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BANKS AS POTENTIALLY CROOKED SECRET-KEEPERS

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ABSTRACT

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Banks As Potentially Crooked Secret Keepers

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Abstract

Bank failures are generally liquidity as well as solvency events. Whether it is households running on banks or banks running on banks, defunding episodes are full of drama. This theater has, arguably, lured economists into placing liquidity at the epicenter of financial collapse. But loss of liquidity describes how banks fail. Bad news about banks explains why they fail. This paper models banking crises as triggered by news that the degree (share) of banking malfeasance is likely to be particularly high. The malfeasance share follows a state-dependent Markov process. When this period's share is high, agents rationally raise their probability that next period's share will be high as well. Whether or not this proves true, agents invest less in banks, reducing intermediation and output. Deposit insurance prevents such defunding and stabilizes the economy. But it sustains bad banking, lowering welfare. Private monitoring helps, but is no panacea. It partially limits banking malfeasance. But it does so inefficiently as households needlessly replicate each others' costly information acquisition. Moreover, if private audits become public, private monitoring breaks down due to free-riding. Government real-time disclosure of banking malfeasant mitigates, if not eliminates, this public goods problem leading to potentially large gains in both non-stolen output and welfare.

Keywords: Financial crises, Deposit insurance, Bank fraud, Bank reform, Moral hazard
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1. Introduction

Banks (our name for financial institutions, broadly defined) have traditionally been modeled as honest entities satisfying liquidity needs via issuance of demand deposits and other short-term liabilities (Gorton and Pennacchi (1990)). Banking crises have been viewed as runs motivated by the fear that others will appropriate one's money (Diamond and Dybvig (1983) and Goldstein and Pauzner (2005)). But deposit insurance has largely eliminated concern about transaction balances. Indeed, the financial crisis of 2007-2008 saw essentially no traditional commercial bank runs (Financial Crisis Inquiry Commission (2011)) by non-institutional investors.[1] Instead, as Covitz et al. (2013) and others document, banks stopped funding one another based on perceptions, some true, some false, that financial institutions had gone bad. The serial collapse of large, highly opaque banks raised concern about the defunding of surviving, but equally opaque, banks. Attempts to pay creditors led to fire sales of "troubled" assets. This fed the defunding panic, producing more implicit and explicit failures. Overnight, bank secret-keeping, which left potential refunders in the dark about each-other's true solvency, went from a sign of collective trust to one of financial distress, if not financial fraud.

Bankruptcies, financial or not, are typically liquidity as well as solvency events.[2] The 29 global financial institutions that failed, either explicitly or implicitly, during the Great Recession, all lost or were about to lose external funding in the run up to their demises. The drama of financial firms running short of cash – J.P. Morgan's dramatic 2007 rescue of Wall Street, the serial collapse of 9,000 commercial-banks in the Great Depression, California's shocking seizure of Executive Life, the panicked resolution of Long Term Capital Management, the Fed's emergency weekend meetings that "saved" Bear Sterns and let Lehman Brothers collapse, the remarkable nationalizations of Fannie Mae, Freddie Mac and AIG, the last minute passage of the Trouble Asset Relief Program, the urgent IMF-ECB bailout of Cypriot banks, etc. – naturally focuses attention on banks' death throes. Yet, how banks fail does not tell us *why* banks fail. Short of pure coordination failure (switching

[1]The Northern Rock run was quickly ended by the extension of deposit insurance by the Bank of England. Similarly, the U.S. Treasury stopped the run on money market funds by backing their bucks.

[2]Illiquidity can, if sufficiently severe, trigger insolvency.

spontaneously to a bad equilibrium), bank failures are triggered by bad news. Historically, this has been bad news about bad banking, where "bad" includes fraudulent, irresponsible, negligent, and incompetent behavior.

Actual or suspected malfeasance has instigated many, perhaps most financial crises. In 1720, insider trading and fraudulent misrepresentation led to collapses of both the South Sea and Mississippi bubbles. The attempted cornering of the U.S. bond market kindled the Panic of 1792. The sale of investments in the imaginary Latin American country of Poyais led to the Panic of 1825. "Wildcat banking" helped produce the Panic of 1837. The embezzlement of assets from the Ohio Life and Trust Co. instigated the Railroad Crisis of 1857 (Gibbons (1907)). Jay Gould and James Fisk's cornering of the gold market precipitated the 1869 Gold Panic. Cooke and Company's failure to disclose losses on Northern Pacific Railroad stock sparked the Panic of 1873. A failed cornering of United Cooper's stocks instigated the Panic of 1907. The Hatry Group's use of fraudulent collateral to buy United Steel, the sale of Florida swamp land, the Match King Hoax, the Samuel Insull fraud and the disclosure of other swindles ushered in the Great Depression.[3] Insider trading and stock manipulation brought down Drexel Burnham Lambert, precipitating the largest insurance failure in U.S. history. And revelation of liar loans, no-doc loans, and NINJA loans laid the groundwork for the demise of major U.S. and foreign financial firms and the Great Recession.[4]

This paper focuses on why banks fail. The reason considered is malfeasance. We treat *intermediation*, not liquidity provision via maturity transformation, as the raison d'être for banks, and the loss of intermediation services, not the loss of liquidity or maturity transformation, as the economic essence of a financial crisis. Our demurral on liquidity and maturity transformation seems justified by theory and fact. As shown by Jacklin (1983, 1986, 1989) and Jacklin and Bhattacharya (1988), bank's heralded role as maturity transformers can be either fully or largely replicated by financial markets alone.[5] But unlike banks, when financial markets transform maturity, they do so without risk of financial panic,

[3] See Pecora Commission (1934).

[4] See Financial Crisis Inquiry Commission (2011).

[5] We include mutual funds, which Jacklin calls "equity deposits", as a financial-market instrument.

which destroys the very liquidity banks are said to provide.[6] There is also scant evidence that banks are effective in transforming maturities.

Our framework is simple – a two-period OLG model with two sectors – farming and banking. Both sectors produce an identical good, corn. Farming is small scale and done by sole proprietors. The banking sector gathers resources from multiple investors and engages in large-scale and more efficient farming. Production in farming is certain. Production in banking is uncertain due to banker malfeasance. Specifically, each period every bank has an identical but random share of dishonest, negligent or incompetent bankers, labeled bad bankers, in their employ. These bankers steal or lose all output arising from investments placed with them.[7] Consequently, if 20 percent of bankers are bad, the banking industry will produce 20 percent less output. An equivalent interpretation of our model is that a share of banks is fully malfeasant. I.e. these bank steal or lose all output from investments and arise in the same proportion as our posited share of bad bankers. In what follows, we reference "the share of bad bankers." But one can substitute these words, "the share of bank output lost due to bad banks."

The share of bad bankers obeys a state-dependent Markov process. On average, the share is low enough and banking is productive enough for banking to generate a higher expected return than farming and, thereby, attract considerable investment. But when a larger than expected number of bad bankers surfaces, the projected future share of bad bankers rises. This causes investors to shift out of banking, potentially abruptly, until sufficient time has passed to lower the expected share of malfeasant bankers. This process produces not just periodic and, potentially, extended banking crises, but also a highly inefficient economy.

Introducing deposit insurance eliminates one problem and introduces another. It ends banking crises but at the price of keeping bad bankers (equivalently, bad banks) in business. This moral hazard is raised in multiple studies including Gertler et al. (2012); Demirgüç-Kunt and Detragiache (1997, 1999, 2002); Calomiris and Haber (2014) and Calomiris et al.

[6] Ironically, banks are heralded for providing liquidity, yet have, historically, precipitated its loss precisely at times when it is of most value.

[7] There are lots of legal ways to "steal," including charging hidden fees, churning portfolios to generate higher fees, cream-skimming the purchase of assets, buying assets at above-market price from reciprocating bankers, and taking on excessive risk.

(2016). The result is higher total output, but more stolen output. Since the government levies taxes to fund its insurance of purloined or lost output, the insurance does nothing to reduce bad-banker risk. Nor does it insure anything real. It simply induces households to invest with banks regardless of the risk. Like a compensated tax, deposit insurance distorts behavior, producing an excess burden.[8]

Monitoring banking practices is another option. But information, once released, becomes a public good. Since households have no incentive to keep the results of their monitoring private, they will likely share what they know. In this case, each household will free-ride on the monitoring of others. This reduces, if not eliminates, monitoring. The first-best policy – disclosure – addresses the opacity problem directly by shutting down malfeasant bankers' modus vivendi, namely operating in the dark. Turning on the lights requires government provision of the missing public good, namely pubic revelation, either in full or in part (depending on cost), of the malfeasance. This weeds out bad banking, raising non-stolen output and welfare. The practical counterpart of this policy prescription is real-time, government disclosure and verification of all bank assets and liabilities to ensure that the net capital invested in banks is actually being used to produce output that's paid to investors and workers.[9]

2. Literature Review

The seminal Bryant (1980) and Diamond and Dybvig (1983) articles modeled bank deposits as insurance against unexpected liquidity needs and bank runs as a switch from a good to a bad equilibrium. These papers sparked a major literature connecting banking to liquidity. Examples include Jacklin (1983), Jacklin and Bhattacharya (1988), Holmström and Tirole (1998), Rochet and Vives (2004), Goldstein and Pauzner (2005), He and Xiong (2012) and Acharya et al. (2011).

Liquidity is a key element of the financial system. But is it really at the heart of banking?

[8]In our model, bad bankers extract resources from the economy, which cannot be reclaimed by the government. Their theft represents aggregate risk against which the government cannot insure. Hence, insurance payments made to households are exactly offset by taxes to cover those payments.

[9]As noted by Kotlikoff (2010), this work can be performed by private firms working exclusively for the government.

And is maturity transformation as important as its prevalence in the literature suggests? The Bryant and Diamond-Dybvig liquidity-insurance/maturity-transformation models predict investment-like returns on demand and other short-term deposits. Yet real returns on transaction accounts have historically been very small, if not negative. Moreover, modern economies are replete with health, accident, auto, homeowners, malpractice, longevity, property and casualty, disability, long-term care insurance, credit cards, and equity lines of credit – all of which provide liquidity in times of personal economic crisis. Then there are financial markets, whose securities can be sold as needed to provide liquidity and transform maturities. Indeed, Jacklin (1989) argues that equity markets can provide as much liquidity insurance as bank deposits and transform maturities just as well. Moreover, they can do so with no danger of bank runs or any other type of financial crisis.[10]

Still, liquidity risk continues to stimulate research. Dang et al. (2017) add a new wrinkle to Diamond and Dybvig (1983), namely the staggered arrival of participants to the liquidity insurance market. They show that banking opacity permits late arrivals to participate in the market since opacity leaves them with no more information than early arrivals. The work by Dang et al. (2017) echoes Hirshleifer (1971), who points out that disclosure is detrimental to those holding claims on overvalued assets. Other researchers, including Holmström and Tirole (1998), Andolfatto (2010), Gorton (2009) and Gorton and Ordonez (2014) warn that public audits, while providing a public good, namely public information, comes at the price of market crashes. Whether policymakers are deliberately limiting audits to protect malfeasant banks is an open question. Either way, today's limited, quasi-voluntary disclosure is of limited value. As Johnson and Kwak (2010) state, "Lehman Brothers ... was more than adequately capitalized on paper, with Tier 1 capital of 11.6 percent, shortly before it went bankrupt in September 2008. Thanks to the literally voluminous report by the Lehman bankruptcy examiner, we now know this was in part due to aggressive and misleading accounting."

[10]Jacklin's proviso is that information between investors and banks not be asymmetric in the context of aggregate risk. We suggest that the asymmetry of information can be eliminated, either fully or largely in the presence or absence of aggregate risk, by real-time government-orchestrated or supervised verification and disclosure of bank assets and liabilities.

Like Stiglitz and Weiss (1981); Diamond (1984); Brealey et al. (1977), we treat the problems incumbent in providing intermediation as arising from asymmetric information – bad bankers know they are bad, household investors do not. However, those studies stress differential knowledge between bankers and borrowers whereas our focus is on differential knowledge between bankers and savers (equivalently, investors). In the former studies, the unobservable was the trustworthiness of borrowers. In our study, the unobservable is the trustworthiness of bankers.

Gertler and Karadi (2011) and Gertler and Kiyotaki (2010) also model financial malfeasance. However, bankers do not steal or otherwise misappropriate output in equilibrium. Borrowing thresholds and the exposure of equity holders to losses keep such behavior from happening. In our model, bad bankers expropriate or lose output in equilibrium unless they are disclosed ex-ante. Disclosure is a natural remedy in our model, but faces real-world objection from a surprising source, namely regulators. Regulators worry that too much disclosure in the midst of a financial meltdown can fuel asset fire sales.[11] But this concern is about ex-post disclosure. Our focus is on ex-ante disclosure, i.e., preventing malfeasance in advance via, in part, initial and ongoing, real-time asset verification.

Our paper extends Chamley et al. (2012), which sets aside the liquidity-insurance/maturity-transformation rationale for banking. Instead it justifies banks based on their principal economic role – financial intermediation. And it models bank runs as arising from actual or perceived malfeasance in the provision of intermediation services. The Chamley et al. (2012) model has a quite different structure and is static. Ours is dynamic. We consider how current malfeasance undermines future financial intermediation, productivity and welfare since current malfeasance generates lingering doubts about the trustworthiness of bankers. The banking "runs" considered here are simply decisions to invest less, at least in the short run, in banks. The associated contraction of the banking sector can be labeled a liquidity crisis. But the crisis is triggered by news of a larger than expected share of bad bankers, not the sudden need for money by of a large segment of the public.

