets to make such a withdrawal.
\( L - \left( \frac{\beta_b (L) + d + I}{\beta_b} \right) \) in face value long term assets and no short term assets at the end of the period.

Following the asset conversion process into the next period, the bank’s long term assets are converted into short term assets at a rate of \( \beta_b \) times face value. Thus the bank will now have

\[
34. \quad \beta_b (L - \left( \frac{\beta_b (L) + d + I}{\beta_b} \right)) = \beta_b (L) - \beta_b (L) - d - I = -d - I
\]

\( Bank \ Total \ Assets = -d - I \)

in short term assets and no long term assets. The bank must now pay its per capita operating cost of \( d \). It attempts to do that out of its short term assets first so it will have \(-d - I + d = -I\) in short term assets remaining. Now the consumer will receive her net income which has an expected value of \( I \). If the consumer’s net income \( I_2 \) was actually more negative than expected (i.e. \( I_2 < I \)), then the bank would not be able to meet the consumer’s full withdrawal. If the bank is not able to meet the consumer’s full withdrawal, the bank fails and the consumer loses the difference.

Thus the consumer’s initial withdrawal \( I_1 \) was just large enough that the bank has exactly the amount it needed to meet its expected obligations in the next period. Had the consumer withdrawn any more money, the bank would be expected to fail in the next period. So equation 32 captures the tipping point for the average withdrawal per consumer relative to the average short term and long term holdings of the bank per consumer before the bank is expected to fail.

This tipping point will now be placed in the context of the whole system. Essentially, if total withdrawals are so high that they decrease the bank’s assets in
the next period below the bank’s expected obligations in the next period, the bank is expected to fail in the next period. Hence any consumer realizing the bank is beyond this tipping point will panic and attempt to withdraw all their assets from the bank in the current period to avoid losing all their assets in the bank failure in the next period. This is the tipping point reached when the sequential service constraint and other ideas from the Diamond Dybvig Equilibria section are fully applied to the PBLM.

There are two panic conditions in this model that are evaluated against this tipping point. First, consumers will panic if they feel other consumers are withdrawing such a large amount from the bank that the bank will not be able to meet its expected obligations in the next period. This is considered a liquidity panic. Second, consumers will also panic if the proportion of panicked consumers they observe is so large that they think the bank will not be able to meet its expected obligations in the next period. This is considered a panic panic. Both of these conditions are evaluated using ad hoc expectations.

**First Condition**

Under this condition, Consumer A is worried that other consumers are withdrawing so much money from the bank that the bank will not be able to meet its expected obligations in the next period. This section describes equation 32 evaluated using the idea of proximity based learning. Let $\zeta^{*}$ be the actual average withdrawal amount of every consumer in the system at the time Consumer A is learning. Let $\pi^{*}$ be the actual average amount of short term assets the bank holds
per consumer at the time A is learning. Let $\xi^{**}$ be the actual average amount of long
term assets the bank holds per consumer at the time A is learning. To gauge the
overall liquidity demands of the system, Consumer A looks at either the cash
holdings of his neighbors or their initial liquidity demands. Consumer A uses this
information to estimate the average withdrawal $\zeta^{***}$ of every other consumer this
period.

$$35. \quad \zeta^{***} = \frac{\sum \text{cash or Initial liquidity demand}}{\text{Number of Consumers}}$$

**Estimated Average Consumer Short Assets = Consumer's Short Assets**

$36. \quad \mathbb{E}[\zeta^{***}] = \zeta^{**}$

Consumer A then estimates how much the bank holds in short term assets
using his own short term assets as the average amount of short term assets held by
every other consumer in the system. Consumer A uses the same method to estimate
the average amount of long term assets held by every other consumer. So if the
consumer holds $J_A$ in short term assets and $J_L$ in long term assets, he estimates the
average short term assets $\pi^{***}$ and long term assets $\xi^{***}$ such that

$$37. \quad \pi^{***} = J_A$$

$$38. \quad \xi^{***} = J_L$$

Consumer A then compares the estimated withdrawals to the estimated bank
assets the bank holds according to equation 32. If the estimated withdrawals are
large enough such that the bank's expected assets in the future cannot meet its
expected obligations, Consumer A will panic and withdraw all her money from the bank.

This condition focuses on Consumer A’s perception of pure liquidity strains based on estimations of the bank’s short term assets according to equation 32.

Consumer A does not have true rational expectations of consumer withdrawals or the bank’s assets. Consumers could have perfect rational expectations given that all variables in the model come from known distributions and all parameters are known. However, calculating these rational expectations would be extremely difficult and not a realistic behavior in practice. Instead Consumer A uses ad-hoc expectations based on the information available to him when he makes his decision. These ad-hoc expectations are not entirely rational as they are instead based on actual information available to the consumer. Consumer A forms beliefs regarding the state of the system based on the information learned and acts accordingly. The use of ad-hoc expectations is deemed to be more appropriate for the PBLM as it attempts to remove ideas like complete visibility into consumer actions and see how panics can develop with limited information. The “estimations” used here are reflective of the decisions that are based on ad-hoc expectations as opposed to perfect rational expectations.

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98 Lovell (1986) reviewed a number of empirical studies looking at the validity of rational expectations. He found that although a number of the models were based on sound micro foundations, empirical evidence suggested that the rational expectations hypothesis should be rejected.
Second Condition

Under this condition, Consumer A is worried that such a large proportion of consumers are panicking that the bank will not be able to meet its expected obligations in the next period. To gauge this, Consumer A looks at his neighbors and observes what proportion of them have panicked. Let the observed proportion be $\theta^*$ such that

$$39. \quad \theta^* = \frac{\text{Number of observed panics}}{\text{Number of consumers observed}}$$

Consumer A uses this information to estimate $\theta^*$ of all consumers will panic this period. Consumer A then estimates how much each panicking consumer will withdraw, $\Omega$, from the bank using his own levels of short term assets, $J_{\text{short}}$, and long term assets, $J_{\text{long}}$. Thus following the rules for asset liquidations,

$$40. \quad \Omega = J_{\text{short}} + \alpha_c(J_{\text{long}})$$

So the expected withdrawal unconditional whether the consumer panicked is $\theta^*$ times $\Omega$.

Consumer A then estimates how much the bank holds in short term assets using his own short term assets as the average amount of short term assets held by every other consumer in the system and the same for his long term assets. So if the consumer holds $J_A$ in short term assets and $J_L$ in long term assets, he estimates the average short term assets $\pi^*$ and long term assets $\xi^*$ such that

$$41. \quad \pi^* = J_A$$

$$42. \quad \xi^* = J_L$$

$^{99}$ Alternatively, Consumer A could look at the average cash holdings of each panicked consumer to determine $\Omega$. 
Consumer A then compares his estimated average "panic withdrawals," $\theta^{***}(\Omega)$, to his estimation of the bank’s assets, $\xi^{***}$ and $\pi^{***}$. This comparison is made using the tipping point equation 32.

This condition focuses on Consumer A's perceived liquidity strains based on estimations of the bank’s assets caused by individuals panicking. The economic intuition and use of ad-hoc expectations here is similar to that for the first condition which focused purely on liquidity strains. Although this condition ultimately comes down to perceived liquidity strains too, the perceived strains stem from the proportion of people panicking.

Under condition 2, the reader can see how a consumer panicking directly induces other consumers to panic. This captures the transmission of panics directly. It makes sense to have a panic condition where panic creates itself. Imagine someone screaming as they witness a murder in the subway. Other passersby do not need to personally witness the murder to feel frightened so long as they receive strong enough signals from their neighbors.