Banks have generally been modeled as honest institutions, which, in their efforts to pro-

[11] See www.sec.gov/spotlight/fairvalue/marktomarket/mtmtranscript102908.pdf.

vide a full, if risky, return to investors, are occasionally stymied by panicked or misinformed creditors. Moreover, bad news about banks is about poor investment returns, not the theft, scams, swindles, Ponzi schemes, excess fees, etc., recorded in, for example, the Security and Exchange Commission's Division of Enforcement's annual reports. The SEC's enforcement actions now total over two per week.[12] Of course, the SEC only reports frauds the agency detects.[13] It is impossible to say how much financial fraud goes undetected. Moreover, there are other federal and state government agencies and branches, such as Massachusetts' Financial Investigations Division, which investigate and prosecute financial crime, but do not provide annual listings of their enforcement actions. And explicit fraud, such as the Madoff or the Stanford Ponzi schemes, is not the only type of fraud at play. Much financial fraud takes subtle forms that is rarely viewed, even by economists, as such. An example is a bank that legally operates based on proprietary information to the detriment of the public. Townsend (1979) models this behavior, albeit without the pejorative connotation. He posits informed agents that force uninformed agents to enter a debt contract to limit the extent to which they must pay to investigate cheating. He applies this to borrowers' incentives to renege on loans but it could equally be applied to banks' incentives to cheat investors.

The obvious policy solution is exposing malfeasant bankers and banking. Such disclosure, as proposed by Kotlikoff (2010) and to a lesser extent by Pagano and Volpin (2012) and Hanson and Sunderam (2013), would go far beyond current practices. It would largely entail real-time verification of bank assets. Take, for example, mortgage verification. Verifying a mortgage application requires determining the employment status, earnings, outstanding debts, and credit record of the mortgagee and appraising the value of the house being purchased. Now, as before the Great Recession, U.S. mortgage verification is in the hands of private lenders, such as the former Country Wide Financial, a company heavily fined for originating and selling fraudulent mortgages.[14] But such verification could readily be done by the government or private companies working solely for the government. Indeed, thanks

[12] https://www.sec.gov/news/newsroom/images/enfstats.pdf

[13] A separate metric for financial fraud is provided by www.ponzitracker.com, which suggests the discovery of one new Ponzi scheme per week in recent years.

[14] See https://www.sec.gov/news/press/2010/2010-197.htm

to its tax records, the government can better verify income on mortgage applications than the private sector. Had such government mortgage verification been in place prior to 2007, there would, arguably, have been few, if any, liar, no-doc, and NINJA loans – all of which appear to have produced a major rise in the perceived and actual share of bad banks.

3. The Model

Agents in our OLG framework work full-time when young and are retired when old. They consume in both periods. Agents born at time t maximize their expected utility, EU_t, given by

$$EU_t = \beta \log c_{y,t} + (1-\beta) E_t \log c_{o,t+1}, \tag{1}$$

over $c_{y,t}$, $c_{o,t+1}$ and $\alpha_{s,t}$, subject to

$$c_{o,t+1} = A_{t+1}[(1-\alpha_{s,t})(1+r_{f,t+1}) + \alpha_{s,t}(1+\tilde{r}_{b,t+1})], \tag{2}$$

and

$$c_{y,t} + A_{t+1} = w_t. \tag{3}$$

The terms $c_{y,t}$ and $c_{o,t+1}$ reference consumption when young and old at t and t+1, w_t is the time-t wage, A_{t+1} equals the time-t saving of generation t, and $r_{f,t+1}$ and $\tilde{r}_{b,t+1}$ are the safe and risky returns to farming and banking. The share of generation $t's$ assets invested in banking is $\alpha_{s,t}$. The s subscript references the state of mean malfeasance this period, which affects the allocation decision. Capital does not depreciate. Optimization entails

$$C_{y,t} = \beta w_t, \tag{4}$$

$$A_{t+1} = (1-\beta) w_t, \tag{5}$$

$$E_t \frac{r_{f,t+1} - \tilde{r}_{b,t+1}}{1 + (1-\alpha_{s,t}) r_{f,t+1} + \alpha_t \tilde{r}_{b,t+1}} = 0. \tag{6}$$

Investment in the two sectors satisfies

$$K_{f,t+1} = (1 - \alpha_{s,t})A_{t+1}, \tag{7}$$

$$K_{b,t+1} = \alpha_{s,t}A_{t+1}. \tag{8}$$

Output is Cobb-Douglas with labor's share equaling $1 - \theta$ in each industry. Farm output at time t, F_t, is given by

$$F_t = Z_f K_{F,t}^{\theta} L_{F,t}^{1-\theta}. \tag{9}$$

A proportion, m_t, of banking output is stolen or lost each period. Henceforth, we reference such lost output simply as "stolen." Non-stolen banking output is, thus

$$B_t = (1 - m_t)Z_b K_{b,t}^{\theta} L_{b,t}^{1-\theta}, \tag{10}$$

and non-stolen output is

$$Y_t^u = F_t + B_t. \tag{11}$$

Total output is

$$Y_t = F_t + Z_b K_{b,t}^{\theta} L_{b,t}^{1-\theta}. \tag{12}$$

Returns to investing in farming and banking satisfy

$$r_{f,t} = \theta Z_f K_{f,t}^{\theta-1} L_{f,t}^{1-\theta}, \tag{13}$$

and

$$\tilde{r}_{b,t} = (1 - m_t)\theta Z_b K_{b,t}^{\theta-1} L_{b,t}^{1-\theta}. \tag{14}$$

Agents invest in banking because the sector is more productive, i.e., $Z_b > Z_f$. But, absent deposit insurance, they diversify due to the risk that banking malfeasance is greater than expected. Malfeasance, m_t, is the sum of two components – its time-t mean, $\bar{m}_t$, plus an i.i.d. shock, ϵ_t, i.e.,

$$m_t = \bar{m}_t + \epsilon_t. \tag{15}$$

Mean malfeasance is either high, $\bar{m}_H$, or low, $\bar{m}_L$, and obeys a Markov process. If $\bar{m}_{t-1} = \bar{m}_H$,

$$\bar{m}_t = \begin{cases} \bar{m}_H & \text{with probability } q_H \\ \bar{m}_L & \text{with probability } 1 - q_H. \end{cases} \tag{16}$$

If $\bar{m}_{t-1} = \bar{m}_L$,

$$\bar{m}_t = \begin{cases} \bar{m}_H & \text{with probability } q_L \\ \bar{m}_L & \text{with probability } 1 - q_L, \end{cases} \tag{17}$$

where $q_H > q_L$. The additional shock, ϵ_{t+1}, is uniformly distributed with the same support, a and b, regardless of the state, i.e.,

$$\epsilon_{t+1} \sim U(a, b). \tag{18}$$

When monitoring is feasible, households can pay to learn about this second shock, ϵ_{t+1}. Households observe the malfeasance share at t and infer the current state of the world, $s_t \in \{L, H\}$, and the transition probability, $q_{s,t} \in \{q_L, q_H\}$. Their optimal allocation choice, $\alpha_{s,t}$, will change given this information. A high state of malfeasance this period will likely persist leading households to invest less in banking. Given eqs. (1) to (8) and (13) to (18), the optimal portfolio choice, $\alpha_{s,t}$, satisfies

$$\begin{aligned} 0 = & q_{s,t} \int_a^b \frac{\tilde{r}^H_{b,t+1}(\alpha_{s,t}, \epsilon_{t+1}) - r^H_{f,t+1}(\alpha_{s,t}, \epsilon_{t+1})}{1 + \alpha_{s,t}\tilde{r}^H_{b,t+1}(\alpha_{s,t}, \epsilon_{t+1}) + (1 - \alpha_{s,t}) r^H_{f,t+1}(\alpha_{s,t}, \epsilon_{t+1})} d\epsilon_{t+1} \\ & + (1 - q_{s,t}) \int_a^b \frac{\tilde{r}^L_{b,t+1}(\alpha_{s,t}, \epsilon_{t+1}) - r^L_{f,t+1}(\alpha_{s,t}, \epsilon_{t+1})}{1 + \alpha_{s,t}\tilde{r}^L_{b,t+1}(\alpha_{s,t}, \epsilon_{t+1}) + (1 - \alpha_{s,t}) r^L_{f,t+1}(\alpha_{s,t}, \epsilon_{t+1})} d\epsilon_{t+1}, \end{aligned} \tag{19}$$

where superscripts reference expected returns if the high and low malfeasance states arise at time $t + 1$.[15] These returns depend on the malfeasance share (both its mean at $t + 1$ and

[15] The first (second) term of eq. (19) captures the marginal effect on utility of increasing the allocation to banking provided the mean malfeasance share at $t + 1$ is high (low). Both terms integrate over the possible realizations of ϵ_{t+1}. The optimal choice of $\alpha_{s,t}$, must be solved numerically. To rule out short-sales, we

ϵ_{t+1}) as well as the allocation of capital to banking, $\alpha_{s,t}$. Reduced forms for these returns are derived in Appendix A.

Capital's allocation between the two sectors is determined at the beginning of each period based on agents' portfolio choice. The allocation of labor, in contrast, is determined at the end of each period such that workers earn the same wage net of malfeasance in both sectors. This condition, our normalization of total labor supply at 1 and the allocation of labor between the two sectors are specified by

$$L_{b,t} + L_{f,t} = 1, \tag{20}$$

$$w_t = (1-\theta)Z_f(K_{f,t}/L_{f,t})^{\theta} = (1-\theta)Z_b(1-m_t)(K_{b,t}/L_{b,t})^{\theta}, \tag{21}$$

and

$$L_{f,t} = \frac{Z_f^{\frac{1}{\theta}}(1-\alpha_{t-1})}{[(1-m_t)Z_b]^{\frac{1}{\theta}}\,\alpha_{t-1} + Z_f^{\frac{1}{\theta}}(1-\alpha_{t-1})}, \tag{22}$$

$$L_{b,t} = \frac{[(1-m_t)Z_b]^{\frac{1}{\theta}}\,\alpha_{t-1}}{[(1-m_t)Z_b]^{\frac{1}{\theta}}\,\alpha_{t-1} + Z_f^{\frac{1}{\theta}}(1-\alpha_{t-1})}, \tag{23}$$

where α_{t-1} references the portfolio share chosen at time $t-1$.

4. Calibration

Table 1 reports our calibration. The time-preference factor, β, is set to 0.5 and capital's share, θ, is set to 0.3. Our assumed mean malfeasance shares are $\bar{m}_H = .50$ and $\bar{m}_L = .22$. The two assumed TFP levels are $Z_f = 10$ and $Z_b = 16$. In combination, these parameters satisfy

$$(1-\bar{m}_H)Z_b < Z_f < (1-\bar{m}_L)Z_b.$$

calibrate the model such that $\alpha_{s,t} \in (0,1)$.

This restriction ensures interior solutions to the share of assets invested in banks. We allow the shock, ϵ_{t+1}, to raise or lower the malfeasance share by .1, i.e., $\{a, b\} = \{-0.1, 0.1\}$. Finally, we set the probabilities of a high mean malfeasance share at $t+1$ to be 0.6 when the mean malfeasance share is high at time t and 0.4 when the mean malfeasance share is low at time t. I.e., $q_H = .6$ and $q_L = .4$.

5. Base Model Results

The model's average values in its stochastic steady state are reported in table 2. Table 3 and table 4 report averages for low and high mean malfeasance states, respectively. The values in these tables are based on a 10,020-period transition. We simulated our model for $10,020$ periods, but consider only data after the first 20 periods in tables 2 to 4. This removes the effect of initial conditions. Assets at $t = 0$ in this simulation were set at the mean level of assets arising in periods 21 through 10,020. $\bar{m}_0 = \bar{m}_L$. We iterated to ensure that mean assets used for A_0 equal mean assets over the 10,000 periods since the path of assets depends on A_0. In simulating alternative banking policies as well as private monitoring over 10,020 periods, we use the same period-by-period draws of mean malfeasance and ϵ_t.

Given our calibration, banking malfeasance has a major economic cost. Across all states, 21.8 percent of output is stolen. In low mean malfeasance states, 17.2 percent is stolen. In high mean malfeasance states, 27.2 percent is stolen. Moreover, average non-stolen output when mean malfeasance is high is 24.7 percent lower than when mean malfeasance is low. Since wages are proportional to output and consumption when young is proportion to wages, both variables are also, on average, 24.7 percent lower in high compared to low states. Consumption when old is only 15.5 percent lower across the two types of states. The reason is that consumption when old includes not just the income on assets, but the principal as well. And the principal is not impacted by banker malfeasance.

Agents respond to bad times in banking by moving their assets into farming. When malfeasance is high, only 28 percent of assets are allocated to banking. When low, the figure is 86 percent. We refer here to the value of α, which determines capital's allocation in the subsequent period. The share of capital in the high state is larger – 54.9 percent, while the share in the low state is smaller – 67.3 percent than suggested by these values for α. This reflects the fact that the high (low) state emerges, in part, from states that are low (high) in the prior period. But when agents see higher prospects for bad (good) times, they take cover (leave their shelter) by setting their values of α appropriately. The fact that agents cannot tell for sure what is coming when it comes to the state of mean malfeasance means that capital is perpetually mis-allocated. This is another economic cost arising from bad bankers in addition to their direct theft of output and their general negative influence on investment in banking. The misallocation of capital is partially offset by the reallocation of labor. On average, banking accounts for 56 percent of total employment. In periods of high mean malfeasance, this figure is 38 percent. It is 74 percent when there is low mean malfeasance.

The average annualized return to investing in banking is 2.04 percent compared with 2.01 percent in farming.[16] Although their mean returns are similar, as the table's standard deviation of returns shows, investing in banking is far riskier than investing in farming. This explains why farming always attracts a goodly share of investment.

Figure 1 plots returns in the two sectors for different values of ϵ_{t+1} and realizations of the time-t+1 malfeasance state assuming A_t equals its average value. The dotted red line shows returns, for different values of ϵ_{t+1}, if the malfeasance state at $t+1$ is high. The solid black line shows returns, for different values of ϵ_{t+1}, if the malfeasance state at $t+1$ is low. The top panels shows annualized returns if the malfeasance state is high at time t. The bottom panels shows returns if the malfeasance state is low at time t.

The right-hand side panels show that higher malfeasance, whether caused by a) moving to or staying in a high malfeasance state at $t+1$ or b) a high draw on ϵ_{t+1}, implies lower returns to banking at $t+1$; i.e., the dotted red curves lie below the solid black curves and both slope downward.

The left-hand side panels show the opposite in the case of the returns to farming. This reflects a greater allocation of labor to farming the greater the share of malfeasance in banking. More labor in farming means a higher marginal product of capital and, thus, a higher return. This effect of labor moving into farming is stronger the smaller the degree of

[16] In forming annualized returns, we assume each period corresponds to 30 years.

malfeasance at time t — the case when relatively little capital will be invested in farming in $t+1$. This explains the larger gap between the red and black curves in the bottom left panel than in the top left panel. Figure 2 plots the distribution of realized returns in period $t+1$ simulated in the 10,000-periods referenced above. This figure, while organized like Figure 1, incorporates changes in A_t from from period to period. The panels on the right consider bank returns. Those on the left consider farm returns. The top (bottom) panels consider returns at $t+1$ when the malfeasance state is high (low) in period t. Finally, the red (black) histogram references high (low) malfeasant states arising at time $t+1$. The vertical bar shows mean returns in each time $t+1$ state.

As expected, bank (farm) returns are lower (higher) at $t+1$ when the $t+1$ malfeasant state is high (low). The position of the histograms reflects different allocations, at time t, in capital between the two sectors. The variance in the histograms reflects the impact of movements of labor across sectors on the return to capital in the two sectors. The impact on a sector's return from employing more labor is greater the smaller the initial allocation of capital to that sector. Figure 3 shows histograms of non-stolen output, assets, annualized farm and banking returns. The histograms' results are unconditional, i.e., they include both high and low malfeasance states in the prior period which explains why they are multi-modal. They are also quite dispersed suggesting that banking malfeasance can produce peaks and troughs in non-stolen output, wages, and assets that are very far apart.

As expected, a switch in the mean malfeasance state from one period to the next produces much greater changes in macro conditions than no switch. Figure 4 records the transition beginning with high average malfeasance, switching to low average malfeasance in period 3, and then switching back to and remaining at high average malfeasance in periods 4 through 10. Figure 5 illustrates the opposite – i.e., a temporary switch from low to high and then back to low average malfeasance. The path of the additional shock to the malfeasance share, ϵ_t, is kept at 0 in both transitions. Consider fig. 4. In period 3, when mean banking malfeasance declines, more labor is allocated to banking and there is an increase in non-stolen output. But since the shock hits after capital has been allocated, there is no immediate impact on the capital stock. There is a major impact in period 4 reflecting agents' decisions to invest more in banking given its higher expected return. Given that high mean malfeasance reoccurs in period 4, this investment decision is an ex-post mistake. But once the capital is allocated, it cannot be reallocated. The ex-post excessive investment in banking draws additional labor into banking. Hence, there is a mis-allocation, again, on an ex-post basis, of labor as well as capital.

Notwithstanding the additional capital and labor allocated to banking, non-stolen output is smaller in period 4 than in, for example, period 2. The fact that the economy is so different in period 4 from, for example, period 2 indicates the importance of beliefs about mean malfeasance – whether those beliefs are correct or, as in this case, incorrect. Indeed, as a comparison of the change in Y_t between periods 2 and 3, on the one hand, and period 3 and 4, on the other, shows, the change in beliefs about the malfeasance shock produces larger output fluctuations than does the shock itself. Another interesting point about the two impulse-response transitions is that one is not the obverse of the other. Consider, for example, the impact on wages. In fig. 4, wages rise above their initial value and then fall below it following the temporary reduction in mean malfeasance. In contrast, in fig. 5 wages fall and gradually return to their period-2 value following a temporary rise in mean malfeasance.

Figure 6 records a third controlled experiment, this one with a prolonged improvement in mean malfeasance. Like the prior two, ϵ_t is set to zero. The economy starts with high mean malfeasance, followed by low mean malfeasance for 6 periods, followed by high mean malfeasance for 2 periods. As a comparison with fig. 5 shows, the economy's path is highly sensitive to the exact sequence of mean malfeasance shocks. This sensitivity, as we've seen, reflects immediate impacts, but, more importantly, the formation of beliefs about the economy's future.

Adding ϵ_t shocks to the mean malfeasance share, we arrive at our baseline transition, fig. 7. The path of these added shocks for the first 10 periods is reported in table 5. We use the same path of shocks to mean malfeasance and ϵ_t in our comparisons below of the baseline economy with the baseline economy augmented to include alternative government banking policies or private monitoring.

6. Deposit Insurance

Deposit insurance insulates savers from losses due to bad bankers, leading to exclusive investment in banking. If the mean share turns out to be low, the insurance succeeds in generating more non-stolen output than would otherwise arise if savers shied away from banks.[17] But if the mean malfeasance share turns out to be high, savers are actually worse off than without deposit insurance. Yes, they are compensated for their loses, but they have to pay taxes to cover the compensation. In short, since the share of malfeasance is an aggregate risk, deposit insurance provides no real insurance in the aggregate. Instead, it simply induces savers to invest exclusively in banking even in times when its highly risky from a macro prospective. Getting savers to over invest in banking when they should engenders, of course, an excess burden.

Under deposit insurance, households receive

$$r_{b,t}^{DI} = (1-m_t)\theta Z_b K_{b,t}^{\theta-1} L_{b,t}^{1-\theta} + m_t \theta Z_b K_{b,t}^{\theta-1} L_{b,t}^{1-\theta} = \theta Z_b K_{b,t}^{\theta-1} L_{b,t}^{1-\theta}. \tag{24}$$

This is financed by a lump-sum tax, $\tau_{DI,t}$, levied on the elderly to prevent redistribution across generations.

$$c_{o,t} = A_t(1 + r_{b,t}^{DI}) - \tau_{DI,t}, \tag{25}$$

where

$$\tau_{DI,t} = A_t m_t \theta Z_b K_{b,t}^{\theta-1} L_{b,t}^{1-\theta}. \tag{26}$$

With deposit insurance, we have,

$$\{K_{f,t+1}, L_{f,t+1}, K_{b,t+1}, L_{b,t+1}\} = \{0, 0, A_{t+1}, 1\} \tag{27}$$

Figure 8 shows the path of the economy with deposit insurance using the same path of

[17] This may explain why deposit insurance is often introduced during crises. Another explanation is that voters do not internalize the need to pay taxes to cover insurance claims.

shocks as the baseline transition in fig. 6. Although total output is higher, non-stolen output and consumption is lower in bad states. Table 6 compares deposit insurance to the baseline. All assets are, as indicated, now allocated to banking in all periods. When the share of bad bankers is low, non-stolen output, wages and consumption are higher. But when the share is high, wages, consumption and saving are lower than would be true absent deposit insurance.[18] Thus, increased allocation to banking due to deposit insurance *increases* the volatility of consumption and non-stolen assets. This accords with findings of Demirgüç-Kunt and Detragiache (1997, 1999, 2002).

We next calculate the factor, λ, needed to compensate both the old and the young, in all states, to make their expected utility in the baseline, denoted $EU_{s,t}$, equal to their expected utility under deposit insurance, denoted $EU'_{s,t}$,

$$EU'_{s,t} = \beta \log \lambda c_{y,t} + (1-\beta) \int_a^b \{q_{s,t} \log \lambda c_{o,t+1}(\bar{m}_H, \epsilon_{t+1}) + (1-q_{s,t}) \log \lambda c_{o,t+1}(\bar{m}_L, \epsilon_{t+1})\} \frac{1}{b-a} d\epsilon_{t+1}, \tag{28}$$

$$= EU_{s,t} + \log \lambda.$$

Hence $\lambda = \exp(EU'_{s,t} - EU_{s,t})$. Expected lifetime utility in the model's stochastic steady state is measured by average realized lifetime utility over 10,000 successive generations born after the 20th period of the transition. For deposit insurance, the value of λ is 1.041 implying households must be compensated with 4.1 percent more consumption in all states to make them as well off as under the baseline case. Stated differently, the excess burden of deposit insurance is a sizable 4.1 percent of consumption.

7. Monitoring Banks

7.1. Private Monitoring

As the behavior of rating companies leading up to the 2008 crisis showed, bank-funded monitoring suffers from the "ratings shopping" examined in Skreta and Veldkamp (2009);

[18] With all output being produced in the banking sector, more output is lost when the share of bad bankers is high.

Sangiorgi et al. (2009) and Bolton et al. (2012). Even if we assume ratings are unbiased, they may be too imprecise to help (Goel and Thakor (2015); Doherty et al. (2009)).[19] As an alternative, we consider monitoring financed by investors, that is, by households. Specifically, we assume young agents can purchase a report that indicates, with probability p, the realization of ϵ_{t+1}.[20] With probability $(1-p)$ no information is gained. In this case, agents make uninformed investment choices.

Let n_t be the percentage of wage income spent on reports. We assume additional expenditure increases the likelihood of receiving information, p, with decreasing marginal effect,[21] i.e., $p = p(n_t)$, where $p(0) = 0$, $p(\infty) = 1$, $p'(n) > 0$ and $p''(n) < 0$, which we capture via[22]

$$p(n_t) = \frac{100n_t}{100n_t + 1}. \tag{29}$$

Households purchase the welfare-maximizing quantity of information, n_t. Returns to capital depend on the aggregate allocation to banking, designated by a bar, which depends on the mix of the two types of agents, informed and uninformed, per

$$\bar{\alpha}_{s,t}(\epsilon_{t+1}) = p\alpha_{I,s,t}(\epsilon_{t+1}) + (1-p)\alpha_{U,s,t}, \tag{30}$$

where $\alpha_{I,s,t}(\epsilon_{t+1})$ is the asset allocation of informed agents and $\alpha_{U,s,t}$ is the asset allocation of uninformed agents. With probability $p(n_t)$, individuals receive information about ϵ_{t+1}

[19] In our model, this is analogous to assuming households cannot determine the accuracy (or honesty) of a rating paid for by banks.

[20] Thus, informed agents know the malfeasance share at $t+1$ will be either $\bar{m}_H + \epsilon_{t+1}$ or $\bar{m}_L + \epsilon_{t+1}$.

[21] This can be micro-founded by assuming that n_t buys many reports with each providing a noisy estimate of the true realization of the shock, ϵ_{t+1}. With likelihood, $p(\bar{x}|\epsilon_{t+1})$, where $\bar{x}$ is the mean estimate given n reports, the precision of the estimate will be increasing in n, parameterized by the variance of the data-generating process for the reports.