**Panic Creates More Panic**

The way the two conditions are set up, Consumer A panicking makes other consumers more likely to panic in two ways. When Consumer A panics, she withdraws all of her assets from the bank. This increases the amount of cash she holds. Since cash holdings are what consumers use to gauge the liquidity strains other consumers are putting on the bank, this makes other consumers more likely to panic under the first condition. Thus panic directly leads to more panic in the first
condition. The second condition describes how Consumer A’s panic directly increases the estimated average panic withdrawals which increases the likelihood of other consumers panicking.

It is interesting to note that the second condition cannot occur until the first condition occurs. The second condition looks at whether or not Consumer A should panic based on the panic behavior of her neighbors. If there are no panics, there can be no panic panic. However, high levels of normal withdrawals could cause Consumer A to panic under the first condition regardless of anybody else’s panic behavior. This has the interesting effect where consumers that learn early in the process may be more likely to panic under the more measured first condition whereas once panics occur, the likelihood of panicking due to the second condition increases. Either way, since panic leads to more panic, consumers that learn later are expected to be more likely to panic than early consumers. Ironically, the consumers that learn last are the ones most likely to lose all their money in a bank failure and the ones most likely to panic.

**Distortion Potential In Estimating Bank Assets**

Consumers only look at their own levels of short and long term assets to estimate the bank’s assets. This can be problematic if a consumer is shocked. When the consumer is shocked, he or she must withdraw a significant portion of their assets in order to pay off the deficit. Thus the consumer would have a very low estimate of the bank’s assets. Getting shocked greatly distorts one’s estimation of the bank’s asset and therefore increases one’s likelihood of panicking. This is not an
unreasonable result especially if one considers the shock to be a period of high stress and humans tend to perform poorly under stress. Further, if systemic shocks are incorporated either directly into the PBLM or into consumer behavior, such a distortion may be desirable. As the PBLM currently stands, this estimation process is prone to distortions. More research and expansion of the model need to be conducted to determine whether or not this should be the case.

A possible alternative would be to allow consumers to expand the information they receive through learning to include the asset levels of other consumers. Essentially, consumers currently estimate bank assets using a sample size of 1 (their own assets). Expanding that sample size through proximity based learning would likely have a similar effect to that of group size on the asset estimation differential. However, this would mean consumers are now essentially sharing their exact levels of personal wealth their neighbors. This seems to be a stretch in terms of what information should be available to consumers. Nevertheless, this approach is one that should be explored in the future. Another interesting alternative would be implementing a weighted average of a consumer’s past asset levels such that the impact of a shock could be smoothed. This could have the same impact of increasing the sample size but still keeping consumers constrained by the knowledge of only their own asset levels. Other alternatives should at least be considered due to the potential for shock distortion in the current estimation process.
Stationarity Problem

Stationarity is a problem in the PBLM because growth is not explicitly accounted for in the panic conditions. While the bank’s assets and consumer assets likely both grow in the same direction, it is very possible they grow at different magnitudes. This is problematic because consumers believe they constitute a per capita share of the bank's assets. If growth rates cause each consumer to no longer hold a per capita share of the bank’s assets, the consumer cannot easily estimate the bank’s assets. Since the decision to panic ultimately comes down to the whether the consumer’s estimated bank assets are large enough to sustain estimated liquidity demands and expected obligations in the next period, any errors in the consumer's estimate of the bank’s assets affect the decision to panic. Any growth in assets should be accounted for so that the consumer can make a panic decision based on an accurate baseline relationship between the bank's assets and consumes' assets.

An alternative approach could have been taken where the PBLM looks at just one cycle like the DD model. In that case, the PBLM would still be an interesting extension of the DD model as the PBLM could follow the same rules but incorporate learning as a panic transmission process. Stationarity would not be an issue with just one cycle as there would be no reason to consider future growth. In a one cycle model under the DD rules, during the learning process, type 1 consumers would liquidate their entire endowment of assets (which would be constant across all

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100 Per capita share is used to indicate that if there are 80 consumers in the system, the expected assets of a consumer should be equal to 1/80 of the bank's actual assets.
Type 2 consumers would look at the proportion of type 1 consumers around them during the learning process and attempt to estimate the true proportion of type 1 consumers in the system. As discussed in the Diamond and Dybvig Equilibria section, this proportion of type 1 consumers would be the basis for whether or not a panic occurs under given banking contracts. Thus panic transmissions could be observed in meaningful ways by incorporating proximity based learning into the DD framework. Unfortunately, the problem with stationarity was realized too late in the process to make the change to a single cycle model. As it stands, the current PBLM lays the foundation for a future model with true risk aversion and optimization that is able to incorporate multiple cycles.

**Unnecessary Panics**

Due to the fact that consumers receive limited information that may or may not be representative of the actual state of the system, there exist “unnecessary panics.” These are panics that occur due to incorrect beliefs consumers develop through the learning process. For example, had the consumer been fully aware of all consumers’ liquidity needs and the bank assets, the consumer would not panic. However, the consumer might observe a group of consumers with particularly high liquidity demands which cause the consumer to overestimate the actual liquidity demands and unnecessarily panic. But as more consumers begin to panic and increase the liquidity demands on the bank, it is possible that a bank that should not have failed due to initial liquidity demands could end up failing as demands become too large when more consumers learn and panic.
If there were complete awareness of information on all consumers and the bank, any time the bank is in a failure position, each consumer would know. This is the case in the DD model. Thus any panic (caused by large initial liquidity demands) under the DD model would always happen in the PBLM as there is no way to avoid the initial liquidity strains on the bank. But the learning process allows for a bank failure to develop before this point given that consumers may incorrectly panic and consequently cause an actual large scale panic and failure situation. The learning process can be thought of as a replacement for the sunspots that may cause bank failures.

**Proximity Based Learning Summary**

The idea of proximity based learning stems from the fact that consumers want to make informed decisions. However, the PBLM generally assumes that consumers do not have access to all the information they could use (i.e. overall liquidity demands, panic proportions, and the bank’s levels of assets). Through the learning process, consumers are able to derive some of this information from small samples. Consumers may sample a group of 10 consumers to identify their average liquidity demands. The consumer then assumes that that sample was representative and that that average is a good estimate for the overall liquidity demands in the system. This of course exposes consumers to drawing incorrect conclusions due to

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101 Note that equation 15 which captures the “DD” tipping point if it were translated into the PBLM is not the same as equation 32 which is the PBLM tipping point. But they are the same in spirit.

non-representative samples. But this is more and better information than solely using one’s own information.

The presence of this learning is very different than the simultaneous and complete distribution of information in the DD model. In the DD model, as soon as any proportion of consumers would attempt to withdraw any amount of assets from the bank such that the bank would fail, all consumers are instantly aware of this fact so they all try to withdraw their entire assets from the bank before it fails. An example of this is given in the section on Diamond-Dybvig equilibria. All consumers essentially have access to information on all other consumers and the bank, hence no one is caught unaware should a bank run occur. Bank runs or bank panics and bank failures are synonymous in the DD model.

Consumers in the PBLM have localized information as opposed to full information. But consumers can pass information to each other via the learning process. Thus the learning process in the PBLM allows for the transmission of panics to be modeled. As discussed earlier in the section, one consumer panicking makes each consumer that has yet to learn more likely to panic. This is effectively communicating panic from one consumer to others. With this process, readers can directly see how individuals panicking can cascade into herd like behavior and eventually cause a bank failure. However, the cascading effect is not simultaneous like it is in the DD model. The proximity based learning process allows information to disseminate through the population in a social network fashion.
Results

Place In Line (Timing)

Please first read the subsection on Timing in the Proximity Based Learning Section. A consumer’s place in line indicates when they are able to learn.

Results were obtained using the following scenario in Table 1 below.