[22] The coefficient, 100, is chosen so that households can spend one percent of income on monitoring and receive information fifty percent of the time. This is sufficient to induce households to monitor.

and allocate according to

$$
\begin{aligned}
0 =& q_{s,t} \frac{\tilde{r}^H_{b,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1}) - r^H_{f,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1})}{1 + \alpha_{s,t}\tilde{r}^H_{b,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1}) + (1-\alpha_{s,t})r^H_{f,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1})} \\
&+ (1-q_{s,t}) \frac{\tilde{r}^L_{b,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1}) - r^L_{f,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1})}{1 + \alpha_{s,t}\tilde{r}^L_{b,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1}) + (1-\alpha_{s,t})r^L_{f,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1})},
\end{aligned} \tag{31}
$$

where subscript $s \in \{L, H\}$ indicates the state at t.[23]

With probability $[1 - p(n_t)]$, individuals purchase reports, but receive no information. Their optimal allocation choice, $\alpha_{U,s,t}$, solves a similar first-order condition to the no-monitoring case (eq. (19)) by integrating over the support of ϵ_{t+1} and the possibility of the two states of the world next period, high and low. All returns are evaluated using aggregate allocation $\bar{\alpha}_{s,t}(\epsilon_{t+1})$ given by eq. (30).

$$
\begin{aligned}
0 =& q_{s,t} \int_a^b \frac{r^H_{f,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1}) - \tilde{r}^H_{b,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1})}{1 + (1-\alpha_{U,s,t})r^H_{f,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1}) + \alpha_{U,s,t}\tilde{r}^H_{b,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1})} d\epsilon_{t+1} \\
&+ (1-q_{s,t}) \int_a^b \frac{r^L_{f,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1}) - \tilde{r}^L_{b,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1})}{1 + (1-\alpha_{U,s,t})r^L_{f,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1}) + \alpha_{U,s,t}\tilde{r}^L_{b,t+1}(\bar{\alpha}_{s,t}, \epsilon_{t+1})} d\epsilon_{t+1}.
\end{aligned} \tag{32}
$$

To recapitulate, with monitoring, households learn with probability $p(n_t)$ the realization of ϵ_{t+1} and choose the optimal allocation, $\alpha_{I,s,t}(\epsilon_{t+1})$, which solves eq. (31). With probability $[1-p(n_t)]$, households receive no information and and make an uninformed allocation, $\alpha_{U,s,t}$, which is the implicit solution to eq. (32). Both solutions must be solved simultaneously. The solution is detailed in Appendix B. Optimal expenditure on monitoring, n_t, is chosen to maximize expected utility

$$
\begin{aligned}
EU(n_t) =& \beta \log c_{y,t}(1-n_t) + (1-\beta)\log A_{t+1}(1-n_t) \\
&+ p(n_t)(1-\beta) \int_{-a}^b \left\{ q_{s,t} \log R^H_{I,t+1}(\epsilon_{t+1}) + (1-q_{s,t}) \log R^L_{I,t+1}(\epsilon_{t+1}) \right\} \frac{1}{b-a} d\epsilon_{t+1} \\
&+ [1-p(n_t)](1-\beta) \int_{-a}^b \left\{ q_{s,t} \log R^H_{U,t+1}(\epsilon_{t+1}) + (1-q_{s,t}) \log R^L_{U,t+1}(\epsilon_{t+1}) \right\} \frac{1}{b-a} d\epsilon_{t+1},
\end{aligned} \tag{33}
$$

[23] In (eq. (31)), we reference $\bar{\alpha}_{s,t}$ rather than $\bar{\alpha}_{s,t}(\epsilon_{t+1})$ to limit notation.

where the gross portfolio return if informed, given state S and ϵ_{t+1}, is

$$R^S_{I,t+1}(\epsilon_{t+1}) = 1 + [1 - \alpha_{I,s,t}(\epsilon_{t+1})]\, r^S_{f,t+1}(\bar{\alpha}_{s,t}(\epsilon_{t+1}), \epsilon_{t+1}) + \alpha_{I,s,t}(\epsilon_{t+1}) r^S_{b,t+1}(\bar{\alpha}_{s,t}(\epsilon_{t+1}), \epsilon_{t+1}), \tag{34}$$

and the gross portfolio return if uninformed, given state S and ϵ_{t+1}, is

$$R^S_{U,t+1}(\epsilon_{t+1}) = 1 + [1 - \alpha_{U,s,t}]\, r^S_{f,t+1}(\bar{\alpha}_{s,t}(\epsilon_{t+1}), \epsilon_{t+1}) + \alpha_{U,s,t} r^S_{b,t+1}(\bar{\alpha}_{s,t}(\epsilon_{t+1}), \epsilon_{t+1}). \tag{35}$$

In eq. (33), the first two terms account for the sure cost to consumption when young and old. The third and fourth terms represent the net gains from monitoring.

Under our calibration, if mean malfeasance is low at time t, households spend 1.13 percent of their income on learning ϵ_{t+1}. This corresponds to a 53.1 percent chance of learning the true potential bad-bank share. If mean malfeasance is high at time t, households do not find it optimal to monitor. This is because the state of mean malfeasance affects returns more than the realization of ϵ_{t+1} so learning is of less value when malfeasance is likely to be high at $t + 1$.

When monitoring is optimal at time t (i.e., when the time-t mean malfeasance state is low), table 7 shows that information on an impending negative shock to ϵ_{t+1} reduces investment in banking, on average, to 45 percent of savings. News of a positive shock triggers a corner solution and individuals invest all their assets in banking, as opposed to an average of 86 percent in the no-monitoring case. The effect of informed individuals on the aggregate allocation also makes this corner solution optimal even for agents for whom monitoring generates no information. Figure 9 and table 8 show that monitoring makes relatively little difference to the economy. Consumption when young and old does tend to be higher with monitoring. But the equilibrium is inefficient as agents replicate their efforts to learn the value of ϵ_{t+1}. Moreover, the downside to early information is more economic volatility. Still, calculated as a compensating variation using eq. (28), households are 1.2 per cent better off in terms of lifetime expected utility than in the baseline if they can monitor. Relative to deposit insurance, however, monitoring improves welfare by 5.4 per cent. This is a substantial differential. Unfortunately, monitoring can suffer from free-riding.

7.2. *Information as a Public Good*

Previously, report results were assumed to be private. We now allow some households who did not receive information to learn the value of ϵ_{t+1} at zero cost with probability l. The decision to purchase reports takes into account the probability of receiving information for free. The probability of receiving information is now d

$$d(n_t) = l + (1 - l)p(n_t) \tag{36}$$

Households take l as given. The marginal increase in the probability of learning the value of ϵ_{t+1} from purchasing an additional report is now reduced based on the extent of these leaks, i.e.,

$$\frac{\partial d}{\partial n_t} = p'(n_t)(1 - l). \tag{37}$$

Clearly, as the fraction of leaked reports, l, increases, the marginal benefit of purchasing reports decreases. This leads to fewer reports in equilibrium. Figure 10 illustrates how the prospect of learning the true value for free reduces private monitoring. If households expect the probability of a leak to be above 0.8, only .02 percent of wages is spent on monitoring, yielding a probability of learning of just .02. Sufficiently high free-riding eliminates monitoring, i.e., the economy reverts to the baseline case where no information on the realization of ϵ_{t+1} is available. The free-riding problem of investor-funded ratings is noted in Warwick Commission (2009).

8. Regulation Through Disclosure

Suppose the government can pay a cost to reduce the average malfeasance share by ϕ, replacing eq. (15) with

$$m_t = (\bar{m}_t - \phi) + \epsilon_{t+1}. \tag{38}$$

To pay for this, we impose a lump sum tax on the old equivalent to the average cost of deposit insurance, $\tau_{Disc,t} = \bar{\tau}_{DI} = 2.93$ or 12.7 percent of output.

$$c_{o,t+1} = A_{t+1}[1 + (1 - \alpha_t) r_{f,t+1} + \alpha_t \tilde{r}_{b,t+1}] - \tau_{Disc,t}. \quad (39)$$

Figure 11 considers the impact of this expenditure assuming the government is able to reduce malfeasance by either $\phi = 0.2$ or $\phi = 0.4$ after spending $\tau_{Disc,t}$. Recall that $\bar{m}_s$ is either $\bar{m}_H = 0.50$ or $\bar{m}_L = 0.22$. The comparison economy is that with deposit insurance. Disclosure raises non-stolen output, wages, capital formation and consumption. Increasing the share of honest bankers encourages households to enter the banking sector in much the same way as deposit insurance. However, deposit insurance does nothing to eliminate fraud. As expected, the economy does far better if government disclosure is high. Average results for both levels of disclosure are reported in tables 9 and 10. Figure 12 compares average output, non-stolen output and lifetime consumption in the regimes discussed. Deposit insurance boosts output, but not non-stolen output or consumption. Monitoring, even ignoring free riding, makes little difference to the equilibrium. Low disclosure references a government-instigated reduction in the share of bad bankers of $\phi = 0.2$. This reduces non-stolen output and consumption considerably despite the high cost of regulation, assumed to be equal to the cost of deposit insurance. High disclosure, reducing the malfeasance share by $\phi = 0.4$, produces further gains.

The downside to a modest reduction in malfeasance is that it encourages investment in banking while still permitting shocks to malfeasance to cause volatility. Volatility under limited disclosure is similar to that under deposit insurance. This is illustrated in fig. 13, which depicts the standard deviation of key variables compared to the baseline. Significant disclosure solves this problem. Table 11 reports compensating variations. They are calculated as the percentage change in consumption, in all states, needed to produce the same expected utility as in the baseline, measured by averaging realized lifetime utility over 10,000 generations beginning after the economy has been operating for 20 periods.[24] The

[24] In making these calculations we consider the same sequence of shocks for each setting.

table shows that, compared with the baseline, deposit insurance is 4.1 percent less efficient, monitoring is 1.2 percent more efficient, a low level of government disclosure is 23.3 percent more efficient, and a high level of government disclosure is 37.9 percent more efficient.

9. Conclusion

Banking crisis, throughout the ages, have been precipitated by the exposure of bad/malfeasant banks (bankers). This news leads the public to defund the banks, often precipitously, which is termed a liquidity crisis. Under this, our paper's view, liquidity crises are the result of, not the cause of financial retrenchment with its attendant economic decline. The medium for financial malfeasance in all its manifestations is financial opacity. Leading up to 2008, opacity provided full cover for liar loans, no-doc loans, NINJA loans, Madoff's swindle, originate-to-distribute abuses, CDOs-squared and other highly complex tranched derivatives, unreported CDS positions, ratings shopping, failures (with government approval) to mark assets to market[25] and the list goes on. The revelation of financial fraud amidst the financial fog produced the rush to liquidity that eventuated in the downfall of so many high profile banks. Had there been no malfeasance there likely would have been no crisis.

If, as modeled here, the revelation of "good" bankers gone bad rather than of bad things happening to good banks is the source of financial crisis, dramatically expanding the government's role in verification and disclosure of assets may be the answer. This prescription is the polar opposite of those who tout opacity as essential for maintaining liquidity of bank liabilities. The difference in perspective arises in the case of counterfeit currency. If no one knows that some currency is counterfeit, both bad and good currency will be sources of liquidity. Disclosing the counterfeits can produce a run on, actually, a run away from the currency. Is society better off suppressing news of the counterfeits and letting them continue to circulate? Doing so maintains liquidity, but permits ongoing theft and risks financial panic if news leaks out. The answer, in practice, is no. Counterfeiters are disclosed and prosecuted as a public service.

No one would expect private citizens to actively investigate counterfeiters. But when it

[25] See Andolfatto and Martin (2013)

comes to banking, many have faulted investors, the vast majority of whom are quite small, for failing to keep track of their banks' behavior. Indeed, the central premise of Dodd-Frank – that public funds will no longer be used to bail out private banks – appears predicated on the assumption that investors, knowing they are at risk, will better monitor their financial institutions. This flies in the face of the free riding problem. Just as government is needed to monitor, uncover, and disclose counterfeiting, our model suggests that government is needed to verify and disclose, in real time, all bank assets and liabilities.

References

Acharya, V., Gale, D., Yorulmazer, T., 2011. Rollover risk and market freezes. The Journal of Finance 66 (4), 1177–1209.

Andolfatto, D., 2010. Essential interest-bearing money. Journal of Economic theory 145 (4), 1495–1507.

Andolfatto, D., Martin, F. M., 2013. Information disclosure and exchange media. Review of Economic Dynamics 16 (3), 527–539.

Bolton, P., Freixas, X., Shapiro, J., 2012. The credit ratings game. The Journal of Finance 67 (1), 85–111.

Brealey, R., Leland, H. E., Pyle, D. H., 1977. Informational asymmetries, financial structure, and financial intermediation. The Journal of Finance 32 (2), 371–387.

Bryant, J., 1980. A model of reserves, bank runs, and deposit insurance. Journal of Banking & Finance 4 (4), 335–344.

Calomiris, C. W., Flandreau, M., Laeven, L., 2016. Political foundations of the lender of last resort: A global historical narrative. Journal of Financial Intermediation.

Calomiris, C. W., Haber, S. H., 2014. Fragile by design: The political origins of banking crises and scarce credit. Princeton University Press.

Chamley, C., Kotlikoff, L. J., Polemarchakis, H., 2012. Limited-purpose banking—moving from "trust me" to "show me" banking. The American Economic Review 102 (3), 113–119.

Covitz, D., Liang, N., Suarez, G. A., 2013. The evolution of a financial crisis: Collapse of the asset-backed commercial paper market. The Journal of Finance 68 (3), 815–848.

Dang, T. V., Gorton, G., Holmström, B., Ordoñez, G., 2017. Banks as secret keepers. American Economic Review 107 (4), 1005–29.

Demirgüç-Kunt, A., Detragiache, E., 1997. The determinants of banking crises-evidence from developing and developed countries. Vol. 106. World Bank Publications.

Demirgüç-Kunt, A., Detragiache, E., 1999. Financial liberalization and financial fragility. The World Bank.

Demirgüç-Kunt, A., Detragiache, E., 2002. Does deposit insurance increase banking system stability? an empirical investigation. Journal of Monetary Economics 49 (7), 1373–1406.

Diamond, D. W., 1984. Financial Intermediation and Delegated Monitoring. Review of Economic Studies 51 (3), 393–414.

Diamond, D. W., Dybvig, P. H., 1983. Bank Runs, Deposit Insurance, and Liquidity. Journal of Political Economy 91 (3), 401–19.

Doherty, N. A., Kartasheva, A. V., Phillips, R. D., 2009. Competition among rating agencies and information disclosure. Wharton School, University of Pennsylvania.

Financial Crisis Inquiry Commission, 2011. Final report of the National Commission on the Causes of the Financial and Economic Crisis in the United States. Public Affairs.

Gertler, M., Karadi, P., 2011. A model of unconventional monetary policy. Journal of Monetary Economics 58 (1), 17–34.

Gertler, M., Kiyotaki, N., 2010. Financial intermediation and credit policy in business cycle analysis. Handbook of monetary economics 3 (3), 547–599.

Gertler, M., Kiyotaki, N., Queralto, A., 2012. Financial crises, bank risk exposure and government financial policy. Journal of Monetary Economics 59 (S), S17–S34.

Gibbons, J. S., 1907. The panic of 1907. Moody's Magazine 4.

Goel, A. M., Thakor, A. V., 2015. Information reliability and welfare: A theory of coarse credit ratings. Journal of Financial Economics 115 (3), 541–557.

Goldstein, I., Pauzner, A., 2005. Demand–deposit contracts and the probability of bank runs. Journal of Finance 60 (3), 1293–1327.

Gorton, G., May 2009. Information, Liquidity, and the (Ongoing) Panic of 2007. American Economic Review 99 (2), 567–572.

Gorton, G., Ordonez, G., 2014. Collateral crises. American Economic Review 104 (2), 343–378.

Gorton, G., Pennacchi, G., 1990. Financial intermediaries and liquidity creation. Journal of Finance 45 (1), 49–71.

Hanson, S. G., Sunderam, A., 2013. Are there too many safe securities? securitization and the incentives for information production. Journal of Financial Economics 108 (3), 565–584.

He, Z., Xiong, W., 2012. Dynamic debt runs. Review of Financial Studies 25 (6), 1799–1843.

Hirshleifer, J., 1971. The private and social value of information and the reward to inventive activity. American Economic Review 61 (4), 561–574.

Holmström, B., Tirole, J., 1998. Private and public supply of liquidity. Journal of Political Economy 106 (1), 1–40.

Jacklin, C. J., 1983. Information and the choice between deposit and equity contracts. manuscript, Graduate School of Business, Stanford University.

Jacklin, C. J., 1986. Banks and Risk Sharing: Instabilities and Coordination. Graduate School of Business, University of Chicago.

Jacklin, C. J., 1989. Demand equity and deposit insurance. Graduate School of Business, Stanford University.

Jacklin, C. J., Bhattacharya, S., 1988. Distinguishing panics and information-based bank runs: Welfare and policy implications. Journal of Political Economy 96 (3), 568–592.

Johnson, S., Kwak, J., 2010. Capital requirements are not enough. Economix blog. New York Times, April 1, p.107, https://economix.blogs.nytimes.com/2010/04/01/capital-requirements-are-not-enough/ [Online; accessed 9-July-2018].

Kotlikoff, L. J., 2010. Jimmy Stewart is dead: Ending the world's ongoing financial plague with limited purpose banking. John Wiley & Sons.

Pagano, M., Volpin, P., 2012. Securitization, transparency, and liquidity. Review of Financial Studies 25 (8), 2417–2453.

Pecora Commission, 1934. Stock Exchange Practices. Public Affairs.

Rochet, J.-C., Vives, X., 2004. Coordination failures and the lender of last resort: was bagehot right after all? Journal of the European Economic Association 2 (6), 1116–1147.

Sangiorgi, F., Sokobin, J., S. Spatt, C., 03 2009. Credit-rating shopping selection and the equilibrium structure of ratings. SSRN Electronic Journal.

Skreta, V., Veldkamp, L., 2009. Ratings shopping and asset complexity: A theory of ratings inflation. Journal of Monetary Economics 56 (5), 678–695.

Stiglitz, J. E., Weiss, A., 1981. Credit rationing in markets with imperfect information. American Economic Review 71 (3), 393–410.

Townsend, R., 1979. Optimal contracts and competitive markets with costly state verification. Journal of Economic Theory 21 (2), 265–293.

Warwick Commission, 2009. On international financial reform: in praise of unlevel playing fields. Tech. rep.

Appendices

A. Deriving Sectoral Returns

Recall that returns to investment in both sectors are given by

$$\begin{aligned} r_{f,t+1} =& \theta Z_f K_{f,t+1}^{\theta-1} L_{f,t+1}^{1-\theta}, \\ r_{b,t+1} =& (1-m_{s,t+1})\theta Z_b K_{b,t+1}^{\theta-1} L_{b,t+1}^{1-\theta}, \end{aligned}$$

and capital allocation is

$$\begin{aligned} K_{b,t+1} =& \alpha_{s,t} A_{t+1}, \\ K_{f,t+1} =& (1-\alpha_{s,t}) A_{t+1}. \end{aligned}$$

Both the malfeasance share at $t+1$ and optimal allocation to banking, $\alpha_{s,t}$, depend on the malfeasance share at t, denoted by subscript $s \in \{L, H\}$. Let superscript $S \in \{L, H\}$ denote the realization at $t+1$ of the mean malfeasance share, $\bar{m}_s \in \{\bar{m}_L, \bar{m}_H\}$. After substituting for capital, returns in each sector conditional on the state realized at $t+1$ are

$$r_{f,t+1}^S = \theta Z_f (1-\alpha_{s,t})^{\theta-1} (A_{t+1})^{\theta-1} (L_{f,t+1}^S)^{1-\theta}, \tag{40}$$

$$r_{b,t+1}^S = \theta (1-m_{s,t+1}) Z_b (\alpha_{s,t})^{\theta-1} (A_{t+1})^{\theta-1} (L_{b,t+1}^S)^{1-\theta}. \tag{41}$$

Labor supply in each industry, conditional on the realized state of the world, s, is

$$L_{f,t+1}^S = \frac{Z_f^{\frac{1}{\theta}} (1-\alpha_{s,t})}{Z_{t+1}^S}, \tag{42}$$

$$L_{b,t+1}^S = \frac{\left[(1-m_{s,t+1}) Z_b\right]^{\frac{1}{\theta}} \alpha_{s,t}}{Z_{t+1}^S}. \tag{43}$$

where we define the average productivity in the two sectors conditional on the realization of state S at t+1 as

$$Z_{t+1}^S = (1-\alpha_{s,t}) Z_f^{\frac{1}{\theta}} + \alpha_{s,t} \left[(1-\bar{m}_S - \epsilon_{t+1}) Z_b\right]^{\frac{1}{\theta}}. \tag{44}$$

Substituting eq. (44) into conditional returns, eqs. (40) and (41) yields

$$r^S_{f,t+1}(\alpha_{s,t}, \epsilon_{t+1}) = \theta \left[A_{t+1} Z^S_{t+1}\right]^{\theta-1} Z_f^{\frac{1}{\theta}}, \tag{45}$$

$$r^S_{b,t+1}(\alpha_{s,t}, \epsilon_{t+1}) = \theta \left[A_{t+1} Z^S_{t+1}\right]^{\theta-1} \left[(1 - \bar{m}_S - \epsilon_{t+1}) Z_b\right]^{\frac{1}{\theta}}. \tag{46}$$

These returns depend on the malfeasance share - both its mean state $\bar{m}_S$ and ϵ_{t+1} - and on the *aggregate* allocation to banking, $\alpha_{s,t}$.

B. Solving for Allocation Decision with Private Monitoring.

The following steps were used to solve for allocation decisions with private monitoring.

1. Informed individuals begin by guessing the uninformed optimal allocation, $\alpha_{U,s,t}$.
2. Use eqs. (30) and (31) to calculate optimal informed allocation, $\alpha_{I,s,t}$, for *any* realization of ϵ_{t+1} in the support $[a, b]$. That is, we construct $\alpha_{I,s,t}(\epsilon_{t+1})$.
3. Use this function to compute aggregate allocation $\bar{\alpha}_{s,t}(\epsilon_{t+1})$, given by eq. (30).
4. The first order condition, eq. (32), gives optimal uninformed allocation, $\alpha_{U,s,t}$.
5. Iterate until the initial guess for optimal uninformed allocation matches the solution, yielding $\alpha_{U,s,t}$ and $\alpha_{I,s,t}(\epsilon_{t+1})$.

Repeating steps 1-5 over a range of values for n_t, and substituting into eq. (33) allows us to find the optimal n_t to maximize expected utility.

Tables and Figures

Parameter	Description	Value
β	Time preference	0.5
θ	Capital share	0.3
Z_f	Farm productivity	10
Z_b	Bank productivity	16
$\bar{m}_H$	Mean malfeasance share in high malfeasance state	0.50
$\bar{m}_L$	Mean malfeasance share in low malfeasance state	0.22
q_H	Probability of high malfeasance at $t+1$, given high malfeasance at t	0.6
q_L	Probability of high malfeasance at $t+1$, given low malfeasance at t	0.4
a	Maximum reduction in malfeasance	-0.1
b	Maximum increase in malfeasance	0.1

Table 1: Parameter Values

Variable		Mean	Std.	Min	Max
Output	Y	23.12	4.25	16.46	29.86
Non-Stolen Output		18.08	3.19	12.38	25.95
Consumption when Young	C_y	6.33	1.11	4.33	9.08
Consumption when Old	C_o	11.75	1.78	8.85	16.51
Annualized Bank Returns		2.04	0.77	0.72	4.01
Annualized Farm Returns		2.01	0.58	0.94	3.52
Allocation to Banking	α	0.57	0.29	0.28	0.87
Bank Capital	K_b	3.88	2.42	1.20	7.93
Farm Capital	K_f	2.45	1.47	0.84	4.60
Savings	A	6.33	1.12	4.33	9.08
Bank Labor	L_b	0.56	0.32	0.08	0.95
Wages	w	12.66	2.23	8.67	18.16

Table 2: Average Values in Model's Stochastic Steady State

Variable		Mean	Std.	Min	Max
Output	Y	24.90	3.81	18.64	29.86
Non-Stolen Output		20.62	2.48	16.17	25.95
Consumption when Young	C_y	7.22	0.87	5.66	9.08
Consumption when Old	C_o	12.74	1.79	9.24	16.51
Annualized Bank Returns		2.68	0.51	1.88	4.01
Annualized Farm Returns		1.53	0.34	0.94	2.3
Allocation to Banking	α	0.86	0.01	0.85	0.87
Bank Capital	K_b	4.41	2.39	1.21	7.85
Farm Capital	K_f	2.14	1.44	0.84	4.60
Savings	A	6.55	1.12	4.39	8.99
Bank Labor	L_b	0.74	0.24	0.34	0.95
Wages	w	14.44	1.74	11.32	18.16

Table 3: Average Values when Mean Malfeasance Share is Low at t

Variable		Mean	Std.	Min	Max
Output	Y	21.33	3.92	16.46	28.79
Non-Stolen Output		15.52	1.04	12.38	18.33
Consumption when Young	C_y	5.43	0.37	4.33	6.41
Consumption when Old	C_o	10.76	1.08	8.85	14.00
Annualized Bank Returns		1.40	0.34	0.72	2.14
Annualized Farm Returns		2.48	0.30	1.84	3.52
Allocation to Banking	α	0.28	0.00	0.28	0.28
Bank Capital	K_b	3.34	2.34	1.20	7.93
Farm Capital	K_f	2.76	1.44	0.85	4.58
Savings	A	6.10	1.06	4.33	9.08
Bank Labor	L_b	0.38	0.28	0.08	0.85
Wages	w	10.87	0.73	8.67	12.83

Table 4: Average Values when Mean Malfeasance Share is High at t

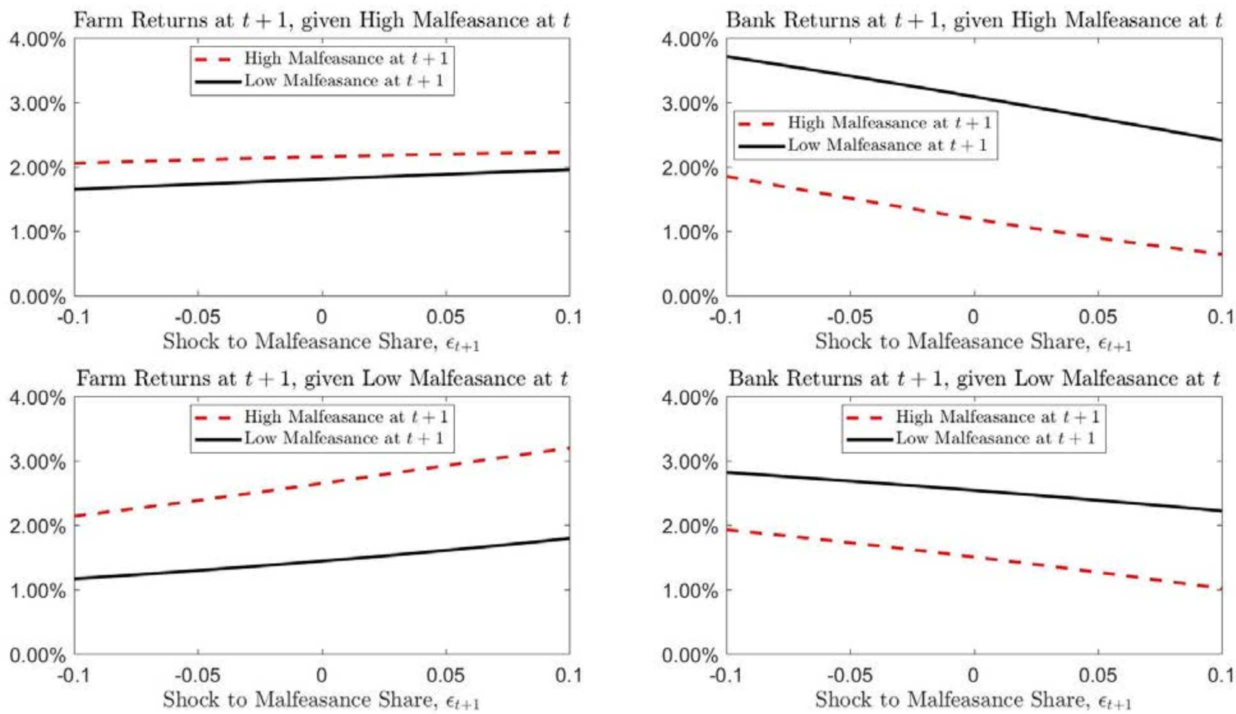

Figure 1: Annualized Returns at $t+1$ Conditional on the Shocks to the Mean Malfeasance Share at $t+1$