Table 1: Parameters for Place In Line

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer Shock Probability</td>
<td>0.5</td>
</tr>
<tr>
<td>Consumer Short Term Endowment</td>
<td></td>
</tr>
<tr>
<td>Consumer Long Term Endowment</td>
<td>100000</td>
</tr>
<tr>
<td>Consumer Gross Income</td>
<td>50000</td>
</tr>
<tr>
<td>Consumer Net Income</td>
<td>-42500</td>
</tr>
<tr>
<td>Consumer Short Term Payout</td>
<td>1.18876</td>
</tr>
<tr>
<td>Consumer Long Term Payout</td>
<td>1.73913</td>
</tr>
<tr>
<td>Consumer Mean Rate of Consumption</td>
<td>0.85</td>
</tr>
<tr>
<td>Consumer Shock Multiplier</td>
<td>2</td>
</tr>
<tr>
<td>Consumer Population</td>
<td>100</td>
</tr>
<tr>
<td>All Consumers Visible</td>
<td>FALSE</td>
</tr>
<tr>
<td>Bank Long Term Asset Return</td>
<td>1.826087</td>
</tr>
<tr>
<td>Bank Short Term Asset Return</td>
<td>1</td>
</tr>
<tr>
<td>Bank Count</td>
<td>1</td>
</tr>
<tr>
<td>Bank Operating Cost</td>
<td>500000</td>
</tr>
<tr>
<td>Consumer Group Size</td>
<td>10</td>
</tr>
<tr>
<td>Bank Assets Not Visible</td>
<td>TRUE</td>
</tr>
</tbody>
</table>

The scenario was executed 200 times using Repast Simphony with Java.103

103 The scenario was only executed 200 times due to issues with the simulation software.
As discussed in the Timing subsection in the Proximity Based Learning Section, the state of the system is dynamic with respect to consumers’ ability to learn and panic. Consumers can only panic when they learn, not before or after. Further, the way panic conditions are structured in the PBLM, panic is expected to lead to more panic under both the liquidity panic condition and panic panic condition. From a system wide standpoint, when the first consumer learns, no consumers will have had the opportunity to panic. Hence there can be at most 0 panicked consumers out of the entire population before he learns. When the last consumer learns, every other consumer has had the opportunity to panic. Thus assuming the probability of panicking is nonzero, the proportion of panics (total number of panicked consumers divided by consumer population size) is expected to be larger later in the system than it is earlier. Since panic is expected to increase the likelihood of others panicking, this should translate into consumers that learn last are more likely to panic than consumers that learn first. Essentially, the later a consumer learns, the greater probability of the consumer panicking. Data regarding the proportion of periods each consumer panicked by place in line is shown below.
Figure 2: Proportion of Panics vs. Place In Line

The above data reflect that the proportion of times a consumer panicked (indicated by the blue diamond labeled “Panic”) does in fact increase as place in line increases. Thus the data reflect that panic does create panic as expected from the theoretical model. This result indicates that there is an effective panic transmission process created by proximity based learning. Proximity based learning is a viable method of understanding how bank failures can organically develop through panic transmission as opposed to using levels of information that lead to completely coordinated panics like the DD model uses.
Data regarding the two different panic conditions is also displayed in the graph. The probability of panicking regardless of condition is nearly identical to the probability of panicking under the liquidity condition. This result was somewhat surprising as the author had hypothesized the panic panic condition would become more “effective” as the number of panics in the system increased. But it appears the reaction to liquidity concerns is stronger than the reaction to panic based liquidity concerns as the two panic conditions are defined in the PBLM. As a result, in the following analysis the separation of the two panic conditions will be dropped and we will only be interested in the proportion of any type of panic.

When consumers learn, the expectation is that the information they obtain from a limited sample size is reflective of the overall state of the system. Thus the proportion of panicked consumers each consumer sees when they learn should approximate the actual proportion of panicked consumers in that system state. These data are presented below according to the consumer's place in line.
These data clearly indicate the expected relationship between the consumer's place in line and the proportion of panicked consumers observed. Since the latter is a proxy for the actual proportion of panicked consumers in the system, we can see that consumers' perceptions of the system change over time (referring to place in line) in a way that matches the expected actual changes in the system state (based on the results in Figure 2). Thus proximity based learning is an effective way for consumers to perceive the state of the system even as the system changes. This is an important result because it means information is disseminating through the system in a manner much more organic than assuming all consumers are aware of all pertinent information (consumer liquidity demands and bank assets) like the DD model does. Further, this allows for the transmission of panics to be modeled as
opposed to only having a single bank run equilibrium where all consumers panic at the same time.

The data collected regarding how consumer responses change as the system changes indicates that proximity based learning is an effective method of panic transmission. The PBLM provides a framework for observing how individual responses of consumers to localized information can cascade into a bank failure. This is a new addition to the literature that future researchers can use to actually explore how panics might spread in more realistic situations when it may be incorrect to assume information is so widely available that either all consumers panic or none do like in the DD model.

**Changing Magnitude of Net Income**

As described in the stationarity section, the expected value of net income $I$ is negative. Increasing the magnitude of net income here refers to consumers consuming a larger portion of their gross income in each period. Recall that

\[
I = E[I] = Y^*(1 - \gamma^* - \lambda \Psi) < 0
\]

which implies

\[
1 - \gamma^* - \lambda \Psi < 0
\]

since $Y^*$, $\gamma^*$, $\lambda$, and $\Psi$ are all at least 0 since they are respectively the consumer's expected gross income, expected average consumption rate, probability of getting shocked, and the income multiplier of the shock. Increasing the magnitude of net income was achieved by increasing the probability of consumers suffering an idiosyncratic shock, $\lambda$. 

Results were obtained using the following scenarios in Table 2 below. Parameters were kept as constant as possible under the stationarity conditions in order to isolate the effect of changing the magnitude of net income. Consumer Long Term Payout was calculated following $\beta_c = \frac{S^*}{S^* + I}$ where $S^*$ was held constant at $100,000$ and $I$ was changed from $-\$82500$, $-\$62500$, $-\$32500$, and $-\$12500$. Bank Long Term Asset Return is equal to Consumer Long Term Payout multiplied by 1.05. The ratio between the two long term returns is constant as is the short term endowment such that the bank’s operating cost is constant in each scenario.

**Table 4: Parameters for Changing Net Income Magnitude**

<table>
<thead>
<tr>
<th></th>
<th>Consumer Expected Net Income</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-82500</td>
</tr>
<tr>
<td><strong>Consumer Shock Probability</strong></td>
<td>0.9</td>
</tr>
<tr>
<td><strong>Consumer Short Term Endowment</strong></td>
<td>100000</td>
</tr>
<tr>
<td><strong>Consumer Long Term Endowment</strong></td>
<td>17499.98688</td>
</tr>
<tr>
<td><strong>Consumer Gross Income</strong></td>
<td>50000</td>
</tr>
<tr>
<td><strong>Consumer Short Term Payout</strong></td>
<td>1</td>
</tr>
<tr>
<td><strong>Consumer Long Term Payout</strong></td>
<td>5.71429</td>
</tr>
<tr>
<td><strong>Consumer Mean Rate of Consumption</strong></td>
<td>0.85</td>
</tr>
<tr>
<td><strong>Consumer Shock Multiplier</strong></td>
<td>2</td>
</tr>
<tr>
<td><strong>Consumer Population</strong></td>
<td>100</td>
</tr>
<tr>
<td><strong>Consumer Group Size</strong></td>
<td>25</td>
</tr>
<tr>
<td><strong>All Consumers Visible</strong></td>
<td>FALSE</td>
</tr>
<tr>
<td><strong>Bank Assets Visible</strong></td>
<td>FALSE</td>
</tr>
<tr>
<td><strong>Bank Long Term Asset Return</strong></td>
<td>6</td>
</tr>
<tr>
<td><strong>Bank Short Term Asset Return</strong></td>
<td>1</td>
</tr>
<tr>
<td><strong>Bank Count</strong></td>
<td>1</td>
</tr>
<tr>
<td><strong>Bank Operating Cost</strong></td>
<td>500000</td>
</tr>
</tbody>
</table>
Each scenario was executed 500 times using Repast Simphony with Java. The results are shown below.\(^{104}\)