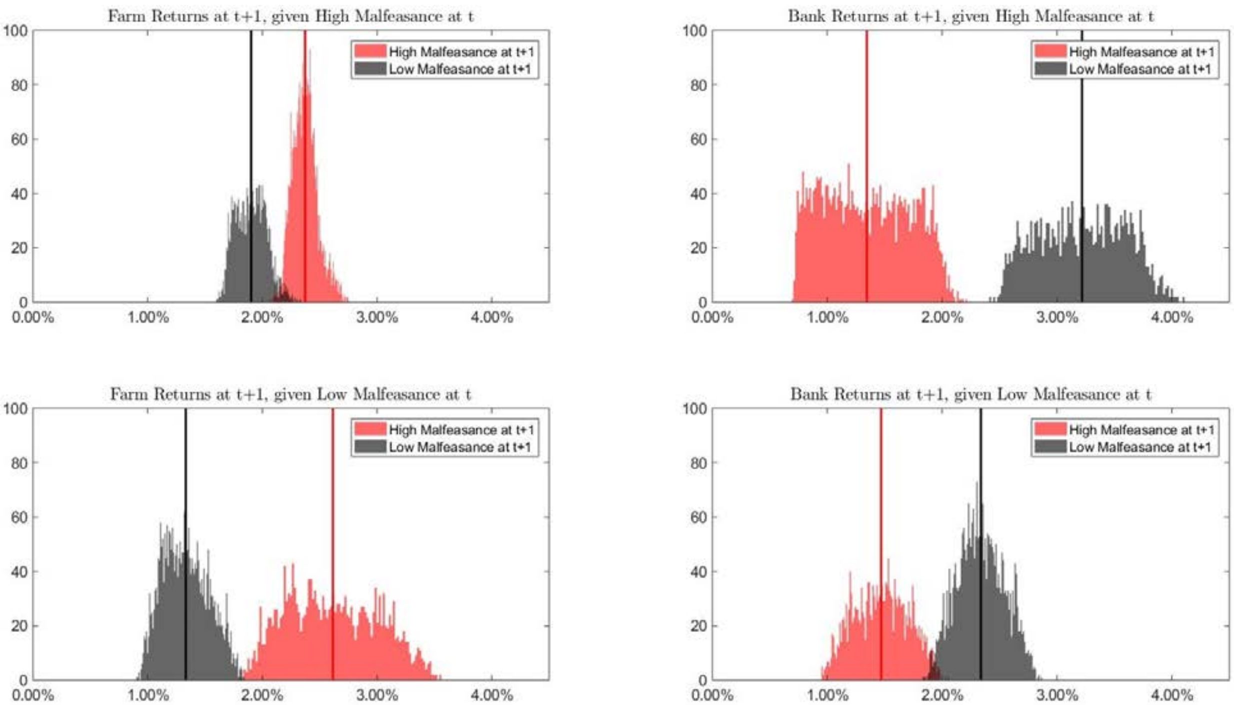

Figure 2: Histograms of Realized Returns conditional on Mean Malfeasance State, $\bar{m}_s$

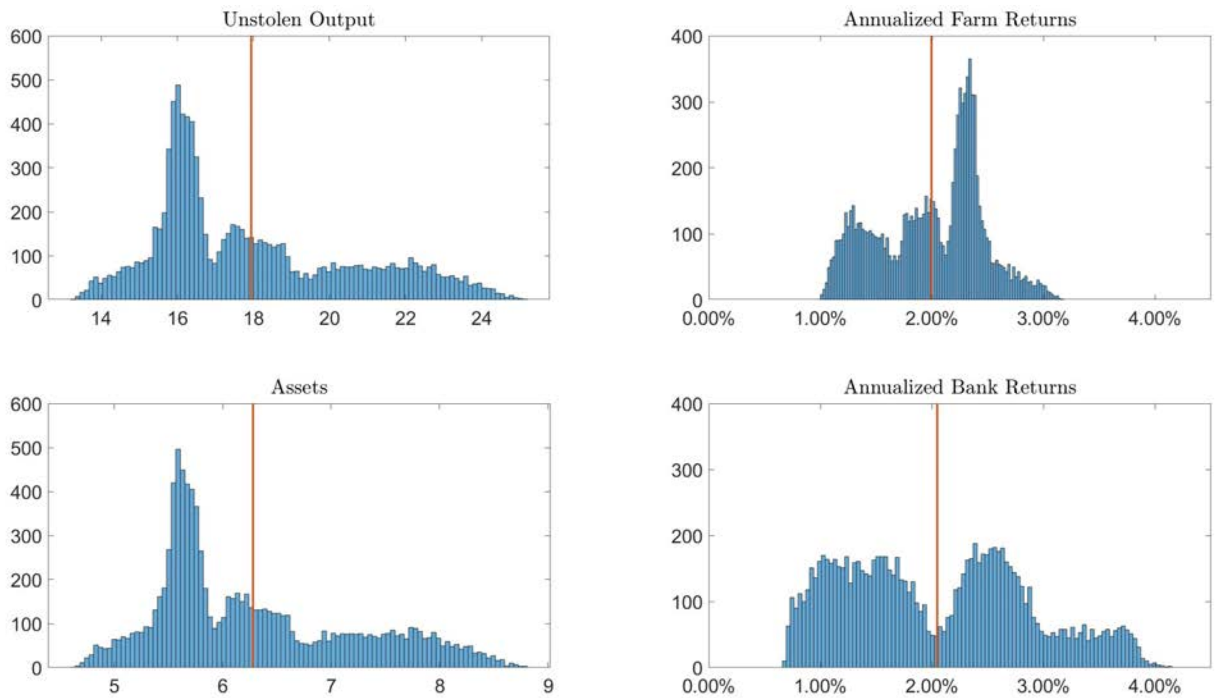

Figure 3: Histograms of Assets, Non-Stolen Output and Returns to Banking and Farming

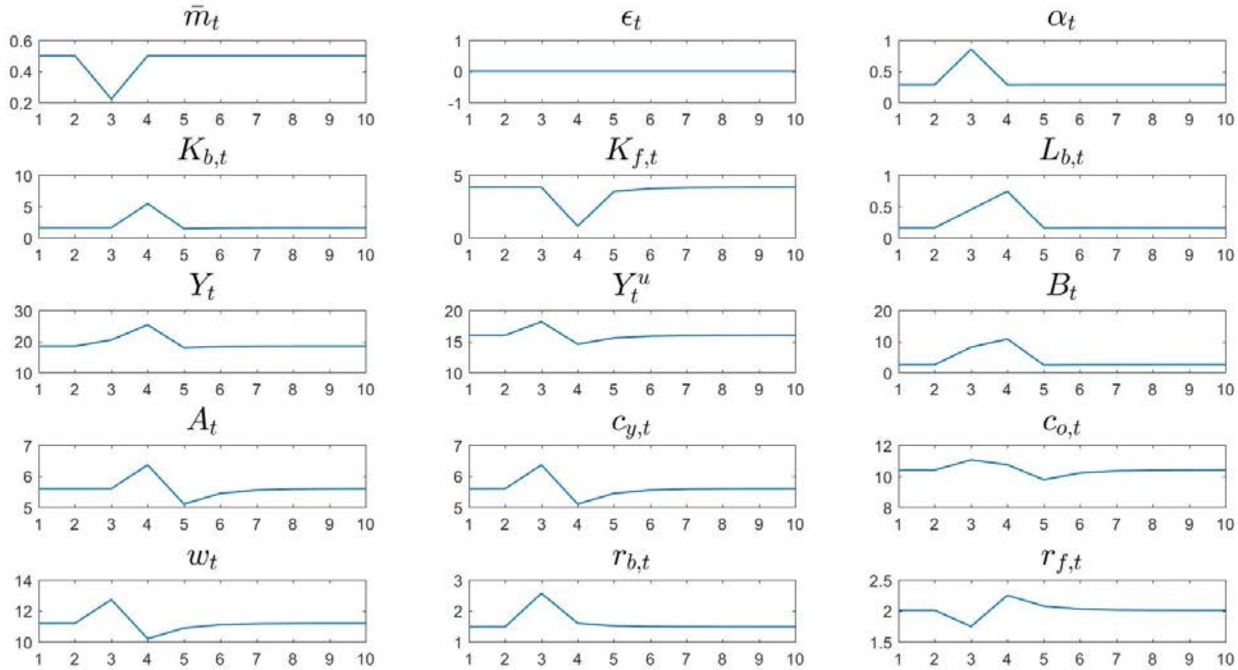

Figure 4: The Economy's Transition – High to Low to High Mean Malfeasance

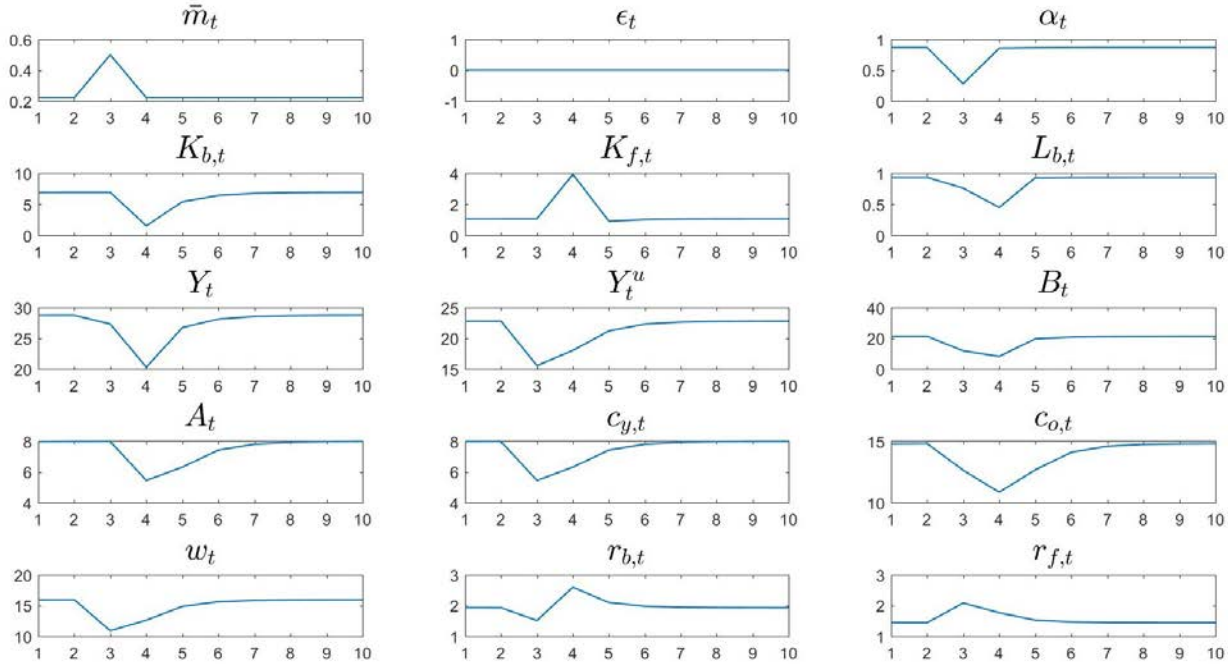

Figure 5: The Economy's Transition – Low to High to Low Mean Malfeasance

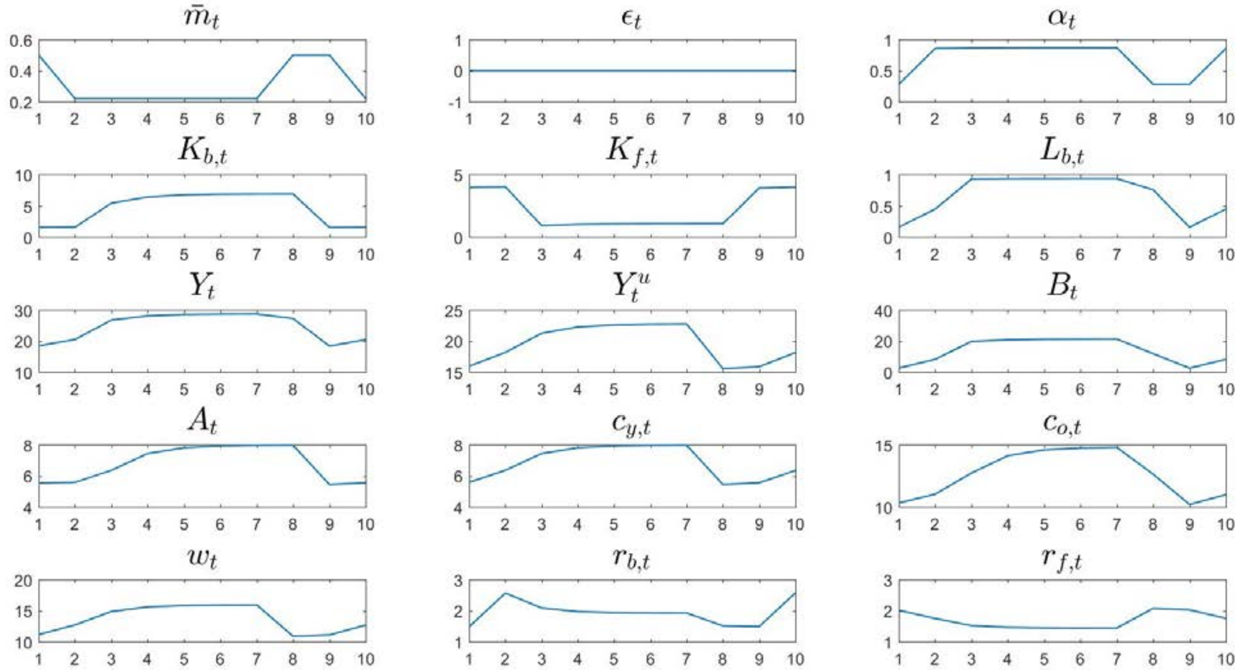

Figure 6: Transition to High Mean Malfeasance after Extended Low Mean Malfeasance

t	1	2	3	4	5	6	7	8	9	10
ϵ	-0.078	-0.050	0.093	0.026	0.063	0.013	0.027	0.062	0.085	0.083