**Table 5: Proportion of Panics vs. Net Income**

<table>
<thead>
<tr>
<th>Net Income</th>
<th>Proportion of Panics</th>
</tr>
</thead>
<tbody>
<tr>
<td>-$82500</td>
<td>0.366672901</td>
</tr>
<tr>
<td>-$62500</td>
<td>0.332824339</td>
</tr>
<tr>
<td>-$32500</td>
<td>0.187701131</td>
</tr>
<tr>
<td>-$12500</td>
<td>0.041617774</td>
</tr>
</tbody>
</table>

**Figure 6: Proportion of Panics vs. Net Income**

\(^{104}\) An alternative set of parameters was initially used, but it did not yield the expected simulation results. This is due to the fact that the previous scenario did not create much probability for a panic. Given that the sample size of 500 is relatively small, the differences resulting from changing the magnitude of net income could not be realized. A decision was made after the fact to use a more volatile scenario that would clearly allow for significant differences even in a small sample size.
Proportion of panics refers to the average proportion of consumers that panicked for any reason in a period. The results clearly indicate that as the magnitude of net income increases, the proportion of panics also increases. This result is not surprising as the decision to panic is based on whether consumers believe the bank will be able to meet its expected obligations in the next period. Expected obligations are the bank’s operating cost and the expected withdrawals. Thus as the magnitude of net income increases, the expected withdrawals increase. Recall the tipping point equation 32 for the average withdrawal per customer.

\[
S^* + \alpha_b \left( \frac{\beta_b (L) + d + I}{\beta_b} \right)
\]

Since \( I < 0 \), as the magnitude of net income increases, the average withdrawal such that the bank will not be able to meet its expected obligations in the next period decreases. Thus the tipping point average withdrawal becomes increasingly closer to the expected withdrawal as the magnitude of net income rises. In a probabilistic sense, the critical point moves closer to the mean of the distribution so the critical point is more likely to occur. When the critical point occurs, consumers panic. The results indicate the positive relationship between the magnitude of net income and the proportion of panic expected from the underlying theoretical model.

Readers may also be interested in the probability of the bank actually failing as the magnitude of net income rises. Those results are given below.

**Table 7: Proportion of Bank Failures vs. Net Income**

<table>
<thead>
<tr>
<th>Net Income</th>
<th>Proportion of Bank Failures</th>
</tr>
</thead>
<tbody>
<tr>
<td>-$82500</td>
<td>0.002588438</td>
</tr>
<tr>
<td>-$62500</td>
<td>0</td>
</tr>
<tr>
<td>-$32500</td>
<td>0</td>
</tr>
<tr>
<td>-$12500</td>
<td>0</td>
</tr>
</tbody>
</table>
Even with relatively high magnitudes of net income, the probability of a bank failure is still quite small. The tipping point for the average withdrawal is still so much greater than the expected withdrawal that a bank failure is extremely unlikely. This is due in part to the fact that tipping point for the bank to actually fail is based on the entire consumer population. In these simulations, that value was 100 consumers. However, when consumers made their personal panic decisions, they were basing those decisions on observations of at most 25 consumers. Following the Central Limit Theorem, it is unsurprising that individual consumers are more likely to perceive a failure than the actual system is to experience one. Additionally, while consumers’ bank asset estimations are subject distortions when consumers are shocked, the bank’s actual assets are not affected nearly as significantly by shocks.

The general results here stem from the fact that when the magnitude of net income increases, the ability of the capital endowment to sustain any temporary increases in consumption is diminished. This is evidenced by the analysis of the tipping point in the section. Thus relatively low capital environments are more vulnerable to bank failures than high capital environments. While this result is not surprising, it indicates that low-capital environments could require benefit from using greater oversight to create a more stable banking system. Avoiding these additional regulations could be thought of as some of the benefits present in

---

105 Consumers look at the lesser of the number of consumers in neighborhood and the learning group size.
106 Low and high here are indicative of the relationship between the magnitude of net income and asset endowment.
wealthier environments due to the fact that they already have large levels of capital. This interpretation is consistent with Honohan (2000) who found that capital requirements in industrial countries were not stringent enough for most developing countries due to differences in economy size. He concluded that “strengthening the hand of national bank regulators” in developing countries was the best way to reduce the “fragility of [weaker] banking systems.”

**Changing αc (Consumer Alpha)**

By holding αb constant (αb = 1) throughout all these simulations, we are able to observe the effect of increasing the differential between αb and αc by simply increasing αc.

Results were obtained using the following scenarios in Table 6 below. Parameters were all kept constant under the stationarity conditions in order to isolate the effect of changing αc.

---

Table 8: Parameters for Changing $\alpha_c$

<table>
<thead>
<tr>
<th></th>
<th>$\alpha_c = 1$</th>
<th>$\alpha_c = 1.5$</th>
<th>$\alpha_c = 1.8$</th>
<th>$\alpha_c = 2.3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer Shock Probability</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Consumer Short Term Endowment</td>
<td>100000</td>
<td>100000</td>
<td>100000</td>
<td>100000</td>
</tr>
<tr>
<td>Consumer Long Term Endowment</td>
<td>17499.987</td>
<td>17499.987</td>
<td>17499.987</td>
<td>17499.987</td>
</tr>
<tr>
<td>Consumer Gross Income</td>
<td>50000</td>
<td>50000</td>
<td>50000</td>
<td>50000</td>
</tr>
<tr>
<td>Consumer Net Income</td>
<td>-82500</td>
<td>-82500</td>
<td>-82500</td>
<td>-82500</td>
</tr>
<tr>
<td>Consumer Long Term Payout</td>
<td>5.71429</td>
<td>5.71429</td>
<td>5.71429</td>
<td>5.71429</td>
</tr>
<tr>
<td>Consumer Mean Rate of Consumption</td>
<td>0.85</td>
<td>0.85</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Consumer Shock Multiplier</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Consumer Population</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Consumer Group Size</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>All Consumers Visible</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
</tr>
<tr>
<td>Bank Assets Visible</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
</tr>
<tr>
<td>Bank Long Term Asset Return</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Bank Short Term Asset Return</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bank Count</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bank Operating Cost</td>
<td>500000</td>
<td>500000</td>
<td>500000</td>
<td>500000</td>
</tr>
</tbody>
</table>

Each scenario was executed 500 times using Repast Simphony with Java. The results are shown below.\textsuperscript{108}

Table 9: Proportion of Panics vs. $\alpha_c$

<table>
<thead>
<tr>
<th>Alpha</th>
<th>Proportion of Panics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha = 1</td>
<td>0.397224858</td>
</tr>
<tr>
<td>Alpha = 1.5</td>
<td>0.688365764</td>
</tr>
<tr>
<td>Alpha = 1.8</td>
<td>0.900157704</td>
</tr>
<tr>
<td>Alpha = 2.3805</td>
<td>0.940229312</td>
</tr>
</tbody>
</table>

Figure 10: Proportion of Panics vs. $\alpha_c$

\textsuperscript{108} An alternative set of parameters was initially used, but it did not yield the expected simulation results. This is due to the fact that the previous scenario did not create much probability for a panic. Given that the sample size of 500 is relatively small, the differences resulting from changing the magnitude of net income could not be realized. A decision was made after the fact to use a more volatile scenario that would clearly allow for significant differences even in a small sample size.
The results clearly indicate that as \( \alpha_c \) increases, the proportion of panics also increases.\(^{109}\) This result is not surprising because \( \alpha_c \) is the rate at which consumers can redeem their long term assets. Increasing \( \alpha_c \) directly increases the total value of consumer assets held at the bank to consumers. The actual value of consumer assets to the bank is unaffected by \( \alpha_c \) since the bank liquidates long term assets at \( \alpha_b \) which will be left unchanged in these scenarios.