Table 5: Path of ϵ_t for First Ten Periods of Transition

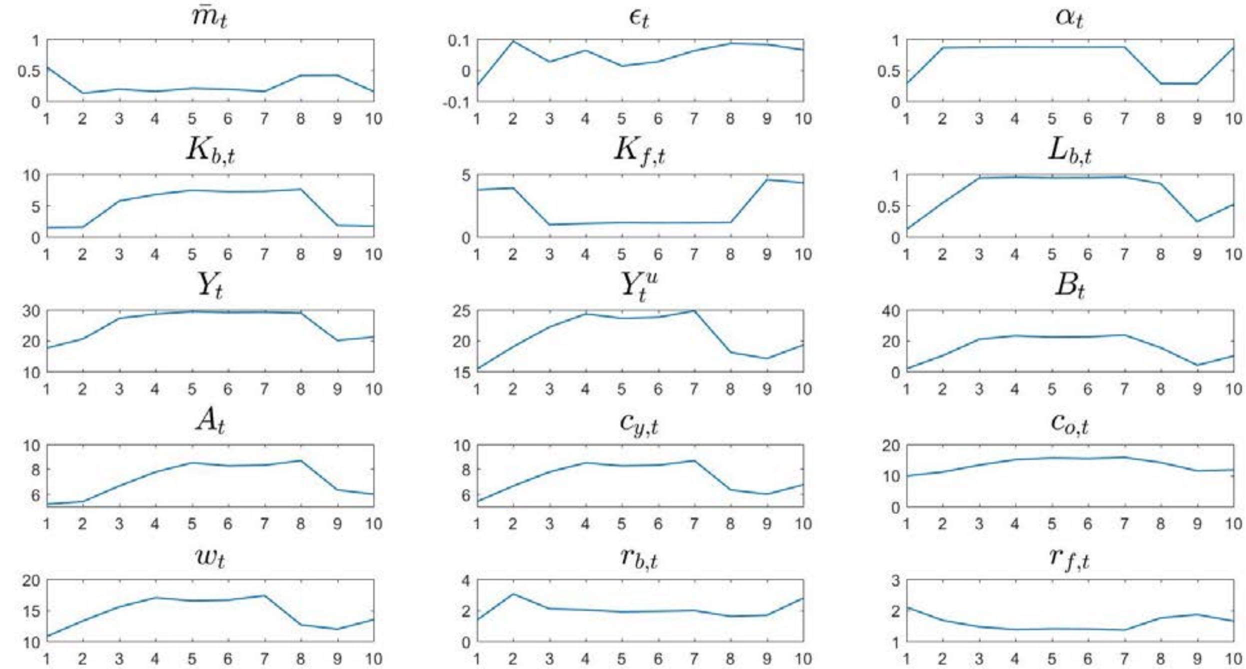

Figure 7: Baseline Transition

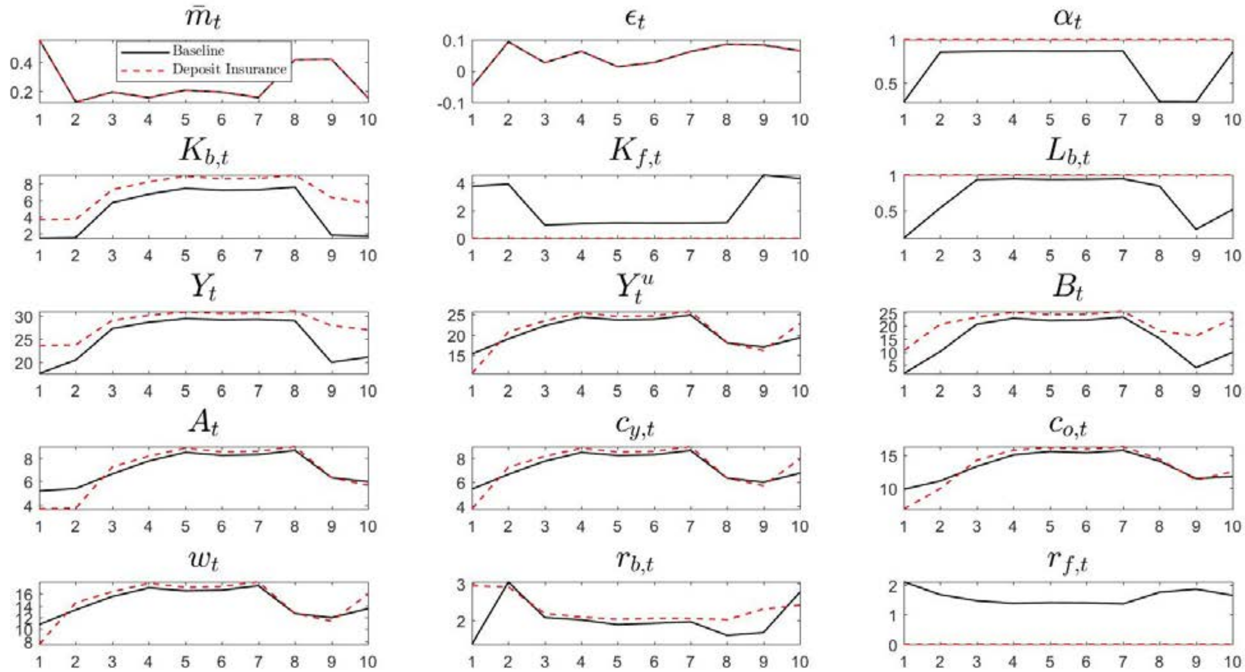

Figure 8: Economy's Transition With and Without Deposit Insurance.

Variable		Baseline Mean	Baseline Std.	Insurance Mean	Insurance Std.	% Change Mean	% Change Std.
Output	Y	23.12	4.25	27.44	2.26	$+19$	-47
Non-Stolen Output		18.08	3.19	17.71	4.75	-2	$+49$
Consumption when Young	C_y	6.33	1.11	6.20	1.66	-2	$+49$
Consumption when Old	C_o	11.75	1.78	11.51	2.66	-2	$+49$
Annualized Bank Returns		2.04	0.77	2.94	0.39	$+44$	-50
Annualized Farm Returns		2.01	0.58	-	-	-100	-100
Allocation to Banking	α	0.57	0.29	1.00	0.00	$+75$	-100
Bank Capital	K_b	3.88	2.42	6.19	1.66	$+60$	-31
Farm Capital	K_f	2.45	1.47	0.00	0.00	-100	-100
Savings	A	6.33	1.12	6.19	1.66	-2	$+49$
Bank Labor	L_b	0.56	0.32	1.00	0.00	$+77$	-100
Wages	w	12.66	2.23	12.40	3.32	-2	$+49$

Table 6: Average Values with Deposit Insurance

Average allocation to banking	Informed of increased stealing $\epsilon_{t+1} > 0$	No information on ϵ_{t+1}	Informed of decreased stealing $\epsilon_{t+1} < 0$
$\alpha_{H,t}$	–	0.28	–
$\alpha_{L,t}$	0.45	1.00	1.00

Table 7: Effect of Information on Allocation to Banking.

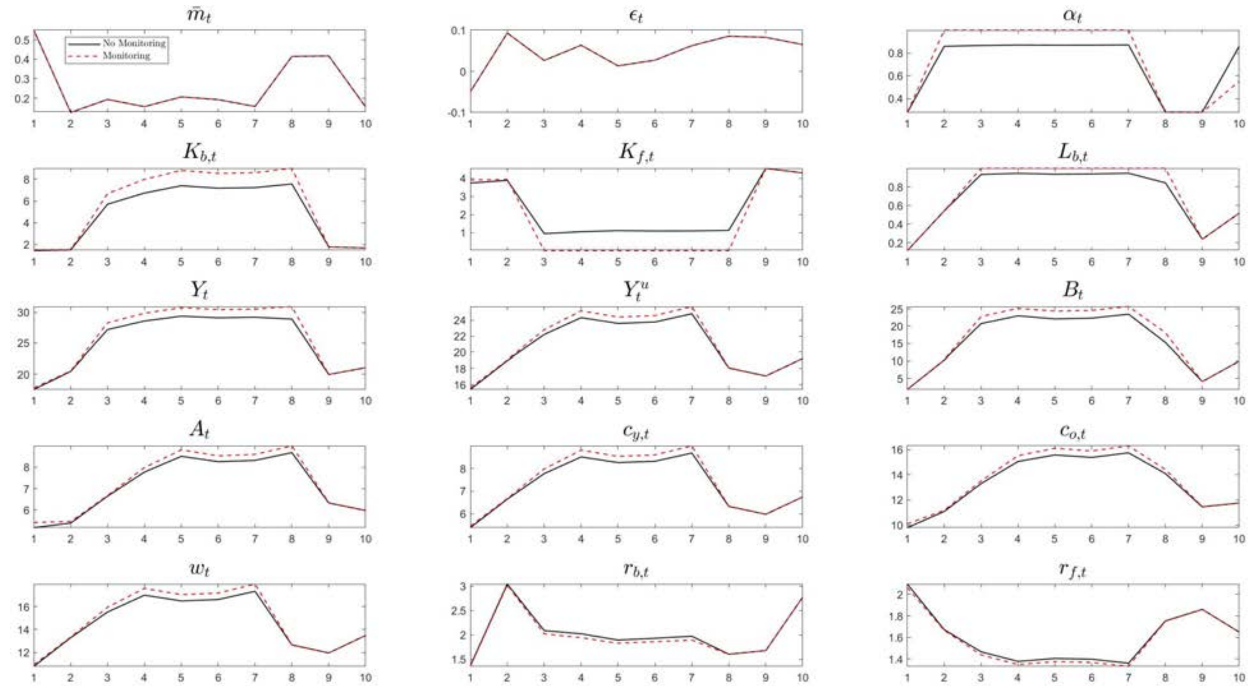

Figure 9: An Example Transition With and Without Monitoring

Variable		Baseline Mean	Baseline Std.	Monitoring Mean	Monitoring Std.	% Change Mean	% Change Std.
Output	Y	23.12	4.25	23.16	4.56	0	+7
Unstolen Output		18.08	3.19	18.31	3.24	+1	+2
Consumption when Young	C_y	6.33	1.11	6.41	1.13	+1	+2
Consumption when Old	C_o	11.75	1.78	11.9	1.83	+1	+3
Annualized Bank Returns		2.04	0.77	2.01	0.78	−2	+1
Annualized Farm Returns		2.01	0.58	1.96	0.53	−2	−7
Allocation to Banking	α	0.57	0.29	0.57	0.32	0	+10
Bank Capital	K_b	3.88	2.42	3.93	2.63	+1	+9
Farm Capital	K_f	2.45	1.47	2.48	1.77	+1	+20
Savings	A	6.33	1.12	6.41	1.14	1	+2
Bank Labor	L_b	0.56	0.32	0.56	0.35	−1	+10
Wages	w	12.66	2.23	12.82	2.27	+1	+2