Thus as \( \alpha_c \) increases, the amount consumers can withdraw when they panic increases. This means when consumers panic, they now place add a greater liquidity demand to the overall system with a higher \( \alpha_c \) than they would have with a lower \( \alpha_c \). Interestingly, this effect does not occur until consumers start to panic as \( \alpha_c \) is actually inconsequential to the liquidity panic condition. Since one liquidity panic must occur before \( \alpha_c \) becomes relevant to the system, increasing \( \alpha_c \) does not

\(^{109}\) It is expected that the two have a logarithmic relationship which has an asymptotic limit of 1 because the proportion of panics cannot exceed 1.
increase the probability of the first panic starting. However, due to the increased
panic withdrawal, increasing $\alpha_c$ increases the likelihood of every panic after the first.
Increasing $\alpha_c$ makes the panic transmission process stronger.

The cost of a consumer liquidating his long term assets is $\beta_c - \alpha_c$. Thus as $\alpha_c$
rises, the cost of early liquidation decreases so consumers are expected be more
willing to panic and liquidate early. This behavior is not explicitly included in the
PBLM as doing so would require true risk-aversion and optimization. However, this
behavior is intuitive and supported by the literature so it is to the benefit of this
study that its results also reflect this idea. In the DD model, expected returns in
period 2 are directly compared to $\alpha_c$. In Equation 13 it is clear that increasing $\alpha_c$ in
the DD leads to greater liquidity demands on the bank and therefore a greater
probability of a bank failure. As a natural extension to the DD model, it makes sense
that this relationship should hold in the PBLM.

Consistent with the above analysis is the idea that the probability of the bank
failing should increase as $\alpha_c$ increases. The data reflected this expected relationship.
These results are given below. Note that in the case where $\alpha_c = 2.3805$, the
proportion of bank failures actually exceeded the proportion of panics. This result is
not entirely surprising given that under proximity based learning, consumers may
not realize they are in a bank failure situation based on the information they
perceive.
Table 11: Proportion of Bank Failures vs. $\alpha_c$

<table>
<thead>
<tr>
<th>Alpha</th>
<th>Proportion of Bank Failures</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.003611673</td>
</tr>
<tr>
<td>1.5</td>
<td>0.320541761</td>
</tr>
<tr>
<td>1.8</td>
<td>0.825581395</td>
</tr>
<tr>
<td>2.3805</td>
<td>0.998005982</td>
</tr>
</tbody>
</table>

Figure 10: Proportion of Bank Failures vs. $\alpha_c$

The difference between $\alpha_c$ and $\alpha_b$ is a measure of the additional liquidity a bank provides to consumers. As the bank provides more liquidity (i.e. a higher $\alpha_c$ ceteris paribus), the probability for a bank failure increases. The simulation results support this conclusion both in the perceptions of the consumers (proportion of panics) and in system response (proportion of bank failures). This relationship is discussed multiple times in the original DD paper as something about which banks and consumers should be concerned as there is a real loss when the bank fails. Other studies such as Goldstein and Pauzner also find a positive relationship between the
differential of \( \alpha_c \) and \( \alpha_b \) and the probability of the bank failing. Thus these simulation results reinforce this finding with the added flavor of proximity based learning as a panic transmission mechanism.

**Changing Group Size**

Group size is the number of neighbors a consumer can look at during their proximity based learning phase. This section looks at the impact of changing the group size on the system.

Results were obtained using the following scenarios in Table 10 below. All other parameters were all kept constant under the stationarity conditions in order to isolate the effect of changing group size.
Table 12: Parameters for Changing Group Size

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Group Size 2</td>
<td>Group Size 5</td>
<td>Group Size 10</td>
<td>Group Size 25</td>
<td>Group Size 100</td>
</tr>
<tr>
<td>Consumer Shock Probability</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Consumer Short Term Endowment</td>
<td>100000</td>
<td>100000</td>
<td>100000</td>
<td>100000</td>
<td>100000</td>
</tr>
<tr>
<td>Consumer Long Term Endowment</td>
<td>17499.987</td>
<td>17499.987</td>
<td>17499.987</td>
<td>17499.987</td>
<td>17499.987</td>
</tr>
<tr>
<td>Consumer Gross Income</td>
<td>50000</td>
<td>50000</td>
<td>50000</td>
<td>50000</td>
<td>50000</td>
</tr>
<tr>
<td>Consumer Net Income</td>
<td>-82500</td>
<td>-82500</td>
<td>-82500</td>
<td>-82500</td>
<td>-82500</td>
</tr>
<tr>
<td>Consumer Short Term Payout</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Consumer Long Term Payout</td>
<td>5.71429</td>
<td>5.71429</td>
<td>5.71429</td>
<td>5.71429</td>
<td>5.71429</td>
</tr>
<tr>
<td>Consumer Mean Rate of Consumption</td>
<td>0.85</td>
<td>0.85</td>
<td>0.85</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Consumer Shock Multiplier</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Consumer Population</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>All Consumers Visible</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
</tr>
<tr>
<td>Bank Assets Visible</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
<td>FALSE</td>
</tr>
<tr>
<td>Bank Long Term Asset Return</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Bank Short Term Asset Return</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bank Count</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bank Operating Cost</td>
<td>500000</td>
<td>500000</td>
<td>500000</td>
<td>500000</td>
<td>500000</td>
</tr>
</tbody>
</table>

Each scenario was executed 500 times using Repast Simphony with Java.\textsuperscript{110}

\textsuperscript{110} An alternative set of parameters was initially used, but it did not yield the expected simulation results. This is due to the fact that the previous scenario did not create much probability for a panic. Given that the sample size of 500 is relatively small, the differences resulting from changing the group size could not be realized. A
During proximity based learning, Consumer A looks at the average liquidity demands of his neighbors to estimate overall liquidity demand in the system.\textsuperscript{111} As group size increases, Consumer A is able to see a larger proportion of the overall consumer population. Following the law of large numbers, as group size increases, Consumer A's estimate of overall liquidity demand should be getting more accurate.

However, liquidity demand in the system is dynamic with respect to the timing of the proximity based learning.\textsuperscript{112} If Consumer A chooses to panic, he will withdraw all of his assets from the bank. His panic and withdrawal increase the liquidity demand in the system. Given that liquidity demand can increase beyond initial levels as consumers have the opportunity to learn, this study chose to compare each consumer's estimate of the current liquidity level at the point in time they learned to the actual liquidity level at that same point in time. Thus as group size increases, this study looked at the differences between consumer estimates of liquidity demands and the actual liquidity demands at the same points in time.\textsuperscript{113}

The standard deviation of these differences was used to determine how accurate the consumers' estimates were. A more accurate set of estimates would

\begin{footnotesize}
\begin{itemize}
\item \textsuperscript{111} Liquidity demand is determined by either the cash holdings of a consumer because the consumer had such great liquidity demands he or she needed to withdraw money from the bank or the consumer's initial liquidity demand if the consumer had net positive income and deposited money into the bank.
\item \textsuperscript{112} Here, timing refers to the consumer's place in line to do proximity based learning. The first consumer to learn is considered to proceed earlier in time than the last consumer to learn.
\item \textsuperscript{113} For example, when if Consumer C is the 52\textsuperscript{nd} person to learn, her estimate of the liquidity demand is compared to the actual liquidity demand in the system when she looks (i.e. the actual liquidity demand after 51 other consumers have already learned).
\end{itemize}
\end{footnotesize}
have a lower standard deviation in the difference than a less accurate set of estimates. In this experiment, a group size of 20 consumers would be expected to yield a lower standard deviation in the estimate differences than a group size of 10 consumers. The actual results are below.

**Figure 13: Standard Deviation of Liquidity Demand Estimation Difference vs. Group Size**

![Standard Deviation of Liquidity Demand Estimation Difference](image)

**Table 14: Standard Deviation of Liquidity Demand Estimation Difference vs. Group Size**

<table>
<thead>
<tr>
<th>Group Size</th>
<th>Standard Deviation of Liquidity Demand Estimation Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group Size 25</td>
<td>2812179.902</td>
</tr>
<tr>
<td>Group Size 10</td>
<td>2896585.175</td>
</tr>
<tr>
<td>Group Size 5</td>
<td>3166120.97</td>
</tr>
<tr>
<td>Group Size 2</td>
<td>3926264.274</td>
</tr>
<tr>
<td>All Consumers Visible</td>
<td>0</td>
</tr>
</tbody>
</table>
The results indicate that as group size increases, the standard deviation between the consumers’ estimate of the current liquidity demand and the actual current liquidity demand decreases. This was the expected relationship following the idea that larger samples should be more representative of the overall system. This relationship plays out in interesting ways regarding the proportion of panic which will be discussed later in the section.

When all consumers were visible, during each consumer’s opportunity to learn, the consumer could see the liquidity demands of the entire system. Thus their “estimate” actually matched the actual liquidity demand in the system. Thus the difference between the estimate and actual was always 0 so it had a standard deviation of 0.

As the group size increases, one would expect to see the standard deviation of the differences approach 0. However, the data shown do not appear to indicate that. The reasoning behind this is the nature of the learning process. The process is coded so that a consumer looks in her surrounding neighborhood of a certain size at the minimum of either the group size or the number of consumers in her neighborhood. For example, if her group size is 25 but there are only 10 consumers in her neighborhood, she will only observe the 10 consumers.

To avoid this constraint, the author could have expanded the consumer’s neighborhood to include the entire simulation environment. Unfortunately, the software package used in this simulation process would be greatly slowed by that
change. Further, that would take away the idea of using geographical proximity as a proxy for social familiarity. This second point is not so important as the resulting geographical proximity is random anyway. For further research, expanding the neighborhood size to the full simulation environment would be an interesting exercise. With that change, we would almost surely see the standard deviation of the difference approach 0 as group size reached the population total.

As group size increases, the proportion of unnecessary panics (panics when the bank is not in an actual failure situation) was expected to decrease.\textsuperscript{114} An unnecessary panic occurs when a consumer misestimates the relationship between the bank’s assets and the overall liquidity demand in the system. The results regarding the accuracy of consumer liquidity estimates suggests that consumers are less likely to significantly overestimate liquidity demands as group size increases. Thus the proportion of panics should decrease due to the decreased chance for overestimating liquidity demands. However, the other part of the panic condition is

\textsuperscript{114} If initial liquidity demands are high enough such that the bank would fail, the bank is expected fail (in either the current period or the next) regardless of whether or not any consumers panic. Liquidity demands never go below their initial level as the learning process only allows for consumers to withdraw more money from the bank (increasing liquidity demands). The overall cost of a bank failure is unaffected by the actions of consumers. However, which consumers pay the cost does depend on consumer actions. Consumer A may incorrectly perceive the system not to be in a bank failure situation so he will not withdraw his assets when he learns and later lose all of his assets once the bank does indeed fail. Thus increasing sample size allows consumers to more accurately diagnose bank failure situations. So with larger sample sizes, consumers that have the opportunity to withdraw early on (the first people in line) are more likely to avoid losing their assets in a bank failure as opposed to consumers at the end of the line that may never have the opportunity to withdraw assets before the bank fails. In summary, increasing group size in a bank failure situation does not negatively affect the system but it shifts the burden from the early learning consumers to the later consumers in line.
the consumer’s estimate of the bank’s assets which is unaffected by group size. This two part nature of the panic condition led to interesting results regarding the relationship between group size and proportion of panic. The results are given below.

**Table 15: Proportion of Panic vs. Group Size**

<table>
<thead>
<tr>
<th>Group Size</th>
<th>Proportion of Panics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group Size 25</td>
<td>0.367087277</td>
</tr>
<tr>
<td>Group Size 10</td>
<td>0.397224858</td>
</tr>
<tr>
<td>Group Size 5</td>
<td>0.413207298</td>
</tr>
<tr>
<td>Group Size 2</td>
<td>0.469592348</td>
</tr>
<tr>
<td>All Consumers Visible</td>
<td>0.646774219</td>
</tr>
</tbody>
</table>
The above results regarding group size and proportion of panics appear to indicate that the proportion of panics actually does decrease as group size increases. However, when all consumers are visible, the proportion of panic actually rises quite significantly. This is due to the problem mentioned above where the decision to panic is based off of both the estimated liquidity demand and the estimated bank assets. The idea that the bank asset estimation process is vulnerable to significant
distortions when the consumer is shocked causes the panic proportion to spike when all consumers are visible.

If Consumer A is shocked, he is likely to panic regardless of the liquidity demand in the system because of his estimate of the bank's assets. If he panics, he withdraws what remaining assets he has from the bank. This withdrawal increases the liquidity demands on the entire system. Since all consumers are visible, every other consumer sees that increased liquidity demand. Thus consumers are constantly perceiving the increased liquidity demands when consumers panic. If a significant proportion of consumers are getting shocked, the combination of the increasing liquidity demands and low estimation of bank assets provides the perfect conditions for large proportions of bank panics. In the scenario above, 90% of consumers were expected to be shocked each period so the result above is no longer so surprising.

Further, bank failures actually occurred 9.1% of the time when all consumers were visible due to the heavy liquidity demands imposed by consumers panicking. This was a significantly larger proportion than what occurred under any of the other group sizes. The bank failure proportions are shown below. Looking deeper into the actual level of bank assets when consumers panicked revealed that 85.9% of the panics that occurred when all consumers were visible were unnecessary.\textsuperscript{115} This is consistent with the idea that although consumer estimates of the liquidity demand

\textsuperscript{115} 85.9% is actually a lower bound on the proportion of the panics that were unnecessary. Data needed to calculate the exact proportion were not recorded.
were accurate, their inaccurate estimate of the bank’s assets led to a less optimal outcome than what occurred with smaller group sizes.\textsuperscript{116}

**Table 17: Proportion of Bank Failures vs. Group Size**

<table>
<thead>
<tr>
<th>Group Size</th>
<th>Proportion of Bank Failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.004491452</td>
</tr>
<tr>
<td>5</td>
<td>0.004344678</td>
</tr>
<tr>
<td>10</td>
<td>0.003611673</td>
</tr>
<tr>
<td>25</td>
<td>0.002594782</td>
</tr>
<tr>
<td>All Consumers Visible</td>
<td>0.091363724</td>
</tr>
</tbody>
</table>

Overall, the results of this section strongly support that consumer estimates of the liquidity demand in the system become more accurate as group size increases. This is beneficial in that consumers are less likely to overestimate liquidity demands by a significant amount which decreases the likelihood of panics in a non failure situation. But more accurate liquidity demand estimates alone are not enough to guarantee better outcomes. Since panicking depends on both liquidity and asset estimations, depending on the asset estimation process, increasing the group size could actually be detrimental as we saw when all consumers were visible. Thus the overall benefit of increasing the information available to consumers regarding liquidity demands is unclear unless the bank asset estimation process is also considered.