Table 8: Average Values with Monitoring

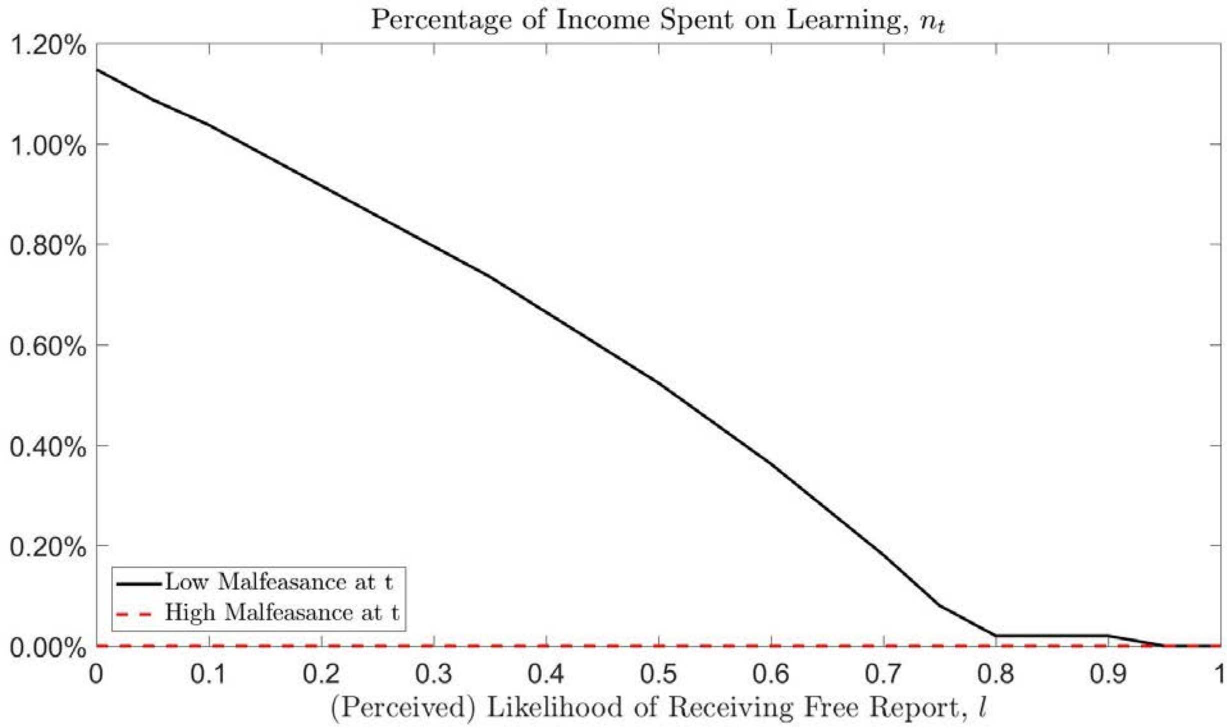

Figure 10: The Effect of Free Reports on Monitoring Expenditure

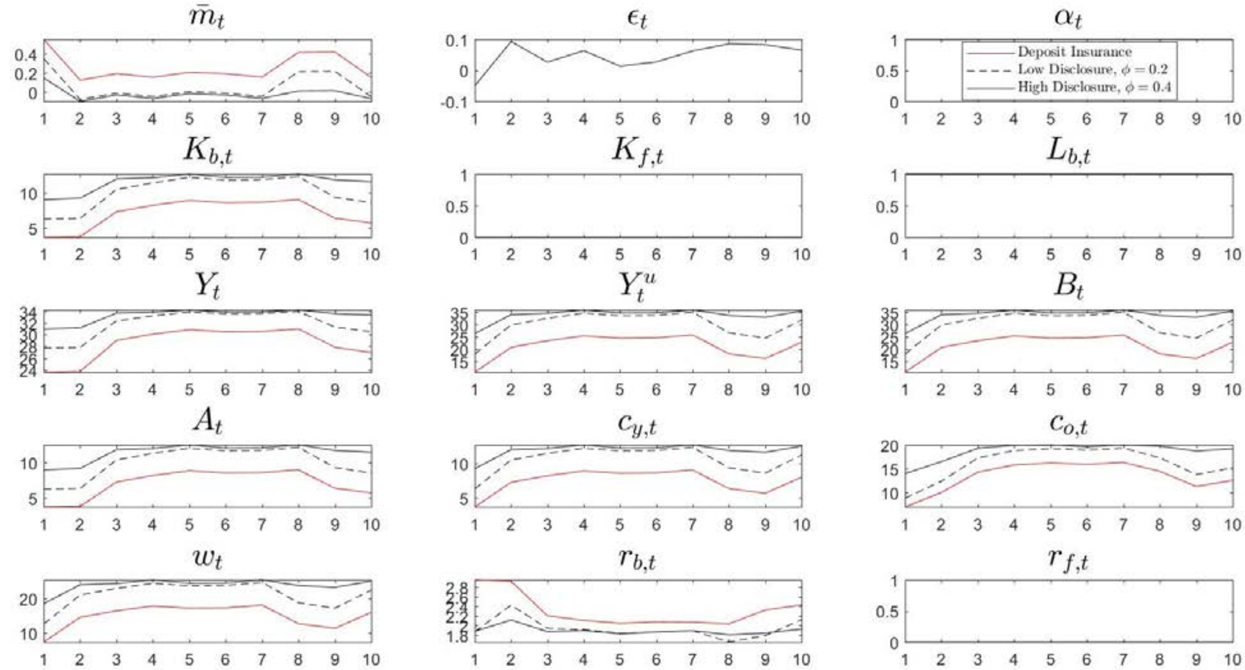

Figure 11: Economies with Low and High Disclosure and Deposit Insurance.

Variable		Baseline Mean	Baseline Std.	Low Disclosure Mean	Low Disclosure Std.	% Change Mean	% Change Std.
Output	Y	23.12	4.25	30.94	1.92	$+34$	-55
Non-Stolen Output		18.08	3.19	26.14	5.33	$+45$	$+67$
Consumption when Young	C_y	6.33	1.11	9.15	1.87	$+45$	$+67$
Consumption when Old	C_o	11.75	1.78	14.06	2.99	$+20$	$+68$
Annualized Bank Returns		2.04	0.77	2.11	0.33	$+3$	-57
Annualized Farm Returns		2.01	0.58	-	-	-100	-100
Allocation to Banking	α	0.57	0.29	1.00	0.00	$+75$	-100
Bank Capital	K_b	3.88	2.42	9.14	1.87	$+136$	-23
Farm Capital	K_f	2.45	1.47	0.00	0.00	-100	-100
Savings	A	6.33	1.12	9.14	1.87	$+44$	$+67$
Bank Labor	L_b	0.56	0.32	1.00	0.00	$+77$	-100
Wages	w	12.66	2.23	18.30	3.73	$+45$	$+67$

Table 9: Average Values with Low levels of Disclosure, $\phi = 0.2$

Variable		Baseline Mean	Baseline Std.	High Disclosure Mean	High Disclosure Std.	% Change Mean	% Change Std.
Output	Y	23.12	4.25	32.75	0.88	+42	-79
Non-Stolen Output		18.08	3.19	31.20	2.79	+73	-12
Consumption when Young	C_y	6.33	1.11	10.92	0.98	+73	-12
Consumption when Old	C_o	11.75	1.78	17.35	1.54	+48	-14
Annualized Bank Returns		2.04	0.77	2.09	0.15	+2	-81
Annualized Farm Returns		2.01	0.58	-	-	-100	-100
Allocation to Banking	α	0.57	0.29	1.00	0.00	+75	-100
Bank Capital	K_b	3.88	2.42	10.92	0.98	+181	-60
Farm Capital	K_f	2.45	1.47	0.00	0.00	-100	-100
Savings	A	6.33	1.12	10.92	0.98	+73	-12
Bank Labor	L_b	0.56	0.32	1.00	0.00	+77	-100
Wages	w	12.66	2.23	21.84	1.96	+73	-12

Table 10: Average values with High Levels of Disclosure, $\phi = 0.4$

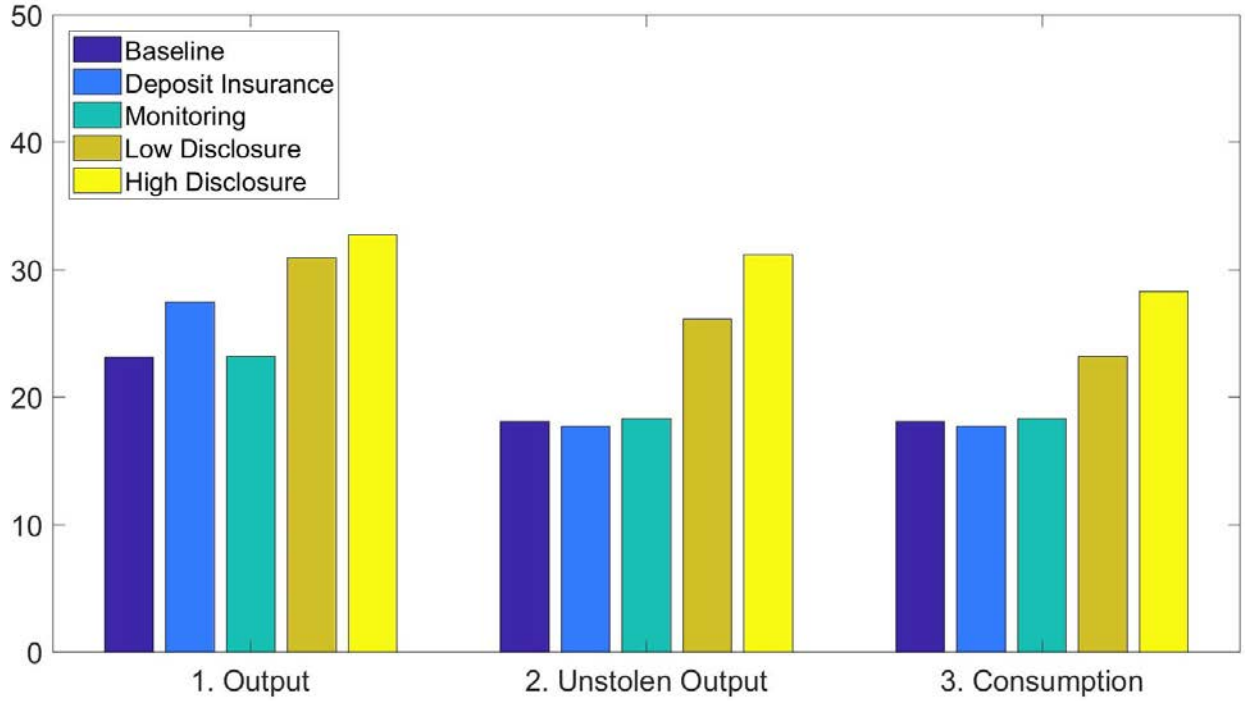

Figure 12: Comparing Means of Aggregates in Different Regimes.

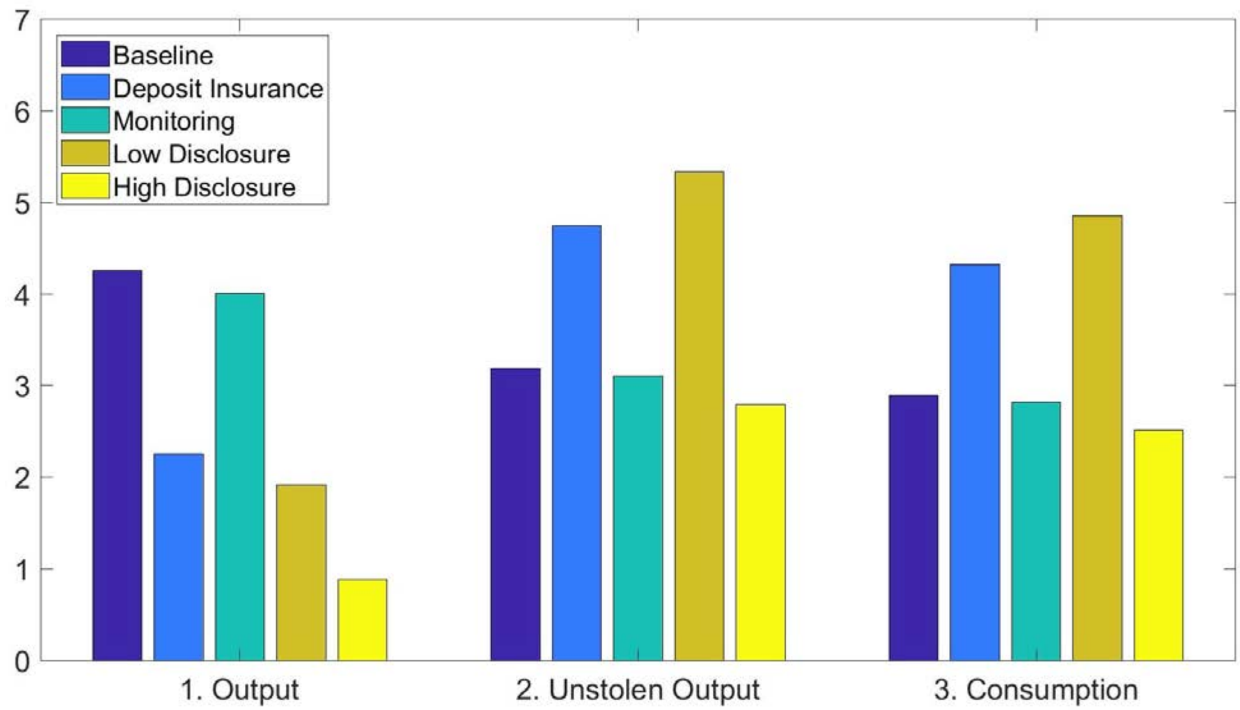

Figure 13: Comparing Variability of Aggregates in Different Regimes.

Regime	Percentage Compensating Differential
Deposit insurance	-4.1%
Monitoring	1.2%
Low disclosure, $\phi = 0.2$	23.3%
High disclosure, $\phi = 0.4$	37.9%

Table 11: Percentage Compensating Variations