\textsuperscript{116} Less optimal refers to the proportion of bank failures in Table 15.
Bank Transparency

Bank transparency is whether or not consumers are able to directly see the assets the bank holds.

Results were obtained using the following scenarios in Table 18 below. Parameters were all kept constant under the stationarity conditions in order to isolate the effect of changing the bank’s visibility.

Table 18: Parameters for Bank Visibility

<table>
<thead>
<tr>
<th></th>
<th>Bank Assets Visible</th>
<th>Bank Assets Not Visible</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer Shock Probability</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Consumer Short Term Endowment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer Long Term Endowment</td>
<td>100000</td>
<td>100000</td>
</tr>
<tr>
<td>Consumer Gross Income</td>
<td>50000</td>
<td>50000</td>
</tr>
<tr>
<td>Consumer Net Income</td>
<td>-42500</td>
<td>-42500</td>
</tr>
<tr>
<td>Consumer Short Term Payout</td>
<td>1.18876</td>
<td>1.18876</td>
</tr>
<tr>
<td>Consumer Long Term Payout</td>
<td>1.73913</td>
<td>1.73913</td>
</tr>
<tr>
<td>Consumer Mean Rate of Consumption</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Consumer Shock Multiplier</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Consumer Population</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>All Consumers Visible</td>
<td>FALSE</td>
<td>FALSE</td>
</tr>
<tr>
<td>Bank Long Term Asset Return</td>
<td>1.826087</td>
<td>1.826087</td>
</tr>
<tr>
<td>Bank Short Term Asset Return</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bank Count</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bank Operating Cost</td>
<td>500000</td>
<td>500000</td>
</tr>
<tr>
<td>Consumer Group Size</td>
<td>10</td>
<td>10</td>
</tr>
</tbody>
</table>

Each scenario was executed 200 times using Repast Simphony with Java.117

117 These scenarios were only executed 200 times each due to issues with the Repast Simphony.
Consumers base their decision to panic on what they expect the bank’s assets to be in the next period compared to expected liquidity demands in the next period. In the general case, consumers are unable to see the actual assets the banks hold. Consumers instead use ad-hoc expectations to estimate the bank’s assets. For example, Consumer A could look at his levels of short and long term assets and estimate that every other consumer has the same levels of assets in the banks. In this manner, Consumer A can use ad-hoc expectations to estimate the bank’s total levels of assets.

However, the bank’s assets are dynamic with respect to the timing of proximity based learning in the same way liquidity demands on the system were dynamic. If Consumer A chooses to panic, he will withdraw all of his assets from the bank. His withdrawal decreases the amount of assets the bank holds. Given that bank assets can decrease beyond initial levels after consumers have received their net incomes, this study chose to compare each consumer’s estimate of the current bank asset levels at the point in time they learned to the actual bank asset levels at the same point in time. The standard deviation of these differences was used to determine how accurate the consumers’ estimates were. A more accurate set of estimates would have a lower standard deviation in the difference than a less accurate set of estimates. Given the way bank assets are estimated in the PBLM, there are only two approaches: either the consumer used ad-hoc expectations or the consumer could see the bank’s assets. The results are below.

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118 This reasoning is nearly identical to that of the consumer estimation of liquidity demand.
Unsurprisingly, the results indicate that when consumers need to use ad-hoc expectations to estimate the bank’s current assets, those estimations are very inaccurate. Much of this inaccuracy comes from the aforementioned distortion when a consumer is shocked. When the bank’s assets are visible, during each consumer’s opportunity to learn, the consumer could see the actual bank’s assets so their “estimate” was completely accurate. Thus the difference between the estimate and actual was always 0 so it had a standard deviation of 0.

When consumers underestimate the bank’s assets, they are more likely to panic. This is problematic in a non-failure situation as panicking increases the overall level of liquidity demands on the banks assets and increases the likelihood of
others panicking. There is also the real cost of panicking and liquidating one's long term assets early. Bank transparency eliminates underestimating bank assets, so we would expect to see the proportion of panics be smaller when there is bank transparency as opposed to when there is not transparency. The results showing the proportion of panics and bank failures are below.

Table 21: Proportion of Panics and Bank Failures vs. Bank Visibility

<table>
<thead>
<tr>
<th></th>
<th>Proportion of Panics</th>
<th>Proportion of Bank Failures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank Assets Not Visible</td>
<td>0.288984735</td>
<td>0</td>
</tr>
<tr>
<td>Bank Assets Visible</td>
<td>0.004627257</td>
<td>0.000714286</td>
</tr>
</tbody>
</table>

These results indicate that consumers misestimating (underestimating) the bank's assets were largely responsible for unnecessary panics. Although these results came from one scenario of parameters and a relatively small sample size, the difference between the proportions of panics when the bank assets were not visible and when they were visible show how poor consumers' ad-hoc expectations of bank assets are. Bank transparency has effect where consumers that are shocked are no longer extremely likely to panic simply by merit of being shocked. Removing this distortion is why the proportion of panics decreased so dramatically when bank assets became visible.

These results indicate that the consumer's ad-hoc expectations for bank assets are easily distorted and responsible for a large proportion of unnecessary

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119 In bank failure situations, bank transparency has no overall effect as it does not change the magnitude of the loss due to a bank failure. It merely affects the distribution of that loss (some consumers might have incorrectly not withdrawn assets when they had the opportunity to due to overestimating bank assets) but since the bank is in a failure situation, the overall cost is inevitable.
panics. However, the economic intuition behind this estimation process is still not unreasonable, especially in the face of no clear alternatives. Under the fair assumption that each consumer only knows his or her own level of assets and that all consumers are expected to have the same level of assets, the ad-hoc expectation process is logical albeit easily capable of being distorted.

Bank transparency eliminates the consequences of overestimating bank assets (there are none in non-failure situations) and underestimating assets (there are plenty in non-failure situations). Thus in non-bank failure situations, bank transparency decreases the probability of costly unnecessary bank panics. The simulation results indicate this is likely a very significant decrease. Based on these results, it is clear that poor consumer estimations of bank assets are responsible for a large proportion of unnecessary panics in the PBLM. To rectify this issue, banks should consider making their assets more visible to avoid consumers from underestimating the bank’s assets and panicking.\textsuperscript{120}

\textsuperscript{120} The author reaches this conclusion based solely on the simulation results. It is quite possible that banks may want to avoid making their assets visible for competitive or privacy reasons.
Bank Transparency and Consumer Visibility

Bank transparency is whether or not consumers are able to directly see the assets the bank holds. Complete consumer visibility is whether or not during the learning phase consumers can see the liquidity demands of all other consumers.

Results were obtained using the following scenarios. Parameters were all kept constant under the stationarity conditions in order to isolate the effect of changing the bank’s visibility.

Table 22: Parameters for Bank Transparency and Consumer Visibility

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Bank Assets Visible and All Consumers Visible</th>
<th>Bank Assets Not Visible and Group Size = 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer Shock Probability</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Consumer Short Term Endowment</td>
<td>100000</td>
<td>100000</td>
</tr>
<tr>
<td>Consumer Long Term Endowment</td>
<td>57500</td>
<td>57500</td>
</tr>
<tr>
<td>Consumer Gross Income</td>
<td>50000</td>
<td>50000</td>
</tr>
<tr>
<td>Consumer Net Income</td>
<td>-42500</td>
<td>-42500</td>
</tr>
<tr>
<td>Consumer Short Term Payout</td>
<td>1.18876</td>
<td>1.18876</td>
</tr>
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<td>Consumer Long Term Payout</td>
<td>1.73913</td>
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</tr>
<tr>
<td>Consumer Mean Rate of Consumption</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Consumer Shock Multiplier</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Consumer Population</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Bank Long Term Asset Return</td>
<td>1.826087</td>
<td>1.826087</td>
</tr>
<tr>
<td>Bank Short Term Asset Return</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bank Count</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bank Operating Cost</td>
<td>500000</td>
<td>500000</td>
</tr>
<tr>
<td>Consumer Group Size</td>
<td>N/A</td>
<td>10</td>
</tr>
</tbody>
</table>

Each scenario was executed 200 times using Repast Simphony with Java.\textsuperscript{121}

\textsuperscript{121} These scenarios were only executed 200 times each due to issues with the Repast Simphony.
Consumers are now able to view the bank’s actual assets and see the liquidity demands of all consumers when they learn now. This scenario combines the previous conditions of bank transparency and complete consumer visibility. Consequently consumers no longer need to use ad-hoc expectations anymore. The differences between bank asset and liquidity demand estimates are always 0 now. For the sake of comparison, these results will be displayed next to results obtained using the same parameters but without both complete consumer visibility and bank asset visibility. The results are below.

**Figure 23: Standard Deviation of Estimation Differences vs. Visibility**

![Graph showing standard deviations of estimation differences vs. visibility](image)
Table 24: Standard Deviation of Estimation Differences vs. Visibility

<table>
<thead>
<tr>
<th></th>
<th>Standard Deviation of Liquidity Demand Estimation Difference</th>
<th>Standard Deviation of Bank Assets Estimation Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank and Consumer</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Visibility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Bank Visibility and</td>
<td>1670744</td>
<td>9278488</td>
</tr>
<tr>
<td>Group Size = 10</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The results indicate that with bank and consumer visibility, consumers are much better at “estimating” as opposed to when consumers lack that visibility. With visibility, it is now expected that no unnecessary panics should occur. This is the same situation as the DD model where either all consumers panic or none of them do because they all act on the same information. The results regarding panic proportion are below.

Figure 25: Proportion of Panic vs. Visibility
Table 26: Proportion of Panic vs. Visibility

<table>
<thead>
<tr>
<th>Bank and Consumer Visibility</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Bank Visibility and Group Size = 10</td>
<td>0.288456471</td>
</tr>
</tbody>
</table>

Under both scenarios, no bank failures occurred. Hence all panics were unnecessary panics. Given that unnecessary panics do not occur with visibility, it is unsurprising that the panic proportion for visibility was 0. The panic proportion without visibility was 0.288. As mentioned throughout this paper, there is a real cost associated with panics. Diamond and Dybvig define it as the cost of recalling loans and interrupting production.\(^{122}\) There is also the real penalty associated with liquidating one’s assets early. Thus panicking is costly and should be avoided unless it is necessary. With bank visibility and consumer visibility, the proportion of unnecessary panics was and will be 0. This means all the costs associated with unnecessary panics are avoided with better visibility. In order to reduce costs associated with unnecessary bank failures, this study suggests the banking system be as transparent as possible about the bank’s assets and liquidity demands.

Increasing group size was found to be an effective way to increase the accuracy of consumer estimates regarding the liquidity demands in the system. Unfortunately this study was unable to explore any effective ways to increase the accuracy of bank asset estimates aside from allowing consumers to directly see the bank’s assets. Several alternatives to the ad-hoc expectation process of bank assets are discussed in the Distortions subsection of the Proximity Based Learning section.

\(^{122}\) DD p.404
Identifying ways to allow consumers to more accurately perceive the actual holdings of the bank without infringing on privacy or competitive concerns is key in preventing unnecessary panics.

Interestingly, the optimal scenario of bank and consumer visibility is the same scenario that this study criticizes for being unrealistic. In practice, this scenario still is impractical. The whole basis for proximity based learning is the assumption that consumers only have access to limited information on the system. However, these results indicate that unnecessary panics are the result of consumers receiving information that does not accurately reflect the state of the system. Thus providing avenues for consumers to understand that the system is not in a failure situation is very helpful in discouraging false panics.

**Conclusion**

**Place in Line**

The analysis of these results supports that proximity based learning is an effective form of communication. As a consumer’s place in line increases, the likelihood of the consumer panicking also increases. This relationship is representative of panics leading to more panic as expected in the theoretical model.

**Magnitude of Net Income**

The analysis of these results supports the mathematical tipping point analysis where as the magnitude of net income increases, the tipping point average withdrawal becomes closer to the expected average withdrawal. As the two
approach each other, it becomes increasingly likely that the actual average
withdrawal could exceed the tipping point and cause consumers to panic and the
bank to fail. This result was consistent with Honohan’s (2000) work which found
smaller economies with less capital were at greater risk of bank failure than
developed economies.

**Changing $\alpha_c$**

The analysis supports that as the liquidity provided by the bank increases (as
$\alpha_c$ increases relative to $\alpha_b$), the probability of both panics and bank failures increase.
This is the expected theoretical relationship found in the DD, Pauzner and Goldstein,
and Chari and Jagannathan.

**Changing Group Size**

The analysis supports that as group size increases, consumers see more
accurate information regarding the liquidity demands on the overall system. This is
the expected relationship under the law of large numbers. It was interesting to note
that although this relationship holds, the proportion of panics does not necessarily
decrease, as the panic condition is also dependent on consumer estimates of the
bank’s assets.

**Bank Visibility**

The analysis supported that when consumers could see the bank’s assets,
their estimates of the bank’s assets matched the actual values. This result was
unsurprising. However, these data revealed how the ad-hoc expectations of the
bank’s assets can be severely distorted when a shocked consumer uses his own
shock-depleted assets as the expected per-capita holdings of the bank. Several
alternatives to prevent this distortion should be explored in future research including using a weighted average of a consumer’s past asset levels and allowing the consumer to view the assets of other consumers so as to increase the sample size. This distortion effect is not clearly a problem intuitively, but for experimental purposes alternatives should at least be considered.

**Bank Transparency and Consumer Visibility**

The analysis supported that consumers were now able to perfectly estimate the bank’s assets and overall liquidity demands on the system. The results actually indicated this was the most optimal scenario as it completely eliminated any unnecessary panics. This is also the most unrealistic scenario as privacy and competitive concerns would likely prevent banks from revealing their assets and prevent consumers from sharing their liquidity needs with all other consumers, not just the consumers they were socially proximal to. It also removes any need for proximity based learning as this is the standard DD case.

The data support all the expected theoretical relationships. Thus proximity based learning is a concept that should be considered for any future research regarding the panic transmission process for any models that build off of the DD framework.

In general, bank panics in the PBLM were largely a result of consumers acting on incorrect limited information. The probability of unnecessary panics could be significantly decreased by making banks more transparent about the assets they hold and the liquidity demands they face. This is a significant solution because if the
probability of an actual bank failure based on expected withdrawals is low, “the only thing we have to fear is fear itself.”

The PBLM is not a perfect model. Stationarity in assets was important in keeping expected tipping points constant over time. Unfortunately true stationarity could not be achieved due to the circular issue where a stationary system should account for the expected loss due to a bank failure, but calculating that expected loss requires knowing the probability of bank panics and failures in a stationary system. There was also the issue of debt forgiveness that makes asset growth tend positive. Thus all results should be taken with the caveat that stationarity in assets may or may not exist.

Regardless of whether or not stationarity holds, it is the firm belief of the author that proximity based learning is an effective method of communication and a more reasonable assumption of what information is available to consumers as opposed to the perfect visibility in the DD model. The PBLM lays the foundation for future research regarding the panic transmission process.

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123 Franklin D. Roosevelt (1933).
124 Given that panics can cascade and cause a strong system to fail.
Works Cited


